LUISS Guido Carli University

Department of Business & Management

Role of Cognitive Processes, Emotional Regulation, Attention, and Intrinsic Motives in explaining the underlying Mechanism and Dynamics of Value Premium: A Mispricing Perspective

Doctoral Thesis

PhD in Management

XXXII Cycle

PhD candidate	**Supervisor**
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To my mother, brother, and dearest friend

Acknowledgments

First and above all, I would like to express my gratefulness to the ALMIGHTY ALLAH for providing me this opportunity, determination, capability, and courage to proceed successfully. I cannot even imagine the completion of my PhD thesis without the blessing of ALMIGHTY ALLAH.

I wish to express my deepest gratitude and sincere appreciation to all the people that have contributed to the completion of this thesis. Firstly, I would like to thank my supervisor, Prof Raffaele Oriani for his support, guidance, constructive comments, and critical inputs.

I would like to thank Prof Matteo De Angelis for guiding me in the fifth chapter. Furthermore, I would like to thank Prof Daniel Richards for his valuable comments and constructive suggestions that improved the quality of chapter two.

I would also like to thank friends of mine, Miss. Saweera Shahyar, Miss. Samia Cornelius and Mr. Manuel Romagnoli for their friendship and support during four years of PhD. In addition, I would like to thank all my PhD colleagues at LUISS for their help and support.

Last and most important, I would like to thank my mother (Mrs. Ronaq Ahmad), father (Mr. Fazal Ahmad) and brother (Mr. Jawad Ahmad) for their endless support and encouragement they provided me, not only during my PhD studies but during my whole life. This thesis is dedicated to them. Without them, I would not have succeeded anything. I sincerely acknowledge the moral and financial support provided by my uncle (Dr. Fazal ur Rehman) and aunt (Mrs. Bilqus Rehman) during my bachelor's and master's degrees.

Thank you.

Table of Contents

Chapter 1

Introduction

Table of Contents

Introduction

1.1. Background

The value investing is the selection of undervalued stocks based on high value-to-market ratios like book-to-market price ratio (BM), cashflows-to-market price ratio (CM), earnings-to-market price ratio (EM), sales-to-market price ratio (SM), and dividend yield (DM)[1]. The value investors do not completely neglect firms' current fundamental strength and growth prospects. They refer to investment as "buying fractional interest in the business" (Klarman & Zweig, 2010). Consequently, they avoid buying stocks of undervalued distressed or failing businesses solely based on standalone value-to-market ratios, termed as value trap (Penman & Reggiani, 2018). They spend considerable time and effort to understand the company's business, current fundamental position, short-run and long-run competitive standing, and quality of the company's management. Based on the systematic valuation process, investors estimate business intrinsic value along with business current market valuation. To protect themselves from the risk of wrong valuation and subsequent loss in business value, investors demand a certain percentage of safety, termed as margin-of-safety. This systematic process infers from the Graham and Dodd investing approach that defines investment as a "thorough analysis" that promises "safety of principal" with a "satisfactory return" [2] (Kok, Ribando & Sloan, 2017). While growth investing is the selection of market-driven high attention overvalued stocks based on low value-to-market ratios. The growth investors are primarily interested in the continuation of firms' sales, earnings, and cashflows growth. They invest in firms with potential growth prospects and avoid a thorough fundamental analysis of firms' current fundamental strength.

The popularity of value investing is attributed to two main reasons. First, literature in finance supports the existence of superiors returns to value investing in the international market across different periods (e.g. Fama & French, 2012). Evidence highlights the tendency of value stocks to outperform growth stocks, termed as value premium (e.g. Fama & French, 1992, 1995). Second, the persistence of value-growth effect provides value investors an opportunity to engage in thorough analysis and identify deviations between market-implied expectation errors (proxied

[1] See Pätäri and Leivo (2017) for detailed literature review on value premium.

[2] Graham and Dodd (1934) recommended three steps to identify value stocks. The first step is the identification of inconsistencies between market price and intrinsic value, secondly, calculation of intrinsic value based on future expected earnings, and finally, intelligent calculation of future expected earning by considering both quantitative and qualitative information associated with stock.

by book-to-market ratio) and business fundamental strength (proxied by Piotraoski (2000) F-score) to generate superior returns (Piotroski & So, 2012). This helps value investors to separate fundamentally strong undervalued firms (or expected winners) from fundamentally weak overvalued firms (or expected losers) (Piotroski, 2000).

There is an ongoing debate on the predictors of the value-growth effect, attributed to both market efficiency and market inefficiency (Chan & Lakonishok, 2004). The advocate of market efficiency supports risk-based compensation explanation that considers superior returns to value-growth strategy as compensation for bearing additional market risks to value firms (e.g. Fama & French, 1992, 1995). While others argue that the market is inefficient and superior return differences are due to investors' pessimistic or optimistic expectations manifested in market-implied stocks mispricing (e.g. Lakonishok, Shleifer & Vishny, 1994). Both explanations approve persistent and time-varying behavior of value-growth effect. But risk-based explanation mainly attempts to justify the causes and persistence of the value-growth effect while mispricing explanation helps to find true value opportunities through a detailed market valuation process (Chan & Lakonishok, 2004; Penman & Reggiani, 2018). It is relevant for investors, financial advisors, financial analysts, and fund managers to identify true value opportunities by using thorough investment analysis to maximize their wealth (Penman & Reggiani, 2018).

Consistent with risk-based explanation, Fama and French (1992) characterized high BM firms as financial distress and subsequent high return as compensation for bearing additional market risk. This evidence is supported by the negative effect of the BM ratio on stock returns and growth rate (Fama & French, 1995; Penman, 1996), and the positive effect of the BM ratio on leverage (Chen & Zhang, 1998; Fama & French, 1992). If the value premium is due to systematic risk than other risk factors may also affect value-growth return differences (Chui, Titman, Wei & Xie, 2012). Consistent with this view empirical evidence confirm high sensitivity of value premium to business risk (Zhang, 2005), investment risk (Merton & Perold, 1993), consumption risk (e.g. Yogo, 2006), displacement risk (e.g. Kogan, Papanikolaou & Stoffman, 2013), and aggregate economic conditions (e.g. Gulen, Xing & Zhang, 2011). Thus, suggesting that superior returns to value stocks may be compensation for additional distress risk.

However, the mispricing explanation argues that value premium is the consequence of investors' over extrapolation of firms' past fundamental strength and underreaction to the changes in value or growth firms' fundamental strength that results in market expectation errors. The value premium is the consequence of reversal in stock prices due to the correction in biased market expectation errors, rooted in value and growth firms' prior performance (Lakonishok et al., 1994). Two main conditions that induce price reversal are: when mispricing is too noisy to update investors' prior beliefs or investors asymmetric response towards market mispricing signals (Hwang & Rubesam, 2013). The higher value-growth return differences are attributed to the subsequent higher price reversal in growth stocks than value stocks. LaPorta, Lakonishok, Shleifer, and Vishny (1997) supported this view and show that high (or low) BM ratio firms experience positive (or negative) earnings surprises. Piotroski and So (2012) and Walkshäusl (2017) find that presence (or absence) of value-growth effect is associated with (or without) ex-ante market expectation errors manifested in pessimistic (or optimistic) expectations reflected in value (or growth) stocks prices. When ex-ante market expectations are congruent (or incongruent) with fundamental strength there are no expectation errors (or existent expectation errors). They further demonstrated that the value-growth effect and revision of market expectations are prominent in firms with higher ex-ante biased market expectation errors.

1.2. Gap, research problem and contribution

The literature on the value premium primarily approaches the value-growth effect to support either a risk-based explanation or a mispricing explanation. This dissertation does not aim to discuss the value-growth effect by either supporting or contradicting risk-based explanation or mispricing-based explanation. But attempts to use insight from a mispricing perspective to explore how individual-level differences in underlaying psychological mechanisms influence investor preferences towards value versus growth investing and subsequent reinvestment decisions (chapter 2 and chapter 5). This dissertation also seeks to investigate how underlying individual-level differences in information acquisition and attention captured in the form of aggregate investors' attention towards firm's fundamental information explain superior return differences to value-growth strategy (chapter 3 and chapter 4).

The investors spend considerable time and effort to understand and thoroughly evaluate business current fundamental strength and future performance. This requires investors to engage in cognitive-intensive information-processing to analyze a large set of information, but their biased information-processing might hold due to limited cognitive capacity and informational processing costs (i.e. time, technology, knowledge, and time constraints) (Barber & Odean, 2008; Da, Engelberg & Gao, 2011; Grossman & Stiglitz, 1980). Such investors might be motivated by market-driven (high sentiment) stocks to amplify the hedonic effect of positive returns than updating prior biased beliefs (Stambaugh, Yu & Yuan, 2012). While emotionally strong investors thoroughly analyze market alternatives to identify potential high return neglected stocks than buying attention-driven stocks (Chen, 2017; Fang & Peress, 2009; Sicherman, Loewenstein, Seppi & Utkus, 2015;). The susceptibility to exhibit emotion-driven biased market expectations or engage in cognitive-intensive information processing is altered by individuals' ability to regulate underlying emotions (Heilman, Crişan, Houser, Miclea & Miu, 2010; Panno, Lauriola & Figner, 2013). This implies that investors' reliance over emotional regulation strategy stimulates or prevent emotion-driven decisions by initiating either intuitive or cognitive decision-making process.

The economic behavior literature provides a significant impact of individual decision-making processes and emotion on the selection of economic choices (e.g. Phelps, Lempert & Sokol-Hessner, 2014). Studies conducted in the stock market setting report that emotions can have sometimes harmful and sometimes beneficial effects on decision-making. Individuals with stronger control over emotions achieve high decision performance and are less prone to biased decisions (e.g. Seo & Barrett, 2007). However, there is a lack of evidence on how investors level differences in the decision-making process and emotion regulation strategy effect the selection of value versus growth stocks. Thereby, chapter two investigate that: Is the investors' reliance on cognitive processes and emotional regulation strategy predict preferences towards the selection of value versus growth stocks. This contributes by identifying distinct decision-making processes and emotional regulation strategies as an underlying mechanism to explain investors' higher or lower preferences towards the selection of value versus growth stocks. It also confirms that cognition and emotion are inextricably intertwined and provide better insight to understand biased investor behavior and market anomalies (Taffler, 2018).

Investors are more (or less) attentive to information on familiar (or neglected) stocks and buy attention-driven stocks. This leads to temporary positive (or negative) price pressure on attention-driven (or neglected) stocks in the short-run and subsequent price reversal in the long-run, resulting in superior returns to neglected stocks (Barber & Odean, 2008; Fang & Peress, 2009). Recent studies document the short-run positive effect of investor attention on asset prices and subsequent price reversal in the long-run (Chen, 2017; Da et al., 2011; Li & Yu, 2012; Vozlyublennaia, 2014). There is scant evidence on how high (or low) aggregate market attention towards emotionally induced attention-driven stocks (or less visible neglected stocks) influences the dynamics of value premium. Chapter three attempts to fill this gap and examine how value premium varies across the level of investors' attention. This chapter extends the understanding of the influence of market participants' attention (towards firms' fundamental information) on the performance of the value-growth strategy. Findings also contribute by suggesting a profitable long-short investment strategy that generates superior returns to value-growth strategy conditioned as low investor attention.

The resource-based view defines intangibles as "strategic resources that enable an organization to create sustainable value but are not available to a large no of firms" (Kristandl & Bontis, 2007). Intangibles are firms' strategic resources that help create value, build sustainable competitive advantage, and drive firms' success and profitability (Asiaei & Jusoh, 2015; Clausen & Hirth, 2016). Firms having less focus on intangibles-intensity are poor investment due to weak growth prospects, while firms focusing more on intangibles-intensity are good investment due to strong growth prospects (Clausen & Hirth, 2016). Despite their importance as a critical strategic resource, investors neglect intangibles as valuation criteria to identify mispriced firms. Chapter four explore the role of investors' attention towards value-enhancing mispricing signals contained in firms' intangibles to generate superior returns than standard value-growth strategy. Chapter four investigates the impact of the interaction between high/low value-to-market ratios and high/low intangibles-intensity on the value premium. Chapter four contributes by confirming that intangibles signal mispricing and together value-to-market ratio and intangibles provide a stronger indicator of mispricing. The intangibles can be used by investors to identify potential high-performance undervalued stocks. Investors can use intangibles together with fundamental analysis heuristics like F-score to identify high-growth fundamentally strong undervalued firms (or low-growth fundamentally weak overvalued firms).

The value stocks are perceived as high-risk stocks and growth stocks are perceived as low-risk stocks (Chan & Lakonishok, 2004; Kok et al., 2017). The literature on sequential decision-making suggests that individuals engage in comparatively higher risk-taking following prior losses than following gains when making later decisions effect, termed an escalation of commitment effect (Staw, 1976). This implies that following prior losses value investors persist with perceived high-risk value stocks because they consistently update valuation analysis before reinvestment decisions (Kok et al., 2017). However, growth investors neglect thorough analysis and prefer to continue with perceived low risk winning growth stocks to amplify the hedonic effect of positive returns. There is a lack of evidence on underlying mechanisms guiding changes in investors' risk-attitude following prior losses and gains. Chapter five fills this gap and uses insight from sequential decision-making, prospect theory, self-determination theory, and word-of-mouth to establish the link between prior and later decision-making (or risk-taking). Chapter five investigate how do investor’s prior decision outcomes influence investor’s decisions to engage in later decisions by achieving underlying intrinsic motives through word-of-mouth. This chapter contributes by confirming that different underlying mechanisms (manifested in intrinsic motives and the valence of word-of-mouth) induce investors to engage in later high-risk or low-risk decisions following prior losses or gains. Findings suggest that investors are not only interested in economic gains but also seek to gain intrinsic motives manifested in the investment. This chapter also has important implications for financial advisors in understanding underlying intrinsic motives that can help to modify clients’ risk-attitude.

-------------Insert table 1-----------

An overview of dissertation chapters consisting of the chapter title, type of study, level of analysis, and status of publication are given in table 1.

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List of tables

Table 1: Overview of dissertation chapters

Chapter no	Title of the chapter	Type of study	Source of data	Level of analysis	No of participants/ Firms-year observations	Journal publication
1	Introduction					
2	Is the investor's reliance on cognitive processes and emotional regulation strategy predict preferences towards the selection of value versus growth stocks?	Empirical study	Four experiments, data collected by using Amazon's Mechanical Turk	Individual-level	408 participants	
3	Is the value premium vary across the level of investors' attention?	Empirical study	S&P 1500 Composite Index, starting from December 2003 until April 2017	Firm-level	17260 firms-year observations	
4	Is the value premium dependent on misvaluation signals manifested in the firms' intangibles-intensity?	Empirical study	S&P 1500 Composite Index, starting from December 1994 until April 2020	Firm-level	30270 firms-year observations	

5	Investor’s Intrinsic Motives and the Valence of Word-of-Mouth in Sequential Decision-Making	Empirical study	Two experiments with two treatments in each experiment, data collected by using Amazon’s Mechanical Turk	Individual-level	906 participants	Published in Journal of Behavioral Finance on 2nd May 2020
6	Conclusion, implications, and future research directions					

Chapter 2

Is the investor's reliance on cognitive processes and emotional regulation strategy predict preferences towards the selection of value versus growth stocks?

Table of Contents

Is the investor's reliance on cognitive processes and emotional regulation strategy predict preferences towards the selection of value versus growth stocks?

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Abstract

The literature on economic behavior highlights the importance of differences in individual-level characteristics like the decision-making process and emotional regulation strategy in predicting the selection and performance of economic choices. However, the literature on value premium has overlooked the effect of the decision-making process and emotional regulation strategy in assessing individual tendency to process fundamental information to select value versus growth stocks. We fill this gap by employing dual-process theory and emotional regulation theory to investigate the impact of Type 1 processing, Type 2 processing, expressive suppression, and cognitive reappraisal on the individual preferences towards the selection of value versus growth stocks. Results confirm that individuals with higher reliance on Type 1 (or Type 2) and expressive suppression (or cognitive reappraisal) exhibit lower (or higher) preferences towards the selection of value versus growth stocks. This indicates that emotions alter an individual's decision-making processes and both emotion and cognition are inherently intertwined from inception to action. These findings have implications for investors to avoid (or seek) investment in emotion-driven fundamentally weak overvalued firms (or fundamentally strong undervalued firms) via regulating emotional inhibitors to engage in thorough decision-making processes.

Keywords

Cognition, emotion, dual-process theory, emotional regulation theory, investor behavior, behavioral finance, emotional finance

2.1. Introduction

The value premium is the buying or selling of value stocks (high value-to-market firms) or growth stocks (low value-to-market firms) to generate superior returns on price reversal[1]. The mispricing explanation of value premium asserts that investors overly extrapolate optimistic (or pessimistic) expectations associated with growth (or value) firms, anchored in historical fundamental information (Lakonishok, Shleifer & Vishny, 1994). The value premium captures the effect of price differences between growth stocks and value stocks on the correction of biased market expectations (LaPorta, Lakonishok, Shleifer & Vishny, 1997). Such investor behavior might be motivated by the underlying psychological mechanism to maintain (or revisit) optimistic or pessimistic expectations to preserve (or avoid) the effect of a gain (or loss) as a positive self-image[2]. Emotion-driven investors are more attentive to (high sentiment) attention-driven stocks to amplify the hedonic effect of gains than updating prior biased beliefs[3]. On the other hand, emotionally stable investors are more interested to identify potentially profitable trading opportunities than buying attention-driven stocks[4]. This implies that susceptibility to exhibit over-optimistic and over-pessimistic behavior is altered by an investor's ability to

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[1] Following influential paper of Fama and French (1992), studies extensively used book-to-market price ratio as proxy to capture value-growth effect. Alternative indicators to identify misvaluation also exist, such as cash flows-to-market price ratio, earnings-to-market price ratio, sales-to-market price ratio and dividend yield (Pätäri & Leivo, 2017).

[22] Karlsson, Loewenstein, and Seppi (2009) document that investors feel good (or bad) with increase (or decrease) in their portfolio market value and pay more attention to information that amplifies the hedonic impact of gains. Consequently, investor attention towards trading after positive return is more heightened than negative return, termed as Ostrich effect. The heightened attention does not mean that investor thoroughly analyze available information but limit their attention to positive returns attention-driven stocks.

[3] Individual investors under cognitive constraints pay attention to small number of familiar and attention-driven stocks. They are net buyer of attention-driven stocks, leading to temporary positive price pressure and reversal in the long-run (Barber & Odean, 2008). Stambaugh, Yu, and Yuan (2012) argued that any long-short strategy that exploit mispricing is dependent on sentiments. They find that performance of such strategies is stronger following high sentiment periods, that is during high sentiment stocks prices deviates from fundamental value (overvaluation) due to market over-optimistic expectations with attention-driven stocks and over-pessimistic expectations with neglected stocks, pushing value stocks prices further down (undervaluation) (termed as market expectations errors; Piotroski & So, 2012). In addition, sentiment-based mispricing is predominantly driven by reversal in prices of overvalued (growth) stocks than undervalued (value) stocks (Walkshäusl, 2017).

[4] Alternative to Ostrich effect, bargain-hunting proposition suggest that investor attention could also increase after negative returns. Investor facing negative returns can revise or search for potential trading alternatives (Sicherman, Loewenstein, Seppi & Utkus, 2016).

regulate emotions[5]. The investor's reliance on emotional regulation strategy stimulate or prevent emotion-driven decisions by initiating either intuitive or cognitive decision-making processes.

Emotion and cognition are not independent of each other but are inherently interdependent from inception to action. The economic behavior literature confirms the significant impact of emotion on decision-making and performance of economic choices (e.g. Phelps, Lempert & Sokol-Hessner, 2014). This view is supported by studies using stock market settings to examine the effect of emotions on decision-making and find that emotions can have sometimes harmful and sometimes beneficial effects on decision-making. The individuals with better emotional control achieve higher decision performance and are less suspectable to cognitive errors (e.g. Seo & Barrett, 2007). Thereby, we use insight from economic behavior literature to examine investor's reliance on cognitive processes and emotional regulation strategy to predict preferences towards the selection of value versus growth stocks.

This study calls in two commonly used theories in economic behavior literature that are dual-process theory and emotional regulation theory to capture the impact of the decision-making process and emotional regulation. The dual-process theory discusses the role of cognition, neural systems, and reasoning in decision-making processes by referring to two qualitatively distinct types that are Type 1 processing (hereafter T1) and Type 2 processing (hereafter T2; Evans & Stanovich, 2013). The emotional regulation theory is characterized by strategies to monitor, control, and modify emotional reactions to achieve desired goals by applying either cognitive reappraisal or expressive suppression (Gross & Thompson, 2007). We expect that investor’s higher reliance over T1 and expressive suppression are attributed to the lower preference towards value versus growth stocks, while, higher dependence on T2 and cognitive reappraisal is associated with a higher preference towards value versus growth stocks. Four online experiments were conducted to validate the proposed hypotheses. Results confirm that the investor selects emotion-driven growth stocks under the influence of T1 and expressive suppression. Whereas, emotionally strong investors consciously override the emotional conflicts

[5] Heilman, Crişan, Houser, Miclea, and Miu (2010), and Panno, Lauriola, and Figner (2013) argued that emotions are generally attributed for interventions in individuals decision-making process, but actually decision-related effects are intervened by emotional regulation strategies.

(i.e. cognitive reappraisal strategy) and employ cognitively demanding T2 to exhibit higher preference towards value versus growth stocks.

The findings contribute to enhance the understanding of the mispricing perspective of value premium by highlighting the role of individual-level differences in terms of cognition and emotion on preferences towards the selection of value versus growth stock. First, following dual-process theory, this study confirms that investors select intuition-based growth stocks and later switches to value stocks due to the intervention of T2. Second, results support individual-level differences in the decision-making process and emotional regulation in explaining investor's preferences towards the selection of value versus growth stocks. Finally, Consistent with the theoretical argument of Taffler (2018), findings support that both cognitive constraints and emotional conflicts combinedly provide a better understanding of investor behavior. This study also provides important implications for investors to avoid undervalued (or overvalued) poor fundamental firms by frequently updating their prior biased beliefs by altering emotional conflicts via a thorough analysis of updated financial statement information.

The paper is organized as follows. Section 2 contains a discussion on theory and hypotheses development. Section 3 provides details on data collection and description of four online experiments. Section 4 documents the results of four experiments. The final section provides a detailed discussion on results, implications for investors, limitations, and future research.

2.2. Theory and hypotheses

This section reviews evidence on the cognitive constraints and emotional conflicts arises in the preferences towards the selection of value versus growth stocks and presents hypothesis development by using dual-process and emotional regulation theory.

2.2.1. Cognitive constraints in the preference towards value versus growth stocks

Behavioral theories predict that the value premium is due to market over-expectations (or under-exceptions) to the firm’s historical performance and fundamental information. These expectations reverse with revision of investor’s prior beliefs according to updated fundamental information. This reversal effect in prices is captured in the form of value premium (Lakonishok et al., 1994; LaPorta et al., 1997). Shefrin (2007) identified three main channels of mispricing that are associated with the investor's cognitive constraints. These three channels can be used to explain investor's preference towards value versus growth stocks: representativeness and affect heuristics, risk and return perception, and market sentiments.

The selection of value versus growth stocks can be attributed to investor's representativeness and affect heuristics. Overreliance on stereotypes makes investors underweight the events that are overdue while, intuition might suggest the occurrence of an overdue event, termed as gambler fallacy. The recency bias – an individual tendency to overweight more recent events - also influence gambler fallacy. According to prospect theory, individuals underweight the overdue outcomes relative to outcomes that are obtained with certainty termed as certainty effect. Such behavior might induce individuals to exhibit risk-aversion through the selection of sure gain economic choices and risk-seeking in the selection of sure loss outcome economic choices (Kahneman & Tversky, 1979). Thereby, individuals act more risk-averse towards overdue event to avoid anticipated losses and less risk-averse with choices having a sequence of positive returns.

The affect heuristic reinforces the representativeness by allowing intuitive expectations based on affective labeling. Investors associate positive (or negative) labeling with fundamentally strong (or poor) winning (or losing) stocks i.e. growth stocks (or value stocks). Investors persist with prior labeling and do not update expectations according to changes in fundamental strength, leading to the overvaluation (or undervaluation) of growth stocks (or value stocks) (Shefrin, 2007). The persistence in the over- and under-valuation further widens the market price gap between growth and value stocks, subsequently leading to a value premium on price reversal (Piotroski & So, 2012).

Another cause of mispricing is the investor’s poor understanding of the association between risk and return. Investor’s associate low (or high) beta with low (or high) value-to-market ratios, and high (or low) market capitalization with high (or low) return firms (Kok, Ribando & Sloan, 2017). This implies that investors have a clear knowledge of both risk and return concepts, but a poor understanding of the association between risk and return (Shefrin, 2007). They associate higher returns to financially strong firms and consider them less risky, while, firms with lower returns are considered as financially distressed (Shefrin, 2005, 2007).

Hence, in practice, investors perceive risk and return as negatively related, not positively correlated as suggested by risk-based perspective (Shefrin, 2007).

Yet another cause of mispricing is the investor's biased response towards market signals. Investors respond differently towards key fundamental signals (like earnings-per-share) and forms biased expectations towards market valuation and expected returns (Shefrin, 2007). Subsequently leading to the asymmetric investor's response to fundamental signals (Hwang & Rubesam, 2013). Overconfident investors respond stronger to confirming signals than conflicting signals (i.e. self-attribution bias), making investors more vulnerable towards expectation errors, leading to overvaluation in growth stocks (Hwang & Rubesam, 2013). Whereas, non-confirming market signals are ignored or considered too noisy to update (i.e. anchoring effect), stimulating pessimistic behavior towards value stocks, consequently pushing the prices further downward (Daniel, Hirshleifer & Subrahmanyam, 2001). Consequently, emotion-driven market valuation does not correspond to the changes in fundamental strength, leading to value premium (i.e. consistent expectation error; Piotroski & So, 2012).

2.2.2. Emotional conflicts in the preference towards value versus growth stocks

Emotional finance highlights that behavioral finance essentially emphasizes the identification and influence of cognitive and judgmental errors on decision-making and ignores the role of human unconscious mental components such as emotions and social dynamics (Taffler, 2018). Investors wish to have pleasant feelings (i.e. gains) but the investment can let down investors and results in painful experience (i.e. anxiety). Both pleasant and unpleasant feelings can lead to emotional conflicts. Investors counter emotional conflicts by using conscious mental efforts to clear unpleasant feelings and retain pleasant feelings.

Investor unconsciously associates “good object” labels with weak fundamentals growth firms, while, neglect the underperforming strong fundamentals value firms and perceive them as “bad objects”. Hence, investors favor emotion-driven growth firms versus neglected value firms to seek pleasant feelings and avoid unpleasant feelings without updating prior biased beliefs, leading to overvaluation of growth stocks and undervaluation of value stocks (Taffler, 2018).

However, informed investors exhibit more control over emotional conflicts and alter emotions to follow a systematic investment strategy. In the “anxiety” situation, they either persist with their investment strategy or timely cut their losses (i.e. loss realization) and reappraise situation as a positive learning experience to update knowledge by identifying causes of losses and preventing them next time by updating decision process (Chu, Im & Lee, 2014). Therefore, economic choices performance is dependent on an individual's ability to regulate emotions to achieve desired outcome experience (Heilman, Crişan, Houser, Miclea & Miu, 2010; Panno, Lauriola & Figner, 2013).

2.2.3. Dual-process theory and preference towards value versus growth stocks

In economic behavior literature, the dual-process theory is extensively used to demonstrate individual economic behavior (e.g. Richards, Fenton-O'Creevy, Rutterford & Kodwani, 2018). The literature provides two distinct decision-processing mechanisms that require apparent cognitive and neurological systems: the first type is intuitive-based processing i.e. T1 and second is reflective-based processing i.e. T2[6]. T1 is characterized as autonomous, fast, unconscious, intuitive, cognitively undemanding, parallel, and hypothetical thinking, like heuristics, whereas, T2 is characterized by controlled, slow, conscious, reflective, systematic, cognitively demanding, serial, and holistic thinking, like analytic intelligence (Evans & Stanovich, 2013; Stanovich & West, 2000). T1 is the default processing mechanism used by decision-makers unless some special circumstances intervene and demand higher computational processing. T2 processing requires cognitive resources, therefore decision-makers mostly rely on intuitive-based decision making to prevent the use of scarce cognitive resources. But such decisions are mostly satisficing rather than optimal (Simon, 1978). Under default interventionist assumption (hereafter DI), fast T1 generates intuitive responses that are intervened and overridden by cognitively demanding T2.

[6] It is important to understand that researchers give the impression that so-called all dual-process theories call for the same underlying generic system (Keren & Schul, 2009). But it is not true, because true dual-process theory employs distant cognitive and neurological systems with varying underlying clusters of attributes. Whereas, System 1 and System 2 refers to generic underlying cognitive or neurological systems with a specific set of attributes for all dual-process theories (Evans, 2008; Stanovich, 2004). Stanovich (1999) started using labels System 1 and System 2 to represent a set of properties and not to reside with any specific theory but later these labels became popular. In addition, Evans (2008) and Stanovich (2004, 2011) provided that use of System 1 or System 2 is misinformed because it does not consist of a single system but multiple overlapping systems. Therefore, Evans (2008), Evans and Stanovich (2013) and Stanovich (2004, 2011) discouraged the use of labels System 1 and System 2 and reverted to quantitatively distant processing labeling of T1 and T2. Therefore, we used labels T1 and T2.

It is important to note that, DI does not mean that T1 always provides incorrect responses and T2 correct responses. It depends on the objective of decision-makers. When responses of T1 are consistent with the goal of decision-makers then T2 does not intervene, whereas, when conflicting responses are provided by T1 then T2 intervenes and correct initial intuition-based responses. One can presume that lower preference towards the selection of value versus growth stocks is because of the intuition-based T1 decision criteria. Investors make decisions based on emotion-driven prior beliefs, resulting in overreaction to fundamental information and selection of growth stocks. Investors overly predict the continuation of recent good performance based on positive affective labeling under the influence of hot hand fallacy and availability bias. To validate the selection of growth stocks, investors seek intuition-based information (i.e. standalone value-to-market ratios) that confirms prior beliefs and ignore non-confirming information such as changes in fundamental strength. This implies that investors confuse informed speculation with informed investment via persisting with prior beliefs and avoiding T2 to select emotion-driven growth stocks. In doing so, investors avoid the anticipated negative emotions associated with expected losses and continue reinvesting in winning stocks (i.e. growth stocks) to maintain the sequence of positive returns.

Hence, we presume that investors are aware of changes in the fundamental strength of growth firms but persist with prior beliefs to avoid the application of limited cognitive resources to select growth stocks. Therefore,

Hypothesis 1: Investors having more reliance on Type 1 processing exhibit lower preference towards the selection of value versus growth stocks.

T2 intervenes to correct initial intuitive T1 responses and implement a cognitively demanding holistic thinking process (Muraven & Baumeister, 2000). The participants using T2 allocate cognitive resources due to the high premium associated with superior decision-making (Pacini & Epstein, 1999). The prospect theory predicts that individuals are less risk-averse in the loss domain and more risk-averse in the gain domain. In the same lines, value investors go against the crowd to prefer value versus growth stocks (i.e. market perceived high-risk investment choices) by using the thorough analysis to earn an excess return as compensation of using limited cognitive resources. This suggests that investors switch from market-perceived low risk-averse choices to market-perceived high risk-averse choices when prospects change from gains to losses.

The value investors not only rely on intuition that is value-to-market ratios but also thoroughly analyzes available quantitative and qualitative information to identify temporarily undervalued quality firms (Kok et al., 2017). In doing so, investors develop a positive association between risk and return, and diversify (or rebalance) portfolio by including the right mix of value and growth stocks (Asness, Frazzini, Israel & Moskowitz, 2015). Similarly, when high incentives are involved in the investment decision, investors allocate limited cognitive resources to employ a systematic decision-making process, reducing the influence of affective heuristics and cognitive errors. Hence, investors that frequently use T2 for investment decisions select underpriced fundamentally strong value stocks. Therefore,

Hypothesis 2: Investors having more reliance on Type 2 processing exhibit higher preference towards the selection of value versus growth stocks.

2.2.4. Emotional regulation theory and preference towards value versus growth stocks

Emotional regulation is an intentional, deliberate, and goal-directed process. The literature on emotional regulation suggests that individuals make efforts to reduce the effect of emotions and divert attention towards a specific goal by suppressing or modifying emotions (Gross, 2002). Hence, one can argue that decision-related effects attributed to emotions are actually intervened by emotional regulation strategies (Heilman et al., 2010; Panno et al., 2013).

Literature in economic behavior provides the positive effect of emotional regulation on economic decision-making (e.g. Heilman et al., 2010; Martin & Delgado, 2011; Seo & Barrett, 2007). Specifically, Martin and Delgado (2011) provide that individuals employing emotional regulation strategy modify their behavior by selecting low-risk choices than participants using no emotional regulation. Yurtsever (2008) provides a negative (or positive) relationship between the use of cognitive reappraisal (or expressive suppression), emotional reaction, and ambiguity tolerance in simulated economic negotiations. This implies that individual reliance over cognitive reappraisal (or expressive suppression) prevents (or stimulate) emotion-driven decisions. Seo and Barrett (2007) find that individuals having better control over emotions can better identify and manage intense feelings to achieve high decision performance.

The cognitive reappraisal strategy reformulates the meaning of the situation to alter emotional responses and reduce the emotional impact of responses on decision-making. While, expressive suppression strategy inhibits the expressive behavior of emotional responses (Gross, 2002). Both strategies influence decision making differently based on their underlying cognitive processes and the timing of the generative process (Richards & Gross, 1999, 2000). Specifically, cognitive reappraisal reduces the effect of emotional constraints at an early stage and does not require continuous cognitive efforts, whereas, expressive suppression requires continuous cognitive efforts to suppress emotional responses (Gross, 2002). Both strategies are effective in diminishing the effect of positive emotions, but cognitive reappraisal is more effective in regulating negative emotions than expressive suppression (Gross, 2002; Richards & Gross, 2000).

Heilman et al., (2010) find that reappraisal strategy is more efficacious in regulating situation-induced negative emotions and change individual behavior to low risk-aversion (Panno et al., 2013). Individuals are mainly interested in reducing the effect of anticipated negative emotions and make efforts to minimize the effect of unpleasant experiences (Sokol-Hessner Hsu, Curley, Delgado, Camerer & Phelps, 2009). In doing so, they apply cognitive reappraisal strategy to reformulate the meaning of expected unpleasant experience by focusing on expected pleasant feelings associated with low risk-averse behavior (i.e. attentional deployment; Panno et al., 2013). Investors reappraise an unpleasant experience as a learning opportunity to update knowledge to identify the causes of losses (Chu et al., 2014). Hence, investors use cognitive efforts to reformulate the meaning of expected outcomes to regulate the effect of emotions to achieve the desired objective.

Individuals who use reappraisal strategy have more control over their emotions and are less influenced by representativeness heuristics, affect heuristics, and market sentiments in response to anticipated pleasant and unpleasant feelings (Yurtsever, 2008). It also helps investors to persist with investment decisions even when market sentiments towards selected investment choices (i.e. value stocks) are low. The reappraisal strategy helps to re-evaluate the high and low market sentiments from different perspectives, reducing the impact of high market sentiments on the decisions. It results in relatively more thoroughly analyzed low risk-averse behavior than emotion-driven intuitive based high risk-averse behavior (Kok et al., 2017). Hence, we predict that investors following cognitive reappraisal strategy to regulate or reformulate emotional conflicts follow more systematic information processing to select undervalued strong firms than emotion-driven overvalued growth firms. Therefore,

Hypothesis 3: Investors having more reliance on cognitive reappraisal strategy exhibit higher preference towards the selection of value versus growth stocks.

Studies on emotional regulation provide mixed evidence on the effectiveness of expressive suppression in reducing the effect of negative emotions. Heilman et al., (2010) used experimentally induced negative emotions (i.e. fear and disgust) with immediate feedback on the outcomes. They provide that expressive suppression is inefficacious in reducing the effect of negative emotions and has no effect on changing the level of risk-aversion. However, Panno et al., (2013) consider emotional regulation as a personality trait and focus on naturally occurring habitual use of emotional regulation strategies of participants. They report that habitual expressive suppression is significantly related to high risk-aversion in the cognitive-deliberative situation. The expressive suppression strategy focuses on reducing negative emotions associated with an expected negative outcome and exhibit high risk-aversion.

Investors are less concerned with the selection of high potential return stocks rather they follow the attention-driven stocks by adopting an expressive suppressive strategy and invest in highly traded stocks. Furthermore, expressive suppression strategy is more cognitively demanding and does not reduce the intensive emotional experience rather intensify the emotional experience (Wenzlaff & Wegner, 2000) and induce impulsive decision making (Leith & Baumeister, 1996). It results in decision-making under the influence of representative heuristics, affect heuristics and emotions. Hence, we assume that investors frequently suppress anticipated negative emotions by avoiding perceived high-risk choices (i.e. value stocks) and prefer market perceived low-risk choices (i.e. growth stocks). Hence,

Hypothesis 4: Investors having more reliance on expressive suppression strategy exhibit lower preference towards the selection of value versus growth stocks.

2.3. Data and method

Existing studies have used a two-response paradigm to experimentally test dual-process DI time course assumption (Bago & De Neys, 2017; Newman, Gibb & Thompson, 2017;

Pennycook & Thompson, 2012; Thompson, Prowse, Turner & Pennycook, 2011). In two-response paradigm, participants are usually presented with two choices reasoning tasks and instructed to quickly provide first response that comes in mind. Afterward, they are presented again with the same problem to provide a final response by taking as much time to think. Thompson and fellows suggest that participants hardly ever changed response and persist with the initial response as a final response. Bago and De Neys (2017) argue that persisting with initial response does not affect DI time course assumption, as long as it is due to the failure to engage in optional T2. However, it poses a major challenge to the validity of the DI time course assumption when the correct logical response is generated by T1. To make sure that the initial response reflects T1, Thompson and fellows proposed four experimental settings to limit T2. Bago and De Neys (2017) adapted Thompson and fellows four experimental settings: instructions only (experiment 1), response deadline (experiment 2), cognitive overload (experiment 3), and response deadline and cognitive overload (experiment 4) and find similar results across four experiments. Like Thompson and fellows, Bago and De Neys (2017) also got a higher percentage of initial intuitive responses followed by no change in the final response. We presume that failure to engage in T2 and higher confidence on initial beliefs might have resulted in a higher percentage of final incorrect responses. Bago and De Neys (2017) considered T2 as "optional" and just focused on ensuring T1 for the initial response but our interest is in both initial T1-based responses and final T2-based responses.

The literature on reasoning and decision-making suggest that T1 responses can be overridden by providing participants with additional information or more emphasized instructions. One group of studies suggests that informing participants about normative decision-making and instructing them to follow a specific procedure to provide a final response can override initial intuitive response (e.g. Evans, Newstead & Byrne, 1993). The other group considers failure to engage in cognitive thinking as the main driver of biased final responses. The debiasing can be done by instructing participants to avoid stereotypical thinking and focus on logical and holistic thinking (e.g. Moutier, Angeard & Houde, 2002). Participants can also be instructed to approach the decision-making from the perspective of experts (e.g. Bialek & Sawicki, 2014), peers, and entrepreneurs (e.g. Bialaszek, Bakun, McGoun & Zielonka, 2016). Bialaszek et al., (2016) find that the peer's perspective makes participants more impulsive and risk-averse, but experts and the entrepreneur's perspective did not change participant behavior.

Besides, expert and entrepreneur perspectives reduce the chances of impulsive decision-making and induce low risk-averse behavior than peer perspective.

We adapted Bago and De Neys (2017) four experiments with similar literal instructions to restrict the influence of T2 on the initial response. Experiments were modified to ensure the intervention of T2 during the final response by instructing participants to reconsider the initial response by using the company's fundamental information and extra time.

In subsequent subsections, we first elaborate on the tool used to collect data. The second subsection elaborates on the pretest study to confirm the validity of proposed base-rate and syllogistic reasoning tasks. The remaining four subsections provide details on participants, materials, and procedures for four experiments.

2.3.1. Data

The data was collected by using Amazon Mechanical Turk, an online platform that facilitates convenient, quick, and quality data collection for research (Buhrmester, Kwang & Gosling, 2011). Amazon Mechanical Turk has been extensively used by economic and financial behavior experimental studies (e.g. Butler et al., 2012; Hass & Beaty, 2018; Mandel & Kapler, 2018 Stagnaro, Pennycook & Rand, 2018; Watford, Braden & Emley, 2018).

A total of four online experiments were conducted and participants were randomly assigned to one experiment[7]. In the beginning, participants were informed about the description and requirements of each experiment. Participants were also provided with an overview of the characteristics of value and growth firms. The "survey code" for payment was provided on completion of the experiment. Each participant was allowed one submission to ensure internal consistency and received $1.00 as compensation for completing the experiment. Few screening questions were embedded in each experiment to confirm the participant's eligibility. These questions were related to stock market investment experience, knowledge of value-to-market ratios like book-to-market price ratio, and fundamental characteristics of value and growth firms. The incorrect responses to screening questions lead to the termination of the experiment and loss of compensation amount. The problem of missing responses was encountered by requiring responses for each reasoning task and questionnaire items to move forward in the experiment.

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[7] The online experiment is available at: https://impresaluiss.eu.qualtrics.com/jfe/form/SV_2bkEgQUQ8eq1J0V

The collected data provided greater generalizability and ecological validity than university student samples because participants were required to have investment experience and their age distribution ranged from 20 years to 49 years (Weber, Weber & Nosić, 2012).

2.3.2. Pretest

2.3.2.1. Participants

A total of 50 participants were recruited to pretest base-rate and syllogistic reasoning problems to cue heuristic (or logical) thinking in participants to capture reliance over T1 (or T2) and expressive suppression (or cognitive reappraisal). The participants consisted of 66% male and 34% female and have right-skewed age distribution (mean age = 31.46, SD = 6.71) that ranged from 20 to 49 years. Participants received $0.5 as compensation for completing the pretest study.

2.3.2.2. Procedure

In the pretest study, each participant was instructed to first fill a questionnaire consisting of Rational Experiential Inventory Short-24 (REI-S24) and Emotional Regulation Questionnaire (ERQ) items. Afterward, participants were presented with one example and eight reasoning problems (four conflicting and four non-conflicting) of both base-rate and syllogistic tasks (questionnaire and reasoning tasks are discussed under "materials" in the next subsection). Participants were presented once with each reasoning task (with extra information for the base-rate task) and instructed to respond by assessing given information without any time restriction.

2.3.2.3. Results

To test the ability of base-rate task to cue selection of heuristic thinking-based growth stocks or logical thinking-based value stocks, correlation estimates are used between the frequency of value versus growth stock choices in four conflicting base-rate task, experiential inventory, rational inventory, cognitive reappraisal, and expressive suppression. The results confirm that value versus growth stock frequency is significantly correlated with experiential inventory and rational inventory in the opposite direction. As predicted, results provide an opposite and significant correlation between value versus growth stocks frequency, cognitive reappraisal, and expressive suppression. The correlation with syllogistic task confirms the base-rate task results by providing similar significant and the opposite correlation between frequency of correct responses, experiential inventory, rational inventory, cognitive reappraisal, and expressive suppression (see appendix A1 for results).

The linear regression model results provide significant positive effect of rational inventory (b=0.381, t-statistics=1.945, p-value=0.058), positive effect of cognitive reappraisal (b=0.458, t-statistics=3.458, p-value=0.001), and significant negative effect of expressive suppression (b=-0.185, t-statistics=-2.677, p-value=0.01) on frequency of value versus growth stocks. Results provide no effect of T1 on the frequency of value versus growth stocks (see appendix A2 for results). These results suggest that participants with stronger reliance over T1 (or T2) processing and expressive suppression (or cognitive reappraisal) exhibit lower (or higher) preferences towards the selection of value versus growth stocks. Thus, findings confirm that base-rate task induces logical thinking in participants and tasks can be used to test hypotheses.

2.3.3. Experiment 1 – instructions only

2.3.3.1. Participants

A total of 103 participants completed experiment 1 and responded to all reasoning problems. The sample consisted of 68% of male and 32% of female, with a mean age of 30.84 years (SD=6.02). The age distribution is right-skewed that ranged from 20 years to 45 years and 56.30% of respondents were spread towards the left side of the distribution. A total of 90.30% of participants reported bachelor's and master’s as higher educational qualifications.

2.3.3.2. Material

We use base-rate and syllogistic reasoning tasks that are extensively used in reasoning and decision-making literature. The base-rate task consists of a description of sample composition, a base-rate probability, and a description that cues stereotype intuitive response. We adapted Pennycook, Cheyne, Barr, Koehler, and Fugelsang (2014) base-rate problem presentation format to reduce the reading time and minimal information that cues stereotypical responses. We also avoided the use of too diagnostic words in the description because it can result in interpretational errors (Pennycook et al., 2014).

We developed nine base-rate reasoning problems in the context of stock-market decision (see appendix B1). Among nine problems, five were no-conflicting problems and four were conflicting problems. All base-rate reasoning tasks consisted of selection between two companies' stocks, where one company reflected characteristics of value firm and the second company exhibit characteristics of a growth firm. In each task, the participants were presented with a description of two real existing companies with neutral names (e.g. "You must select between company ALPHA stocks and company BETA stocks"). Next, participants were presented with a first descriptive sentence (e.g. "The Book-to-Price ratio of ALPHA is 1.0x, whereas BETA Book-to-Price ratio is 0.28x."), providing company information designed to trigger intuition-based stock selection. Finally, participants were presented with the expected rate of return and standard deviations of returns (based on 10 years historical prices) for both stocks (e.g. "ALPHA expected return is 7.96% and deviation in returns is 20.76%, whereas BETA expected return is 6.54% and deviation in returns is 44.59%."). Participants were instructed to select one company based on the first intuitive response that quickly comes in mind. After that, they were presented again with the same task and extra fundamental information like current ratio, debt ratio, return on assets, assets turnover, dividend per share, etc. to trigger the T2.

In each base-rate problem, ALPHA stock represents value stock and BETA stock represents growth stocks. The example presented in brackets is conflicting reasoning problem because standalone value-to-market ratio trigger selection of stock BETA while ALPHA provide a higher expected return relative to per unit deviation in returns. Additionally, extra fundamental information (see appendix B1) also suggests the selection of stock ALPHA. It was expected that participants select BETA stock as an initial intuitive response based on standalone value-to-market ratio and corrects initial response due to intervention of T2 (i.e. selection of ALPHA stock) in the conflicting reasoning problem. In no-conflict reasoning problem, descriptive information and expected return (with standard deviation) signal selection of same company stock (i.e. growth stock). Hence, it was expected that participants select intuition driven BETA stock as initial choice and persisted with the same choice because of the relatively stronger fundamentals than ALPHA. Based on the DI time course assumption, we are interested in validating the direction of change from the first intuitive response (i.e. growth stock) towards T2 final response (i.e. value stock) for conflicting problems.

In the syllogistic reasoning task, participants were presented with a major premise (e.g. When market prices go up, stocks provide short term gain opportunity), a minor premise (e.g. Stock X market price goes up) and a conclusion (e.g. Stock X provide short term gain opportunity). The objective of the syllogistic reasoning task was to evaluate the participant's ability to analyze whether a conclusion logically flows from the sequence of premises or not. The syllogistic reasoning task was used to test the validity of base-rate problem results that whether they were based on random guessing or based on the application of T2 (Bago & De Neys, 2017; Evans, 2008; Stanovich, 2004). It was expected that participants employing T2 have a similar trend for both base-rate and syllogistic tasks. A total of nine syllogistic reasoning tasks were developed (see appendix B2). Four tasks logical validity of the conclusions conflicted with premises while the remaining five provided logically valid conclusions drawn from premises (no-conflict syllogistic problem).

Before the start of each experiment, respondents were instructed to respond REI-S24 and ERQ items. The REI-S24 is a shortened version of the Rational-Experiential Inventory to measure respondent’s frequent reliance on T1 and T2, separately and independently (REI: Pacini & Epstein, 1999). The ERQ is a 10-items self-reported scale, measuring separately cognitive reappraisal (6-items) and expressive suppression (4-items; Gross & John, 2003; see appendix B3 & B4).

2.3.3.3. Procedure

In experiment 1, participants were instructed that we are interested in their first intuitive response. Later they will be presented with the same problem again together with the firm’s fundamental information to think and reassess their selection and provide a final response. They can take as much time to provide a final response. Respondents were also instructed to provide response confidence after each initial and final response. We also recorded the time taken by participants to provide initial response and final response.

In the first part of the experiment, participants were instructed to fill a questionnaire consisting of REI-S24 and ERQ items. In the second part, participants were provided with one practice problem of each task followed by the respective eight base-rate and syllogistic reasoning tasks. In each reasoning problem, participants were reminded to provide initial intuitive responses and to use extra information (incase of the base-rate task) and extra time to provide the final response.

2.3.4. Experiment 2 – response deadline

2.3.4.1. Participants

A total of 102 participants completed experiment 2. The final participants consisted of 64.7% of male and 35.3% of female. The mean age of participants was 32.23 years (SD=6.624) with ranges from 23 years to 48 years. The age distribution is right-skewed with 58.8% participants younger than mean age. A total of 93.00% of participants report bachelor's or higher degree as the highest level of education. Before conducting experiment 2, 70 extra participants were recruited for reading pretest to identify the reading deadline to restrict the intervention of T2. The participants received $0.3 in compensation for completing the reading pre-test.

2.3.4.2. Material and procedure

In experiment 2, experiment 1 was repeated but respondents were given a deadline to provide an initial intuitive response. The rationale of using the deadline is to limit T2 and allocate time that participants only take to read the reasoning task. There are no absolute criteria to illustrate the information processing time-based division between T1 and T2. Hence, we adapted Bago and De Neys (2017) approach to conduct reading pretest to determine the deadline for both reasoning tasks. In the reading pretest, respondents were instructed that we are only interested in the time that they take to read the problem and select one choice. In reading pretest exercise, respondents were required to read and select any choice for every nine base-rate problems and nine syllogistic problems. The results of the reading pre-test provided the average time of 16.98s (SD=6.80) for base-rate problems and 13.30 (SD=5.78) for the syllogistic reasoning problem. Hence, for experiment 2, we introduced a deadline of 17s for base-rate problem and 13s deadline for syllogistic reasoning problem to restrict the intervention of T2 in the initial response.

Like experiment 1, respondents were provided with the same instructions, screening questions, and both types of reasoning problems but with a deadline. The only difference was the introduction of the deadline to ensure the initial intuitive response. Also, on-screen timer and reminder were shown to remind participants to select a quick initial response and proceed in the experiment.

2.3.5. Experiment 3 – cognitive overload

2.3.5.1. Participants

A total of 101 respondents, consisting of 59.4% male and 40.6% of female completed the experiment. The mean age of respondents was 31.78 years (SD=7.22) and ranged from 22 years to 49 years. A total of 58.4% of the participants were younger than 31 years. A total of 88.1% of respondents reported bachelors and higher degree as the highest level of educational qualification.

2.3.5.2. Materials and procedure

In experiment 3, experiment 1 was repeated with concurrent use of cognitive load task – the dot memorization task (Miyake, Friedman, Rettinger, Shah & Hegarty, 2001). The rationale behind using the cognitive load task is to load the participant's memory and prevent the use of T2. At the beginning of each reasoning task, participants were shown a 3 x 3 matrix with four crosses in complex combinations for 3s. Participants were instructed to memorize the matrix and select the right matrix from the given options after providing an initial response. Experiment 3 used the same instructions, screening questions, reasoning tasks, and procedure as Experiment 1. The only difference was the use of cognitive load tasks before presenting the reasoning problem for the first time and selection of the correct matrix from given four options after providing an initial response.

2.3.6. Experiment 4 – response deadline and cognitive overload

2.3.6.1. Participants

A total of 102 participants completed experiment 4. The participants consisted of 61.8% of male and 38.2% female. The mean age of participants was 31.92 years (SD=6.98) and ranged from 21 to 48. A total of 53.9% of participants were having age lower than mean age. A total of 57.8 % of participants reported bachelors and 30.4% reported masters as higher educational levels.

2.3.6.2. Materials and procedure

In experiment 4, both deadline and cognitive overload were used at the same time to completely dismiss the influence of Type 2 processing on the initial response. In experiment 4, participants were instructed to memorize 3 x 3 matrix and select the correct matrix after the initial response. Afterward, participants were instructed to respond within the deadline (i.e. 17s for the base-rate problem and 13s for the syllogistic problem). Hence, experiment 4 repeated experiment 1 but with both deadline and cognitive overload to restrict the intervention of T2.

2.4. Results

For comparison across four experiments, we present results together in one section. Here, it is important to note that the theoretical grounding of this study is based DI time course assumption. Therefore, it is important to validate that the participant's initial response is based on T1 and later persistence or change in initial response is under the influence of T2, and not due to random guessing. Thereby, we first analyzed the validity of the DI time course assumption by using accuracies of final responses, the direction of change, and the stability index across four experiments (Bago & De Neys, 2017). We use multilevel mixed-effect logistic regression and multinomial mixed-effect logistic regression to test the variation across four experiments and within each experiment at a single response-level and direction of change category level. Afterward, we use a multilevel mixed-effect linear model to test hypotheses of study by using the frequency of final correct responses of conflicting base-rate and syllogistic problems as a dependent variable.

2.4.1. Accuracy of final responses

Table 1 reports the results of accuracy of final responses of both reasoning tasks across four experiments. Results suggest dominance of correct responses for no-conflict reasoning problems (i.e. base-rate=95.71%, and syllogistic=93.38%)[8]. This supports DI assumption that individuals select intuition cued initial response and persist with the selected choice as a final response.

The average accuracy rate for base-rate and syllogistic conflicting problems are 59.31% and 55.94%, respectively. These accuracies are higher than accuracies obtained by existing

[8] The null model of multilevel logistic regression for no-conflicting base-rate and syllogistic problems provide significant intercept value (base-rate: b=3.263, t=9.525, p-value= 0.000, Odds ratio= 26.125, and syllogistic: b=3.520, t=8.387, p-value= 0.000, Odds ratio= 33.786) with insignificant variation in intercept (base-rate: var(b)=0.548, Z=1.041, p>0.1, and syllogistic: var(b)=0.834, Z=1.048, p>0.1), suggesting no variation at experiment-level for individuals final responses.

studies that used two-response paradigm (e.g. Bago & De Neys, 2017), implying that emphasized instructions and extra fundamental information induced participants to engage in T2 and override the initial intuitive response. This evidence is consistent with the DI time course assumption that initial T1-based intuitive choices (i.e. growth stock) are corrected by the intervention of T2 (i.e. selection of value stock).

We use multilevel mixed-effect logistic regression to test variation accuracies across and within each experiment at the response-level. The null model (no-predictor model) for base-rate conflicting problems provide significant intercept value, b=0.377, t=7.853, p = 0.000, Odds ratio= 1.458, suggesting that 37.7% variance is common between four experiments. The variance in intercept is insignificant, var(b)=0.002, Z=0.212, p>0.1, implying that there is no variation across experiments and response-level factors explain variation within each experiment. The level 2 model is run by using response time and final accuracy as response-level factors. Results provide highly significant positive coefficient values of response time, b=0.383, t=20.945, p-value<0.001, odds ratio= 1.467, and response accuracy, 0.037, t=7.700, p-value<0.001, odds ratio=1.038. This suggests that the probability of solving the problem correctly increases with higher response time and confidence level. This indicates that participants spending higher time in analyzing information and having higher confidence on selected choices are more likely to select value versus growth stocks.

The null model for syllogistic conflicting problems also provides significant intercept value, b=0.239, t=4.834, p= 0.000, Odds ratio= 1.270, suggesting that 23.90% variance was common across experiments. The variance in intercept is insignificant, var(b)=0.003, Z=0.290, p>0.1, suggesting that there is no variation at the experiment-level. The response-level model (model 2) provide significant effect of response time, b=0.257, t=9.408, p<0.001, odds ratio= 1.293, and response confidence, b=0.031, t=4.168, p<0.001, odds ratio=1.032. This confirms the findings of the base-rate conflicting problem that participants employing higher time and having more confidence in their selected choices are more likely to select cognitively induced correct responses versus intuitive based incorrect responses. This illustrates that the results of base-rate problems are not because of the random guessing but the consequence of T2.

-------------- Insert table 1 -------------

2.4.2. Direction of change

The direction of change refers to the direction in which individuals change their initial response to the final response by engaging in the rethinking process. In the context of this study, the direction of change shows participants persistence or change in initial response to final response. Four directions of change are exhibited by participants: first is the initial incorrect intuitive response with no change in final response, second is the initial incorrect intuitive response with the change to correct final response, third is the initial correct response changed to incorrect final response, and fourth is the initial correct response followed by no change in the final response. In the context of conflicting reasoning problems, the first direction of change is the selection of intuition-based response (i.e. growth stock) with no change in final response (represented as “00”). The second category is the intuitive based response (i.e. growth stocks) change to T2-based final response (i.e. value stock) (represented as “01”). The third category is T2-based response (i.e. value stocks) change to Intuitive based response (i.e. growth stock) (represented as “10”) and the final category is T2-based initial response (i.e. value stock) with no change in final response (represented as “11”). In the case of no-conflicting reasoning problem, the first category represented incorrect response (i.e. value stock) follow by no change in final response (represented as “00”). The second category is incorrect response (i.e. value stock) follow by a correct intuitive based final response (i.e. growth stock; represented as “01”). The third category is intuitive based correct “initial response (i.e. growth stock) follow by an incorrect response (i.e. value stock; represented as “10”) and final category is intuitive based correct initial response (i.e. growth stock) follow by no change (represented as “11”).

Table 2 reports the direction of change for no-conflict problems and shows the dominance of “11” direction of change with an overall average value of 90.69% and 93.57% for base-rate and syllogistic problems, respectively. This supports the DI time course assumption and suggests that participants select T1-based growth stocks and persist with initial choice unless a conflict arises between decision objective and selected choices. In this study, fundamentals also favored the selection of growth stocks as a final response, hence it can be argued that participants persisted with the initial response after considering the validity of initial response based on available information.

Table 3 provide categories of the direction of change for conflicting base-rate and syllogistic problems. The table suggests the dominance of “01” and “00” categories in both types of reasoning problems. The overall average of “01” and “00” in base-rate problems was 54.47% and 39.40%, respectively. For both categories, overall, 93.87% of participants select initial intuitive response based on the T1. Among them, 39.40% persist with the same intuitive response, while 54.47% utilize fundamental information and changed their final response due to the intervention of T2. This confirms the DI time course assumption that individuals first select response cued by intuitive thinking and later persisted with the same response or change it with the intervention of T2 processing. The difference across experiments at the level of categories of the direction of change is tested by using the null model of the multinomial logistic regression model. The null model for conflict base-rate provide insignificant intercept value, $b=0.408$, $t=0.093$, $p> 0.1$, Odds ratio= 1.503, suggesting that there is no common variation between categories of direction change. In addition, variation in intercept provide no variation across categories of direction of change ($var(b)=91.338$, $Z=1.087$, p-value>0.1).

In the syllogistic problems, “01” and “00” are dominant categories with an overall average of 51.59% and 43.20%. The null model for syllogistic problems also provide insignificant intercept value, $b=0.443$, $t=0.101$, p-value> 0.05, Odds ratio= 1.557, and insignificant variation in intercept, $var(b)=89.375$, $Z=1.086$, p-value>0.05. As indicated above, syllogistic problem results also confirm the selection of initial intuitive response and later persistence or change of initial response due to the intervention of T2. Hence confirming the results of base-rate problems.

The prevalence of “10” and “11” categories in conflicting base-rate (i.e. overall average of 1.29% and 4.84%, respectively) and syllogistic problems (i.e. overall average of 0.86% and 4.35%, respectively) confirm that most of the participants follow instructions and provide first intuitive response. In the same lines, 54.47% and 51.59% of participants in conflicting base-rate and syllogistic problems use T2 to provide a final response. This implies that participants follow instructions to use fundamental information and reassess initial response by using T2.

--------------- Insert table 2 & 3 --------------

2.4.3. Stability index analysis

For conflict base-rate problems, the direction of change analysis provides two dominant trends: intuitive initial response with no change in final response and initial intuitive response with a change in the final response. For hypothesis testing, our interest is in the frequency of final correct responses i.e. T2-based selection of value stocks. Before conducting empirical analysis, we analyze participant-level consistency in the sequence of final correct responses to check variability in the final response selection. To do so, we follow Bago and De Neys (2017) stability index analysis. In the context of this study, five possible categories of stability index are possible at participant-level. Participants with four correct final responses have a stability index of 100%, three correct responses have a stability index of 75%, two responses have a stability index of 50%, one correct response has stability index of 25%, and zero correct responses had stability index of 0%. It is important to note that final correct responses for conflicting (or no-conflicting) base-rate problems referred to as the selection of value (or growth) stock.

Table 4 provides the results of the stability index for conflicting base-rate and syllogistic problems. The results show the dominance of 100% and 0% stability index, suggesting that most of the participants provide 4 correct final responses (i.e. value stocks) and 0 correct responses (i.e. growth stocks). The overall average of 100% stability index is 52.94% and 0% stability index is 31.31%. Participants with 100% of correct responses are referred to as value investors and participants with no correct responses as growth investors. Table 4 reports higher overall average of 100% stability index (i.e. 47.79%) and 0% stability index (i.e. 34.80%) for syllogistic problems. This confirms base-rate results and suggests that base-rate responses are not due to random guessing because random selection would have resulted in a higher proportion of stability index of 75%, 50%, and 25%.

-------------- Insert table 4 --------------

2.4.4. Hypothesis testing

Our objective is to test the impact of decision-making and emotional regulation on the preferences towards the selection of value versus growth stocks. We use participant's tendency to select value versus growth stocks as the dependent variable and measured as a sum of value stock choices as the final response in four conflicting base-rate problems. Like the stability index, there are five possibilities of value stock choices frequency that are 4, 3, 2, 1, and 0. We consider the dependent variable as the frequency of correct responses not ordered categories and employ a mixed-effect linear model for hypotheses testing. Before hypothesis testing, we check the correlation between the main variables (see table 5) and found no correlation between independent variables. However, results provide a significant negative correlation between value versus growth stocks frequency, experiential inventory and expressive suppression, and significant positive correlation between value versus growth stocks frequency, rational inventory, and cognitive reappraisal.

-------------- Insert table 5 --------------

The results of the null (no-predictor) model of the mixed-effect linear model provide a significant intercept value, b=2.3725, Z=26.16, p-value= 0.000, suggesting that 2.372 mean frequency response common across four experiments. The variation in intercept is insignificant, var(b)= 1.23E-22, Z=0.0448, p>0.1, implying that variation in intercept from mean value across experiments is not different from zero and there is no need to develop model at experiment-level. The interclass correlation confirms no need of an experiment-level model and provides negligible variation across experiments (Interclass Correlation Coefficient; ICC= 3.65E-23). While the variance in residual (participant-level variance) is statistically significant, var(residual)=3.3563, Z=14.2828, p-value=0.000, suggesting that variation from experiment-level mean is significantly explained by participant-level predicator. Hence, we develop a participant-level (level 1) model to capture variations across participants within each experiment.

The level 1 model is developed by using the participant's tendency to engage in T1 (experiential inventory), T2 (rational inventory), cognitive reappraisal, and expressive suppression. The results suggest improvement in model with incorporation of participant-level predictors and provide a higher difference in AIC value (intercept only model AIC=1657.887, level 1 model AIC=1249.972, ΔAIC=407.915). The variance in residual is still significant (i.e. var(residual)=1.1852, Z=14.2117, p-value=0.0000) but estimate value is weak, suggesting explanatory power of participant-level indicators. In addition, likelihood-ratio test provides significant LR chi2 value (i.e. chi2 (6) = 419.91, p=0.000), implying that participant-level random model shows better model fit.

-------------- Insert table 6 --------------

The results of participant-level predictors are given in table 6. The results provide the statistically significant negative effect of experiential inventory (i.e. T1) on the frequency of value versus growth stock responses, b=-0.91002, Z=-19.15, p-value=0.000, suggesting that participants scoring high on the experiential inventory are less likely to select correct responses (value stocks) versus incorrect responses (growth stocks), confirming hypothesis 1. We also find a significant positive effect of rational inventory (i.e. T2) on the frequency of value stock responses, b=0.6971, Z=14.46, p-value=0.000. This suggests that participants engage in rational rethinking mostly select correct final response (i.e. value stock) than incorrect response (i.e. growth stock), confirming hypothesis 2. As predicted, we find that more reliance on T1 is associated with a lower preference towards value versus growth stocks, and the tendency to engage in T2 is related to a higher preference towards the selection of value versus growth stocks.

The results provide a significant positive effect of cognitive reappraisal on the frequency of value versus growth stock responses, b=0.1055, Z=4.01, p-value=0.000, confirming hypothesis 3. This suggests that participants with a higher score on cognitive reappraisal select more correct responses (i.e. value stocks) versus incorrect responses (i.e. growth stocks). Results also confirm hypothesis 4 and provide a significant negative effect of expressive suppression on the frequency of value stocks, b=-0.1390, Z= -5.30, p-value=0.000. This indicates that participants relying on expressive suppression are more inclined to select incorrect responses (i.e. growth stocks) versus correct responses (i.e. value stocks). As hypothesized, results confirm that stronger reliance over cognitive reappraisal results in higher preference towards value versus growth stocks, while higher reliance on expressive suppression is associated with a lower preference towards value versus growth stocks.

--------------- Insert table 7 --------------

We also develop the frequency of correct responses for the syllogistic task to confirm the results of the base-rate task. The results provide significant intercept value for syllogistic task, b=2.2377, Z=24.54, p-value= 0.000, with insignificant variation in intercept value, var(b)= 2.92E-23, Z=0.0414, p>0.1. Results also show significant variation in residual value, var(residual)=3.3920, Z=14.2828, p-value=0.000. The results show no variation at the experiment level but a significant explanation by the participant-level predictor. The participant-level model also confirms the findings of the base-rate task and suggest a negative impact of experiential inventory and expressive suppression on the frequency of correct responses, and positive association with rational inventory and cognitive reappraisal (see table 7). As predicted, participants select incorrect responses based on emotion-driven intuitive thinking, while, others employ rational thinking and cognitive reappraisal to select correct responses.

2.4.5. Robust analysis

The stability index indicates two dominant responses categories i.e. 100% with four correct responses (value stocks) and 0% with four incorrect responses (growth stocks). We exclude participants with 3, 2, and 1 correct response and label participants with four correct responses as value investors and participants with no correct responses as growth investors. We generate a binary dependent variable by coding participants with four correct responses as value stock choice (i.e. 1) and zero correct response as growth stock choice (i.e. 0). A total of 216 participants are coded as "1" and 127 participants as "0", remaining 65 participants are dropped from the analysis. The null model of the mixed-effect logistic model suggests no need to develop an experiment-level model because most of the variation in the frequency of correct responses are explained by participant-level predictor (refer to section 4.4). Hence, we use a participant-level perspective to test the robustness of results and apply the logistic regression model.

-------------- Insert table 8 --------------

Table 8 reports the results of the logistic regression model. The LR chi2 shows the better model fit than no predictor model (i.e. chi2(6)=299.21, p=0.000). The results provide a significant negative coefficient value of experiential inventory, b=-2.3526, Z=-8.08, p=0.000, Odds ratio=0.095118, confirming hypothesis 1. The results also confirm hypothesis 2 and provide a significant positive coefficient of rational inventory, b=1.6834, Z=7.47, p=0.000, odds ratio=5.3842. This implies that participants following intuitive based T1 show a higher probability to select growth stocks, while participant's reliance over T2 is associated with a higher likelihood to invest in value stocks. As predicted results also confirm a positive effect of cognitive reappraisal, b=0.3102, Z=2.96, p=0.003, odds ratio=1.3637, and negative effect of expressive suppression, b=-0.5592, Z=-4.73, p=0.000, odds ratio=0.5716, on the likelihood of selecting value versus growth stocks. This confirms hypotheses 3 and 4 and suggests that participants exhibiting a stronger application of cognitive reappraisal show a higher preference towards value versus growth stocks, while, participants with a higher reliance on expressive suppression reflect a lower preference towards value versus growth stocks.

2.5. Discussion and conclusion

The literature on the value premium mainly focuses on the predictors, persistence, and performance of the value premium. Proponents of risk-based explanation consider value premium as compensation for bearing additional risk, while behavioral explanation supports a mispricing perspective of superior performance. The research in economic behavior provides that individual differences in the decision-making processes and emotional regulation strategy are significant predictors of an individual's risk-taking behavior. There is a lack of evidence on how an individual's differences in reliance on the decision-making process and emotion regulation influence the preferences towards value versus growth stocks. We address this gap and capture the impact of individual differences in the decision-making process (by using dual-process theory) and emotional regulation (by using emotional regulation theory) on an individual's preferences towards value versus growth stocks. We conducted four online experiments to collect data from participants having prior or current stock market experience.

The results confirm that an individual's reliance on T1 (T2) and expressive suppression (cognitive reappraisal) are associated with lower (higher) preferences towards the selection of value versus growth stocks. This indicates that cognition and emotion combinedly influence an individual's investment decision-making. Consistent with evidence in the economic literature that cognition and emotion are not independent but are inherently interdependent from inception to action (e.g. Phelps et al, 2014). We find that individuals select emotionally mediated growth stocks by engaging in intuitive T1 processing, while emotionally stable individuals anticipate negative emotions and engage in cognitive T2 processing to select strong fundamentals value stocks. Emotionally motivated individuals seek to amplify the hedonic effect of positive feelings associated with prior positive returns and continue investing in market-driven growth stocks (Karlsson, Loewenstein & Seppi, 2009). However, emotionally stable individuals anticipate negative emotions as a learning opportunity to thoroughly analyze investment alternatives (Chu et al., 2014).

Richards et al., (2018) examined investor's susceptibility towards disposition effect by using System 1, System 2, expressive suppression, and cognitive reappraisal. They find that investor's reliance on System 1 (or System 2) has higher (or lower) susceptibility towards disposition effect. Cognitive reappraisal reduces the disposition effect while expressive suppression shows no effect on disposition effect. Also, Barber and Odean (2008) provide that investors pay attention to a small set of stocks due to cognitive constraints and hence buy attention-driven stocks. Merton (1987) documents that investors only pay attention to a limited number of large stocks and neglect less visible stocks that later earn higher positive returns. Consistent with preceding evidence, we find that an individual’s reliance on intuitive T1 processing (or cognitive T2 processing) and expressive suppression (cognitive reappraisal) reflect higher preference to select attention-driven growth stocks (or neglected value stocks).

Karlsson et al., (2009) find that investors are more attentive to the increase in portfolio market value and magnify the hedonic effect of positive returns by just focusing on positive feelings than negative feelings (termed as Ostrich effect). Alternatively, investor attention towards negative returns can also increase due to curiosity and search for potentially profitable alternatives (Sicherman, Loewenstein, Seppi & Utkus, 2016). Soe and Barrett (2007) provide that investors experiencing intense feelings tend to achieve higher decision-making performance. The investor's tendency to distinguish current feelings from decision-making performance exhibit stronger control over emotions and prevent possible biased behavior. In the same lines, we show that individuals employ emotion-embedded T1 processing to persist with growth stocks without updating biased expectations anchored in standalone value-to-market ratio. Whereas, emotionally strong individuals can reappraise feelings to thoroughly analyze available fundamental information to make an informed investment decision.

Our findings contribute to the improvement of knowledge in three main areas. First, we add to the literature on cognition by confirming the applicability of the DI time course assumption in the context of investment decision-making. Consistent with dual-process theory, we provide that individuals first selected T1-based growth stocks, and later some individuals failed to engage in the rethinking process by persisting with growth stocks (Bago & De Neys, 2017). While others successfully engage in the rethinking process and switch to T2-based value stocks. We contribute by proving that emphasized instructions and additional information debiased intuitive responses and overridden T1 by inducing T2 (e.g. Moutier et al., 2002). Individuals approach decision-making as experts and utilized additional information to rethink and provided the final correct response (e.g. Bialek & Zielonka, 2016). Hence, we conclude that individuals can avoid selection of intuition-based weak fundamental overvalued stocks (i.e. growth stocks) or undervalued poor fundamental value stocks by engaging in T2 and select strong fundamental value or growth stocks.

Second, an individual’s differences in the selection of value versus growth stocks are attributed to the use of T1 or T2 and managing emotions by using expressive suppression or cognitive reappraisal. Individuals frequently using T1 and expressive suppression show a lower preference towards value versus growth stocks, while individuals engage in T2 and cognitive reappraisal reflect higher preference towards value versus growth stocks. Results confirm that growth investors select investment choices based on standalone value-to-market ratios, while value investors utilize fundamental information to select a fundamentally strong value or growth stocks. This indicates that susceptibility towards the selection of growth versus value stocks increases with more reliance over T1 and suppression of negative emotions. Kok et al., (2017) find that value investors do not primarily rely on standalone value-to-market ratios but thoroughly analyze available fundamental information. Consistent with their argument we find that growth investors rely on prior biased expectations anchored in value-to-market ratio to select emotion-driven growth stocks, whereas value investors are more emotionally stable and utilize updated fundamental information to make informed investment decisions. Like Graham and Dodd (1934), we argue that value investor takes informed decisions while other (growth) investors are more prone to informed speculation.

Individuals engage in loss aversion through the exhibition of hot hand fallacy and self-attribution bias suppresses negative emotions to select market-driven growth stocks (Shefrin, 2007). The use of T2 enables individuals to allocate cognitive resources to evaluate available information and avoid the selection of weak fundamental value stocks. Individuals simulate the expected emotions associated with each outcome to reformulate the meaning of negative emotions (Sokol-Hessner Hsu et al., 2009) and divert attentional deployment towards expected positive emotions (Gross & John, 2003) to update prior beliefs based on updated fundamental information (Kok et al., 2017). Consequently, resulting in a thorough analysis of investment alternatives (Chu et al., 2014) and reappraisal of negative emotions into positive emotions to select strong fundamentals value firms (Gross & John, 2003; John & Gross, 2007). Hence, we conclude that individuals who employ T1 processing and expressive suppression are more impulsive and susceptible to the selection of emotion-driven over-valued weak fundamentals growth stocks. While the use of T2 and cognitive reappraisal results in more self-control and facilitates the selection of systematically analyzed undervalued strong fundamentals value stocks. This supports Graham and Dodd (1934) view that investment is the selection of choices based on thorough analysis by managing emotional conflicts.

Third, we confirm that both cognition and emotions provide a better understanding of preference towards the selection of value versus growth stocks (Taffler, 2018). We conclude that individuals associate “pleasant” and “exciting” feelings with emotionally preferred growth stocks and persist with prior biased beliefs to select growth stocks and neglect emotionally “tainted” undervalued value stocks. However, an individual's reliance over cognitive reappraisal enables them to reevaluate affective labeling by considering updated fundamental information and induce selection of truly strong fundamental value stocks.

The findings provide important implications for investors to employ T2 to select undervalued value stocks. The result suggests that individuals mostly select emotion-driven intuitive choices that can result in biased investment selection. As suggested by Graham and Dodd (1934), investors thoroughly analyze available information by managing emotional inhibitors, but such processes are difficult to apply because of cognitive limitations and emotional constraints. Our results indicate that individuals can avoid the selection of undervalued (overvalued) poor fundamental stocks by reducing reliance over T1 and diverting attentional deployment towards the use of T2. This facilitates frequent updates of prior biased beliefs to avoid the selection of emotion-driven investment choices. This cognitive-deliberative situation induces individuals to reformulate negative emotions by diverting attention towards positive emotions associated with investment choices.

Investors can overcome the selection of intuitive investment choices by developing a list of important fundamental indicators that can help to rethink and update prior beliefs or intuitive investment choices. In doing so, investors can deploy T2 and cognitive reappraisal to achieve the desired objective and select undervalued strong fundamental value stocks.

The theoretical framing and methodology of the current study have both strengths and weaknesses. In terms of theoretical framing, strength is that study provided the combined effect of cognition and emotion is explaining individual preferences towards the selection of value versus growth stocks but overlooked the influence of other personality traits like extroversion, conscientiousness, openness, emotional stability, and agreeableness. Studies like Gross and John (2003) and John and Gross (2004) provided the relationship between emotional-regulation and personality characteristics. Hence, one can presume that personality traits might moderate or mediate the effect of the decision-making process and emotional regulation on the selection of value versus growth stocks. For instance, higher reliance over T2 (T1) processing and cognitive reappraisal (expressive suppression) might increase (decrease) openness to experience, leading to more (less) preference to selection of value versus growth stocks.

Strengths on methodological sides are that the study adapted a two-response paradigm in the context of stock selection and confirmed that respondents followed experiment instructions to provide an initial intuitive response. We also provide methodological validation of emphasized instructions and extra information in inducing T2 to override initial intuitive response. We used four experimental settings to induce initial T1-based response and T2-based response but did not manipulate emotional-regulation strategies. In hypothesis testing, we considered the decision-making process and emotional regulation strategies as naturally occurring personality characteristics. Hence, future research can manipulate emotional-regulation strategies together with the decision-making process. Our study provides strong ecological validity than university student samples and better measurement validity because of using direct measurement constructs of the decision-making process and emotional-regulation strategies. The data of this study is collected online and one might argue that there is less control over participants than laboratory-based experiments or personally conducted surveys. But we tried to ensure participant's interest and control by inserting emphasized instructions and screening questions during experiments. But future research can replicate the current study by using different samples through controlled laboratory-based experiments or can use data from real-time investors by collaborating with financial institutions and brokers, as conducted by Weber et al., (2013) and Richards et al., (2018).

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List of tables

Table 1: Accuracies of final responses of base-rate and syllogistic reasoning problems

	Base-rate reasoning problems		Syllogisms reasoning problems	
Experiment	Conflict	No-conflict	Conflict	No-conflict
Experiment 1	59.95% (49.05)	91.99% (27.17)	54.61% (49.84)	92.96% (25.61)
Experiment 2	55.88% (49.71)	95.09% (21.61)	52.69% (49.98)	95.34% (21.09)
Experiment 3	62.37% (48.50)	97.02% (16.99)	58.91% (49.26)	98.01% (13.94)
Experiment 4	59.06% (49.23)	98.77% (11.01)	57.59% (49.48)	99.27% (8.55)
Average (SD)	59.31% (49.14)	95.71% (20.27)	55.94% (49.66)	96.38% (18.67)

In this table, first value represents the percentage of correct final response at the individual-response level and the standard deviation is given in parenthesis

Table 2: Direction of change of no-conflicting base-rate and syllogistic reasoning problems

	Base-rate (no-conflicting) reasoning problems			
Experiment	"00"	"01"	"10"	"11"
Experiment 1	6.31% (26)	8.5% (35)	1.7% (7)	83.5% (344)
Experiment 2	3.68% (15)	6.86% (28)	1.23% (5)	88.24% (360)
Experiment 3	2.72% (11)	4.21% (17)	0.25% (1)	92.82% (375)
Experiment 4	0.73% (3)	0.49% (2)	0.49% (2)	98.28% (401)
Average (SD)	3.37% (55)	5.02% (82)	0.92% (15)	90.69% (1480)
	Syllogistic (no-conflicting) reasoning problems			
Experiment	"00"	"01"	"10"	"11"
Experiment 1	4.61% (19)	4.61% (19)	2.43% (10)	88.35% (364)
Experiment 2	1.72% (7)	3.92% (16)	2.94% (12)	91.42% (373)
Experiment 3	1.49% (6)	1.73% (7)	0.5% (2)	96.29% (389)
Experiment 4	0.25% (1)	0.98% (4)	0.49% (2)	98.28% (401)
Average (SD)	2.02% (33)	2.82% (46)	1.59% (26)	93.57% (1527)

In this table, first value represents the direction of change at individual-response level and the standard deviation is given in parenthesis

Table 3: Direction of change of conflicting base-rate and syllogistic reasoning problems

Base-rate (conflicting) reasoning problems				
Experiment	"00"	"01"	"10"	"11"
Experiment 1	37.38% (154)	55.34% (228)	2.67% (11)	4.61% (19)
Experiment 2	43.63% (178)	54.17% (221)	0.49% (2)	1.72% (7)
Experiment 3	37.13% (150)	55.45% (224)	0.50% (2)	6.93% (28)
Experiment 4	39.46% (161)	52.94% (216)	1.47% (6)	6.13% (25)
Average (SD)	39.40% (643)	54.47% (889)	1.29% (21)	4.84% (79)
Syllogistic (conflicting) reasoning problems				
Experiment	"00"	"01"	"10"	"11"
Experiment 1	44.42% (183)	50% (206)	0.97% (4)	4.61% (19)
Experiment 2	45.83% (187)	50.98% (208)	1.47% (6)	1.72% (7)
Experiment 3	40.59% (164)	51.98% (210)	0.5% (2)	6.93% (28)
Experiment 4	41.91% (171)	53.43% (218)	0.49% (2)	4.17% (17)
Average (SD)	43.20% (705)	51.59% (842)	0.86% (14)	4.35% (71)

In this table, first value represents direction of change at individual-response level and standard deviation is given in parenthesis

Table 4: Stability Index of conflicting base-rate and syllogistic reasoning problems

Base-rate (conflicting) reasoning problems					
Experiment	100%	75%	50%	25%	0%
Experiment 1	48.54% (50)	7.77% (8)	4.85% (5)	12.62% (13)	26.21% (27)
Experiment 2	51.96% (53)	2.94% (3)	0 (0)	6.86% (7)	38.24% (39)
Experiment 3	56.44% (57)	0 (0)	5.94% (6)	11.88% (12)	25.74% (26)
Experiment 4	54.90% (56)	2.94% (3)	0 (0)	7.84% (8)	34.31% (35)
Average (SD)	52.94% (216)	3.43% (14)	2.70% (11)	9.80% (40)	31.31% (127)
Syllogistic (conflicting) reasoning problems					
Experiment	100%	75%	50%	25%	0%
Experiment 1	42.72% (44)	7.77% (8)	6.8% (7)	10.68% (11)	32.04% (33)
Experiment 2	46.085 (47)	5.88% (6)	0.98% (1)	6.86% (7)	40.20% (41)
Experiment 3	50.50% (51)	5.94% (6)	2.97% (3)	9.90% (10)	30.69% (31)
Experiment 4	51.96% (53)	4.90% (5)	0.98% (1)	5.88% (6)	36.27% (37)
Average (SD)	47.79% (195)	6.13% (25)	2.94% (12)	8.33% (34)	34.80% (142)

In this table, first value represents stability index at participant-level and the standard deviation is given in parenthesis

Table 5: Correlation matrix

	Value versus growth stocks frequency	Syllogistic correct responses frequency	Experiential inventory (Type 1)	Rational inventory (Type 2)	Cognitive reappraisal	Expressive suppression
Value versus growth stocks frequency	1					
Syllogistic correct responses frequency	.919**	1				
Experiential inventory (Type 1)	-.634**	-.569**	1			
Rational inventory (Type 2)	.493**	.494**	-0.09	1		
Cognitive reappraisal	.180**	.143**	-0.086	0.023	1	
Expressive suppression	-.248**	-.257**	0.086	-0.077	0.023	1

** represents p=0.01

Table 6: Level 1 mixed-effect linear model (conflicting base-rate reasoning problems)

Value versus growth stocks frequency	Coefficient	Standard error	z	p-value	95% Confidence Interval	
Experiential inventory (Type 1)	-0.91002	0.047512	-19.15	0.0000	-1.00315	-0.8169
Rational inventory (Type 2)	0.697189	0.048207	14.46	0.0000	0.602706	0.791672
Cognitive reappraisal	0.105548	0.026304	4.01	0.0000	0.053992	0.157103
Expressive suppression	-0.13907	0.026245	-5.3	0.0000	-0.19051	-0.08763
Gender	-0.13037	0.113591	-1.15	0.2510	-0.353	0.092264
Age	0.011445	0.008126	1.41	0.1590	-0.00448	0.027372
Intercept	2.676858	0.426951	6.27	0.0000	1.840049	3.513666

Table 7: Level 1 mixed-effect linear model (conflicting syllogistic reasoning problems)

Syllogistic correct responses frequency	Coefficient	Standard error	z	p-value	95% Confidence Interval	
Experiential inventory (Type 1)	0.712113	0.053365	13.34	0.0000	0.607519	0.816708
Rational inventory (Type 2)	-0.81598	0.052597	-15.51	0.0000	-0.91907	-0.71289
Cognitive reappraisal	0.081306	0.029118	2.79	0.0050	0.024236	0.138376
Expressive suppression	-0.15223	0.029054	-5.24	0.0000	-0.20917	-0.09528
Gender	-0.01029	0.12576	-0.08	0.9350	-0.25677	0.236201
Age	0.010866	0.008997	1.21	0.2270	-0.00677	0.028499
Intercept	2.21238	0.47134	4.69	0.0000	1.288571	3.13619

Table 8: Logistic regression model

Value versus growth stocks frequency	Coefficient	Standard error	z	p-value	Odds ratio	95% Confidence Interval	
Experiential inventory (Type 1)	-2.35264	0.291083	-8.08	0.0000	0.095118	0.0951177	-1.782127
Rational inventory (Type 2)	1.68348	0.225411	7.47	0.0000	5.384259	5.384259	2.125278
Cognitive reappraisal	0.3102348	0.104728	2.96	0.0030	1.363745	1.363745	0.5154983
Expressive suppression	-0.5592946	0.118289	-4.73	0.0000	0.5716121	0.5716121	-0.3274514
Gender	-0.1589769	0.432946	-0.37	0.7130	0.853016	0.853016	0.6895821
Age	0.0505738	0.031695	1.6	0.1110	1.051874	1.051874	0.112696
Intercept	1.939184	1.562752	1.24	0.2150	6.953077	6.953077	5.002122

Appendix

Appendix A

Appendix A1: Correlation table

	Value versus growth stocks frequency	Syllogistic correct responses frequency	Experiential inventory (Type 1)	Rational inventory (Type 2)	Cognitive reappraisal	Expressive suppression
Value versus growth stocks frequency	1					
Syllogistic correct responses frequency	.954**	1				
Experiential inventory (Type 1)	-.861**	-.881**	1			
Rational inventory (Type 2)	.954**	.955**	-.861**	1		
Cognitive reappraisal	.970**	.963**	-.881**	.966**	1	
Expressive suppression	-.916**	-.884**	.828**	-.875**	-.906**	1

** represents p-value=0.01

Appendix A2: Regression results

Value versus growth stocks frequency	Coefficient	Std. Error	t-statistics	p-value
Experiential inventory (Type 1)	0.010	0.112	0.088	0.930
Rational inventory (Type 2)	0.381	0.196	1.945	0.058
Cognitive reappraisal	0.458	0.133	3.458	0.001
Expressive suppression	-0.185	0.069	-2.677	0.010
Gender	0.035	0.138	0.257	0.799
Age	0.000	0.010	0.045	0.964
(Constant)	-0.268	0.804	-0.333	0.741
R-squared	0.952	F-statistics	143.495	
Adjusted R-squared	0.946	p-value	0.000	

Appendix B

Appendix B1: Base-rate reasoning problems

The cashflow-to-price ratio of ALPHA is 5.75%, whereas BETA cashflow-to-price ratio is 0.97%.

ALPHA expected return is 14.25% and deviation in returns is 14.93%, whereas BETA expected return is 43.12% and deviation in returns is 40.18%.

Which company stocks you select for investment:

- ALPHA stocks
- BETA stocks

Extra details

Fundamentals of ALPHA and BETA

	Company ALPHA	Company BETA
Current ratio	0.8x	1.5x
Gross profit margin	53.00%	78.50%
R&D expenditure/sales	6.80%	17.10%
Selling & advertising expenses/sales	28.30%	38.90%
Capital expenditure/total assets	1.47%	1.64%

(Non-conflicting)

The Book-to-Price ratio of ALPHA is 1.0x, whereas BETA Book-to-Price ratio is 0.28x.

ALPHA expected return is 7.96% and deviation in returns is 20.76%, whereas BETA expected return is 6.54% and deviation in returns is 44.59%.

Which company stocks you select for investment:

- ALPHA stocks
- BETA stocks

Extra details

Fundamentals of ALPHA and BETA

	Company ALPHA	Company BETA
Debt ratio	0.37x	0.24x
Cashflows from operations-to-net income ratio	1.36x	-7.69x
ROA	4.70%	-1.50%
Assets turnover	0.4x	0.3x

Capital expenditure/total assets	1.78%	1.66%
Dividend per share	$1.64	$0.00

(Conflicting)

The earnings yield (earnings-to-price ratio) of ALPHA is 11.50%, whereas BETA earnings yield is 1.30%.

ALPHA expected return is 7.96% and deviation in returns is 20.76%, whereas BETA expected return is 86.00% and deviation in returns is 34.14%.

Which company stocks you select for investment:

- ALPHA stocks
- BETA stocks

Extra details

Fundamentals of ALPHA and BETA

	Company ALPHA	Company BETA
Current ratio	0.6x	4.3x
Gross profit margin	43.50%	65.80%
Free Cashflows margin	12.10%	12.30%
ROA	4.70%	13.80%
assets turnover	0.4x	0.7x
Selling & advertising expenses/sales	0.00%	16.90%
R&D expenditure/sales	27.60%	45.50%
Capital expenditure/total assets	1.78%	2.18%

(Non-conflicting)

The sales-to-price ratio of ALPHA is 1.43x, whereas BETA sales-to-price ratio is 0.14x.

ALPHA expected return is 16.82% and deviation in returns is 36.27%, whereas BETA expected return is 24.83% and deviation in returns is 25.05%.

Which company stocks you select for investment:

- ALPHA stocks
- BETA stocks

Extra details

Fundamentals of ALPHA and BETA

	Company ALPHA	Company BETA
Current ratio	1.4x	12.3x
Gross profit margin	34.50%	65.20%
Cashflows from operations-to-net income ratio	0.35x	2.64x
Free Cashflows margin	3.60%	29.20%
R&D expenditure/sales	0.00%	13.30%
Dividend per share	$0.92	$1.84

(Non-conflicting)

The cashflow-to-price ratio of ALPHA is 11.49%, whereas BETA cashflow-to-price ratio is 2.55%.

ALPHA expected return is 29.09% and deviation in returns is 29.26%, whereas BETA expected return is 44.03% and deviation in returns is 53.78%.

Which company stocks you select for investment:

- ALPHA stocks
- BETA stocks

Extra details

Fundamentals of ALPHA and BETA

	Company ALPHA	Company BETA
Current ratio	4.1x	0.9x
ROA	7.30%	0.70%
Assets turnover	2.0x	0.5x
Capital expenditure/total assets	6.85%	2.54%
Dividend per share	$1.34	$0.00

(Conflicting)

The accrual ratio of ALPHA is -0.15x, whereas BETA accrual ratio is 0.044x.

ALPHA expected return is 26.06% and deviation in returns is 15.53%, whereas BETA expected return is 43.64% and deviation in returns is 53.50%.

Which company stocks you select for investment:

- ALPHA stocks
- BETA stocks

Extra details

Fundamentals of ALPHA and BETA

	Company ALPHA	Company BETA
Gross profit margin	84.40%	83.40%
Cashflows from operations-to-net income ratio	1.75x	1.72x
Free Cashflows margin	33.30%	23.00%
ROA	23.30%	16.80%
assets turnover	1.2x	0.8x
R&D intensity (R&D expense/sales)	19.90%	12.70%
Dividend per share	$1.88	$0.00

(Conflicting)

The dividend yield of ALPHA is 1.70%, whereas BETA dividend yield is 4.80%.

ALPHA expected return is 24.63% and deviation in returns is 25.05%, whereas BETA expected return is 33.98% and deviation in returns is 62.19%.

Which company stocks you select for investment:

- ALPHA stocks
- BETA stocks

Extra details

Fundamentals of ALPHA and BETA

	Company ALPHA	Company BETA
Current ratio	12.3x	1.9x
Gross profit margin	65.20%	38.50%
Free Cashflows margin	29.20%	8.90%
ROA	6.50%	0.90%
R&D expenditure/sales	13.30%	0.00%
Capital expenditure/total assets	4.48%	1.20%
Dividend per share	$1.84	$0.60

(Non-conflicting)

The earnings yield (earnings-to-price ratio) of ALPHA is 10.30%, whereas BETA earnings yield is 0.10%.

ALPHA expected return is 31.19% and deviation in returns is 54.50%, whereas BETA expected return is 33.98% and deviation in returns is 62.19%.

Which company stocks you select for investment:

- ALPHA stocks
- BETA stocks

Extra details

Fundamentals of ALPHA and BETA

	Company ALPHA	Company BETA
Debt ratio	0.72x	0.58x
Gross profit margin	39.30%	38.50%
ROA	12.00%	0.90%
assets turnover	1.6x	0.9x
Capital expenditure/total assets	8.73%	1.20%
Dividend per share	$1.20	$0.6

(Conflicting)

The Book-to-Price ratio of ALPHA is 1.0x, whereas BETA Book-to-Price ratio is 0.06x. ALPHA expected return is 37.40% and deviation in returns is 89.14%, whereas BETA expected return is 86.00% and deviation in returns is 34.14%.

Which company stocks you select for investment:

- ALPHA stocks
- BETA stocks

Extra details

Fundamentals of ALPHA and BETA

	Company ALPHA	Company BETA
Current ratio	3.32x	6.07x
Debt ratio	11.78%	12.4%
Gross profit margin	37.59%	68.39%
ROA	8.89%	8.59%
R&D expenditure/sales	0.00%	14.71%
Selling & advertising expenses/sales	28.56%	39.92%
Δ Selling & advertising expenses/sales	0.89%	-3.28%

(Non-conflicting)

Appendix B2: Syllogistic reasoning problems

Premise 1: All profitable firms have growth in sales.

Premise 2: Firm Y has a growth in sales.

Conclusion: Firm Y is a profitable firm.

(No-conflict: Valid/Believable)

Premise 1: All undervalued high book-to-price ratio firms provide return opportunity

Premise 2: Company X provides return opportunity

Conclusion: Company X is a distressed undervalued firm

(Conflict: Valid/Unbelievable)

Premise 1: Fundamentally strong firms provide a higher return

Premise 2: High-risk firms are fundamentally strong

Conclusion: High-risk firms provide a higher return

(No-conflict: Invalid/Unbelievable)

Premise 1: High-risk firms provide a higher return

Premise 2: Amazon provides a higher return

Conclusion: Amazon is a high-risk firm

(Conflict: Valid/Unbelievable)

Premise 1: When market prices go up, stocks provide short term gain opportunity

Premise 2: Stock X market price goes up

Conclusion: Stock X provide short term gain opportunity

(No-conflict: Valid/Believable)

Premise 1: Investment attractive firms have consistent historical growth in fundamentals

Premise 2: Company X is an investment attractive firm

Conclusion: Company X has consistent historical growth in fundamentals

(Conflict: Invalid/Believable)

Premise 1: All profitable firms have growth in sales

Premise 2: Firm Y is a profitable firm

Conclusion: Firm Y has growth in sales

(Conflict: Invalid/Believable)

Premise 1: High market capitalization firms have strong growth prospects

Premise 2: Firms investment in growth prospects is a risky decision

Conclusion: High market capitalization firms take risky decisions

(No-conflict: Invalid/Unbelievable)

Premise 1: Analysts followed firms have a high level of market interest

Premise 2: High market interest firms are overvalued

Conclusion: Analysts follow overvalued firms

(No-conflict: Valid/Unbelievable)

Appendix B3: The Rational Experiential Inventory Short 24 (REI-S24)

Rational scale = Rational ability subscale + rational preference subscale

Rational ability subscale

1. I have a logical mind.
2. I am not a very analytical thinker-r
3. I am much better at figuring things out logically than most people.
4. I am not very good at solving problems that require careful logical analysis. –r
5. Using logic usually works well for me in figuring out problems in my life.
6. Reasoning things out carefully is not one of my strong points.-r

Rational preference subscale

7. Knowing the answer without having to understand the reasoning behind it is good enough for me. –r
8. I prefer complex to simple problems.
9. I enjoy problems that require hard thinking.
10. I don't like to have to do a lot of thinking. -r
11. I enjoy intellectual challenges.
12. I try to avoid situations that require thinking in depth about something. –r

Experiential scale= Experiential ability + experiential favourability

Experiential ability subscale

13. When it comes to trusting people, I can usually rely on my gut feelings.
14. I suspect my hunches are often inaccurate. -r
15. I trust my initial feelings about people.
16. If I were to rely on my "gut feelings," I would often make mistakes. -r
17. I believe in trusting my hunches.
18. I don't have a very good sense of intuition. –r

Experiential preference subscale

19. I don't think it is a good idea to rely on one's intuition for important decisions.-r
20. I often go by my instincts when deciding on a course of action.

21. I generally don't depend on my feelings to help me make decisions.- r
22. I like to rely on my intuitive impressions.
23. I don't like situations in which I have to rely on intuition.-r
24. I think there are times when one should rely on one's intuition.

These questions are measured on 5 point Likert scale ranging from 1, definitely false, 2 mostly false, 3 undecided/ equally true or false, 4 mostly true, 5 definitely true.
-r means the items were reversed.

Appendix B4: Emotional Regulation Questionnaire

Cognitive reappraisal

1. When I want to feel more positive emotion (such as joy or amusement), I change what I'm thinking about.
2. When I want to feel less negative emotion (such as sadness or anger), I change what I'm thinking about.
3. When I'm faced with a stressful situation, I make myself think about it in a way that helps me stay calm.
4. When I want to feel more positive emotion, I change the way I'm thinking about the situation.
5. I control my emotions by changing the way I think about the situation I'm in.
6. When I want to feel less negative emotion, I change the way I'm thinking about the situation.

Expressive suppression

1. I keep my emotions to myself.
2. When I am feeling positive emotions, I am careful not to express them.
3. I control my emotions by not expressing them.
4. When I am feeling negative emotions, I make sure not to express them.

These questions are measured on 7 point Likert scale ranging from 1, strongly disagree, 2 disagree, 3 slightly disagree, 4 uncertain, 5 slightly agree, 6 agree, 7 strongly agree.

Chapter 3

Is the value premium vary across the level of investors' attention?

Table of Contents

Is the value premium vary across the level of investors' attention?

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Abstract

This paper attempts to investigate the impact of investors' attention on the value premium. We find superior return differences to bivariate strategy that conditions value-growth strategy also as low investor attention, while return differences to value-growth strategy that is conditioned as high investor attention provide return differences that are indifferent from zero. We show that superior return differences to value-growth strategy across low attention are attributed to mispricing by using common risk factors, sentiment analysis, cross-sectional regression, and market expectation errors approach. The findings suggest that investor attention contributes to generating superior return differences to standard value-growth strategy. Our findings suggest investors to consider an investment strategy that takes a long position in value stocks conditioned as low investor attention and a short position in growth stocks conditioned as low investor attention.

Keywords

Investor attention, the SEC's EDGAR log files, value premium, mispricing, neglected stocks, attention-driven stocks

3.1. Introduction

The value premium is the buying and selling of high book-to-market ratio stocks (i.e. value stocks) and low book-to-market ratio stocks (i.e. growth stocks) to earn superior returns on price reversal (Lakonishok, Shleifer & Vishney, 1994). Two competing explanations are used to elucidate artifacts of the value premium. The risk-based perspective considers superior returns to value stocks as compensation for relatively higher distress risk than growth stocks (e.g. Fama & French, 1992). While, mispricing explanation infers value premium as the outcome of investors' underreaction or overreaction towards market-implied expectations to value stocks and growth stocks, anchored in historical fundamental information (Piotroski & So, 2012). The value premium captures the price correction effect arising from the reversal in investors' biased expectations towards updated fundamental information (LaPorta, Lakonishok, Shleifer & Vishny, 1997).

The risk-based explanation implies that investors possess unlimited cognitive processing capacity. Investors attempt to consider available market alternatives and analyze a large set of information, but their biased information processing holds due to limited cognitive capacity and overconfidence (Barber & Odean, 2008; Barberies & Shleifer, 2003; Grossman & Stiglitz, 1980). In the overconfidence approach of Daniel, Hirshleifer and Subrahmanyam (2001), investors are overconfident about their abilities and misinterpret private economic factors information that influences firms' future performance. Thus, pushing positive pressure on asset prices with similar characteristics on the arrival of misinterpreted information and later subsequent price reversal. According to the style investing approach of Barberies and Shleifer (2003), investors categorize stocks into different styles based on common characteristics, inducing positive (or negative) co-movement between common (or dissimilar) characteristics stocks (e.g. value vs growth stocks or high tech vs low tech firms, etc.). Stocks belonging to common characteristics that performance well becomes overpriced, leading to subsequent low returns and transfer of funds to other stocks categories based on relative performance. The limited cognitive resources are associated with investor limited attention to economic factors information. The literature on investor attention and information acquisition provides that investors largely pay more (or less) attention to common (or dissimilar) characteristics stocks and buy market-driven familiar stocks (or avoid less-visible neglected stocks), leading to temporary positive (or negative) price pressure on attention-driven stocks (or neglected stocks) in short-run and subsequent reversal in the long-run (e.g. Barber & Odean, 2008; Chen, 2017; Da, Engelberg & Gao, 2011; Fang & Peress, 2009; Li & Yu, 2012; Vozlyublennaia, 2014). Motivated by the theoretical grounding of investor overconfidence approach, style investing, investor attention, and information acquisition, we attempt to investigate the influence of investors' attention on the value premium. That is, how the value premium varies across the level of investors' attention to firm-specific fundamental information. This further allows us to differentiate between competing risk-based explanation and mispricing explanation in explaining the dynamics of the value premium.

On theoretical grounds, either informed rational investor behavior or overconfident market-driven investor behavior could be predominant. In an efficient market, informed investors can arbitrage away mispricing by using firm-specific fundamental information to earn superior returns, the superior returns due to systematic economic factors remains. We expect stronger value premium predictability as investors become attentive to extensive fundamental information and make informed trading decisions. Investors correctly update prior extrapolated biased performance expectations to value stocks and growth stocks, enabling them to identify potential high (or low) performance value and growth stocks. Investors make smaller trades on such private information to prevent quick information disclosure to market makers and reduce the probability of attention-driven trading. Informed investors assume camouflage of noise traders to conceal their trading pattern from market makers and noise traders to prevent the concentration of private information, evident in the U-shaped curve over the trading period (Admati & Pfleiderer, 1988; Kyle, 1985). Therefore, informed investors trade frequently by either buying value stocks or selling growth stocks to take advantage of private information, leading to the positive impact of investor attention towards fundamental information on value premium.

On the other hand, in an inefficient market, overconfident investors misinterpret firm-specific fundamental information, inducing positive price pressure on a set of common characteristics stocks (i.e. market-driven growth stocks) and negative price pressure on dissimilar characteristic stocks (i.e. neglected value stocks), and subsequent price reversal. We expect weaker (or stronger) value premium as investors take a long position in attention-driven (or neglected) value stocks and short in attention-driven (or neglected) growth stocks. Investors mainly focus on attention-driven growth stocks (or neglect less visible value stocks), leading to attention-induced positive price pressure (or negative price pressure) that temporarily put upward (or downward) pressure on growth stock prices (or value stock prices) in the short run. The incongruence between attention-driven stock prices (or neglected value stock prices) and their fundamental strength results in market expectations errors. The correction of biased market expectations stimulates the reversal of (previously) attention-driven stock prices, leading to a positive value-growth effect. The strength of the value-growth effect depends on the speed and magnitude of reversal in previous attention-driven growth stock prices. This suggests a negative association between attention and value-growth effect.

We confirm that the value premium varies across the level of investor attention by using data from U.S. firms listed on the S&P 1500 Composite index from December 2003 to April 2017. We used daily access files provided by the Securities Exchange Commission (SEC), known as Electronic Data Gathering and Retrieval (EDGAR) log files to capture investor attention. Results support that value stocks with low investor attention (value-and-low-attention) outperforms growth stocks with low investor attention (growth-and-low-attention) and return differences are insignificant between value stocks with high investor attention (value-and-high-attention) and growth stocks with high investor attention (growth-and-high-attention). These results are robust across three measures of investor attention and firm size. Our findings are consistent with investor recognition hypothesis that investors' persistence with neglected value stocks generates superior returns on price reversal. The return differences are primarily driven by the price reversal of previously high attention growth stocks. The trading strategy that takes a long position in value-and-low-attention stocks and a short position in growth-and-low-attention stocks generate superior value premium.

We employ common risk factors, sentiment analysis and arbitrage capital, Fama-Macbeth cross-sectional regression approach, and Piotroski-So expectation errors approach to confirm that return differences between value-growth strategy across the low level of investor attention (i.e. VL-GL) are attributed to mispricing explanation. The results provide a significant positive effect of alpha and insignificant effect of the Fama-French three-factor model and the five-factor model common risk factors. The sentiment analysis confirms that lagged sentiment index negatively impacts the return differences at a low level of investor sentiment across value-growth strategy

(VL-GL) and these superior returns are linked with the availability of arbitrage capital. Fama-MacBeth cross-sectional regression provides a positive effect of high BM firms and the negative effect of low attention on stock returns. Finally, the Piotroski-So expectation errors approach confirms that return differences across incongruence and congruence strategy are significant across low investor attention. Taken together, four approaches confirm that superior return differences between value-and-low-attention stocks and growth-and-low-attention stocks are explained by mispricing assumption.

This study contributes to literature along two main dimensions. First, the findings contribute by suggesting that considering investor attention and information acquisition of a set of common characteristics of similar stocks as investment selection criteria can generate superior returns. By doing so, investors can overcome the chances of investing in overpriced common characteristics stocks and can select neglected underpriced fundamentally strong stocks. This further suggests that investors should follow a systematic process to identify undervalued strong fundamental stocks. This systematic process infers from the Graham and Dodd (1934) investing approach that defines investment as a "thorough analysis" that promises "safety of principal" with a "satisfactory return" (Kok, Ribando & Sloan, 2017). Second, our findings propose a profitable strategy that takes a long position in value-and-low-attention stocks and a short position in growth-and-low-attention stocks.

In the remainder of the paper, section 2 comprises hypothesis development and literature on investor attention measurement. Section 3 presents our methodology and presents descriptive statistics. Section 4 reports the results of univariate and bivariate sorted portfolios. In a subsequent section (i.e. section), we examine whether observed returns behavior is attributed to mispricing explanation or risk-based explanation. Section 5 report the main conclusions of the paper.

3.2. Literature review

In this section, we present theory and hypothesis development and review literature on the investors' attention measurement.

3.2.1. Theory and hypothesis development

The mispricing explanation predicts that the value premium captures price deviations between investors' pessimistic (or optimistic) expectations associated with future performance to value (or growth) firms. These biased expectations arise due to contradiction between value (or growth) firm's performance market-implied expectations and fundamental strength, anchored in investors tendency to extrapolate historical fundamental information and lack of attention or neglect towards updated fundamental information. Such investors overlook the mean-reverting tendency of stock prices towards fundamental strength (Lakonishok et al., 1994).

Piotroski and So (2012) developed and tested the market expectation errors approach in the context of U.S. equity market data. They propose that value firms (or growth firms) reflect overly extrapolated pessimistic (or optimistic) expectations implied by the high (or low) book-to-market ratio (hereafter BM ratio). The existent (or non-existent) market expectation errors and subsequent price reversal can be identified ex-ante by incongruence (or congruence) between market expectation errors and fundamental strength reflected by Piotroski F-score (Piotroski, 2000). Walkshäusl (2017) confirmed the robustness of the market expectation errors approach by using European equity market data. They find that the value premium is attributed to incongruence (or congruence) between market-implied expectations and fundamental strength. The higher performance of the incongruent strategy is primarily attributed to price reversal in growth stocks with weak fundamental strength.

Investor limited attention has been hypothesized as one of the important predictors of investor's trading behavior. For example, Pashler and Johnston (1998) provide that limited cognitive constraints lead to individual limited attention. Arbel, Carvell, and Strebel (1983) document that less visible stocks receive less attention and are mostly neglected by financial institutions. Merton (1987) provides that trading requires information collection on a large set of stocks but due to limited attention investor focus of a small set of familiar stocks. Chen (2017), Fang and Peress (2009), and Odean (1999) show that investor information acquisition is limited to a small set of familiar attention-driven stocks. Hirshleifer and Teoh (2003) provide evidence on investors' attention to the firm's disclosure and the subsequent effect on trading behavior and asset pricing. They conclude that investors could make sense of aggregate firm's disclosures because they might feel trouble in processing disaggregate firm's disclosures. Peng and Xiong

(2006) document that investors' limited attention stimulates heightened investors’ attention to sector-wide and market-wide information and lowered attention to fundamental information, consequently leading to category learning.

Arbel et al., (1983) provide that less visible neglected small firms earn higher return premium than medium and large size firms due to informational inefficiencies. Merton (1987) proposed investor recognition hypothesis and postulates that investors are attentive to a small number of familiar stocks and ignore less visible stocks that later earn higher returns. Chen (2017), and Fang and Peress (2009) provide confirming evidence to investor recognition hypothesis and document the negative impact of high attention on index returns, supporting that less visible stocks earn higher returns than familiar stocks. Barber and Odean (2008) proposed investor attention theory and find that retail investors are net buyers of attention-driven stocks. The investor's high attention results in temporary attention-induced price pressure in the short-run and price reversal in the long-run. They attribute short-run positive price pressure to investors’ limited attention and inability to process a large set of information. As a result, investors make uninformed trading decisions to buy attention-driven stocks. Da et al., (2011) document that investors buy attention-driven stocks that cause a short-run increase in asset pricing and subsequent reversal in the long-run. Bijl, Kringhaug, Molnár, and Sandvik (2016) find that high attention results in negative stock returns.

If value premium is an outcome of mispricing that is, attention-induced positive (or negative) price pressure on attention-driven stocks (or neglected stocks) and higher return premium for less visible neglected stocks. We assume that the value premium is more pronounced between neglected value stocks and previously high attention-driven growth stocks. The value premium grows stronger (or weaker) with investors high attention towards attention-driven stocks (or neglected stocks). The value premium is weaker or negligible between high attentive value stocks and growth stocks. However, the value premium is stronger between neglected value stocks and neglected growth stocks. The value premium strength is dependent on the extent of price reversal of previously high attention-driven but currently neglected growth stocks that face stronger negative price pressure due to investors' neglect.

Bijl et al., (2015) document that a trading strategy that considers buying low attention stocks and selling high attention stocks generates superior returns. Li, Wang, Yan, and Zhao

(2019) provide that a long-short strategy between low attention stocks with positive earnings announcements and low attention stocks with negative earnings announcements earns superior returns, respectively. Gao, Wang, and Yan (2019) document that long-short strategy that takes in low attention stocks with the highest volatility spread and in low attention stocks with the lowest volatility spread earns superior returns, respectively. Hence, we propose that a trading strategy that takes a long position in value-and-low-attention stocks and short position in growth-and-low-attention stocks earns superior returns. Therefore,

Hypothesis 1: Value firms with low attention outperform growth firms with low attention but there are no return differences between value firms with high attention and growth firms with high attention.

We predict that return difference between value-and-low-attention stocks and growth-and-low-attention stocks are a consequence of mispricing. Hence,

Hypothesis 2: The return differences between value firms with low investor attention and growth firms with low intangibles-intensity are attributed to mispricing.

3.2.2. Literature on the measurement of investor attention

Measuring investor attention is critical to capture the exact impact of investor attention on asset pricing. However, there are no exact determinants of investor attention and consequently no specific measurement of investor attention. Literature provides a series of proxies to measure investor attention that captures the effect of investor attention on the dynamics of asset pricing in multiple settings. These proxies consist of trading volume, firm size (Chordia & Swaminathan, 2000; Lo & Wang, 2000), price limit-hit frequency (Lin, Ko, Lin & Yang, 2017), option trading volumes (Wang, 2017), advertising expense (Chemmanur, Thomas & Yan, 2009), informational overload (Hirshleifer, Lim, & Teoh, 2009), event timing such as important information disclosures on Friday versus other weekdays (DellaVigna & Pollet, 2009) and trading hours versus non-trading hours (Francis, Pagach & Stephan, 1992), news and headlines (Barber & Odean, 2008), Google Search Volume Index (SVI) for retail investors (Da et al., 2011), and news and reading searches on Bloomberg for sophisticated investors (Ben-Rephael, Da & Israelsen, 2017) among others.

Firm size and trading volumes are commonly used proxies of investors' attention. Larger firms tend to have higher trading volumes. They attract attention due to higher media coverage and interest of sophisticated investors (Lo & Wang, 2000). Such behavior contributes towards investors' neglect towards other firms in the portfolio, leading to the heightened fundamental uncertainty of portfolio (Peng, 2005). Chordia and Swaminathan (2000) provide that trading volume better captures attention than firm size because trading volume can isolate the impact of attention of both short-run and long-run price continuation and reversals. Barber and Odean (2008) argue that trading volume is a more direct measure to capture investor attention. But both firm size and trading volume proxy for other economic factors as well, like liquidity and information asymmetry, and divergence of opinion (Chordia & Swaminathan, 2000). Hence, both firm size and trading volumes are noisy measures and fail to capture the extent of investor attention and information processing.

Considering these limitations, studies have gained insight to differentiate in investors' attention intensity towards information processing by using corporate events like earnings announcements (EAs). Francis, Pagach, and Stephan (1992) proposed trading hours as information events. They find investor underreaction to EAs during non-trading hours. Hirshleifer et al., (2009) document that markets are less attentive to numerous EAs made in a single trading day and show strong post-earnings announcement drifts. DellaVigna and Pollet (2009) suggested the use of Friday versus other trading weekdays to proxy investor attention. They report markets weaker response to EAs made on Fridays that subsequently translates into stronger post-earnings announcement drift in next week. Wang, Yan, Zhang, and Gao (2018) document that heightened investor attention measured as non-Friday announcements, high pre-earnings option trading, and few EAs substantially increases market response and leads to weaker post-earnings announcement drifts. Lin et al., (2017) argue stocks attract more attention closer to lower or upper price limits. They suggest that investors are more attentive to stocks with frequent limit price events.

Da et al., (2011) used Google SVI as a proxy to capture retail investor attention. They argued that SVI is a more direct indicator of investor attention because SVI represents the extent of investors' attention and information acquisition of a specific firm. They document the significant positive effect of SVI on investor trading behavior. Ben-Rephael et al., (2017) used the concept of information search on the internet and proposed the use of news search and news-reading activities on Bloomberg as a measure of sophisticated investors' attention. They argued that the Bloomberg terminal represents the most appropriate measure of sophisticated investors' attention because they mainly use the Bloomberg terminal for information acquisition. They provide that sophisticated investors respond faster to news events than retail investors.

Recently, studies like Drake, Darren, Roulstone, and Jacob (2015), Lee, Ma, and Wang (2015), Loughran and McDonald (2017), and Ryans (2017) proposed use of daily access files provided by the Securities Exchange Commission (SEC), known as Electronic Data Gathering and Retrieval (EDGAR) log files to capture investor attention. The EDGAR log files provide the daily activity of downloads of sets of information disclosures like annual reports. These studies argue that EDGAR log files have more advantages than other measures of investors' attention. First, the EDGAR is the metadata repository of company corporate filings and contains a comprehensive set of corporate reports like quarterly reports, annual reports, IPOs prospectus, etc. Search engines like Google also redirect users to the EDGAR database for corporate filings. Second, EDGAR log files keep records of information users like IP address, timestamp, and accession number. The log files can also be used to track the investors' requests for information. Chen, Cohen, Gurun, and Lou (2020) used EDGAR log files to investigate the effect of investors' information search on portfolio choices. Third, the EDGAR log files span over a longer period, starting from January 1, 2003 to June 30, 2017.

There is significant evidence indicating that retail investors have higher limited attention constraints than sophisticated investors and retail investors exhibit attention-driven trading behavior that subsequently affects stock prices. For example, Mayer (2014) documents that attention-driven trading behavior is motivated by an overreaction to stock prices and subsequent reversal towards fundamental value. This effect is dominant in retail investors that are most likely to engage in small trades that might be responsible for pricing anomalies (e.g., Collins, Gong & Hribar, 2003; Da et al., 2011). The notion of limited attention also influences the behavior of sophisticated investors and subsequently stock prices. For example, Abarbanell and Bushee (1998) document that analysts are unable to efficiently utilize readily available information in firms’ fundamental ratios. Corwin and Coughenour (2008) report that portfolio specialists allocate significant attention towards most actively traded stocks that exhibit less price improvement. Such specialists assign limited attention to remaining stocks in their portfolio and assign higher liquidity to more attentive stocks than inattentive stocks. Hirst and Hopkins (1998) show that analysts are not able to properly analyze complex financial disclosures. Teoh and Wong (2002) provide that analysts commit discretionary accruals errors for new equity issues. Analysts exhibit optimistic discretionary accruals expectations based on past accounting accruals. Taken together preceding evidence, we assume that limited attention spans over both retail and sophisticated investors. The EDGAR log files provide an appropriate measure to capture investor attention.

3.3. Methodology

In this section, we present the measurement of investor attention by using EDGAR access log files. We provide details on variables and data used in the study and conclude with descriptive statistics of data.

3.3.1. Investor attention measure

In this study, we use EDGAR access log files to measure investors' attention towards a specific company. The log files are not in ready to use format because files contain download information requests by computer programs "robots" and human readers. It is critical to screen out computer programs' information downloads and retain only human downloads to measure investor attention. The log files do not reveal the identity of computer programs or human readers requesting the information.

Literature provides three alternative screening methods that are Drake et al., (2015), Loughran and McDonald (2017), and Ryans (2017) to extract investors' attention indicator. These three methods vary in terms of treating download requests to screen out computer programs. Drake et al., (2015) propose excluding IP addresses that make more than 5 and 1000 corporate filings requests in each minute and day, respectively. Loughran and McDonald (2017) suggest screening out of IP addresses that make more than 50 corporate filings requests in a single day. Ryans (2017) consider humans do not request more than 500 requests in a single day and that they do request corporate filings of more than 3 companies or 25 filings items in a single day. Ryans (2017) compared these three methods and extracted humans' corporate filings requests for each measure and provide daily processed EDGAR log files for each of the three measures. We use processed EDGAR log files for three proposed measures from Professor James Ryan website[1] to explore the effect of investor attention on the dynamics of the value-growth effect.

3.3.2. Variables, data, and descriptive statistics

This subsection provides definitions and measurement of variables used in this study. The size of the firm is measured by using market capitalization that represents the market equity at the end of April (t). Following Fama and French (1992), book-to-market ratio (BM) is used as the main indicator to proxy the value-growth effect. The BM is the ratio of the book value of equity at the end of the fiscal year (t-1) to the market value of equity at the end of April (t). We used three measures to capture investor attention as proposed by Drake et al., (2015), Loughran and McDonald (2017), and Ryans (2017) and labeled as A_{DRT}, A_{LM}, and A_{R}.

Momentum (Mom) is measured as cumulative prior twelve months returns skipping the most recent month returns before portfolio formation (Jegadeesh & Titman, 1993). We proxy the firm's fundamental strength by using Piotroski (2000) proposed F-score. The F-score is the composite index of nine fundamental measures, ranges from 0 to 9. The low (or high) F-score indicates weak (or strong) fundamental strength. The F-score consists of three main categories of fundamental indicators that is profitability, leverage and liquidity, and operational efficiency. Four fundamental indicators represent profitability: return on assets, cash flows from operations, change in return on assets, and accruals. Three fundamentals indicators measure leverage: change in long term debt, change in current ratio, and issuance of equity. Two fundamental indicators measure operations efficiency: change in gross margin and change in asset turn over. The positive indicator value is equal to 1 and 0 otherwise except equity issue, where equity is 0 and 1 otherwise. The firms having the size, BM ratio, A_{DRT}, A_{LM}, $A_{R,}$ and F-score were included in the sample. We exclude firms with a negative BM ratio.

We use data from all constituent companies listed in the S&P 1500 Composite Index, starting from December 2003 until April 2017. The fundamental information for F-score goes back to December 2001. The S&P 1500 Composite Index covers 90% of U.S. equity market capitalization and comprises of S&P 500 (consisting of large market capitalization firms), S&P

[1] Daily processed EDGAR log files for each of three measurements are provided by Professor James Ryans on his personal website at: http://www.jamesryans.com

MidCap 400 (consisting of medium market capitalization firms), and S&P SmallCap 600 (consisting of small market capitalization firms)[2]. The price and performance index data for each firm is obtained for analysis. The performance index of the S&P 1500 Composite Index is used as the market standard. The monthly total return for individual firm and market index is measured as the percentage difference of monthly stock and market performance index. The prices and stock performance index data are collected from Thomson DataStream and firms' fundamental data from the Worldscope database[3]. By following Lakonishok et al., (1994), we ensure that fundamental data is available before portfolio formation and calculation of monthly total returns. We match fiscal year-end fundamental data (t-1) with total monthly returns at the beginning of May (t) to the subsequent year at the end of April (t+1). The firm must have had appeared in the composite list for at least 12-months and if the firm is delisted then its returns are replaced with size-matched decile average returns.

To obtain size-adjusted returns, we sort stocks into equally weighted deciles based on size at the end of April (t) and calculate monthly average returns of each decile. The size decile average returns are subtracted from each stock's monthly total returns to obtained size-adjusted market returns. We calculate market-adjusted returns to compare the monthly total returns of firms against market performance. The market-adjusted returns are obtained as total monthly stock returns minus total monthly market returns.

We screen total monthly returns data by using the screening procedure suggested by Ince and Porter (2006). First, monthly returns that are over 300% and reverted within one month are considered as missing to mitigate the effect of suspicious returns. Second, we drop the total monthly returns of stocks with a market price of less than $1.00 to avoid the effect of small and illiquid firms on our results. We mitigate the possibility of abnormal observations by winsorize fundamental variables at 1% and 90% levels. The analysis is based on 17,260 firms-year observations with an average of 1,232 firms' observations per year for 14 years (2003-2017).

-------------Insert table 1-----------

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[2] Refer to S&P Composite 1500 index website for further details on methodology of composite index construction: https://us.spindices.com/indices/equity/sp-composite-1500

[3] Data item codes along with their definition as given in Worldscope used to get variables of this study are presented in appendix A.

Table 1 reports descriptive statistics of the main variables that are obtained as time-series averages of firms-year observations. The median size of our sample is 1947 million dollars with a mean size of 8749 million dollars. The median (mean) of BM ratio is 0.43 (0.53), median (mean) of total monthly return is 1.17% (1.43%). Most importantly monthly median (mean) of investors' attention measures i.e., A_{DRT}, A_{LM}, and A_R are 452 (905), 329 (669), and 402 (735), suggesting that median returns are associated with low investor attention. The descriptive statistics suggest that most firms in our sample are small-size with median attention of less than the mean value, indicating that mean total returns (i.e. 1.43%) are driven by small-size firms. This implies that total monthly returns are largely driven by neglected small-size firms and not by attention-driven large size firms.

3.4. Returns on univariate and bivariate value-growth strategies

In this section, we examine the effect of univariate sort and bivariate sort on return differences. First, we examine the effect of univariate sort by using BM ratio and investor attention on return differences. We test that value stocks (V) outperform growth stocks (G), and low investor attention (L) generates higher returns than high investor attention (H). After confirming univariate assumptions, we test our main hypothesis that value-and-low-attention stocks (VL) outperform growth-and-low-attention stocks (GL), but value-and-high-attention stocks (VH) do not outperform growth-and-high-attention stocks (GH). We use the BM ratio as the main indicator of the value-growth effect. Investor attention is measured by using A_{DRT}, A_{LM}, and A_R. We examine the sensitivity of bivariate strategy across firm size that is small-size firms versus large-size firms.

3.4.1. Univariate strategy

At the end of April (t) each year, we sort stocks by using BM ratio, A_{DRT}, A_{LM}, and A_R. A firm is allotted to value portfolio (or growth portfolio) if the BM ratio falls in high (or low) decile of BM portfolios. A firm is allotted to low (or high) investor attention portfolio if investor attention measure is in low (or high) decile of investor attention portfolios. For each portfolio, we calculate monthly total returns, size-adjusted returns, and market-adjusted returns staring from May (t) to the end of the subsequent year April (t+1) and portfolios are rebalanced each year at the end of April (t+1).

-------------Insert table 2-----------

Table 2 reports average monthly total returns, size-adjusted returns, market-adjusted returns, and characteristics of firms sorted in portfolios based on BM ratio and three measures of investor attention. Panel A of table 2 presents results of BM-based univariate sorted decile portfolios and show higher total monthly returns to high BM ratio decile (i.e. 1.75% monthly returns, 0.48% size-adjusted returns, and 0.83% market-adjusted returns) than low BM ratio decile (i.e. 1.21% monthly returns, -0.03% size-adjusted returns, and 0.41% market-adjusted returns). The high (or low) decile consists of relatively large (or small) size firms. The results show a statistically significant value-growth effect in the U.S. equity market. The high BM firms earn superior monthly returns of 0.54% per month than low BM firms. The average total return differences after adjusting for size and market returns are 0.48% per month and 0.83% per month, respectively. This indicates that monthly returns differences are not driven by the size and value-growth strategy earns superior returns than market returns. These results are consistent with the literature on the superior performance of the value-growth strategy (e.g. Fama & French, 1992).

Panel B, C, and D report higher monthly returns of low decile[4] than high decile[5] for A_{DRT}, A_{LM}, and A_R. The low decile investor attention firms are small-size and high decile investor attention firms are large-size, confirming that small firms are less visible and neglected while investors are more attentive to large-size firms. The results provide the strong effect of investor attention on average total monthly return differences in the U.S. equity market. The firms with low investor attention earn superior monthly returns of 0.20% per month for A_{DRT}, A_{LM}, and A_R. The average total return differences after adjusting for size and market returns range from 0.30% to 0.32% per month for A_{DRT}, A_{LM}, and A_R, and 0.19% per month for A_{DRT}, A_{LM}, and A_R, respectively. This indicates that monthly returns differences are not driven by firms' size and low-high investor attention strategy earns higher returns than market returns. We also note that return differences in investor attention-based low and high decile for A_{DRT}, A_{LM},

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[4] Monthly total returns ranges from 1.36% to 1.38% per month for A_{DRT}, A_{LM}, and A_R, size-adjusted returns ranges from 0.05% to 0.06% per month for A_{DRT}, A_{LM}, and A_R, and market-adjusted returns ranges from 0.47% to 0.49% per month for A_{DRT}, A_{LM}, and A_R

[5] Monthly total returns ranges from 1.16% to 1.18% per month for A_{DRT}, A_{LM}, and A_R, size-adjusted returns ranges from -0.26% to -0.24% per month for A_{DRT}, A_{LM}, and A_R, and market-adjusted returns ranges from 0.28% to 0.30% per month for A_{DRT}, A_{LM}, and A_R

and A_R are similar, suggesting that three measures capture a qualitatively similar effect on returns. The results of the univariate-based sort on investor attention are consistent with findings of previous studies that low investor attention to less-visible small neglected firms have a positive impact on total monthly returns (e.g. Arbel et al., 1983; Bijl et al., 2016; Chen, 2017; Fang & Peress, 2009; Merton, 1987). Consistent with Bijl et al., (2016), we confirm that an investment strategy that takes a long position in low investor attention firms and short position in high investor attention earns superior returns.

3.4.2. Bivariate strategy

After confirming return differences across univariate sort, we study return differences across bivariate sort as given in panel A, B, and C of table 3. We test average monthly returns differences between value-and-low-attention firms and growth-and-low-attention firms (VL-GL), and average monthly return differences between value-and-high-attention firms and growth-and-high-attention firms (VH-GH).

------------Insert table 3-----------

Results in panel A, B, and C of table 3 show that bivariate strategy that conditions value stocks and conditions growth stocks also as low investor attention, earns statistically significant positive average monthly value premium (i.e. 1.06% per month for A_{DRT}, 0.94% per month for A_{LM}, and 0.98% for A_R) than standard unconditional value-growth strategy (i.e. 0.54% per month). These returns differences are consistent after adjusting for firm size (i.e. 0.75% per month for A_{DRT}, 0.62% per month for A_{LM}, and 0.66% for A_R) and market performance (i.e. 0.95% per month for A_{DRT}, 0.86% per month for A_{LM}, and 0.88% for A_R). However, a bivariate value-growth strategy that conditions value stocks and growth stocks also as high investor attention earns average total monthly returns, size-adjusted returns market-adjusted returns that are indistinguishable from zero. We note that total monthly return differences, size-adjusted return differences, and market-adjusted return differences to VL-GL strategy are almost similar, suggesting that three investor attention measures capture qualitatively similar effects in bivariate strategy. The results indicate that an investment strategy that takes a long position in value-and-low-attention stocks and short position in growth-and-low-attention stocks earns higher value premium than standard value-growth strategy.

Our results confirm the investor-recognition hypothesis, suggesting that investors' persistence with less visible neglected value stocks earns a higher premium than previously attention-driven growth stocks. The higher conditioned value premium can be attributed to price reversal attributed to investors' neglect towards previously attention-driven growth stocks that further magnify the premium on neglected value stocks. The superior return differences are also consistent with theoretical predictions that investors limited attention contributes towards neglect to process salient fundamental signals (e.g. Hirshleifer, Lim & Teoh, 2011, Hirshleifer & Teoh, 2003; Peng & Xiong, 2006;). Hirshleifer, Hsu, and Li (2018) find that attention-driven investors do not perform fundamental analysis and neglect salient difficult-to-process information such as innovative originality. This trend is prominent in high valuation-uncertainty firms. This indicates that investor inattention to value-enhancing characteristics of value firms and heightened attention on characteristics of attention-driven growth firms leads to overvaluation (i.e. positive price pressure) of growth-and-high-attention firms and substantial negative price pressure on growth-and-low-attention stocks (due to prior high attention and subsequent neglect on price reversal). That widens the returns gaps between value-and-low-attention stocks and growth-and-low attention stocks.

Li et al., (2019) find that long-short strategy between positive earnings announcement with low attention firms and negative earnings announcement with low attention firms earns superior returns of 2.83% per month. Gao et al., (2019) provide that investment strategy that takes a long position in the highest volatility spread with low investor attention outperforms short position in lowest volatility spread with low investor attention. Consistent with preceding evidence, we find superior returns ranges from 1.06% to 0.94% for three attention measures, indicating that investor persisting with value-and-low-attention stocks earns superior returns on correction of biased market expectations towards fundamental strength of both value and growth stocks.

3.4.3. Size segment results

In this subsection, we test the persistence of our findings across small-size and large-size firms. Based on market equity we divide firms into small-size and large-size segments. Firms above the median of market equity at the end of April (t) are classified as large-size firms and firms below the median are grouped as small-size firms. Table 4 presents the univariate and bivariate sort by using the same procedure as table 3. Panel A presents univariate sort of small-size and large-size firms by using BM ratio and panel B, C and D shows bivariate sort based on BM ratio conditional to investor attention (measured as A_{DRT}, A_{LM}, and A_{R}).

------------Insert table 4-----------

Results in panels A suggest persistence of value-growth effect in both small-size and large-size firms. The differences in average total monthly returns, size-adjusted returns, and market-adjusted returns are significantly different from zero, confirming that value stocks outperform growth stocks despite differences in firm size. The results suggest that the value-growth effect is quantitively more prominent in small-size firms than large-size firms. The panels B, C, and D of Table 5 confirm our finding of bivariate strategy for both size segments, which means that value-and-low-attention stocks outperform growth-and-low-attention stocks. The results are robust in terms of size-adjusted and market-adjusted returns difference. Hence, confirming that findings in table 3 are not largely limited to small-size firms but large-size firms also earn significant superior value premium. A value-growth strategy that takes a long position in value-and-low-attention stocks and a short position in growth-and-low-attention stocks earns more than 2.14% (0.68%) per month of average total monthly returns, 1.83% (0.70%) per month size-adjusted returns, and 2.14% (0.50%) per month market-adjusted returns among small (large) size firms.

Collectively, the findings presented in section 4 strongly support the dependence of the value-growth effect on the level of investor attention, confirming hypothesis 1. The value-growth effect across low investor attention generate higher value premium than standard value-growth strategy.

3.5. Mispricing explanation

In this section, we employ Fama-French common risk factors, sentiment analysis, and limit to arbitrage capital, Fama-MacBeth cross-sectional approach, and Piotroski and So (2012) proposed market expectation errors approach to examine that superior returns to VL-GL strategy are attributed to mispricing.

3.5.1. Common risk factors

In this subsection, we examine whether return differences between value-and-low-attention stocks and growth-and-low-attention stocks (VL-GL) are explained by common risk factors as documented by asset pricing models. We regress returns differences of VL-GL strategy and VH-GH strategy on Fama and French (1993) three factors model, Carhart (1997) momentum factor and Fama and French (2015) five factors model: market risk (measured as market excess returns; MKT) based on the beta, size effect (SMB; small minus big; returns differences between small and big firms), value-growth effect (HML; high minus low BM ratio; returns differences between high BM ratio and low BM ratio firms), profitability effect (RMW; robust minus weak; returns difference between profitable and unprofitable firms), investment effect (CMA; conservative minus aggressive; returns differences between high internal investment and low internal investment firms) and momentum (WML; winner minus loser; returns differences between past winners and past losers). We estimate the following models by using data on average monthly return differences to VL-GL and VH-GH strategies.

$$Premium_{it} = \alpha_i + \beta_{MKT} MKT_t + e_{it} \tag{1}$$

$$Premium_{it} = \alpha_i + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{WML} WML_t + e_{it} \tag{2}$$

$$\begin{aligned} Premium_{it} = {} & \alpha_i + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{RWM} RMW_t \\ & + \beta_{CMA} CMA_t + \beta_{WML} WML_t + e_{it} \end{aligned} \tag{3}$$

In model 1, 2, and 3, $Premium_{it}$ is the return differences for VL-GL or VH-GH portfolios of each month. The first regression model refers to CAPM and the second regression describes the three-factor model with momentum effect and model 3 represents the five-factor model with momentum effect. We estimate risk factors by following Fama and French (1993), Carhart (1997), and Fama and French (2015). The market excess return (MKT) is the S&P Composite 1500 index monthly excess risk-adjusted returns (based on the 1-month U.S. Treasury bill rate). The risk factors are estimated by using two-to-three sort based on firm size, BM ratio, operating profit, investment, and momentum at the end of the fiscal year. SMB is the average monthly total returns on the three small-size portfolios minus average total returns on the three large-size portfolios. HML is the average monthly total returns on two high BM ratio portfolios minus two low BM ratio portfolios. RMW is the average monthly total returns on two high operating profit portfolios minus two low operating profit portfolios. CMA is the average monthly total returns on two high investment portfolios minus two low investment portfolios. The momentum factor (WML) is formed by using the two-to-three sort of firm size and momentum at the end of April (t). Momentum is the cumulative prior 12-month returns skipping the most recent month before portfolio formation (Jegadeesh & Titman, 1993). WML is the average total monthly returns on two high momentum portfolios minus two low momentum portfolios. The two-to-three sort represents the division of firms based on the median of firm size measured at the end of April (t) as a split point, firms lower than the median are grouped as small-size firms and firms higher than the median are grouped as large-size firms. The second sort is based on the 30th and 70th percentile of respective variables for each firm size segment.

The risk-based explanation hypothesizes that the superior return differences to VL-GL strategy are positively associated with market risk (represented by beta) because superior returns are compensation to investors for taking a higher risk.

-------------Insert table 5-----------

Table 5 provides parameter estimates of CAPM, the three-factor model with a momentum factor, and the five-factor model with a momentum factor of average monthly total return difference to VL-GL and VH-GH strategies. We note that alpha in panel A, B, and C are positive and statistically significant for VL-GL strategy (0.01 per month). The market risk beta has a statistically insignificant positive (for panel A) and negative estimates (for panel B and C, indicating that superior returns differences to VL-GL strategy are not attributed to systematic risk rather negative sign suggest that interaction between value-growth strategy at the low level of investor attention reduces firms systematic risk. This appears consistent with the mispricing explanation. In contrast, alphas are either negative (for A_{DRT}) or positive (A_{LM}, and A_R), but statistically insignificant for VH-GH strategy (ranges from -0.01 to 0.01).

The return differences to VL-GL strategy are insensitive towards common risk factors. However, VH-GH is more sensitive towards the value factor (HML). The negative significant effect of HML provides that a significant proportion of strategy return differences are explained by prior negative returns. This indicates that return differences are attributed to the price reversal of stocks. The results of A_{DRT} as a measure of investor attention are robust with A_{LM}, and A_R as measures of investor attention. Hence, we conclude that superior returns differences to VL-GL strategy are significantly positive in both conditional and unconditional settings. However, return differences to the VH-GH strategy are not significantly explained by risk-adjusted factors in both conditional and unconditional settings. These findings are inconsistent with the risk-based explanation.

3.5.2. Sentiment analysis and limits to arbitrage capital

The long-short strategies that exploit mispricing are influenced by the level of market sentiments (Stambaugh, Yu & Yuan, 2012). The level of mispricing is high during high market sentiments because the market overly extrapolates firms' past fundamentals into the future, resulting in the overvaluation of stocks. This effect is stronger in high attention-driven growth stocks than neglected undervalued value stocks. The performance of sentiment-driven mispricing is primarily driven by overvaluation in (growth) stocks. The mispricing strategy that takes a long position in undervalued stocks and a short position in overvalued stocks earn superior returns following a high sentiment period. In contrast, the level of undervaluation is high during low market sentiment due to overly pessimistic expectations with future performance. In the same lines, we assume that the superior return differences to VL-GL strategy are predominantly due to price reversal and undervaluation in low attention growth stocks during low sentiment periods. This implies that high sentiment periods prevent investors from investing in neglected value stocks and divert interest towards high attention-driven overvalued growth stocks. Following high sentiment periods, prices of overvalued stocks reverse, and undervaluation is prominent in low sentiment periods. Hence, we expect a negative impact of lagged market sentiment on return differences to the VL-GL strategy.

The performance of a mispricing based strategy is dependent on the availability of arbitrage capital. The superior returns to VL-GL strategy can be weakened by the restriction on the availability of arbitrage capital because a lack of capital prevents market participants to take a long position in low attention value stocks. Hence, we expect a negative effect of a shortage of arbitrage capital on the performance of VL-GL strategy.

We used Baker and Wurgler (2006) proposed the sentiment index[6] that captures the time-varying effects of market sentiment. The proposed sentiment index is a component of five

[6] Refer to Baker and Wurgler (2006) for measurement of sentiment index. The sentiment index is available at Jeffery Wurgler's website: http://people.stern.nyu.edu/jwurgler/data/Investor_Sentiment_Data_20190327_POST.xlsx.

sentiment proxies that are orthogonalized to six macroeconomic indicators to overcome the effect of business cycle variations. The positive sentiment index represents a high level of sentiment and the negative index represents a low level of sentiment. We use Hu, Pan, and Wang (2013) proposed the noise index[7] that captures changes in the availability of arbitrage capital by measuring aggregate variability in the U.S. Treasury bonds prices. The higher value of the noise index suggests a shortage of arbitrage capital, while low noise index suggests the availability of arbitrage capital. The analysis reported in table 6 covers the period from the start of May 1995 until the end of April 2017.

-------------Insert table 6-----------

Table 6 reports the effects of lagged sentiment index and noise index on returns difference to VL-GL and VH-GH strategies. The results provide a statistically significant negative effect of lagged sentiment index and lagged noise index on VL-GL strategy while results show a statistically insignificant effect of lagged sentiment index and lagged noise index on VH-GH strategy. Results suggest that value-and-low-attention stocks outperform growth-and-low-attention stocks following high sentiment periods. The low sentiment period increases the undervaluation of value stocks and significant price reversal in previously high attention overvalued growth stocks. The results provide that restriction to arbitrage capital weakens the performance of the VL-GL strategy.

These results indicate that prices of growth stocks reverse following high sentiment periods, pushing high attention growth stock prices down and pushing low attention value stock prices upward, leading to the superior performance of low attention value stocks. The negative effect of lagged noise index suggests that the lack of arbitrage funds limits investors (arbitragers) ability to take a long position in low attention value stocks to take advantage of mispricing. When mispricing is identified, buying undervalued stock is much easier in the market than selling overvalued stocks (Stambaugh, Yu & Yuan, 2015). Lack of arbitrage capital together with difficulty is taking a short position in overvalued stocks elongates mispricing in the market.

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[7] Refer to Hu et al., (2013) for measurement of noise index. The noise index is available at Jan Pan’s website: http://en.saif.sjtu.edu.cn/junpan/Noise_Measure_2019Q3.xlsx.

3.5.3. Cross-sectional return predictability

The portfolio-level analysis provides an important tool to examine the impact of variation in the level of a variable of interest but most of the cross-sectional information is lost during portfolio-level analysis. It is difficult to make inferences about the influence of other unique variables on the value-growth return differences. Therefore, we examine the return predictability of BM ratio and investor attention by controlling cross-sectional fundamental indicators. For this reason, we use Fama and MacBeth (1973) proposed a cross-sectional regression model with additional controls.

$$\begin{aligned} R_{it+1} = {} & a_1 Value_{it} + a_2 Growth_{it} + a_3 LowAttention_{it} + a_4 HighAttention_{it} \\ & + b_1 Value_{it} * LowAttention_{it} + b_2\, Value_{it} \\ & * HighAttention_{it} + b_3 Growth_{it} * LowAttention_{it} \\ & + b_4 Growth_{it} * HighAttention_{it} + c_1 Sizerank_{it} \\ & + c_2 Momrank_{it} + c_3 Betarank_{it} + c_4 Illiqtyrank_{it} + e_{it} \end{aligned} \tag{4}$$

Where

R_{it+1} - represents one-month buy-and-hold total returns beginning at the start of May (t) until end of next year April (t+1)

$Value_{it}$ – dummy variable = 1 if the BM ratio is in high decile, and 0 otherwise

$Growth_{it}$ – dummy variable = 1 if the BM ratio is in low decile, and 0 otherwise

$LowAttention_{it}$ – dummy variable = 1 if the investor attention measure is in low decile, and 0 otherwise

$HighAttention_{it}$ – dummy variable = 1 if the investor attention measure is in high decile, and 0 otherwise

$Sizerank_{it}$ – the market capitalization decile at the end of April (t) each year

$Momrank_{it}$ – the momentum decile, measured as of prior 12-months returns skipping the most recent month, updated each month and decile are formed by cumulative 12-month momentum values at the end of April (t) each year

$Betarank_{it}$ – the beta decile, measured each month and decile are formed by using cumulative 12-monthly betas at the end of April (t) each year

$Illiqtyrank_{it}$ – the illiquidity decile, measured each month and decile is formed by using cumulative 12-months illiquidity values at the end of April (t) each year

-------------Insert table 7-----------

Table 7 reports the results of Fama and MacBeth (1973) based model estimations for the entire sample of stocks for each of three measures of investor attention (i.e. A_{DRT}, A_{LM}, and A_{R}). The monthly returns are matched with fundamental information each year at the end of April (t) for portfolio formation.

Model 1 estimates return-predictability of value stocks, growth stocks, low investor attention, and high investor attention effects. Model 2 consists of interaction terms between value and growth stocks, and low and high investor attention and test their effect on return predictability. Model 3 checks the robustness of model 1 and 2 and combine both direct and interaction effects after controlling for common fundamental indicators.

Table 7 reports statistically significant positive estimates to value stocks and low investor attention, and negative estimates to growth stocks and high investor attention (model 1). This shows that firms with high (low) BM ratio and low (high) attention firms experience positive (negative) returns. The results provide significant positive coefficients for value-and-low-attention stocks (i.e. 0.69% per month) and significant negative estimate for growth-and-low-attention stocks (i.e. -0.62% per month) (model 2). This is consistent with the mispricing assumption that value-and-low-attention stocks earn a higher return, while previously attention-driven growth stocks experience negative returns due to lack of attention and reversal in prices (i.e. negative price pressure). The results also provide significant positive coefficient for value-and-high-attention stocks (i.e. 0.59% per month). The positive high estimates to value-and-low-attention stocks are robust after controlling for firm size, momentum, beta, and illiquidity (model 3). We find significant negative firm size and illiquidity effect, and significant positive effect of momentum and beta. This suggests that small-illiquid risky firms with prior good performance experience superior returns. The results for three investor attention measures (i.e. A_{DRT}, A_{LM}, and

A_R) are qualitatively similar, indicating results robustness across different measurements of investor attention.

The co-efficient tests [value stocks – growth stocks] (V-G) and [low attention – high attention] (L-H) indicate that value stocks outperform growth stocks (1.54% per month; model 1) and low investor attention outperforms high investor attention (ranges from 0.48% per month to 0.50% per month across A_{DRT}, A_{LM}, and A_R; model 1). These effects persist when interaction terms and controls are added in model 3 but from model 1 to model 3 returns differences decline. Next, we test the co-efficient differences in [value stocks x low attention – growth stocks x low attention] (VL-GL) and [value stocks x high attention – growth stocks x high attention] (VH-GH) strategies. Results indicate that value-and-low-attention stocks significantly outperform growth-and-low-attention stocks, while returns on value-and-high-attention stocks are indifferent from returns on growth-and-high-attention stocks (model 2 and model 3). These results are qualitatively similar for three investor attention measures (i.e. A_{DRT}, A_{LM}, and $A_{R)}$, indicating that return differences persist across different measurements of investor attention.

3.5.4. Market expectation errors approach

In this subsection, we use Piotroski and So (2012) proposed the market expectation errors approach to explicitly examine mispricing assumptions. The market expectation errors approach is based on the interaction between market-implied expectations (deviation in market expectations and captured as changes in BM ratio) and fundamental strength (measured as Piotroski F-score). According to rational pricing assumption, high BM firms (i.e. value firms) experience weak fundamental strength, whereas low BM firms (i.e. growth firms) experience strong fundamental strength. There is congruence between market-implied expectations and fundamental strength, suggesting no expectation errors. The value premium arises because of the higher risk associated with value firms (Fama & French, 1995). However, mispricing explanation arguments that market overly extrapolates past fundamental performance, resulting in a deviation between market-implied expectations and updated financial strength. The underreaction (or overreaction) to the changes in value (or growth) firm’s fundamental strength leads to existent expectation errors (Piotroski & So, 2012). The value premium captures changes in prices due to correction in biased market expectation errors (Lakonishok et al., 1994; LaPorta, et al., 1997).

$$R_{it+1} = a_1 Growth_{it} + a_2\, Growth_{it}\ x\ LowFscore_{it} + a_3\, Growth_{it}\ x\ MidFscore_{it} + \ a_4 Middle_{it} + a_5 Value_{it} + a_6\, Value_{it}\ x\ MidFscore_{it} + a_7\, Value_{it} x\ HighFscore_{it} + b_1 LowAttention_{it} + b_2 HighAttention_{it} + b_3 Growth_{it}\ x\ LowAttention_{it} + b_4 Growth_{it}\ x\ HighAttention_{it} + \ b_5 Value_{it}\ x\ LowAttention_{it} + b_6\, Value_{it}\ x\ HighAttention_{it}\ + c_1 Sizerank_{it} + c_2 Momrank_{it} + \ e_{it} \quad (5)$$

Where

R_{it+1} – represents one-month buy-and-hold total returns beginning at the start of May (t) until end of next year April (t+1)

$Value_{it}$ – dummy variable = 1 if the BM ratio is in high decile, and 0 otherwise

$Growth_{it}$ – dummy variable = 1 if the BM ratio is in low decile, and 0 otherwise

$HighFscore_{it}$ – dummy variable = 1 if the F-score is greater than or equal to 6, and 0 otherwise

$LowFscore_{it}$ – dummy variable = 1 if the F-score is lower than or equal to 3, and 0 otherwise

$MidFscore_{it}$ – dummy variable = 1 if the F-score is greater than 3 and lower than 6, and 0 otherwise

$LowAttention_{it}$ – dummy variable = 1 if the investor attention measure is in low decile, and 0 otherwise

$HighAttention_{it}$ – dummy variable = 1 if the investor attention measure is in high decile, and 0 otherwise

$Sizerank_{it}$ – the market capitalization decile at the end of April (t) each year

$Momrank_{it}$ – the momentum decile, measured as of prior 12-months returns skipping the most recent month, updated each month and decile are formed by cumulative 12-month momentum values at the end of April (t) each year

The model specification is similar to Piotroski and So (2012) with additional interaction terms that allow us to control for the effect of intersection between BM ratio, F-score, and investor attention on return predictability across congruent and incongruent strategy (by using co-efficient tests).

------------Insert table 8-----------

Table 8 presents Piotroski and So (2012) based model for the entire stocks sample. In each model specification of table 8, monthly returns at the end of April (t) are matched with fiscal year-end fundamental information. Model 1 estimates return-predictability of value stocks, growth stocks without controls as estimated by Piotroski and So (2012), and model 2 estimates the same model as model 1 but with firm size and momentum as controls. Model 3 and 4 incorporate the main effect of investor attention categories and interaction terms of BM ratio and investor attention in model 2 to test their impact on return predictability. The co-efficient test is used to capture the impact of congruent and incongruent strategy on return-predictability and return differences to congruent and incongruent strategy. Model 3 and 4 are estimated by using three measures of investor attention (i.e. A_{DRT}, A_{LM}, and A_{R}).

First, we examine Piotroski and So (2012) market expectation errors approach assumption. The model 2 results show that value stocks with high F-score earn superior significant positive returns (1.51% per month) than the other two interaction categories of value stocks. The growth firms with high F-score (i.e. Growth) earn significant negative returns (-1.30% per month) and the other two categories of growth stocks show insignificant returns. The coefficient test replicates Piotroski-So congruent and incongruent strategy. Piotroski and So (2012) assumed that there are no returns differences to congruent strategy while incongruent strategy earns positive returns differences. The congruent strategy coefficient test reports the returns differences between value stocks with weak fundamentals (i.e. Value) and growth stocks with strong fundamentals (i.e. Growth), whereas incongruent strategy reports the returns differences between value stocks with strong fundamentals (i.e. Value x HighFscore) and growth stocks with weak fundamentals (i.e. Value x HighFscore). The coefficient test of model 2 provides insignificant returns (-1.00% per month) to congruent strategy and significant positive returns (2.36% per month) to incongruent strategy, suggesting that the value-growth effect is significantly higher when BM ratio is incongruent with fundamental strength. We further test the return differences between incongruent and congruent strategy, results provide significant positive return differences (3.36% per month). The return differences between incongruent and congruent strategy are greater than returns on incongruent strategy (3.36% > 2.36%), suggesting that overvaluation and subsequent reversal in congruent strategy further strengthen the return on incongruent strategy. These results are qualitatively similar for models 3 and 4 across three measures of investor attention (i.e. A_{DRT}, A_{LM}, and A_R). These findings confirm Piotroski and So (2012) mispricing based market expectation errors assumption that the return differences between value minus growth stocks are significantly large when market-implied expectations (i.e. BM ratio) are incongruent with fundamental strength.

The model 3 and model 4 provides the significant positive effect of low attentions (i.e. coefficient value ranges from 0.16% per month to 0.24% per month) and significant negative effect of value-and-low-attention stocks (i.e. coefficient value ranges from 0.43 per month to 0.59% per month). If return differences between incongruent and congruent strategies are driven by mispricing, low investor attention induces more undervaluation (less overvaluation) and high investor attention leads to more overvaluation (less undervaluation). Therefore, return differences between incongruent and congruent strategies must remain positive across low and high investor attention. Results provide significant positive coefficient value of 0.1% per month for coefficient difference [(incongruent strategy – congruent strategy) x low investor attention - (incongruent strategy – congruent strategy) x high investor attention] ((Incong – Cong) x L - (Incong – Cong) x H). This indicates that the return differences between low and high investor attention corroborate positive returns to incongruent strategy minus congruent strategy, confirming the efficacy of market expectation errors approach across low and high investor attention. These findings are consistent with the mispricing explanation that low (high) investor attention leads to undervaluation (overvaluation) of value or growth stocks. On subsequent price reversal, prices of previously high attention low fundamental strength growth stocks go further down (i.e. negative price pressure), while prices of less visible neglected high fundamental strength value stocks revert to fundamental value. The negative price pressure to low attention growth stocks and upward price movement of high fundamental value stocks magnifies the returns to incongruent strategy.

Collectively, the findings in section 5 strongly support that superior returns to VL-GL strategy are attributed to mispricing assumption, confirming hypothesis 2. The common risk factor analysis concluded that high performance to VL-GL strategy is not attributed to compensation for high risk due to the insignificant effect of beta and common risk factors. The alpha provided a significant positive effect on return differences. The sentiment analysis provided the negative effect on returns differences to VL-GL strategy, attributing return differences to positive (or negative) price reversal of undervalued value stocks (or overvalued growth stocks). The cross-sectional fundamental information supports the positive effect of the BM ratio and the negative effect of investor attention on monthly total returns. Finally, the market expectation errors approach confirms that investor attention corroborates the efficacy of incongruent strategy and low investor attention magnifies the return to incongruent strategy.

3.6. Conclusion

In this paper, we present evidence on how the value premium varies across the level of investor attention and whether attention-induced value premium dynamics are explained by risk-based explanation or mispricing explanation. We find that investors hold limited cognitive resources and trade in a small set of familiar or market-driven (overvalued) growth stocks while neglecting less visible value stocks. This leads to attention-driven temporary positive price pressure on growth stocks and the undervaluation of neglected value stocks. On subsequent price reversal, attention-driven overvalued growth stocks revert to fundamental value under low attention-induced negative price pressure, leading to positive return premium to less visible neglected (undervalued) value stocks. Our empirical findings are consistent with the mispricing explanation. We confirm that return differences to value-and-low-attention stocks earn superior returns than growth-and-low-attention stocks (VL-GL) and return differences to value-and-high-attention stocks and growth-and-high-attention stocks (VH-GH) are indifferent from zero. These findings are robust across small-size and large-size firms.

Consistent with the investor-recognition hypothesis, we find that investor persistence with less visible neglected value stocks provides superior value premium than prior attention-induced overvalued growth stocks. Results support limited attention prediction that investors limited attention contributes towards the neglect of salient fundamental information and investment in attention-driven stocks. Investor lack of attention leads to undervaluation of fundamentally strong (value) stocks and overvaluation of fundamentally weak (growth) stocks. The subsequent price reversal and correction in biased expectations induce negative price pressure on previously attention-driven stocks and reversal of value-and-low-attention stocks prices towards fundamental value, leading to superior return premium to neglected value stocks. Consistent with Gao et al., (2019), and Li et al., (2019), we find that investment strategy that takes a long position is value-and-low-attention stocks and short position in growth-and-low-attention stocks generate superior value premium than standard value-growth strategy. Investors can take advantage of attention-driven neglect of other investors and earn superior returns by buying value-and-low-attention stocks and selling growth-and-low-attention stocks.

We confirm that return differences to value-growth strategy across low attention are attributed to mispricing by using common risk factors, sentiment analysis, cross-sectional regression, and market expectation errors approach. The asset pricing models show a significant positive impact of alpha and insignificant effects of common risk factors under the Fama-French three-factor model and the five-factor model. The sentiment analysis confirms that high market sentiment overly exaggerates attention-driven stock prices and negatively influence returns on VL-GL strategy. The cross-sectional regression confirms the positive impact of the BM ratio and the negative impact of attention measures on stock returns. Piotroski and So (2012) expectation errors approach confirms that low attention strengthens the incongruence between market-implied expectations and strengthens return differences between fundamentally strong undervalued firms (value firms) and fundamentally weak overvalued firms (growth stocks).

This study contributes to the existing literature on value premium along two dimensions. First, the finding suggests that low attention stocks produce superior returns because of sophisticated investors (funds managers, institutional investors, etc.) neglect, less discussion, and low following of less visible stocks that subsequently generate high returns on price reversal. This effect is more prominent in previously high attention driven overvalued stocks because low attention towards previously high attentive stocks exerts strong negative price pressure. This results in a significant price reversal of low attention growth stocks than low attention value stocks. The persistence with low attention neglected stocks than low attention growth stocks (previously high attention-driven growth stocks) can provide a much appealing trading strategy. Hence, investor attention and sentiment have an impact on superior return differences to value-growth strategy. This persistence of investors with low attention and strong fundamental value stocks infers from the Graham and Dodd (1934) investing approach that defines investment as a "thorough analysis" that promises "safety of principal" with a "satisfactory return" (Kok et al., 2017).

Second, our findings propose a profitable strategy to generate superior returns than standard value-growth strategy. The portfolio strategy that considers investor attention to develop portfolios provides statistically significant higher returns. The trading strategy that takes a long position in value-and-low-attention stocks and a short position in growth-and-low-attention stocks generate superior returns. Both retail investors and sophisticated investors can take advantage of limited cognitive constraints of other investors to identify strong fundamental value-and-low-attention stocks to generate higher returns than other market participants.

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List of tables

Table 1: Descriptive statistics

Variables	Mean	Std.Dev	Skewness	Kurtosis	25th Percentile	Median	75th Percentile
Total monthly returns	1.43	1.07	1.33	20.19	-4.02	1.17	6.41
Firm size (millions)	8749	21800	4.90	29.77	765	1947	6201
BM ratio	0.53	0.40	2.22	9.96	0.27	0.43	0.66
A_{DRT}	905	426.84	162.71	35675.21	205	452	976
A_{LM}	669	4192.98	171.74	38359.63	159	329	667
A_{R}	735	3494.98	170.65	38256.99	188	402	815
Momentum	0.16	0.50	8.09	246.04	-0.09	0.11	0.33
F-score	6	1.31	-0.27	2.77	5	6	7

This table reports descriptive statistics of the main variables used in this study. Total monthly return is the average one-month ahead buy-and-hold monthly return. Size is the market capitalization, defined as stock price multiplied by the number of shares outstanding at the end of April (t) in millions of dollars. Book-to-market (BM) ratio is the book value of equity at the end of the fiscal year (t-1) divided by market equity at the end of April (t). Three measures to capture investor attention as proposed by Drake et al., (2015), Loughran and McDonald (2017), and Ryans (2017) and labeled as A_{DRT}, A_{LM}, and A_{R}. Momentum (Mom) is the cumulative prior 12 months returns skipping the most recent month return. Piotroski (2000) F-score is the composite indicator of a firm's fundamental strength consisting of nine fundamental measures. The table presents mean, standard deviation, skewness, kurtosis, 25^{th} percentile, median and 75^{th} percentile of the variables.

Table 2: Univariate sorted portfolios based on book-to-market ratio and investor attention

Panel A: BM-based portfolios

Portfolios	Raw returns	Size-adjusted returns	Market-adjusted returns	Firm size (millions)	BM ratio	Firms-year observations
Low	1.21	-0.03	0.41	19102	0.11	1732
2	0.98	-0.31	0.16	13509	0.21	1723
3	1.23	-0.07	0.41	11353	0.28	1724
4	1.29	-0.05	0.42	10374	0.34	1724
5	1.42	0.06	0.49	8313	0.40	1724
6	1.44	0.02	0.53	7495	0.48	1726
7	1.48	0.04	0.57	6430	0.56	1726
8	1.44	-0.01	0.55	4223	0.67	1722
9	1.59	-0.02	0.63	3966	0.83	1725
High	1.75	0.45	1.24	2718	1.38	1734
High-Low	0.54	0.48	0.83			
t-statistics	6.34	3.73	6.95			

Panel B: A_{DRT}-based portfolios

Portfolios	Raw returns	Size-adjusted returns	Market-adjusted returns	Firm size (millions)	BM ratio	Firms-year observations
Low	1.38	0.06	0.49	5845	139	1750
2	1.39	0.16	0.49	1909	293	1727
3	1.44	0.12	0.56	1914	371	1722
4	1.55	0.14	0.65	2215	440	1726
5	1.55	0.13	0.66	2589	524	1724
6	1.54	0.04	0.66	3624	630	1723
7	1.50	0.02	0.61	4818	774	1726
8	1.41	-0.15	0.53	7811	973	1724
9	1.36	-0.29	0.46	13643	1308	1724
High	1.18	-0.24	0.30	43379	3377	1714
Low-High	0.20	0.30	0.19			

t-statistics	2.07	3.15	2.19			

Panel C: A_{LM}-based portfolios

Portfolios	Raw returns	Size-adjusted returns	Market-adjusted returns	Firm size (millions)	BM ratio	Firms-year observations
Low	1.36	0.05	0.47	5923	87	1749
2	1.44	0.21	0.56	1852	189	1726
3	1.44	0.15	0.55	2030	242	1726
4	1.59	0.09	0.67	2031	288	1729
5	1.50	0.08	0.61	2525	344	1720
6	1.49	0.01	0.59	3462	415	1721
7	1.46	0.02	0.58	4825	510	1726
8	1.45	-0.15	0.57	7659	658	1726
9	1.42	-0.23	0.51	14047	932	1724
High	1.16	-0.25	0.28	43414	2873	1713
Low-High	0.20	0.30	0.19			
t-statistics	2.08	3.09	2.23			

Panel D: A_R-based portfolios

Portfolios	Raw returns	Size-adjusted returns	Market-adjusted returns	Firm size (millions)	BM ratio	Firms-year observations
Low	1.37	0.06	0.49	5874	118	1751
2	1.36	0.20	0.47	1788	248	1725
3	1.57	0.13	0.66	1951	311	1724
4	1.43	0.08	0.56	2123	371	1725
5	1.56	0.18	0.65	2571	438	1726
6	1.60	0.05	0.71	3485	522	1720
7	1.43	-0.10	0.53	4797	629	1746
8	1.42	-0.04	0.55	8251	793	1743
9	1.40	-0.31	0.49	13365	1066	1724
High	1.17	-0.26	0.30	43500	2667	1714
Low-High	0.20	0.32	0.19			
t-statistics	2.06	3.24	2.04			

This table reports the average monthly total returns, size-adjusted returns, and market-adjusted returns from May (t) to the end of the subsequent year April (t+1) along with firms' characteristics sorted in respective portfolios. Panel A provides average monthly returns of univariate sort portfolios based on book-to-market ratio and Panel B, C and D report monthly univariate sort portfolios based on three measures used to capture investor attention as proposed by Drake et al., (2015), Loughran and McDonald (2017), and Ryans (2017) and labeled as A_{DRT}, A_{LM}, and A_{R}, formed at the end of April (t). A firm is assigned to value portfolio or growth portfolio if the book-to-market ratio is above 90th percentile or below 10th percentile. A firm is assigned to the high investor attention or low investor attention portfolios if the respective investor attention measure is above 90th percentile or below 10th percentile. V-G represents the average monthly return differences between value portfolio and growth portfolio. L-H shows the average monthly return differences between low investor attention and high investor attention portfolios.

Table 3: Bivariate sorted portfolios based on book-to-market ratio and investor attention

Portfolio	Raw returns		Size-adjusted returns		Market-adjusted returns		Characteristics					
	Mean	t-statistics	Mean	t-statistics	Mean	t-statistics	Firms-year observations	Firm size (millions)	BM ratio	A_{DRT}	A_{LM}	A_{R}
Panel A: Bivariant-based portfolios (BM & A_{DRT})												
VL	1.92	6.50	0.18	0.60	0.98	3.56	181	2760	1.40	76		
VH	1.63	5.46	0.35	1.17	0.72	2.52	179	12622	1.37	2574		
GL	0.86	4.13	-0.57	-2.66	0.04	0.19	182	16148	0.11	208		
GH	1.23	6.55	0.18	0.93	0.46	2.61	181	70640	0.11	4857		
VL-GL	1.06	2.92	0.75	2.04	0.95	2.79						
VH-GH	0.40	1.13	0.17	0.48	0.26	0.77						
Panel B: Bivariant-based portfolios (BM & A_{LM})												
VL	1.90	6.46	0.15	0.51	0.99	3.61	181	2736	1.40		50	
VH	1.58	5.63	0.32	1.14	0.68	2.57	179	12325	1.36		2014	
GL	0.96	4.70	-0.47	-2.24	0.13	0.67	182	15446	0.11		135	
GH	1.19	6.47	0.14	0.73	0.37	2.15	181	71520	0.11		4375	
VL-GL	0.94	2.62	0.62	2.01	0.86	2.57						
VH-GH	0.33	1.16	0.19	0.55	0.31	0.98						

Panel C: Bivariant-based portfolios (BM & A_R)										
VL	1.92	6.49	0.17	0.57	1.00	3.60	181	2772	1.41	67
VH	1.64	5.59	0.37	1.26	0.75	2.71	179	12587	1.38	2091
GL	0.94	4.54	-0.49	-2.32	0.11	0.57	184	16076	0.11	182
GH	1.18	6.24	0.13	0.66	0.39	2.19	181	70171	0.11	3746
VL-GL	0.98	2.71	0.66	2.05	0.88	2.61				
VH-GH	0.46	1.32	0.24	0.69	0.36	1.10				

This table reports the average monthly returns of bivariate sort portfolios based on both book-to-market ratio and investor attention (labeled as A_{DRT}, A_{LM}, and A_R) formed at the end of April (t). Portfolios are rebalanced every 12 months (at the end of April) to form new portfolios each year. VL-GL shows average monthly return differences between portfolios of value-and-low-attention firms and growth-and-low-attention firms. VH-GH shows average monthly return differences between portfolios of value-and-high-attention firms and growth-and-high-attention firms. Monthly raw returns are calculated as the percentage difference of monthly total market performance index. Size-adjusted returns are measured by the net of return on its matched size decile return. Market-adjusted returns are measured as net returns on total monthly market returns. The table also reports characteristics: firms-year observation, firm size, book-to-market ratio, and respective investor attention measure for the corresponding portfolios.

Table 4: Size-segment univariate and bivariate sorted portfolios based on book-to-market ratio and investor attention

	Small-size firms							Large-size firms						
Portfolio	Raw returns		Size-adjusted returns		Market-adjusted returns			Raw returns		Size-adjusted returns		Market-adjusted returns		
	Mean	t-statistics	Mean	t-statistics	Mean	t-statistics	Firms-year	Mean	t-statistics	Mean	t-statistics	Mean	t-statistics	Firms-year
Panel A: Univariate based portfolios														
Value	2.33	21.76	0.42	3.84	1.32	12.70	870	1.32	13.56	0.31	3.25	0.32	3.88	868
Growth	1.20	10.36	-0.37	-3.08	0.34	3.04	878	0.99	19.12	-0.11	-2.12	-0.23	-4.88	878
V-G	1.13	7.17	0.79	4.87	0.98	6.37		0.33	3.45	0.44	429.00	0.55	6.89	
Panel B: Bivariant-based portfolios (BM & A_{DRT})														
VL	2.64	5.32	0.69	1.37	1.76	3.73	94	1.47	5.59	0.31	1.19	0.50	2.16	95
VH	3.61	5.94	1.91	2.91	2.70	4.29	94	0.81	2.45	-0.27	-0.81	0.02	0.08	94
GL	0.40	1.42	-1.26	-4.28	-0.47	-1.70	96	0.78	2.95	-0.40	-1.52	-0.02	-0.08	96
GH	1.93	4.85	0.37	0.90	0.97	2.50	96	1.25	5.20	0.21	0.84	0.48	2.10	96
VL-GL	2.24	3.91	1.95	3.35	2.23	4.08		0.69	2.23	0.71	2.36	0.52	2.02	
VH-GH	1.68	2.31	1.54	1.98	1.73	2.35		-0.44	-1.09	-0.48	-1.15	-0.46	-1.22	
Panel C: Bivariant-based portfolios (BM & A_{LM})														
VL	2.61	5.28	0.66	1.32	1.72	3.68	94	1.51	5.76	0.37	1.28	0.54	2.34	94
VH	3.73	6.16	2.04	3.17	2.77	4.45	93	1.12	3.46	0.04	0.13	0.34	1.15	94
GL	0.30	1.04	-1.37	-4.56	-0.55	-1.98	96	0.83	3.21	-0.33	-1.27	0.04	0.21	96

GH	2.22	5.18	0.65	1.47	1.29	3.09	96	1.15	4.83	0.10	0.41	0.35	1.56	96
VL-GL	2.31	4.04	2.03	3.49	2.27	4.17		0.68	2.21	0.70	2.28	0.50	2.01	
VH-GH	1.51	2.03	1.38	1.77	1.48	1.97		-0.03	-0.05	-0.06	-0.13	-0.01	-0.03	
Panel D: Bivariant-based portfolios (BM & A_R)														
VL	2.51	5.09	0.51	1.02	1.65	3.51	94	1.56	5.88	0.39	1.48	0.59	2.54	95
VH	3.56	5.95	1.99	3.10	2.69	4.35	93	0.75	2.30	-0.33	-0.98	-0.03	-0.11	94
GL	0.37	1.28	-1.32	-4.43	-0.49	-1.75	96	0.85	3.29	-0.31	-1.21	0.08	0.34	96
GH	2.14	5.06	0.56	1.28	1.18	2.86	96	1.26	5.04	0.21	0.83	0.45	1.91	96
VL-GL	2.14	3.75	1.83	3.14	2.14	3.91		0.71	2.56	0.70	2.45	0.51	2.09	
VH-GH	1.42	1.94	1.43	1.83	1.51	2.03		-0.51	-1.22	-0.54	-1.29	-0.48	-1.28	

This table reports the average monthly total returns, size-adjusted returns, and market-adjusted returns from May (t) to the end of the subsequent year April (t+1). Panel A provides average monthly returns of univariate sort portfolios based on book-to-market ratio separately for small-size and large-size firms, formed at the end of April (t). Panel B, C, and D report average monthly returns of bivariate sort portfolios based on both book-to-market ratio and investor attention (labeled as A_{DRT}, A_{LM}, and A_R) separately for small and large size firms, formed at the end of April (t). Firms are divided into small-size and large-size firms. Firms below the median of firm size at the end of April (t) are classified as small-size firms and firms above the median are grouped as large-size firms. Portfolios are rebalanced every 12 months (at the end of April) to form new portfolios each year. A firm is assigned to value portfolio or growth portfolio if the book-to-market ratio is above 90th percentile or below 10th percentile. A firm is assigned to the high investor attention or low investor attention portfolios if the respective investor attention measure is above 90th percentile or below 10th percentile. V-G represents the average monthly return differences between value portfolio and growth portfolios. L-H shows the average monthly return differences between low investor attention and high investor attention portfolios. VL-GL shows average monthly return differences between portfolios of value-and-low-attention firms and growth-and-low-attention firms. VH-GH shows average monthly return differences between portfolios of value-and-high-attention firms and growth-and-high-attention firms. Monthly raw returns are calculated as the percentage difference of monthly total market performance index. Size-adjusted returns are measured by the net of return on its matched size decile return. Market-adjusted returns are measured as net returns on total monthly market returns.

Table 5: Common risk factors regression

	BM ratio and A_{DRT}				BM ratio and A_{LM}				BM ratio and A_{R}			
	VL-GL		VH-GH		VL-GL		VH-GH		VL-GL		VH-GH	
	Co-efficient	t-statistics	Co-efficient	t-statistics	Co-efficient	t-statistics	Co-efficient	t-statistics	Co-efficient	t-statistics	Co-efficient	t-statistics
Panel A: CAPM												
Alpha	0.01*	2.25	-0.00	-0.01	0.01*	2.12	0.00	0.16	0.01*	2.04	0.00	0.18
MKT	0.03	0.23	0.52*	3.22	0.02	0.14	0.44*	2.81	0.04	0.30	0.50*	3.22
Panel B: Three-factor model with momentum factor												
Alpha	0.01*	2.81	-0.00	-0.18	0.01*	2.63	0.00	0.00	0.01*	2.55	0.00	0.07
MKT	-0.13	-1.55	0.31*	2.70	-0.14	-1.60	0.20	1.89	-0.14	-1.71	0.27*	2.61
SMB	0.08	0.55	0.09	0.57	0.08	0.56	0.21	1.38	0.06	0.45	0.16	1.11
HML	0.36*	2.54	0.57*	3.06	0.34*	2.39	0.57*	2.99	0.41*	3.18	0.65***	3.57
WML	-0.60***	-4.24	-0.65***	-4.11	-0.57***	-3.77	-0.62***	-4.18	-0.65***	-4.73	-0.60***	-3.67
Panel C: Five-factor model with momentum factor												
Alpha	0.01*	2.29	-0.00	-0.25	0.01*	2.17	-0.00	-0.01	0.01*	2.11	-0.00	-0.04
MKT	-0.07	-0.78	0.33*	3.14	-0.09	-0.93	0.21	1.94	-0.08	-0.90	0.29*	3.17
SMB	0.11	0.69	0.07	0.34	0.09	0.62	0.17	1.04	0.10	0.67	0.14	0.85
HML	0.25	1.56	0.46*	2.48	0.24	1.39	0.49*	2.47	0.36*	2.30	0.55*	2.95
RMW	0.27	1.15	-0.05	-0.25	0.18	0.77	-0.07	-0.36	0.26	1.23	0.01	0.04
CMA	0.37	1.26	0.42	1.93	0.38	1.21	0.34	1.53	0.18	0.62	0.40	1.84

WML	-0.61***	-4.44	-0.64***	-3.79	-0.58***	-3.93	-.61***	-3.88	-0.67***	-4.95	-0.59*	-3.42

* p < 0.050, ** p < 0.010, *** p < 0.001

This table reports the results from time series regression to explain average return differences to VH-GL and VL-GH strategies. The return differences are regressed on market excess return (MKT), size factor (SMB), value factor (HML), profitability factor (RMW), investment factor (CMA), and momentum factor (WML). Panel A, B, and C provide CAPM, the three-factor model with momentum factor, and the five-factor model with a momentum factor. The VL-GL strategy takes a long position in value-and-low-attention stocks and a short position in growth-and-low-attention stocks. The VH-GH strategy takes a long position in value-and-high-attention stocks and a short position in growth-and-high-attention stocks. The table reports coefficient estimates and Newey-West adjusted t-statistics in parentheses along with the significance level.

Table 6: Sentiment analysis and arbitrage to capital

	BM & A_{DRT}		BM & A_{LM}		BM & A_{R}	
	VL-GL	VH-GH	VL-GL	VH-GH	VL-GL	VH-GH
Intercept	0.04	0.02	0.03	0.02	0.03	0.04
	(0.75)	(0.31)	(0.62)	(0.41)	(0.53)	(0.57)
Sentiment index	-0.34*	-0.34	-0.36*	-0.36	-0.33*	-0.36
	(-2.35)	(-1.85)	(-2.63)	(-2.32)	(-2.17)	(-1.99)
Noise index	-0.13*	0.14	-0.13*	0.12	-0.10*	0.13
	(-2.46)	(1.28)	(-2.52)	(1.27)	(-2.01)	(1.24)

* $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$

This table reports the results from time-series regression to explain average return differences to VL-GL and VH-GH strategies. The return differences are regressed on Baker and Wurgler (2006) sentiment index and Hu et al., (2013) noise index. The VL-GL strategy takes a long position in value-and-low-attention stocks and a short position in growth-and-low-attention stocks. The VH-GH strategy takes a long position in value-and-high-attention stocks and a short position in growth-and-high-attention stocks. The table reports coefficient estimates and Newey-West adjusted t-statistics in parentheses along with the significance level.

Table 7: Fama-MacBeth cross-sectional regression

	BM & A_{DRT}			BM & A_{LM}			BM & A_R		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept	-0.10	-0.18	-0.05	-0.13	-0.19	-0.11	-0.12	-0.19	-0.08
	(-0.34)	(-0.70)	(-0.19)	(-0.45)	(-0.71)	(-0.41)	(-0.45)	(-0.71)	(-0.30)
Value stocks (V)	1.16***		0.51	1.16***		0.59	1.16***		0.45
	(9.98)		(1.16)	(10.00)		(1.34)	(9.98)		(1.07)
Growth stocks (G)	-0.38***		-0.77*	-0.38***		-0.65	-0.38***		-0.59
	(-5.05)		(-2.30)	(-5.12)		(-1.90)	(-5.08)		(-1.74)
Low attention (L)	0.18*		0.11	0.20*		0.13	0.21*		0.14*
	(2.52)		(1.57)	(2.93)		(1.92)	(2.94)		(1.99)
High attention (H)	-0.30***		-0.30***	-0.29***		-0.26*	-0.29***		-0.29***
	(-3.91)		(-3.74)	(-3.84)		(-3.19)	(-3.80)		(-3.54)
Value stocks x low attention (VL)		0.69**	0.57*		0.81***	0.52		0.77***	0.44
		(3.23)	(2.01)		(3.67)	(1.66)		(3.72)	(1.30)
Value stocks x high attention (VH)		0.59*	0.46		0.48*	0.36		0.53*	0.36
		(2.83)	(1.32)		(2.26)	(1.20)		(2.65)	(1.26)
Growth stocks x low attention (GL)		-0.62***	-0.17		-0.65***	-0.27		-0.59***	-0.20
		(-4.48)	(-1.02)		(-4.74)	(-1.62)		(-8.50)	(-1.20)
Growth stocks x high attention (GH)		0.19	0.27		0.20	0.28		0.15	0.41
		(1.47)	(0.92)		(1.61)	(0.79)		(1.20)	(1.32)
Size rank	-0.20***	-0.20***	-0.20***	-0.20***	-0.20***	-0.20***	-0.20***	-0.20***	-0.20***
	(-8.74)	(-8.51)	(-8.62)	(-8.73)	(-8.52)	(-8.61)	(-8.75)	(52.32)	(-8.63)
Momentum rank	0.52***	0.51***	0.52***	0.52***	0.52***	0.52***	0.57***	0.50***	0.52***

	(52.33)	(52.31)	(52.35)	(52.34)	(52.38)	(52.38)	(5.21)	(5.54)	(52.37)
Illiquidity rank	-0.08*	-0.09***	-0.08*	-0.08*	-0.08***	-0.08***	-0.08***	-0.09***	-0.08*
	(-3.40)	(-3.83)	(-3.34)	(-3.38)	(-3.81)	(-3.34)	(-3.40)	(-3.82)	(-3.36)
Beta rank	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***
	(5.23)	(5.55)	(5.27)	(5.22)	(5.54)	(5.28)	(5.21)	(5.54)	(5.27)
Coefficient test									
V - G	1.54***		1.28*	1.54***		1.24*	1.54***		1.04*
	(11.42)		(2.38)	(11.47)		(2.27)	(11.43)		(1.98)
L - H	0.48***		0.41***	0.49***		0.39***	0.50***		0.43***
	(4.62)		(-3.89)	(4.87)		(3.72)	(4.82)		(4.01)
(V - G) x L - (V - G) x H	0.01***		0.01*	0.01***		0.01*	0.01***		0.01*
	(4.24)		(2.01)	(4.39)		(2.00)	(4.38)		(2.01)
VL - GL		1.31***	0.74*		1.46***	0.79*		1.36***	0.64*
		(5.17)	(2.28)		(5.64)	(2.34)		(5.50)	(1.98)
VH - GH		0.40	0.19		0.28	0.08		0.38	-0.04
		(1.64)	(0.44)		(1.14)	(0.19)		(1.60)	(-0.10)

* $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$

This table reports the results from Fama-MacBeth based time-series regression to explain the effects of BM ratio and intangibles-intensity on monthly total returns. The table reports the results of the full stocks sample for each of three investor attention measures labeled as A_{DRT}, A_{LM}, and A_R. Model 1 reports return-predictability estimates of value, growth, low investor attention, and high investor attention. Model 2 reports estimates of interaction terms of concurring and conflicting signals. Model 3 combines individual and interaction estimates along with controls. The coefficient test reports the differences between estimates of the main regression. The table reports coefficient estimates and Newey-West adjusted t-statistics in parentheses along with the significance level.

Table 8: Piotroski-So cross-sectional regression

			BM & A_{DRT}		BM & A_{LM}		BM & A_{R}	
Variable	Model 1	Model 2	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
Panel A: Cross-sectional regression								
Growth	1.24***	-1.30***	-1.09***	-1.48***	-1.13***	-1.42***	-1.13***	-1.34***
	(11.72)	(-10.14)	(-6.65)	(-4.30)	(-6.90)	(-4.06)	(-6.80)	(-3.81)
Growth x HighFscore	-0.22	-0.85	-0.86	-0.83	-0.87	-0.85	-0.87	-0.86
	(-0.26)	(-1.09)	(-1.09)	(-1.06)	(-1.10)	(-1.08)	(-1.11)	(-1.09)
Growth x MidFscore	-0.04	0.10	0.09	0.09	0.09	0.09	0.09	0.09
	(-0.27)	(0.80)	(0.72)	(0.70)	(0.72)	(0.68)	(0.72)	(0.70)
Middle	1.36***	-0.89***	-0.67***	-0.63***	-0.71***	-0.69***	-1.13***	-0.67***
	(45.07)	(-11.68)	(-5.27)	(-4.81)	(-5.51)	(-5.25)	(-6.80)	(-5.03)
Value	-2.55***	-2.30***	-2.28***	-2.26***	-2.27***	-2.26***	-2.28***	-2.25***
	(-5.12)	(-5.08)	(-5.04)	(-4.97)	(-5.02)	(-4.99)	(-5.04)	(-4.98)
Value x MidFscore	-1.23*	-1.06*	-1.04*	-1.04*	-1.04*	-1.04*	-1.05*	-1.04*
	(-2.73)	(-2.57)	(-2.52)	(-2.15)	(2.51)	(-2.52)	(-2.53)	(-2.53)
Value x HighFscore	3.53***	1.51***	1.67***	1.28*	1.63***	1.29*	1.64***	1.17*
	(8.04)	(3.71)	(4.00)	(2.12)	(3.92)	(2.20)	(3.92)	(2.01)
Low intention (L)			0.21*	0.16*	0.23*	0.17*	0.24*	0.18*
			(2.96)	(2.17)	(3.36)	(2.53)	(3.37)	(2.54)
High intention (H)			-0.34***	-0.34***	-0.33	-0.29***	-0.33***	-0.32***
			(-4.52)	(-4.18)	(-4.38)	(-3.60)	(-4.41)	(-3.97)

Growth stocks x low				-0.15		-0.24		-0.18
attention				(-0.88)		(-1.49)		(-1.09)
Growth stocks x high				0.31		0.25		0.30
attention				(0.92)		(0.44)		(0.90)
Value stocks x low				0.59*		0.54		0.43
attention				(1.99)		(1.76)		(1.40)
Value stocks x high				0.17		0.15		0.27
attention				(0.57)		(0.44)		(0.94)
Size rank		-0.12***	-0.13***	-0.13***	-0.13***	-0.13***	-0.13***	-0.13***
		(-13.89)	(-14.19)	(-14.02)	(-14.19)	(-14.01)	(-14.19)	(-14.12)
Momentum rank		0.52***	-0.52***	0.52***	0.52***	0.52***	0.52***	0.52***
		(53.16)	(53.24)	(53.24)	(53.26)	(53.27)	(53.27)	(53.25)
Panel B: Coefficient test								
Congruent strategy	-3.79***	-1.00*	-1.19*	-0.78	-1.14*	-0.84	-1.15*	-0.91
(Cong)	(-7.46)	(-2.11)	(-2.44)	(-1.35)	(-2.36)	(-1.46)	(-2.37)	(-1.60)
Incongruent strategy	3.75***	2.36*	2.53*	2.89*	2.50*	2.14*	2.51*	2.03*
(Incong)	(3.98)	(2.69)	(2.85)	(2.17)	(2.82)	(2.18)	(2.83)	(2.07)
Incong - Cong	7.54***	3.36*	3.72*	2.10*	3.64*	2.98*	3.66*	2.94*
	(6.09)	(2.91)	(3.15)	(2.13)	(3.09)	(2.27)	(3.10)	(2.24)
(Incong-Cong) x L -			0.01*	0.01*	0.01*	0.01*	0.01*	0.01*
(Incong-Cong) x H			(2.19)	(1.99)	(2.13)	(1.99)	(2.13)	(2.01)

* p < 0.050, ** p < 0.010, *** p < 0.001

This table reports the results from Piotroski-So based time-series regression to explain buy-and-hold average monthly returns. Panel A provides one-month buy-and-hold estimates starting from May (t) to the end of next year April (t+1). For robustness, estimates are presented by using three measures of investor attention (labeled as A_{DRT}, A_{LM}, and A_{R}). The independent variables are measured as dummy variables. Model 1 and 2 reports return-predictability estimates of value stocks, growth stocks, and interaction terms as done by Piotroski and So (2012). Model 3 includes the effect of low and high investor attention. Model 4 additionally adds interaction terms between value/growth stocks and low/high investor attention. The table reports coefficient estimates and Newey-West adjusted t-statistics in parentheses along with the significance level. The coefficient test reports the differences between estimates of the main regression. The coefficient test reports return differences to Piotroski and So (2012) proposed congruent and incongruent strategies. The congruent strategy coefficient test reports the returns differences between value stocks with weak fundamentals and growth stocks with strong fundamentals, whereas incongruent strategy reports the returns differences between value stocks with strong fundamentals and growth stocks with weak fundamentals. The coefficient test also reports the difference between incongruent and congruent strategy and the difference between incongruent and congruent strategy across low and high investor attention.

Appendix

Appendix A

Table A1: Data items, codes and definitions as given in DataStream

Variable	Data item	Definition of variable
Book value of Common equity	WC03501	This represents common shareholders' investment in a company.
Cash flows from operations	WC04201	This represents the sum of net income and all non-cash charges or credits. It is the cash flow of the company.
Closing price	P	This represents the official closing price.
Common Shares Outstanding	WC05301	This represents common shareholders' investment in a company.
Cost of good sold	WC01051	This represents specific or direct manufacturing cost of material and labor entering in the production of finished goods. This represents the purchase price of items sold, as well as indirect overhead such as freight, inspecting, and warehouse costs. Service Organizations may refer to this as Cost of Services.
Long term debt	WC03251	This represents all interest-bearing financial obligations, excluding amounts due within one year.
Net income before extraordinary items	WC01551	This represents income before extraordinary items and preferred and common dividends, but after operating and non-operating income and expense, reserves, income taxes, minority interest and equity in earnings.

Purchase of common and preferred stocks	WC04751	This represents funds used to increase the outstanding shares of common and/or preferred stock.
Return index	RI	This shows a theoretical growth in value of a shareholding over a specified period, assuming that dividends are re-invested to purchase additional units of an equity or unit trust at the closing price applicable on the ex-dividend date.
Sale of common and preferred stocks	WC04251	This represents funds used to decrease the outstanding shares of common and/or preferred stock.
Sales	WC01001	This represents gross sales and other operating revenue less discounts, returns and allowances.
Total assets	WC02999	This represents the sum of total current assets, long term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets.
Total current assets	WC02201	This represents cash and other assets that are reasonably expected to be realized in cash, sold or consumed within one year or one operating cycle.
Total current liabilities	WC03101	This represents debt or other obligations that the company expects to satisfy within one year.
Trading volume	VO	This shows the number of shares traded for a stock on a particular day.

Chapter 4

Is the value premium dependent on mispricing signals manifested in the firms' intangibles-intensity?

Table of Contents

Is the value premium dependent on mispricing signals manifested in the firms' intangibles-intensity?

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Abstract

This paper examines whether value premium is dependent on mispricing signals manifested in the firm's intangibles-intensity. We confirm that value stocks with high intangibles-intensity outperform growth stocks with low intangibles-intensity, while return differences between value stocks with low intangibles-intensity and growth stocks with high intangibles-intensity are not different from zero. The return differences to investment strategy that takes a long position in value stocks with high intangibles-intensity and a short position in growth stocks with low intangibles-intensity cannot be explained by a risk-based explanation. However, findings confirm that return differences to observed strategy are attributed to mispricing explanation. This implies that high value-to-market ratios and high intangibles-intensity combinedly provide a powerful measure of mispricing. These findings have implications for investors to consider intangibles as the main predictor to assess firms' current competitive position and value creation ability to improve performance of standard value-growth strategy.

Keywords

Value premium, mispricing signals, intangibles, value creation, VAIC, ROTA rank measure

4.1. Introduction

Literature in finance supports the buying (or selling) of high (or low) value-to-market firms[1] to generate superior returns, termed as value premium. Intangibles[2] are strategic resources that help firms to create value, build sustainable competitive advantage (Asiaei & Jusoh, 2015), and drive firms' success and profitability (Clausen & Hirth, 2016). Firms focusing less on intangibles-intensity are on average poor investments due to weak financial prospects in their current structure. In contrast, firms with high intangibles-intensity are more attractive investments due to extensive value creation resources (Clausen & Hirth, 2016). Despite their importance, intangibles are often neglected as a valuation indicator to identify undervalued and overvalued firms to earn superior returns. In this paper, we fill this gap and examine the impact of the interaction between high/low value-to-market ratios and high/low intangibles-intensity on the value-growth returns. Our focus is motivated by the growing importance of intangibles as an important driver for corporate success by considering firms' current intangibles-intensity standing relative to industry and market intangibles-intensity levels.

There is an ongoing debate on the artifacts of the value premium. The risk-based explanation asserts that superior return to high book-to-market (BM) firms (or value firms) is the compensation for bearing higher systematic risk than low BM firms (or growth firms) (Fama & French, 1992, 1993). If the value premium is due to systematic risk than other risk factors may also affect value-growth return differences (Chui, Titman, Wei & Xie, 2012). Consistent with this view empirical evidence provide that value premium is highly sensitive towards business risk (Zhang, 2005), investment risk (Merton & Perold, 1993), consumption risk (Yogo, 2006), displacement risk (Gârleanu, Kogan & Panageas, 2012), and aggregate economic conditions

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[1] Following Fama and French (1992), book-to-market ratio (BM) is the commonly used value-to-market indicator to identify undervalued and overvalued firms. Alternative indicators to identify misvaluation also exist, such as cash flows-to-market price ratio (CM), earnings-to-market price ratio (EM) , sales-to-market price ratio (SM) and dividend to market price ratio (Pätäri & Leivo, 2017). In this study, we use CM, EM and SM as an alternative measure to identify undervalued and overvalued firms.

[2] Literature in intellectual capital recognizes intellectual capital as intangibles assets that drive firm's value creation processes and are not directly recorded on the firm's financial accounts like tangible assets. In addition, tangibles represent totality of skills, knowledge and expertise possessed by employees that adds to firm's value creation process (Burgman, Roos, Ballow & Thomas, 2005; Demediuk, 2002; Wyatt & Abernethy, 2008). Hence, intangibles and intellectual capital are considered interchangeable throughout this paper.

(Bansal, Dittmar & Lundblad, 2005). Thus, suggesting that value premium may be compensation for distress risk.

However, the mispricing explanation argues that value premium is the consequence of naïve investors' over extrapolation of firms' past fundamental strength and underreaction to the changes in value or growth firms' fundamental strength, resulting in market expectation errors. The value premium is the consequence of reversal in stock prices due to the correction in biased market expectation errors rooted in value and growth firms' prior performance (Lakonishok, Shleifer & Vishney, 1994). The higher value-growth return differences are attributed to the subsequent higher price reversal in growth stocks than value stocks. LaPorta, Lakonishok, Shleifer, and Vishny, (1997) supported this view and show that high (or low) BM ratio firms experience positive (or negative) earnings surprises. In the same lines, Piotroski and So (2012) and Walkshäusl (2017) find that presence (or absence) of value-growth effect is associated with (or without) ex-ante market expectation errors manifested in pessimistic (or optimistic) expectations reflected in value (or growth) stocks prices. When ex-ante market expectations are congruent (or incongruent) with fundamental strength there are no expectation errors (or existent expectation errors). They further demonstrated that the value-growth effect and revision of market expectations are prominent in firms with higher ex-ante biased market expectation errors.

Consistent with mispricing explanation, Bali, Demirtas and Hovakimian, (2010) and Walkshäusl (2015, 2017) find that undervaluation and overvaluation signals manifested in prior equity financing decisions contribute towards market expectation errors and explains the higher return to conditioned value-growth strategy. Building on their findings, we thereby suggest that the value-growth effect is a consequence of revision in biased market expectation errors and the mispricing view can help the market to identify fundamental strength indicators that capture mispricing in value or growth stocks (Walkshäusl, 2015).

Extensive evidence in finance suggests that incongruence in market expectations and fundamental strength is due to investor's lack of attention, neglect of salient information, limited cognitive abilities, and complex information processing demands[3]. One such type of such

[3] Some studies reported investors lack of attention and neglect to difficult-to-process information contained in different proxies used to measure innovation that result in undervaluation (e.g. Hirshleifer, Hsu & Li, 2018). Detail discussion is provided in section 2.

complex and difficult-to-process information is the assessment of valuation signals manifested in intangibles. This assessment process is difficult because traditional value measures of revenue, income, and cash flows often mislead whether the value is created or destroyed. However, assessing intangibles requires broad knowledge and a deeper understanding of the main dimensions of the firm's value creation process. These dimensions consist of a firm's human capital, structural capital, relational capital, innovation capital, and capital employed[4]. The better utilization of intangibles by firms leads to higher productivity, value creation efficiency, sustainable competitive advantage, and higher market value (Pulic, 2004). This implies that the market is inefficient in assessing mispricing signals revealed in firms' intangibles, providing a window of opportunity to identify undervalued (or overvalued) high (or low) intangibles-intensive firms. If high (or low) value-to-market ratios and high (or low) intangibles-intensity signals undervaluation (or overvaluation), then both indicators can combine to provide a powerful measure of mispricing. When both indicators agree then the conditional probability to earn superior returns is high but if both signals disagree then the conditional probability to earn superior returns is low. The investment strategy that takes a long position in value firms with high intangibles-intensity and a short position in growth firms with low intangibles-intensity might earn superior returns on price reversal. Thereby, we ask the following question: Is the value premium dependent on mispricing signals manifested in the firms' intangibles-intensity?

Indeed, we confirm that value-growth returns are strongly dependent on undervaluation and overvaluation signals manifested in the firms' intangibles-intensity. We employ U.S. firm's data listed on the S&P Composite 1500 index from December 1994 until May 2020. The intangibles-intensity is measured by using the modified Value-Added Intellectual Coefficient rank measure (m-VAIC rank measure). The results show that value firms with high intangibles-intensity (value-and-high-intangibles firms) outperform growth firms with low intangibles-intensity (growth-and-low-intangibles firms) (VH-GL), which indicates that concurring undervaluation signals (i.e. value-and-high-intangibles firms) provide a powerful measure of

[4] Human capital refers to essential human knowledge, capabilities, and experience required by the organization to innovate in order to achieve firm's objectives. The structural capital comprises of organization internal processes, routines, databases, systems and culture that facilitates sound functioning of the business. The relational capital reflects corporate image, reputation, and relationship with suppliers and customers (Bontis, Chua & Richardson, 2000). Innovation capital consist firm's investment in R&D to develop skills and knowledge that improves value creation processes and strengthen competitive advantage. Capital employed accounts for financial capital and physical capital invested in the firm (Nadeem, Dumay & Massaro, 2019).

mispricing. Whereas, return differences between value firms with low intangibles-intensity (value-and-low-intangibles firms) and growth firms with high intangibles-intensity (growth-and-high-intangibles firms) (VL-GH) are indistinguishable from zero, which shows that conflicting undervaluation and overvaluation signals do not agree and ability of the individual indicator to signal mispricing is low. These findings are robust to an alternative measure of intangibles (i.e. return of tangibles assets; ROTA rank measure) and alternative value-to-market ratios (i.e. CM ratio, EM ratio, and SM ratio). We confirm that the investment strategy to take a long position in value-and-high-intangibles stocks (VH) and a short position in growth-and-low-intangibles stocks (GL) is not driven by superior returns in extraordinary periods rather persist over a longer period.

We used three approaches to confirm that observed returns differences are consistent with mispricing and not with the risk-based explanation. First, common risk factors cannot completely explain the return differences to VH-GL strategy and negative loading on beta for VH-GL strategy suggest that return difference is not compensation for higher risk. The misvaluation factor (i.e. undervaluation minus overvaluation; UMO) shows significant positive loadings, which suggest that return differences to VH-GL strategy are significantly explained by misvaluation factor. We note that the superior return differences to VH-GL strategy are prominent following high sentiment periods and lack of arbitrage capital limit investors to take advantage of mispricing, which further elongates mispricing. Second, Fama and MacBeth (1973) based cross-sectional regression provide the positive effect of BM ratio and intangibles-intensity on returns, confirming that higher stock returns are attributed to high BM firms and high intangibles-intensity firms. Finally, we use Piotroski and So (2012) market expectation errors approach that explicitly tests mispricing assumption. We find that return differences to incongruence and congruence strategy significantly improves across high/low intangibles-intensity. Considering together the findings of three approaches, we confirm that returns differences to VH-GL strategy are attributed to mispricing.

The findings of this study contribute towards literature in finance and highlight the role of intangibles as a firm-specific indicator that signals mispricing and subsequently can strengthen value premium. The findings have implications for investors to consider intangibles as the main predictor to assess firms' current competitive position and value creation ability relative to standard value-growth investment strategy. Additionally, it contributes by suggesting that investors should not solely rely on financial statement analysis heuristics like F-score to identify superior return opportunities because traditional performance measures overlook firms' value creation prospects manifested in their efforts to sustain, improve and build on intangibles capabilities relative to counterparts.

In the remainder of the paper, section 2 comprises literature and hypothesis development. Section 3 presents our methodology and presents descriptive statistics. Section 4 reports the results of univariate and bivariate sorted portfolios, robustness checks by using alternative intangibles measure and value-to-market ratios, and long-term performance of interaction strategy. In a subsequent section (i.e. section 5), we examine whether observed returns behavior is attributed to mispricing explanation or risk-based explanation. Section 6 report the main conclusions of the paper.

4.2. Literature and hypotheses development

The resource-based view defines intangibles as "strategic resources that enable an organization to create sustainable value but are not available to a large no of firms" (Kristandl & Bontis, 2007). Under this view, intangibles are distinct resources that are hard to acquire and determine how efficiently the firm converts inputs into outputs. Managing intangibles helps firms to achieve sustainable competitive edge (sometimes termed as "competitive moat"; Hirshleifer, Hsu & Li, 2018), enhance productivity, firm value, and determine performance differences among rival firms (Clausen & Hirth, 2016).

Literature in finance supports the positive impact of components of intangibles: Patents and research and development investment (Yu & Hong, 2016), capital investment (Amir, Guan & Livne, 2007), advertising expenditure (Joseph & Wintoki, 2013), innovative efficiency (Hirshleifer, Hsu & Li, 2013), and innovative originality (Hirshleifer et al., 2018) on firm performance and stock returns. Most relevant to our study, Clausen and Hirth (2016) proposed an earnings-based indirect aggregate indicator of intangibles-intensity that captures the current contribution of different asset classes and intangibles towards value creation. They find that intangibles positively add to the firms' value and can be used to gauge the firms' productivity by considering the current status of intangibles. The intangibles measure is effective in capturing productivity and firms' value even during the financial crisis 2008-2012. They show that high intangible-intensive firms have lower leverage and consequently lower financial distress risk. They further proposed the use of intangibles to better capture changes in firms' productivity and value. Hence, intangibles can provide an important indicator to capture firms' efforts to sustain and enhance productivity. It also captures incongruence between the firm's current level of intangibles and market-implied expectations associated with firm performance.

Two studies in accounting literature that is: Nadeem, Gan, and Nguyen (2018) and Nadeem, Dumay, and Massaro (2019) confirmed resource-based view by providing the positive impact of intangibles (measured as VAIC) on firm performance. Nadeem et al., (2018, 2019) endorsed the importance of human capital, structural capital, and capital employed in enhancing firms' performance. They further stress on investors to understand the importance of intangibles in predicting the firm's performance. However, accounting literature overlooked the importance of aggregate intangibles in separating expected winners and losers to generate superior returns.

Literature in intellectual capital supports the role of intellectual capital (or intangibles) in enhancing competitive advantage, organization efficiency, financial performance and market value (e.g. Chen, Cheng & Hwang, 2005; Clarke, Seng & Whiting, 2011; Nimtrakoon, 2015; Sardo & Serrasqueiro, 2018; Sydler, Haefliger & Pruksa, 2014). Specifically, Chen et al., (2005) used data of Taiwanese firms and find a positive impact of intangibles on firms' financial performance, market value, revenue growth, and employee productivity. Clarke et al. (2011) show the significant positive effect of aggregate VAIC, human capital efficiency, and capital employed efficiency on firm performance, market value, revenue growth, and employee productivity. Sydler et al., (2014) used data of pharmaceutical and biotechnology companies to demonstrate that current year expenditure in intangibles significantly improves the firm's financial performance. They confirm that intangibles components independently and combinedly leads to the development of a firms' sustainable competitive resource.

Nimtrakoon (2015) focused on the high-technology sectors of the five largest economies in ASEAN to examine the influence of intangibles on firms' performance and market value. Nimtrakoon (2015) shows a positive impact of intangibles on the firms' performance and market value. Nimtrakoon reports significant differences among five countries in connection to four components of modified-VAIC but no difference in aggregate modified-VAIC. Sardo and Serrasqueiro (2018) used data from 14 European countries to examine the influence of intangibles on firms' profitability and market value. Results provide a positive association between intangibles and profitability. They further suggested that growth opportunities are positively linked with profitability and this association is enhanced by efficient utilization of intangibles.

Based on the preceding evidence, current firms' performance, market expectations, and value creation ability are largely dependent on firm's investment in intangibles (Nadeem et al., 2018). High intangibles-intensive firms positively add (or create) to current value and drive firms' market expectations. Low intangibles-intensive firms destruct (or reduce) current firm value and negatively influence firms' market expectations. However, congruence between market expectations and high/low intangibles is not always true (i.e. no market expectation errors; Piotroski & So, 2012). Mostly, the market fails to valuate true stock price justified by updated fundamentals strength including intangibles, resulting in incongruence between market expectations and fundamental strength. This implies that the market is inefficient in identifying mispricing signals manifested in intangibles. Because valuating intangibles requires broader knowledge and a deeper understanding of the firm's current intangibles status and its role in enhancing the firm's value. This valuation process requires investors to process complex sets of information that demands high cognitive resources.

Due to limited cognitive resources, investors neglect and pay less attention to difficult-to-process information contained in mispricing indicators like intangibles. This argument is supported by studies that have examined the effect of innovation (by using different proxies to measure innovation) on stock price valuation. For example, Lev, Sarath, and Sougiannis (2005) provide that the market extrapolates positive prospects of high R&D firms attributed to high technical uncertainty associated with the innovation process that results in mispricing. Cohen, Diether, and Malloy (2013) reports that investors' inability to consider firms' past R&D expenditure to ex-ante predict future firms' performance, results in underpricing of R&D expenditure. Chen, Chen, Liang, and Wang (2013) utilize R&D spillover as a measure of innovation and provide that investors underprice the R&D spillover effect due to the lack of knowledge to measure R&D spillover. Hirshleifer et al., (2013) employ innovative efficiency (measured as no of patents and citation divided by R&D expenditure) to examine firms' innovation activities and find that investors underprice innovation efficiency because investors lack the knowledge to estimate economic implications of patents and citations as an outcome of R&D expenditure. Hirshleifer et al., (2018) provide the role of innovative originality as a value-enhancing resource that determines organization ability to convert innovative concepts into implementable forms to generate profit. The valuation of innovative originality requires broad knowledge and a deeper understanding of firms' current fundamental status and future ability to navigate the transformation of innovative concepts into products. Investors pay less attention to difficult-to-process information and unable to valuate innovative originality that results in mispricing. Thereby, investors tend to neglect or pay less attention to mispricing signals contained in innovative originality.

Under the mispricing explanation, the value premium is due to incongruence between market-implied expectations and fundamental strength. This suggests that market-implied expectations proxied by value-to-market ratios signal mispricing and the inability of value-to-market ratios to identify market-implied expectations are most likely due to the noise component of value-to-market ratios. Similarly, firms' interest to enhance intangibles-intensity reflects the management forecast of firms' performance prospects. Firms with strong growth prospects invest more in improving both firms' current and future value-enhancing activities through investment in intangibles-intensity (Nadeem et al., 2018). In contrast, firms' that expect a decline in future demand reduces investment in intangibles-intensity to minimize expenses and to maintain streams of positive returns. The intangibles-intensity reveal management expectations and provide better insight into firms' internal processes than traditional measures of performance. Thus, intangibles signal management future expectations and might potentially be informative about mispricing. However, intangibles-intensity can also be a noisy indicator to capture intangibles-intensity. For example, firms may increase (or decrease) investment in intangibles-intensity due to industrial competition like the technology industry, pharmaceuticals, food products, and iron and steels. Following Bali et al., (2010) argument, if value-to-market ratios and intangibles-intensity signals mispricing than the noise component of both indicators is uncorrelated, combining these indicators can generate a more powerful measure of mispricing. When both indicators signal concurring undervaluation (or overvaluation), the likelihood that superior return differences are as a consequence of mispricing is high than noise. In contrast, when both indicators signal conflicting undervaluation or overvaluation, the power of signals to identify mispricing is low and signals are more likely to be due to noise.

We develop the following two hypotheses. The first hypothesis tests the dependence of value premium on valuation signals manifested in firms' intangibles. Therefore,

Hypothesis 1: Value firms with high intangibles-intensity outperform growth firms with low intangibles-intensity, but value firms with low intangibles-intensity do not outperform growth firms with high intangibles-intensity.

Second, we predict that return difference between value firms with high intangibles-intensity and growth firms with low intangibles-intensity are a consequence of mispricing rather than compensation to value firms for bearing additional market risk. We assume that market-implied expectations manifested in high (low) value-to-market ratios are incongruent (or congruent) with high (low) intangibles-intensive firms', attributing value premium to mispricing. Hence,

Hypothesis 2: The return differences between value firms with high intangibles-intensity and growth firms with low intangibles-intensity are attributed to mispricing.

4.3. Data and methodology

4.3.1. Measurement of intangibles

Pulic (1998) proposed fundamental information-based the Value-Added Intellectual Coefficient (VAIC) to measure intellectual capital (or intangibles) contribution towards value-creation. The VAIC measures intellectual capital efficiency (ICE) – expressed as a sum of human capital efficiency (HCE) and structural capital efficiency (SCE) – and capital employed efficiency (CEE). The following is the formulation of VAIC:

$$VAIC = ICE + CEE \tag{1}$$

$$ICE = HCE + SCE \tag{2}$$

$$VAIC = HCE + SCE + CEE \tag{3}$$

HCE measures firms' value-creation ability through investment in its employees and measured as value-added (VA) – measured as total revenue earned by firm minus all expenses incurred in raw material and operational overheads – divided by human capital (HC), which is employees' salaries and wages. SCE measures the capital created by the firms by using structural capital (SC) and is measured as SC divided by the difference between VA and HC. Finally, CEE measures firm's value creation ability by using shareholder capital and calculated as VA divided by capital employed (CE) that represents financial capital invested in the firm. The VAIC is represented as:

$$VAIC = \frac{VA}{HC} + \frac{SC}{VA} + \frac{VA}{CE} \tag{4}$$

Most studies have used VAIC as a measure of intellectual capital in different sectors and countries (e.g. Chen et al., 2005; Clarke et al., 2011; Nimtrakoon, 2015; Sardo & Serrasqueiro, 2018, Ståhle, Ståhle & Aho, 2011) because VAIC is simple, straight forward and based on financial statements information. It provides an objective and verifiable measure of intangibles that facilitate cross-firm, cross-sector, and cross-country comparison of value-creation efficiency (Pew Tan et al., 2007).

Despite VAIC extensive use as a measure of value creation efficiency, the model is criticized for measurement issues and failure to capture the totality of intangibles resources. Iazzolino and Laise (2013) highlight two critical issues in the formulation of the VAIC model. First, the VAIC model employs overlapping variables for calculation. For example, VAIC captures only invested capital efficiency and human resource efficiency than aggregate intellectual capital efficiency. The model confuses assets with expenses and does not properly treat them. The operating profit is an outcome of firm current investment in operations (i.e. expenses) whereas depreciation and amortization are due to firm past investment (i.e. assets) (Ståhle et., 2011). Comparing VAIC with different definitions of intellectual capital, Ståhle et al., (2011) argue that the VAIC does not provide a representative measure of intellectual capital. The measurement of SCE is not representative (Nimtrakoon, 2015; Ståhle et al., 2011; Vishnu & Gupta, 2014). SC is measured as employees' cost (EC) minus VA. However, the remainder represents operating profit, depreciation, and amortization that is comparable to the operating margin and has nothing to do with firm structural capital.

Recent studies modified and extended the VAIC by introducing alternative measurements of SC and new variables like innovation capital, relational capital, and process capital. For example, Nimtrakoon (2015), Ulum, Ghozali, and Purwanto (2014), and Vishnu and Gupta (2014) proposed adding relational capital efficiency (RCE) in the VAIC. Nimtrakoon (2015) and Vishnu and Gupta (2014) find no improvement in the explanatory power of the standard model but Ulum et al., (2014) reports significant improvement in the explanatory power of the modified model. Vishnu and Gupta (2014) used R&D expense as an alternative measure to capture SC but find no improvement in the explanatory power of the model. Nadeem et al., (2019) argue that Ståhle et al., (2011) criticize both measurement and missing variables. However, studies only emphasized on introducing new variables but overlooked the measurement aspect (e.g. Nimtrakoon, 2015; Vishnu & Gupta, 2014). These studies used the same VA and efficiency measurement – the perfect superimposition of SC and HC – as suggested by Pulic. Nadeem et al., (2019) analyze measurement issues and argument that investment on employees has long term benefits, so employees' costs must be treated as an asset, not an expense. Similarly, R&D is an investment that helps to convert knowledge and skills into value creation processes and strengthens firms' competitive advantage. They modified VA by considering employee's costs and R&D as assets. Nadeem et al., (2019) argue that the Pulic original model measures HCE or CEE as VA divided by HC or CE, which represents value-added per dollar of HC or CE investment, but measurement of SCE resembles more VA efficiency rather than SCE. Hence, they replaced SCE with innovation capital efficiency (ICE), measured as VA divided by R&D expenditure. They find improved and consistent results across 10 emerging and developed economies and suggested to use the modified model in place of the standard model.

Proceeding with the above discussion, we use the modification proposed by Nadeem et al., (2019), Nimtrakoon (2015), Ulum et al., (2014), and Vishnu and Gupta (2014) to present modified VAIC model. We propose that relational capital and innovation capital both drive firm value creation activities and together both better predict and measure the firm value creation efficiency. We consider selling and marketing-related expenses (S&ME) as firm investment and add back in VA. We add marketing expenses in Nadeem et al., (2019) proposed VA and relational capital efficiency as the second component of SCE together with ICE. Hence, the modified VAIC model can be represented as:

$$VA = NI + EC + I + T + DP + R\&D + S\&ME \tag{5}$$

$$m - VAIC = HCE + RCE + ICE + CEE \tag{6}$$

$$m - VAIC = \frac{VA}{HC} + \frac{VA}{RC} + \frac{VA}{IC} + \frac{VA}{CE} \tag{7}$$

Prior studies suggest that intellectual capital efficiency is significantly affected by exogenous factors like business cycle variations and cross-industry variations (e.g. Chen et al., 2005; Firer & Williams, 2003; Pew Tan et al., 2007). One period model is not able to capture such variation. To capture these effects studies have controlled for year and industry effect by using dummy control variables. In this study, our strategy is to sort stocks based on BM ratio and intangibles across industries and years. An absolute measure may provide biased and inconsistent formulation to capture intangibles by controlling for cross-industry and cross-year variations in intangibles. To overcome this issue, we follow Clausen and Hirth (2016) proposed three steps rank measure mechanism that subtracts by-industry-and-by-year median HCE or RCE or ICE or CEE from each absolute value of HCE or RCE or ICE or CEE. This difference is then normalized by the by-industry-and-by-year standard deviation to control for cross-industry and cross-year variations. In the next step, normalized differenced values of HCE, RCE, ICE, and CEE value are added to get overall modified-VAIC (m-VAIC) value. In the end, year-based ranking is applied to get the rank of individual m-VAIC and avoid reliance on the absolute size of sum normalized differenced value. A high-rank of m-VAIC corresponds to high intangibles-intensity or high-value creation processes and firms classified as low-rank m-VAIC have low intangibles-intensity or low-value creation (or value destruction) processes. From now on, we refer ranked modified-VAIC as “m-VAIC ranked measure” and its two categories as high intangibles-intensity and low intangibles-intensity.

Clausen and Hirth (2016) proposed an indirect measure to capture intangibles-intensity that is ROTA rank measure. ROTA rank measure captures the productivity of intangibles relative to tangible assets, which shows that how well firms perform in terms of earnings before interest, tax, depreciation, and amortization (EBITDA) per tangible assets, termed as ROTA. As ROTA is a noisy measure of intangibles driven earnings, Clausen and Hirth (2016) adjusted ROTA for cross-industry and cross-year variations and applied ranking to get ROTA rank measure (as discussed in preceding paragraph). A firm classified as high ROTA rank represents high intangibles-intensity and firm with low ROTA rank refers to low intangibles-intensity. In this study, we use the m-VAIC rank measure as the main measure of intangibles due to its extensive application as a measure of intangibles efficiency and ROTA rank measure as an alternative measure to check the robustness of our findings.

To validate proposed modification in the original VAIC model, we test the validity of HCE, RCE, ICE, CEE rank measures, and aggregate m-VAIC ranked measure in predicting firm performance (i.e. return on assets (ROA) and return on equity (ROE)) and market value (i.e. BM ratio). Results are given in appendix A. Results provide statistically highly significant positive (or negative) impact of individual rank components, aggregate m-VAIC rank measure, and ROTA rank measure on ROA and ROE (or BM ratio). This suggests that firm capital employed in human capital, relational capital, innovation capital and aggregate intangibles improves firm performance and enhances market value. As four individual components and aggregate m-VAIC rank measure significantly predict firm profitability and market value and our objective is to investigate the impact of aggregate firm intangibles on value premium, therefore we use aggregate m-VAIC ranked measure and not individual rank components for further analysis and hypothesis testing.

4.3.2. Variables, data, and descriptive statistics

The definitions and measurements of the variables used in this study are as follows. A firm's market capitalization (size) is market equity at the end of April (t) – stock price multiplied by the number of shares outstanding. BM is the ratio of the book value of equity at the end of the fiscal year (t-1) to market equity at the end of April (t). We use market equity at the end of April (t) to ensure that fundamental information is known to the market and stock prices are already adjusted for changes in the firm's fundamental strength (Lakonishok et al., 1994). This makes certain that incongruence (or congruence) between market price and fundamental strength is due to existent (or no) market expectation errors (Piotroski & So, 2012). Cashflows-to-market price (CM) is the ratio of cash flows from operations at the end of the fiscal year (t-1) to market equity at the end of April (t). Earnings-to-market price (EM) is the ratio of net income before extraordinary items at the end of the fiscal year (t-1) to market equity at the end of April (t). Sales-to-market price (SM) is the ratio of sales at the end of the fiscal year (t-1) to market equity at the end of April (t). Momentum (Mom) is the cumulative prior 12-months returns skipping the most recent month returns before portfolio formation (Jegadeesh & Titman, 1993).

We use two firm-level fundamentals information-based intangibles measures that facilitate cross-industry and cross-year comparison. Intangibles represent the totality of value created using intangible resources or the ability of a firm to create value by efficient utilization of tangible resources. We identified two measures to capture the firms' intangibles efficiency that are m-VAIC rank measure and return on intangible assets (ROTA) rank measure.

We use Piotroski (2000) F-score methodology to proxy the firm's fundamental strength. The F-score is the composite measure of nine firm fundamental indicators that range from a minimum of 0 to a maximum of 9, the low (or high) score indicates a firm weaker (or stronger) fundamental strength. The nine firm-level indicators are classified into three categories: Profitability, leverage and liquidity, and operating efficiency. Four variables are used to measure profitability: return on assets (ROA), cash flows from operations (CFO), change in return on assets (ΔROA), and accruals (ACC). Three variables are used to measure leverage: change in long term debt (ΔLD), change in the current ratio (ΔCR), and issuance of equity (EI). The remaining two variables: change in gross margin (ΔGM) and change in asset turn over (ΔAT) are used to measure operations efficiency. An individual indicator is equal to 1 if an indicator is positive or zero otherwise except equity issue, which is equal to 1 when a firm did not issue equity and zero otherwise. The sum of the individual indicator score is equal to F-score. The measurement of F-score is given as follow:

$$F - score = S\_ROA + S\_CFO + S\_\Delta\mathrm{ROA} + \mathrm{S\_ACC} + \mathrm{S\_\Delta LD} + \mathrm{S\_\Delta CR} + \mathrm{S\_EI} + \mathrm{S\_\Delta GM} + \mathrm{S\_\Delta AT} \quad (8)$$

The firm must have a market capitalization (Size), BM ratio, CM ratio, EM ratio, SM ratio, m-VAIC ranked measure, ROTA ranked measure, and F-score values available to be included in the sample.

We study all constituent companies included in the S&P Composite 1500 Index from the end of December 1994 until the end of April 2020. However, for some accounting-level information data goes back to December 1992. The S&P Composite 1500 index is the aggregate index consisting of the companies included in the S&P 500, the S&P MidCap 400, and the S&P SmallCap 600 indices and covers approximately 90% of U.S. equity market capitalization[5]. It provides investors an investable benchmark that replicates overall U.S. equity market performance. It is available in both price and performance index – incorporates ordinary cash dividends and special cash dividends. Our sample is free from survivorship bias because all constituents of the S&P Composite 1500 index were included in the sample during and at the end of the considered sample period. We obtain monthly total returns[6] from Thomson Datastream

[5] Refer to S&P Composite 1500 index website for further details on methodology of composite index construction: https://us.spindices.com/indices/equity/sp-composite-1500

[6] Monthly total return is calculated as the percentage difference of monthly stock performance index.

and firm-level fundamental information from the Worldscope database for composite index constituents[7]. We also ensure that firm-level accounting information is known to market before calculation of total returns that they are used to explain (Lakonishok et al., 1994). Specifically, we match previous fiscal year-end accounting information (t-1) with total returns starting from the current year May (t) to the subsequent year April (t+1) throughout this paper. We compute BM, CM, EM, and SM ratios by using the firm's market equity at the end of April (t). To be included in the sample firms must have had appeared in the composite index for at least 12-months after fiscal year-end (t-1) and if stock is delisted from the composite index, its monthly returns are replaced with matching size decile until following April (t+1) and the portfolio is rebalanced for subsequent 12-months.

To calculate size-adjusted returns, we sort all stocks that meet the above-mentioned criteria into decile portfolios (for each year) based on the firm size at the end of April (t). Equally weighted decile size-portfolios monthly average returns are computed, and each size decile monthly average returns are subtracted from corresponding stock monthly total returns to obtain a monthly size-adjusted return. We also calculate market-adjusted returns to test the performance of proposed strategies relative to market performance. The market-adjusted returns are computed as the total monthly stock return minus total monthly market return[8].

Following Ince and Porter (2006), we apply two return screenings procedures. First, any monthly total returns above 300% that are reversed within one month are considered as missing to mitigate the effect of suspicious returns[9]. Second, we avoid the potential error arising from the total monthly returns of stocks with a price of less than \$1.00. We eliminate potential biases arising from small, low-price, and illiquid firms by requiring stocks to have a minimum of \$1.00 price at the end of each month, otherwise treated as missing.

To mitigate the effect of extreme observations on our computation, we winsorize firm-level fundamental variables at 1% and 99% levels. We exclude firms with a negative book value (Fama & French, 1992) and negative m-VAIC value (Firer & Williams, 2003). The analysis is

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[7] Data item codes along with their definition as given in Worldscope used to get variables of this study are presented in appendix B.
[8] Monthly market total return is obtained as the percentage difference of monthly total market performance index.
[9] Specifically, if $R_t > 300\%$ or $R_{t-1} > 300\%$, and $(1+ R_t) \times (1+ R_{t-1}) - 1 < 50\%$ than both if R_t and R_{t-1} are treated as missing.

based on 30,272 firms-year observations with an average of 1,211 firms' observations per year for 25 years (1995-2020). Our sample is similar to Bali et al., (2010) that consisted of 35,165 U.S. firms-year observations with an average of 1,172 firms' observations per year for 30 years (1972-2002).

-------------Insert table 1-----------

Table 1 presents descriptive statistics of the main variables used in this study. The summary statistics are calculated as time-series averages of firms-year observations. We note that the median size of our sample is 1757 million dollars with a mean size of 8463 million dollars. The median (mean) of the BM ratio is 0.42 (0.52), median (mean) of total monthly returns is 1.07% (1.28%), and the intangibles median is 50%. This shows that most firms in the sample are small size undervalued firms and mean total returns (i.e. 1.28%) may not be driven by large size overvalued firms. Additionally, the total monthly returns are largely driven by high intangibles-intensive undervalued firms and not by low intangibles-intensive overvalued firms.

4.4. Returns on univariate and bivariate value-growth strategies

In this section, we first test the baseline strategy that value stocks (V) outperform growth stocks (G) and high intangibles-intensive firms (H) earns superior returns than low intangibles-intensive firms (L). After confirming the baseline assumption, we test hypothesis 1 that value-and-high-intangibles stocks (VH) outperform growth-and-low-attention stocks (GL), but value-and-low-attention stocks (VL) do not outperform growth-and-high-intangibles stocks (GH). Following Bali et al. (2010) and Walkshäusl (2015), we test the sensitivity of interaction strategy across alternative measures of value-growth strategy (i.e. CM EM, and SM ratios), intangibles-intensity measure (i.e. ROTA rank measure), firm size (small-size versus large-size firms) and long-term holding periods.

4.4.1. Univariate strategy

At the end of each April (t), we develop portfolios by using univariate sort based on BM ratio and m-VAIC rank measure. The BM ratio is measured by using firm book value at the end of the fiscal year (t-1) and firm market value at the time of portfolio formation (t). The m-VAIC rank measure is based on fiscal year-end fundamentals. A firm is assigned to value portfolio or growth portfolio if the BM ratio is above 70th percentile or below 30th percentile. A firm is assigned to a high intangibles-intensive portfolio or low intangibles-intensity portfolio if the m-VAIC rank measure is above 70th percentile or below 30th percentile. For each portfolio, we calculate monthly total returns, size-adjusted returns, and market-adjusted returns from May (t) to the end of the subsequent year April (t+1). Each year at the end of April (t+1) portfolios are rebalanced and new portfolios are formed.

-------------Insert table 2-----------

Table 2 provides average monthly total returns, size-adjusted returns, market-adjusted returns, and characteristics of firms sorted in portfolios based on BM ratio, m-VAIC rank measure, and interaction of both variables. Panel A of table 2 presents estimates of univariate sorted portfolios. Panel A reports a statistically significant value-growth effect in the U.S. equity market. The value stocks outperform growth stocks with an average monthly total return difference of 0.59%. The average monthly total return difference is not driven by firm size because results show 0.24% superior average monthly size-adjusted return to value-growth strategy. Furthermore, the value-growth strategy also earns returns of 0.47% average per month higher than market returns. This indicates that our results are consistent with recent literature on outperformance of value-growth strategy (e.g. Fama & French, 1992, 1998).

Panel A of table 2 reports the strong effect of intangibles-intensity on average total monthly return differences in the U.S. equity market. The firms with high intangibles-intensity earn 0.65% per month higher than firms with low intangibles-intensity. This effect persists after accounting for firm size and market performance, which means that firms with a high emphasis on intangibles-intensity are rewarded with 0.62% higher average monthly size-adjusted and 0.62% monthly market-adjusted returns. These results confirm the finding of previous studies that intangibles drive corporate success (e.g. Chen et al., 2005; Clausen & Hirth, 2016; Nimtrakoon, 2015; Sardo & Serrasqueiro, 2018; Sydler et al., 2014). Comparing our findings with Hirshleifer et al., (2018) that examined the effect of innovative originality on return predictability. They find that high innovative originality strongly influences predictability of positive returns and this effect is more prominent in high valuation-uncertainty firms. We also confirm that a long-short strategy conditioned on intangibles-intensity provides higher average monthly total returns than standard value-growth strategy. The firm’s characteristics suggest that value firms are on average small in size than growth firms, and small-size firms benefit more from investing in intangibles-intensity than large-size firms (Fama & French, 1992).

4.4.2. Bivariate strategy

After having confirmed the baseline assumption, we check the effect of bivariate sorts on average total monthly return differences as given in panel B of table 2. We test the average monthly returns differences between value-and-high-intangibles firms and growth-and-low-intangibles firms (VH-GL), and average monthly return differences between value-and-low-intangibles firms and growth-and-high-intangibles firms (VL-GH).

Results in panel B of table 2 show that bivariate strategy that conditions value stocks also as high intangibles-intensive and conditions growth stocks also as low intangibles-intensive (VH-GL) generate statistically significant positive average monthly value premium (i.e. 1.27% per month). This average monthly return is greater than standard unconditional value-growth strategy (i.e. 1.27% > 0.59%). The bivariate returns difference is consistent after adjusting for firm size and market performance (i.e. 0.88% per month size-adjusted return and 1.13% per month market-adjusted return). However, a bivariate value-growth strategy that conditions value stocks also as low intangibles-intensive and conditions growth stocks also as high intangibles-intensive (VL-GH) earns average monthly return difference of -0.11% per month total returns, -0.38% per month size-adjusted return and -0.19% per month market-adjusted returns and these returns differences are indifferent from zero. Hence, we observe that the bivariate strategy that takes a long position in value-and-high-intangibles stocks and short position in growth-and-low-intangibles stocks (VH-GL) generate higher value premium than standard value-growth strategy.

Comparing our results with Bali et al., (2010) that investigate the effect of value-growth strategy conditioned on whether firms are equity issuers or equity purchasers in the U.S. equity market. They found significant one-year ahead returns of 9.90% (0.82% per month) on a strategy that takes a long position in value firms that are also equity purchasers and growth firms that are also equity issuers. Walkshäusl (2015) confirmed the robustness of Bali et al., (2010) findings by using European equity market data. In line with their findings, we note that return differences to value-growth strategy are due to market expectation errors that are dependent on valuation signals contained in intangibles-intensity. We note that firms' characteristics confirm that higher value premium to VH-GL is due to market expectation errors associated with undervalued firms.

There is no difference in BM ratio characteristics of VH and VL or GH and GL. The undervalued small-size firms significantly contribute to enhancing firm returns than large-size overvalued growth firms. This indicates that small-size firms benefit more from undervaluation of intangibles-intensity than overvaluation of intangibles-intensity to large-size firms. Consistent with Hirshleifer et al., (2018), we observe that intangibles-intensity can be considered as an aggregate measure to capture the effect of "competitive moat" to generate superior returns.

4.4.3. Alternative intangibles-intensity measure

To check the robustness of average monthly return differences to value-growth strategy conditional on firm intangibles-intensity, we use ROTA rank measure as an alternative measure of intangibles-intensity. Results in table 3 replicate univariate and bivariate strategy by using the BM ratio and ROTA rank measure. Panel A of table 3 provides a univariate sort of stock by using the ROTA rank measure. The stocks sorted based on ROTA rank measure provide statistically significant average monthly superior returns of 0.44% between high ROTA rank stocks (H) and low ROTA rank stocks (L). The size-adjusted and market-adjusted returns differences are 0.56% per month and 0.39% per month, indicating that value premium persists after controlling for size and market performance. Results in panel B of table 3 provide a bivariate strategy by using the BM ratio and ROTA rank measure. The results suggest that the VH-GL strategy earns significant superior returns of 1.29% per month, while returns to VL-GH strategy are relatively small (i.e. 0.39% per month). The results correspond to table 2 and suggest that the value-growth strategy conditioned to intangibles-intensity regardless of intangibles measurement generates superior returns, which means a strategy that takes a long position in value-and-high-intangibles stocks outperforms growth-and-low-intangibles stocks.

-------------Insert table 3-----------

4.4.4. Alternative value-growth measures

The BM ratio is a commonly used indicator to proxy the value-growth effect, but alternative measures had been used as indicators of the value-growth effect. Following Pätäri and Leivo (2017), we use CM, EM, SM ratios as alternative measures to proxy the value-growth effect and test the robustness of results given in table 2.

-------------Insert table 4-----------

Table 4 provides univariate and bivariate strategy results by using CM ratio, EM ratio, and SM ratio. The portfolios are developed by using the same procedure as in table 2 except we exclude negative CM and EM ratios from corresponding portfolios. Panel A in table 4 presents univariate sort of stocks based on CM ratio, EM ratio, and SM ratio. The results show significant value premium by using: CM ratio (i.e. 0.51% per month), EM ratio (i.e. 0.47% per month), SM ratio (i.e. 0.83% per month). The average monthly returns differences are also statistically significant after adjusting for firm size and market performance for CM ratio (0.36% per month average size-adjusted return and 0.40% per month average market-adjusted return), EM ratio (0.29% per month size-adjusted return and 0.34% per month average market-adjusted return), and SM ratio (0.58% per month size-adjusted return and 0.47% per month average market-adjusted return). Hence, results show an existent value-growth effect regardless of indicators used to proxy value-growth effect. Consistent with U.S based portfolio formation studies, the SM ratio generates higher return differences across value-to-market ratios (Pätäri & Leivo, 2017).

Panel B in table 4 presents a bivariate strategy and confirms that VH-GL earns significant positive average total monthly return differences that range from 1.14% per month to 1.44% per month for alternative measures. The bivariate strategy is consistent after controlling for firms' size and total market returns, which show that bivariate strategy earns size-adjusted returns difference of more than 1.03% per month and market-adjusted returns difference more than 1.06% per month for both alternative measures. However, returns differences to VL-GH are very small and statistically not different from zero. Hence, we note that the value-growth effect corresponds to results in table 2 and suggests that value-and-high-intangibles stocks significantly outperform growth-and-low-intangibles stocks irrespective of indicator used to proxy the value-growth effect.

4.4.5. Size segment results

Prior research suggests that the value-growth effect is more prominent in small-size firms than large-size firms (Fama & French, 2006). Following Walkshäusl (2017), we test the persistence of our findings across small-size and large-size firms. Based on market equity we divide firms into small-size and large-size segments. Firms above the median of market equity at the end of April (t) are classified as large-size firms and firms below the median are grouped as small-size firms. Table 5 presents the univariate and bivariate sort by using the same procedure as table 2. Panel A presents univariate sort of small-size and large-size firms by using BM ratio and panel B reports results of the bivariate sort based on BM ratio conditioned to intangibles-intensity (measured as the m-VAIC rank measure).

-------------Insert table 5-----------

Results in panels A suggest parsimony of value-growth effect in both small-size and large-size firms. The differences in average total monthly returns, size-adjusted returns, and market-adjusted returns are significantly different from zero, confirming that value stocks outperform growth stocks, despite differences in firm size. The panels B of table 5 confirm our finding of bivariate strategy for both size segments, which means that value-and-high-intangibles stocks outperform growth-and-low-intangibles stocks (1.31% per month for small-size firms and 0.92% per month for large-size firms). The results are robust in terms of size-adjusted, and market-adjusted returns differences. Hence, confirming that findings in table 2 are not largely limited to small-size firms but large-size firms also generate significant superior value premium. A value-growth strategy that takes a long position in value-and-high-intangibles stocks and a short position in growth-and-low-intangibles stocks earns more than 1.31% (0.92%) per month of average total monthly and 1.12% (0.85%) per month size-adjusted returns and 1.22% (0.78%) per month market-adjusted returns among small (large) size firms.

4.4.6. Long term performance

In this subsection, we check whether value-growth strategy conditioned on firms' intangibles-intensity persist over longer periods or are driven by extreme returns during extraordinary periods. We calculate annual cumulative average monthly total returns, size-adjusted returns, and market-adjusted returns differences for VH-GL and VL-GH strategies. Figure 1 depicts the annual cumulative average monthly total returns differences to VH-GL portfolios with dark-colored bars and returns differences to VL-GH with light-colored bars. It is clear from figure 1 that for a complete sample period of 25 years, 21 years VH-GL strategy generates superior returns differences than the VL-GH strategy. Similarly, figure 2 (or figure 3) presents the annual cumulative average size-adjusted (or market-adjusted) returns differences to VH-GL and VL-GH strategies. VH-GL strategy earns for 21 years excess size-adjusted and market-adjusted returns. Thus, we conclude that findings in table 2 persist over longer periods, and the efficacy of VH-GL strategy persists over longer periods.

-------------Insert figure 1, 2 and 3-----------

Collectively, the findings presented in section 4 strongly support the dependence of the value-growth effect on the valuation signals manifested in firms’ intangibles-intensity, confirming hypothesis 1. The interaction of high/low value-to-market ratios and high/low intangibles-intensity generate higher value premium than standard value-growth strategy.

4.5. Mispricing explanation

In this section, we examine that superior return differences between value-and-high-intangibles stocks and growth-and-low-intangibles stocks are attributed to mispricing. Under mispricing assumption, noise between mispricing indicators (VH or VL or GH or GL) is uncorrelated and the conditional probability of superior value-premium is higher due to mispricing than noise (Bali et al., 2010). Table 1 reports the correlation coefficient between value-to-market ratios and intangibles measures. Results show that a cross-sectional correlation between value-to-market ratios and m-VAIC (or ROTA) rank measure ranges from -0.06 (or -0.27) to 0.06 (or 0.01), indicating no correlation between measures. This confirms our proposition that superior returns to VH-GL strategy are due to mispricing. To further confirm the mispricing explanation of bivariate strategy, we test hypothesis 2 and examine whether findings provided in section 4 are explained by mispricing explanation or risk-based explanation.

Following Walkshäusl (2015; 2017), we employ four different approaches to identify whether observed average monthly return differences reported in table 2 are attributed to mispricing or risk-based explanation. We employ common risk factors, investor sentiment, and availability of arbitrage capital, Fama-MacBeth proposed a cross-sectional level returns predictability approach, and Piotroski and So (2012) proposed the market expectation errors approach.

4.5.1. Common risk factors

We first investigate whether return differences between value-and-high-intangibles stocks and growth-and-low-intangibles stocks are explained by common risk factors as documented by asset pricing models. We utilize returns differences to VH-GL strategy VL-GH strategy relative to CAPM, Fama and French (1993) three-factors model, Carhart (1997) momentum factor and Fama and French (2015) five-factors model. The CAPM controls for market risk (measured as market excess returns; MKT) based on the beta, three-factor model controls for common risk factors associated with size effect (SMB; returns differences between small and big firms), value-growth effect (HML; returns differences between high BM ratio and low BM ratio firms), five-factor model additionally control for profitability effect (RMW; robust minus weak; returns difference between profitable and unprofitable firms), investment effect (CMA; conservative minus aggressive; returns differences between high internal investment and low internal investment firms) and Carhart (1997) momentum effect (WML; returns differences between past winners and past losers). We estimate the following models by using monthly average return differences to VH-GL and VL-GH portfolios.

$$Premium_{it} = \alpha_i + \beta_{MKT} MKT_t + e_{it} \quad (9)$$

$$Premium_{it} = \alpha_i + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{WML} WML_t + e_{it} \quad (10)$$

$$Premium_{it} = \alpha_i + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{RWM} RMW_t + \beta_{CMA} CMA_t + \beta_{WML} WML_t + e_{it} \quad (11)$$

In model 9, 10, and 11, $Premium_{it}$ is the return difference to VH-GL or VL-GH portfolios for each month. Model 9 refers to CAPM, model 10 describes the four-factor model with a momentum effect, and model 11 provides the five-factor model with a momentum effect. We estimate risk factors by following Fama and French (1993) and Carhart (1997). The market excess return (MKT) is the S&P Composite 1500 index monthly excess risk-adjusted returns (based on the 1-month U.S. Treasury bill rate). The size factor (SMB) and value factor (HML) are estimated by using two-to-three sort based on firms' size and BM ratio at the end of each April (t). SMB is the average monthly total returns on the three small-size firms' portfolios minus average total returns on the three large-size firms' portfolios. HML is the average monthly total returns on two high BM firms' minus two low BM firms' portfolios. RMW is the average monthly total returns on two high operating profit firms minus two low operating profit firms' portfolios. CMA is the average monthly total returns on two high investment firms minus two low investment firms' portfolios. The momentum factor (WML) is formed by using the two-to-three sort of firm's size and momentum at the end of April (t). Momentum is the cumulative prior 12-month returns skipping the most recent month before portfolio formation (Jegadeesh & Titman, 1993). WML is the average total monthly returns on two high momentum portfolios minus two low momentum portfolios. The two-to-three sort represents the division of firms based on the median of firms size measured at the end of April (t) as a split point, firms lower than the median are grouped as small-size firms and firms higher than the median are grouped as large-size firms. The second sort is based on the 30th and 70th percentile of respective variables for each size segment.

The risk-based explanation hypothesizes that superior returns to value stocks are compensation for facing higher business risks. Under risk-based explanation, our findings that value-and-high-intangibles stocks outperform growth-and-low-intangibles stocks and no return differences between value-and-low-intangibles stocks and growth-and-high-intangibles stocks imply that among value firms only high intangibles-intensive firms are susceptible to higher risk and among growth firms only low intangibles-intensive are susceptible to lower risk. This can be true if both high/low value-to-market ratio and high/low intangibles-intensity are considered to capture different components of equity risk. Value firms are considered to have poor future business prospects and thus have higher business risk than growth firms. High intangibles-intensive firms face high uncertainty risk associated with sunk cost, internal financing constraints, and productivity of different components of intangibles[10]. Low intangibles-intensive firms face relatively low sunk cost risk, low financing constraints, and low productivity risk because they try to persist with their prior productivity routine and try to reduce expenses. The business risk to value-and-high-intangibles stocks (VH) would be magnified by a high investment risk to achieve, develop, or sustain high intangibles-intensity. However, the high business risk faced by value stocks is reduced by a low risk of low intangibles-intensity (VL). The high business risk of value stocks with low risk of low intangibles-intensity makes VH risk comparable to low risk of growth stocks and high risk of high intangibles-intensity (GH). Under risk-based explanation, we expect the superior return differences to VH-GL strategy is positively associated with market risk (represented by beta).

-------------Insert table 6-----------

[10] Hirshleifer et al., (2018) provide that return predictability of innovative originality is prominent in firms with higher valuation uncertainty and lower investors' attention. Such firms have high dependability on innovative originality for positive future performance.

Table 6 reports parameter estimates of CAPM, three-factor model, and five-factor models with momentum effect to average monthly total return differences to VH-GL and VL-GH strategies. We note that alpha in panel A, B, and C are positive and statistically strongly significant for VH-GL strategy. However, alpha is negative and statistically significant for the VL-GH strategy. The market risk (beta) has a statistically significant negative value for VL-GH strategy in panels A, B, and C. This indicates that superior return differences to value-and-high-intangibles stocks are not attributed to systematic risk rather the interaction strategy reduces firms' systematic risk. This appears consistent with the mispricing explanation. Bali et al., (2010) find similar results for superior returns differences between value stocks that are equity purchasers and growth stocks that are equity issuers.

The return differences to VH-GL and VL-GH strategies show similar sensitivity towards size (SMB), value (HML), profitability (RMW), and momentum (HML) factors, indicating that return differences are driven by large-size, profitable, undervalued and investment-intensive firms. However, VH-GL is more sensitive towards the momentum (HML) factor. Hence, we observe that superior return differences to VH-GL strategy are not explained by a risk-based explanation after controlling for common risk factors. The average monthly total return differences are not compensation for higher equity risk to value firms with high intangibles-intensity, which is consistent with the mispricing explanation.

We explicitly test the mispricing assumption by introducing misvaluation factors in model 9, model 10, and model 11. We examine whether intangibles-intensity-based misvaluation factor can capture average total monthly return differences to VH-GL and VL-GH strategies in an assets pricing model framework (model 11, 12, and 13). The misvaluation factor i.e. undervaluation minus overvaluation (UMO) is estimated by using two-to-three sort based on firms' size and m-VAIC rank measure at the end of each April (t). UMO is based on average total monthly return differences to two high intangibles-intensive firms minus two low intangibles-intensive firms' portfolios. According to the mispricing assumption if return differences show positive (or negative) loadings on UMO factors then superior returns resemble undervalued (or overvalued) firms. The positive (or negative) loadings on UMO predict firms subsequent higher (or lower) performance on correction of market expectation errors based on firms' intangibles-intensity.

$$Premium_{it} = \alpha_i + \beta_{MKT}MKT_t + \beta_{UMO}UMO_t + e_{it} \quad (11)$$

$$Premium_{it} = \alpha_i + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{WML}WML_t + \beta_{UMO}UMO_t + e_{it} \quad (12)$$

$$Premium_{it} = \alpha_i + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{RWM}RWM_t + \beta_{CMA}CMA_t + \beta_{WML}WML_t + \beta_{UMO}UMO_t + e_{it} \quad (13)$$

Panel D, E, and F in table 6 reports UMO factors estimates in asset pricing model framework to average total monthly return differences of VH-GL and VL-GH strategies. Adding UMO lower alpha values to VH-GL strategy, suggesting a decrease in the predictability of alpha to VH-GL strategy. The misvaluation factor is effective in capturing significant returns differences to VH-GL and VL-GH strategies in assets pricing models framework. Consistent with mispricing assumption UMO load statistically significant positive in asset pricing model framework (i.e. range from 0.95% to 0.96% per month) for VH-GL strategy and UMO load statistically significant negative in assets pricing model framework (i.e. range from -1.10% to -1.11% per month) for VL-GH strategy, which suggests that returns differences to VH-GL strategy is driven by undervalued firms and returns differences to VL-GH strategy is driven by overvalued firms. The two subsample periods reveal similar results as given by the full sample period and suggest high persistence of VL-GH strategy over two subsample periods. Therefore, results strongly support the mispricing assumption for VL-GH strategy. We repeat the UMO factors analysis by using ROTA rank measure and find quantitatively similar results as reported in panel D, E, and F in table 6. Results are given in appendix C.

4.5.2. Sentiments analysis and limits to arbitrage capital

A long-short strategy that is grounded in the exploitation of mispricing is influenced by the high level of investors sentiments (Stambaugh, Yu & Yuan, 2012). The performance of such strategy should be stronger following periods of high investor sentiment. During high sentiment periods, stock prices deviate from fundamentals due to investors' overly extrapolated optimistic expectations with firms' past performance (market expectation errors). The sentiment-driven mispricing is primarily induced by overvaluation in (growth) stocks that are attractive to optimistic investors (Stambaugh et al., 2012). This implies that stocks ex-ante perceived as overvalued are strongly influenced by the high sentiment period than ex-ante perceived (value) undervalued stocks (Baker & Wurgler, 2006). The higher returns to mispricing-based long-short strategy are mainly arising due to taking a short position in overvalued stocks following the high sentiment period (Stambaugh et al., 2012).

In our context, the superior return differences to VH-GL strategy is predominantly due to overvalued growth-and-low-intangibles stocks, which implies that high level of sentiment strongly influences investors' strategy to take a short position in growth-and-low-attention stocks than a long position in value-and-high-attention stocks. Hence, we expect that superior return differences to VH-GL strategy are positively associated with periods of the high investors' sentiment, whereas return differences to VL-GH strategy are not influenced by periods of the high investors' sentiment.

Even though sentiment-driven investors may influence market-wide mispricing that may earn superior returns by taking a long position in undervalued value-and-high-intangibles stocks and a short position in growth-and-low-intangibles stocks. However, restrictions on the availability of arbitrage capital can weaken the performance of VH-GL strategy as the arbitragers are not able to take advantage of mispricing by taking a long position in undervalued value-and-high-intangibles stocks. Hence, we expect that superior return differences to VH-GL strategy are negatively associated with a shortage of arbitrage capital, whereas return differences to VH-GL strategy are not influenced by the shortage of arbitrage capital.

We employ Baker and Wurgler (2006) proposed the sentiment index[11] to capture the time-varying effects of sentiment. Their sentiment index is a component of five sentiment proxies that are orthogonalized to six macroeconomic indicators to remove business cycle variations. The positive sentiment index values represent the high level of sentiment and negative index values represent the low level of sentiment. Hu, Pan, and Wang (2013) proposed the noise index[12] to capture changes in the availability of arbitrage capital by measuring aggregate variability in the U.S. treasury bonds prices. The higher value of noise index suggests a shortage of arbitrage capital, while low value suggests the availability of arbitrage capital. The sentiment

[11] Refer to Baker and Wurgler (2006) for measurement of sentiment index. The sentiment index is available at Jeffery Wurgler's website: http://people.stern.nyu.edu/jwurgler/data/Investor_Sentiment_Data_20190327_POST.xlsx.

[12] Refer to Hu et al., (2013) for measurement of noise index. The noise index is available at Jan Pan's website: http://en.saif.sjtu.edu.cn/junpan/Noise_Measure_2019Q3.xlsx.

index is available until the end of December 2018 and the noise index is available until the end of March 2019. The analysis reported in table 7 covers the period from the end of April 1995 until the end of December 2018.

-------------Insert table 7-----------

Panel A in table 7 presents results on the effects of the lagged value of sentiment index and noise index on returns difference to VH-GL and VL-GH strategies. Consistent with our predictions, results provide a statistically significant positive effect of lagged sentiment index and significant negative effect of lagged noise index to VH-GL strategy while results show the statistically insignificant negative effect of lagged sentiment index and lagged noise index to VL-GH strategy. Results confirm that growth-and-low-intangibles stocks are overvalued in the market and following high sentiment periods their market prices further detach from fundamental strength. The negative effect of lagged noise index suggests that the lack of arbitrage funds limits investors (arbitragers) to take a long position in undervalued value-and-high-intangibles stocks. When overvaluation is identified, buying undervalued stock is much easier in the market than selling overvalued stocks (Stambaugh, Yu & Yuan, 2015). Lack of arbitrage capital together with difficulty to take a short position in overvalued stocks elongates mispricing in the market.

Consistent with our prediction, panel B in table 7 reports the significant negative effect of sentiment on returns to GL strategy. This confirms that the superior performance of the VL-GH strategy is attributed to the short position. Growth-and-low-intangibles stocks exhibit a negative effect on returns, while sentiment does not influence returns of other portfolio forming strategies. Consistent with the prediction of arbitrage asymmetry, we find a negative effect of noise index on returns to GL strategy, while a lack of arbitrage capital does not affect other strategies. This indicates that the lack of arbitrage capital limits the buying of value-and-high-intangibles stocks that allow growth-and-low-intangibles stocks to stay overvalued for longer and strengthens return differences to VH-GL strategy on price reversal.

4.5.3. Cross-sectional return predictability

The portfolio-level analysis provides a useful approach to investigate the impact of variation in variables of interest. However, most of the cross-sectional level information is lost through aggregation, consequently, it becomes difficult to draw inferences about variables exhibiting unique information to predict returns behavior. Therefore, we further scrutinize the results of tables 2 and 3 and examine the predictive power of BM ratio and intangibles-intensity by controlling other cross-sectional fundamental indicators. We use Fama and MacBeth (1973) proposed a cross-sectional regression model with additional controls.

We estimate monthly cross-sectional regression of average total monthly buy-and-hold returns on BM ratio, and intangibles-intensity along with firm size, momentum, beta, illiquidity, and return-weighted variables as controls (represented by model 14). The firm size and momentum are commonly used controls (e.g. Piotroski & So, 2012). Bali et al., (2010) confirmed the robustness of their findings by using beta and illiquidity as controls. By following their proposed firm-level model, we also include beta and illiquidity as controls in our model. The beta is estimated monthly for all stocks using a minimum of 24 months past returns up to 60 months returns by using the S&P composite 1500 index as a market portfolio (Fama & French, 1996). Illiquidity is measured as the monthly stock return divided by monthly trading volume in dollars (Amihud, 2002). Following Walkshäusl (2015), we add Asparouhova, Bessembinder, and Kalcheva (2013) proposed return-weighted variable – monthly returns are weighted with prior month returns - to control for the noise in prices that may be present in cross-sectional regression. The BM ratio and firm size are updated annually at the end of April (t) and intangibles-intensity is also updated annually at the end of the fiscal year (t-1). We estimate the following model each month.

$$R_{it+1} = a_1 BM_{it} + a_2 Intangibles_{it} + b_1 Size_{it} + b_2 Momentum_{it} + b_3 Beta_{it} + b_4 Illiquidity_{it} + b_5 returnweighted_{it} + e_{it} \tag{14}$$

Under mispricing assumption, the value-and-high-intangibles stocks and growth-and-low-intangibles stocks reflect concurring undervaluation (or overvaluation) signals between value (or growth) stocks and high (or low) intangibles-intensity. Whereas, value-and-low-intangibles stocks and growth-and-high-intangibles stocks reflect conflicting signals undervaluation (or overvaluation) signals. Combining concurring mispricing indicators i.e. value stocks and high intangibles-intensity can generate a more powerful measure of mispricing. We predict that value-and-high-intangibles stocks exhibit high return predictability than other combinations of value/growth stocks and high/low intangibles-intensive. Portfolios containing value-and-high-intangibles stocks outperform growth-and-low-intangibles, but portfolios consisting of conflicting signals stocks i.e. value-and-low-intangibles stocks and growth-and-high-intangibles stocks underperform, attributing indicator signals as noise. In contrast, as discussed above, under risk-based explanation superior returns to value/growth and high/low intangibles-intensive strategy is generally compensation for higher risk. The large return differences to VH-GL and small return differences to VL-GH are due to offsetting effect of risk but holding one of both value/growth or high/low intangibles-intensity indicators constant, other indicators should still reflect the significant effect on return differences. Which implies that holding either value/growth effect or high/low intangibles-intensity effect in concurring or conflicting portfolios would offset the higher (or lower) return to other indicator and there is no difference in return predictability across concurring and conflicting portfolios.

-------------Insert table 8-----------

Table 8 reports the results of Fama and MacBeth (1973) based model for the entire stocks sample, concurring stocks sample, and conflicting stocks sample. In each model specification, monthly returns are matched with fundamental information each year at the end of April (t) for portfolio formation. To check the robustness of results, we estimate the model by using both m-VAIC rank measure and ROTA rank measure. Model 1, 2, and 3 estimates return-predictability of BM ratio and intangibles-intensity. Model 4 incorporates controls in model 3 to confirm the robustness after controlling for cross-sectional indictors.

The results in table 8 of the full sample provide a statistically significant strong positive effect of BM ratio and m-VAIC rank measure in univariate model 1 and model 2. The coefficient estimates of BM ratio and intangibles-intensity grows stronger in multivariate model 3. The positive estimates and high strength of the BM ratio increase after controlling for cross-sectional indicators. This suggests that value stocks and high intangibles-intensity drive firm returns. Firms with high (low) BM ratio and high (low) intangibles-intensive firms experience positive (negative) returns. We find a small significant negative effect of size and positive effect of momentum. As our sample includes S&P small firms therefore size effect shows small size effect. The momentum effect is highly significant and suggests a positive effect of recent performance on returns. The beta shows a small positive effect on returns.

The results presented under concurring sample provides a significant positive effect of BM ratio and intangibles in univariate and bivariate model 1, 2, and 3. In model 3, coefficient estimates of BM ratio and intangibles are greater than the univariate model, indicating that together both variables strengthen cross-sectional returns. This significant and stronger effect persists after adding controls in the model. We note that coefficient estimates of BM ratio and intangibles (model 4) in the concurring sample are greater than model 4 of the full sample, indicating higher explanatory power of BM ratio and high intangibles-intensity in concurring mispricing indicators. This is consistent with the mispricing assumption that return predictability to BM ratio and intangibles statistically strengthen in the concurring sample than the full sample.

There are significant differences in coefficient estimates and significance of BM ratio and intangibles as we move from concurring to a conflicting subsample. In model 3, the BM ratio is significant, but the intangibles coefficient is small and insignificant. The significance and magnitude of the BM ratio coefficient decline in model 4 but intangibles show small but significant coefficient estimates. The coefficient estimates are much smaller than the full sample model 4 estimates. This is inconsistent with the risk-based explanation that assumes explanatory power of BM ratio and intangibles do not depend on the sample.

We repeat the same analysis by using ROTA rank measure and find quantitively similar results as in table 8. The results using ROTA rank measure are given in appendix D. Our findings are consistent with the mispricing explanation that concurring mispricing indicators provide better return predictability than conflicting mispricing indicators. The return predictability of indicators in the conflicting sample does not become insignificant but estimates and significance of both conflicting indicators weaken. Similarly, the concurring sample exhibit stronger coefficient estimates relative to conflicting indicators. Hence, confirming that high BM ratio and high intangibles-intensity combinedly provide a stronger indicator of mispricing.

4.5.4. Market expectation errors approach

In this subsection, we explicitly investigate the mispricing assumption by employing Piotroski and So (2012) proposed market expectation errors approach that is based on the interaction between BM ratio and fundamental strength measured as Piotroski F-score. In the market expectation errors approach the BM ratio proxy for the strength of implied-market expectations associated with firms' prior performance. High (or low) BM ratio signals optimistic (or pessimistic) market expectations. The F-score captures in general firms' improvement or deterioration in recent fundamental strength. High (or low) F-score signals firms strong (or weak) fundamentals strength (Piotroski, 2000).

According to rational pricing assumption, value firms with a high BM ratio experience weak fundamental strength, whereas growth firms with low BM ratio experience strong fundamental strength. There is congruence between market-implied expectations and fundamental strength, implying no expectation errors (Piotroski & So, 2012). Hence, the value premium arises because of the higher risk associated with value firms (Fama & French, 1995). However, mispricing explanation arguments that market overly extrapolates past fundamental performance, giving rise to deviations between market-implied expectations and updated financial information. The underreaction (or overreaction) to the changes in value (or growth) firms' fundamental strength leads to existent expectation errors (Piotroski & So, 2012). The value premium arising due to corrections in biased market expectation errors (Lakonishok et al., 1994; LaPorta et al., 1997).

Piotroski and So (2012) employed U.S. equity market data and confirmed the mispricing assumption. They document that presence (or absence) of value-growth effect is associated with (or without) ex-ante expectation errors manifested in pessimistic (or optimistic) expectations reflected in value (or growth) stock prices. When ex-ante expectations are congruent (or incongruent) with fundamental strength there are no expectation errors (or existent expectation errors). They further demonstrate that the value-growth effect and revision of market expectations are prominent in firms with ex-ante biased market expectations. Recently, Walkshäusl (2015, 2017) confirmed the findings of Piotroski and So (2012) by using European equity market data and provide that large return differences between value stocks with equity purchaser and growth stocks with equity issuers are explained by mispricing assumption.

We employ a similar cross-sectional regression model as used by Piotroski and So (2012) with additional intangibles-intensity measures and interaction terms. We estimate monthly cross-sectional regression of monthly buy-and-hold returns on BM ratio based value and growth stocks, intangibles-intensity based high and low intangibles-intensity, interaction terms between categories of BM ratio and F-score, and interaction terms between categories of BM ratio and intangibles-intensity along with firm size rank and momentum rank as controls.

$$
\begin{aligned}
R_{it+1} = {} & a_1 Growth_{it} + a_2\ Growth_{it}\ x\ LowFscore_{it} \\
& + a_3\ Growth_{it}\ x\ MidFscore_{it} + \ a_4 Middle_{it} + a_5 Value_{it} \\
& + a_6\ Value_{it}\ x\ MidFscore_{it} + a_7\ Value_{it}\ x\ HighFscore_{it} \\
& + b_1 HighIntangibles_{it} + b_2 LowIntangibles_{it} \\
& + b_3 Growth_{it}\ x\ HighIntangibles_{it} \\
& + b_4 Growth_{it}\ x\ LowIntangibles_{it} \\
& + \ b_5 Value_{it}\ x\ HighIntangibles_{it} \\
& + b_6\ Value_{it}\ x\ LowIntangibles_{it}\ + c_1 Sizerank_{it} \\
& + c_2 Momrank_{it} + \ e_{it}
\end{aligned}
\tag{15}
$$

Where

R_{it+1} - represents one-month buy-and-hold total returns beginning the start of May (t) until end of next year April (t+1)

$Value_{it}$ – dummy variable = 1 if the BM ratio is above 70% percentile, and 0 otherwise

$Growth_{it}$ – dummy variable = 1 if the BM ratio is below 30% percentile, and 0 otherwise

$Middle_{it}$ – dummy variable = 1 if the BM ratio is above 30% percentile and below 70 percentile, and 0 otherwise

$HighFscore_{it}$ – dummy variable = 1 if the F-score is greater than or equal to 6, and 0 otherwise

$LowFscore_{it}$ – dummy variable = 1 if the F-score is lower than or equal to 3, and 0 otherwise

$MidFscore_{it}$ – dummy variable = 1 if the F-score is greater than 3 and lower than 6, and 0 otherwise

$HighIntangibles_{it}$ – dummy variable = 1 if the m-VAIC rank or ROTA rank measure is above 70% percentile, and 0 otherwise

$LowIntangibles_{it}$ – dummy variable = 1 if the m-VAIC rank or ROTA rank measure is below 30% percentile, and 0 otherwise

$Sizerank_{it}$ – the market capitalization decile at the end of April (t) each year

$Momrank_{it}$ – the momentum decile, measured as of prior 12-months returns skipping the most recent month, updated each month and decile are formed by cumulative 12-month momentum values at the end of April (t) each year

-------------Insert table 9-----------

Table 9 presents the estimation sets of Piotroski and So (2012) based model for the entire stocks sample. In each model specification, monthly returns are matched each year with fundamental information at the end of April (t) for portfolio formation. To check the robustness of results, we estimate the model by using both m-VAIC rank measure and ROTA rank measure. Model 1 and 2 estimates return-predictability of value stocks, growth stock, and interaction terms, as proposed by Piotroski and So (2012). Model 3 incorporates the main effect of intangibles-intensity categories and model 4 further adds interaction terms between value stocks, growth stocks and intangibles-intensity to test their impact on return predictability. Model 4 checks the robustness of model 3 by incorporating controls in the model. The co-efficient test is used to test the impact of congruent and incongruent strategy on return-predictability and return differences to congruent and incongruent strategy across categories of intangibles-intensity.

We first investigate whether Piotroski and So (2012) market expectation errors approach is applicable in our data sample. We note that model 2 results show that value stocks with strong F-score earn superior positive returns (0.23% per month) than other two interaction categories of value stocks (i.e. value stocks with middle F-score and low F-score). Similarly, growth firms with strong F-score earn significant negative returns (-1.61% per month). The coefficient test duplicates Piotroski and So (2012) proposed congruent and incongruent strategies. The congruent strategy coefficient test reports the returns differences between value stocks with weak fundamentals and growth stocks with strong fundamentals, whereas incongruent strategy reports the returns differences between value stocks with strong fundamentals and growth stocks with weak fundamentals. The coefficient test of model 2 provides insignificant returns (0.41% per month) to incongruent strategy and significant positive returns (1.89% per month) to incongruent strategy, confirming that the value-growth effect is significantly higher when BM ratio is incongruent with fundamental strength. We further test the return differences between incongruent and congruent strategy, results provide significant positive return differences (1.49% per month). The results are qualitatively similar for model 3 and model 4 for both m-VAIC rank measure and ROTA rank measure. These findings confirm Piotroski and So (2012) mispricing based market expectation errors assumption that the return differences between value minus growth stocks are significantly large when the BM ratio is incongruent with fundamental strength.

As the above findings confirm that the large return differences are due to the incongruence between market-implied expectations and fundamental strength. If return differences between incongruent and congruent strategies are driven by mispricing and intangibles-intensity also captures mispricing, then returns differences between incongruent and congruent strategies must remain positive across high intangibles-intensity and low intangibles-intensity. Hence, we expect a positive significant return differences between incongruent and congruent strategy across intangibles-intensity [(incongruent strategy – congruent strategy) x high intangibles-intensity - (incongruent strategy – congruent strategy) x low intangibles-intensity] ((Incong – Cong) x H - (Incong – Cong) x L). Model 3 (without controls) and model 4 (with controls) provide a statistically significant positive estimate of the coefficient test (i.e. 0.01% per month). Results are also similar for model 3 and model 4 of the ROTA rank measure. These results are consistent with the mispricing assumption that high intangibles-intensity further magnifies the returns differences to incongruent strategy, whereas low intangibles-intensity does not contribute towards improving the performance of the congruent strategy. Hence, undervaluation and overvaluation signals manifested in intangibles-intensity together with BM ratio provides a powerful measure of mispricing.

Collectively, the findings in section 5 strongly support hypothesis 2. The superior returns to VH-GL are not attributed to common risk factors, value-and-high-intangibles stocks are not risky and higher returns to VH-GL are capture by the undervaluation minus overvaluation factor. The VH-GL strategy earns superior returns following a high sentiment period and lack of arbitrage capital elongates the mispricing. The cross-sectional regression suggests that high intangibles-intensity significantly improves the predictability of the value-growth effect. Similarly, Piotroski and So (2012) market expectation errors approach confirms that intangibles-intensity captures mispricing and provide powerful measure along with BM ratio to capture undervaluation and overvaluation.

4.6. Conclusion

An investment strategy that takes a long position in high value-to-market ratio firms and a short position in low value-to-market, earns superior abnormal returns termed as value premium. However, there is an ongoing discussion on the sources of the value premium. Risk-based explanation arguments high returns to value stocks as compensation for high risk, whereas mispricing explanation assumes value premium is the consequence of market underreaction (or overreaction) to the changes in the fundamental strength of undervalued (or overvalued) value (or growth) stocks.

In this paper, we argue that firms' current intangibles-intensity status – reflects firms' commitment towards improving firm performance – can be used as a mispricing indicator to identify misvalued firms. The assessment of intangibles-intensity requires a broad knowledge of the main dimensions of intangibles. It provides investors with an opportunity to separate value-and-high-intangibles stocks from growth-and-low-intangibles stocks to generate superior returns. Hence, intangibles-intensity with BM ratio can provide a powerful measure of mispricing.

We analyzed value-growth effect conditional on firms being as high/low intangibles-intensive. We considered that high BM ratio and high intangibles-intensity signals undervaluation and when both signals agree, the conditional probability of superior abnormal returns is high. We employed two rank indicators to measure intangibles i.e. m-VAIC rank measure and ROTA rank measure. We used U.S. equity market data to confirm that value-and-high-intangibles stocks significantly outperform growth-and-low-intangibles stocks. The findings are robust by using an alternative measure of intangibles-intensity i.e. ROTA rank measure and other commonly used measures of value-to-market ratios. We observe qualitatively similar superior returns in small-size and large-size firms. The proposed strategy is also robust over longer periods and superior returns are not driven by extraordinary periods.

We used several approaches to confirm the mispricing explanation of superior returns to the proposed investment strategy i.e. VH-GL. The findings of common risk factors provided that superior returns to VH-GL strategy are not fully explained by common risk factors and negative loading on market risk confirmed that superior returns are not due to high-risk compensation. The UMO showed significant positive factor loading, confirming superior returns as a consequence of misvaluation. The results further confirmed that superior returns to VH-GL strategy are large following high sentiment periods and lack of arbitrage capital effect arbitrager ability to take advantage of mispricing. The firm-level cross-sectional regression indicates that high intangibles-intensity significantly improves the returns on value-growth strategy and together high BM ratio and value creation provide a powerful measure of mispricing. Finally, we employed Piotroski and So (2012) market expectation errors approach and find that return differences to incongruence and congruence strategies are enhanced across intangibles-intensity. Hence, confirming the superior returns to an interaction between value/growth strategy and high/low intangibles-intensity strategy is attributed to mispricing.

The findings of this study contribute by highlighting the importance of fundamental information to identify mispricing to generate superior returns. The intangibles-intensity can be used by investors to assess firms' current relative competitive status and performance prospects termed as "competitive moat". In doing so, they can enhance the performance of standalone value-to-market ratio-based investment strategy. The findings also suggest that investors should not only rely on fundamental analysis heuristics like F-score because traditional measures of performance overlook firms' efforts to improve the value creation process. The aggregate measure like m-VAIC significantly capture value creation intensity and helps investors to identify high intangibles-intensive fundamentally strong undervalued firms to generate superior returns.

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List of tables and figures

Table 1: Descriptive statistics

Variables	Mean	Std.Dev	Skewness	Kurtosis	25th Percentile	Median	75th Percentile
Total monthly returns	1.28	11.34	1.07	15.18	-4.47	1.07	6.54
Firm size (millions)	8463	21800	4.94	30.04	669	1757	5621
BM ratio	0.52	0.40	2.25	10.02	0.26	0.42	0.65
CM ratio	0.12	0.11	2.31	11.53	0.06	0.09	0.14
EM ratio	0.03	0.11	-3.78	23.30	0.02	0.05	0.07
SM ratio	1.35	1.68	3.13	14.68	0.42	0.81	1.54
m-VAIC rank measure	0.50	0.29	0.00	1.80	0.25	0.50	0.75
ROTA rank measure	0.50	0.29	-0.07	1.80	0.25	0.50	0.75
Momentum	0.15	0.51	6.49	169.63	-0.11	0.10	0.33
F-score	6	1.32	-0.26	2.79	5	6	7

Cross-sectional correlation coefficient				
	BM ratio	CM ratio	EM ratio	SM ratio
m-VAIC rank measure	-0.06	-0.03	0.06	0.21
ROTA rank measure	-0.27	-0.18	0.01	-0.09

This table reports descriptive statistics and correlation coefficient of the main variables used in this study. Total monthly return is the average one-month ahead buy-and-hold monthly return. Size is the market capitalization, defined as stock price multiplied by the number of shares outstanding at the end of April (t) in millions of dollars. Book-to-market (BM) ratio is the book value of equity at the end of the fiscal year (t-1) divided by market equity at the end of April (t). Cash flows-to-market (CM) ratio is the cash flows from operations at the end of the fiscal year t-1 divided by market equity at the end of April (t). Earnings-to-market (EM) ratio is the net income before extraordinary items at the end of fiscal year t-1 divided by market equity at the end of April (t). Sales-to-market price (SM) is the ratio of sales at the end of the fiscal year (t-1) to market equity at the end of April (t). The modified Value-Added Intellectual Coefficient (m-VAIC) ranked measure is the modified form of Pulic (1998) proposed VAIC model, m-VAIC is the aggregate measure of intangibles-intensity measured as a sum of human capital efficiency rank, relational capital efficiency rank, innovation capital efficiency rank, and capital employed efficiency. Return on tangibles assets (ROTA) rank measure is the indirect measure to capture intangibles-intensity and measured as earnings before interest, tax, depreciation, and amortization at the end of the fiscal year (t-1) divided by tangible assets at the end of the fiscal year (t-1). Momentum (Mom) is the cumulative prior 12 months returns skipping the most recent month return. Piotroski (2000) F-score is the composite indicator of a firm's fundamental strength consisting of nine fundamental measures. The table presents mean, standard deviation, skewness, kurtosis, 25th percentile, median and 75th percentile of the variables.

Table 2: Univariate and bivariate sorted portfolios based on book-to-market ratio and intangibles-intensity

Portfolio	Raw returns		Size-adjusted returns		Market-adjusted returns		Characteristics			
	Mean	t-statistics	Mean	t-statistics	Mean	t-statistics	Firms-year observations	Firm size (millions)	BM ratio	m-VAIC rank measure
Panel A: Univariant portfolios										
Value	1.58	41.03	0.11	2.73	0.66	17.84	9087	3490	0.96	
Growth	0.99	30.45	-0.13	-3.82	0.19	6.21	9118	15101	0.19	
V-G	0.59	11.65	0.24	4.56	0.47	9.74				
High intangibles-intensive	1.53	46.51	0.24	7.02	0.65	20.82	9087	6760		0.85
Low intangibles-intensive	0.88	25.46	-0.38	10.82	0.03	10.82	9117	9979		0.15
H-L	0.65	13.66	0.62	12.67	0.62	13.61				
Panel B: Bivariant portfolios										
VH	1.80	26.68	0.29	4.12	0.86	13.10	2732	3010	0.96	0.85
VL	1.22	17.68	-0.19	-2.68	0.33	4.97	2740	4615	0.96	0.15

GH	1.33	23.06	0.19	3.37	0.52	9.62	2738	11272	0.19	0.85
GL	0.53	8.86	-0.59	-9.46	-0.27	-4.81	2751	19375	0.19	0.15
VH-GL	1.27	14.18	0.88	9.37	1.13	13.07				
VL-GH	-0.11	-1.21	-0.38	-4.21	-0.19	-2.25				

This table reports the average monthly total returns, size-adjusted returns, and market-adjusted returns from May (t) to the end of the subsequent year April (t+1) along with firms' characteristics sorted in respective portfolios. Panel A provides average monthly returns of univariate sort portfolios based on book-to-market ratio and intangibles-intensity (measured as the m-VAIC rank measure) formed at the end of April (t). Panel B reports average monthly returns of bivariate sort portfolios based on both book-to-market ratio and intangibles intensity (measured as the m-VAIC rank measure) formed at the end of April (t). Portfolios are rebalanced every 12 months (at the end of April) to form new portfolios each year. A firm is assigned to value portfolio or growth portfolio if the book-to-market ratio is above 70th percentile or below 30th percentile. A firm is assigned to the high intangibles-intensive portfolio or low intangibles-intensity portfolio if the m-VAIC rank measure is above 70th percentile or below 30th percentile. V-G represents the average monthly return differences between value portfolio and growth portfolios. H-L shows the average monthly return differences between high intangibles-intensive firms' portfolios and low intangibles-intensive portfolios. VH-GL shows average monthly return differences between portfolios of value-and-high-intangibles firms and growth-and-low-intangibles firms. VL-GH shows average monthly return differences between portfolios of value-and-low-intangibles firms and growth-and-high-intangibles firms. Monthly raw returns are calculated as the percentage difference of monthly total market performance index. Size-adjusted returns are measured by the net of return on its matched size decile return. Market-adjusted returns are measured as net returns on total monthly market returns. The table also reports characteristics: firms-year observation, firm size, book-to-market ratio, and m-VAIC rank measure for the corresponding portfolios.

Table 3: Univariate and bivariate sorted portfolios based on book-to-market ratio and an alternative measure of intangibles-intensity

Portfolio	Raw returns		Size-adjusted returns		Market-adjusted returns		
	Mean	t-statistics	Mean	t-statistics	Mean	t-statistics	Firms-year observations
Panel A: Univariant portfolios							
High intangibles-intensive	1.55	46.82	0.33	9.58	0.66	20.64	9087
Low intangibles-intensive	1.11	29.70	-0.23	-5.91	0.27	7.30	9118
H-L	0.44	8.72	0.56	10.79	0.39	8.11	
Panel B: Bivariant portfolios							
VH	1.80	28.00	0.34	5.09	0.86	13.68	2732
VL	1.67	21.28	0.16	1.98	0.80	10.42	2740
GH	1.30	20.94	0.18	2.90	0.46	7.92	2738
GL	0.51	8.46	-0.66	-10.32	-0.28	-4.75	2751
VH-GL	1.29	14.54	1.01	10.81	1.14	13.21	
VL-GH	0.39	3.87	-0.02	-0.22	0.34	3.53	

This table reports the average monthly total returns, size-adjusted returns, and market-adjusted returns from May (t) to the end of the subsequent year April (t+1). Panel A provides average monthly returns of univariate sort portfolios based on intangibles-intensity (measured as ROTA rank as an alternative measure) formed at the end of April (t). Panel B reports average monthly returns of bivariate sort portfolios based on both book-to-market ratio and intangibles intensity (measured as ROTA rank measure) formed at the end of April (t). Portfolios are rebalanced every 12 months (at the end of April) to form new portfolios each year. A firm is assigned to value portfolio or growth portfolio if the book-to-market ratio is above 70th percentile or below 30th percentile. A firm is assigned to the high intangibles-intensive portfolio or low intangibles-intensity portfolio if ROTA rank measure is above 70th percentile or below 30th percentile. V-G presents the average monthly return differences between value portfolio and growth portfolio. H-

L shows the average monthly return differences between high intangibles-intensive firms' portfolio and low intangibles-intensive portfolio. VH-GL shows average monthly return differences between portfolios of value-and-high-intangibles firms and growth-and-low-intangibles firms. VL-GH shows average monthly return differences between portfolios of value-and-low-intangibles firms and growth-and-high-intangibles firms. Monthly raw returns are calculated as the percentage difference of monthly total market performance index. Size-adjusted returns are measured by the net of return on its matched size decile return. Market-adjusted returns are measured as net returns on total monthly market returns.

Table 4: Univariate and bivariate sorted portfolios based on alternative measures of value-to-market ratios and intangibles-intensity

	Cash flows-to-market price ratio							Earnings-to-market price ratio							Sales-to-market price ratio						
Portfolio	Raw returns		Size-adjusted returns		Market-adjusted returns			Raw returns		Size-adjusted returns		Market-adjusted returns			Raw returns		Size-adjusted returns		Market-adjusted returns		
	Mean	t-statistics	Mean	t-statistics	Mean	t-statistics	Firms year observations	Mean	t-statistics	Mean	t-statistics	Mean	t-statistics	Firms year observations	Mean	t-statistics	Mean	t-statistics	Mean	t-statistics	Firms year observations
Panel A: Univariant portfolios																					
Value	1.54	43.70	0.20	5.57	0.63	18.51	9087	1.39	43.75	0.09	2.75	0.48	15.79	9087	1.71	45.09	0.29	7.48	0.80	21.71	9080
Growth	1.03	27.81	-0.16	-4.17	0.23	6.51	8047	0.92	18.82	-0.20	-4.07	0.14	3.08	4886	0.88	26.04	-0.29	-8.16	0.06	2.00	8099
V-G	0.51	9.97	0.36	6.85	0.40	8.11		0.47	8.09	0.29	4.91	0.34	5.92		0.83	16.43	0.58	11.01	0.74	15.05	
Panel B: Bivariant portfolios																					
VH	1.80	28.62	0.41	6.39	0.85	14.07	2732	1.62	28.77	0.30	5.10	0.69	12.76	2732	1.85	29.66	0.46	7.07	0.94	15.46	2730
VL	1.14	18.57	-0.13	-2.10	0.27	4.57	2739	0.99	17.76	-0.26	-4.67	-0.14	2.47	2740	1.48	20.46	0.06	0.87	0.58	8.30	2737
GH	1.32	19.97	0.13	1.90	0.52	8.41	2426	1.32	15.05	0.20	2.27	0.08	6.86	1473	1.23	20.59	0.07	1.22	0.42	7.47	2735

GL	0.61	9.00	-0.60	-8.31	-0.20	-3.09	2419	0.39	4.54	-0.73	-8.09	-0.40	-4.83	1476	0.41	6.53	-0.78	-12.03	-0.42	-7.09	2748
VH-GL	1.18	12.73	1.01	10.45	1.06	11.86		1.23	11.93	1.03	9.57	1.09	11.01		1.44	16.34	1.24	13.51	1.36	16.02	
VL-GH	-0.18	-1.99	-0.26	-1.82	-0.26	-2.00		-0.33	-2.18	-0.46	-2.40	-0.43	-2.36		0.09	1.78	-0.01	-0.09	0.16	1.78	

This table reports the average monthly total returns, size-adjusted returns, and market-adjusted returns from May (t) to the end of the subsequent year April (t+1). Panel A provides average monthly returns of univariate sort portfolios based on cash flows-to-market price ratio, earnings-to-market price ratio, and cash flows-to-market price ratio formed at the end of April (t). Panel B reports average monthly returns of bivariate sort portfolios based on cash flows-to-market price ratio or earnings-to-market price ratio or cash flows-to-market price ratio, and intangibles intensity (measured as the m-VAIC rank measure) formed at the end of April (t). Portfolios are rebalanced every 12 months (at the end of April) to form new portfolios each year. A firm is assigned to value portfolio or growth portfolio if the book-to-market ratio is above 70th percentile or below 30th percentile. A firm is assigned to the high intangibles-intensive portfolio or low intangibles-intensity portfolio if the m-VAIC rank measure is above 70th percentile or below 30th percentile. V-G represents the average monthly return differences between value portfolio and growth portfolio. H-L shows the average monthly return differences between high intangibles-intensive firms' portfolios and low intangibles-intensive portfolios. VH-GL shows average monthly return differences between portfolios of value-and-high-intangibles firms and growth-and-low-intangibles firms. VL-GH shows average monthly return differences between portfolios of value-and-low-intangibles firms and growth-and-high-intangibles firms. Monthly raw returns are calculated as the percentage difference of monthly total market performance index. Size-adjusted returns are measured by the net of return on its matched size decile return. Market-adjusted return is measured as net returns on total monthly market returns.

Table 5: Size-segment univariate and bivariate sorted portfolios based on book-to-market ratio and intangibles-intensity

	Small-size firms							Large-size firms						
Portfolio	Raw returns		Size-adjusted returns		Market-adjusted returns			Raw returns		Size-adjusted returns		Market-adjusted returns		
	Mean	t-statistics	Mean	t-statistics	Mean	t-statistics	Firms-year observations	Mean	t-statistics	Mean	t-statistics	Mean	t-statistics	Firms-year observations
Panel A: Univariant portfolios														
Value	1.93	31.67	0.25	4.04	0.98	16.32	4547	1.08	25.88	0.03	0.80	0.21	5.56	4544
Growth	1.28	24.12	-0.15	-2.74	0.43	8.22	4563	0.87	20.48	-0.12	-2.84	0.10	2.57	4559
V-G	0.65	8.08	0.40	4.85	0.55	6.94		0.21	3.63	0.16	2.60	0.11	2.06	
Panel B: Bivariant portfolios														
VH	2.07	20.11	0.40	3.75	1.09	10.76	1371	1.38	18.01	0.32	4.13	0.49	6.70	1370
VL	1.60	13.82	-0.07	-0.57	0.68	6.00	1372	0.80	11.39	-0.23	-3.30	-0.01	-0.24	1371
GH	1.59	17.45	0.19	2.01	0.77	8.73	1374	1.15	15.19	0.16	2.11	0.37	5.22	1373
GL	0.75	7.57	-0.72	-6.80	-0.12	-1.26	1376	0.46	5.89	-0.53	-6.62	-0.29	-4.01	1375
VH-GL	1.31	9.18	1.12	7.45	1.22	8.60		0.92	8.45	0.85	7.63	0.78	7.76	
VL-GH	0.01	0.07	-0.26	-1.70	-0.90	-0.63		-0.35	-1.85	-0.39	-1.99	-0.38	-1.94	

This table reports the average monthly total returns, size-adjusted returns, and market-adjusted returns from May (t) to the end of the subsequent year April (t+1). Panel A provides average monthly returns of univariate sort portfolios based on book-to-market ratio separately for small-size and large-size firms, formed at the end of April (t). Panel B reports average monthly returns of bivariate sort portfolios based on both book-to-market ratio and intangibles intensity (measured as the m-VAIC rank measure) separately for small and large size firms, formed at the end of April (t). Firms are divided into small-size and large-size firms. Firms below the median of firm size at the end of April (t) are classified as small-size firms and firms above the median are grouped as large-size firms. Portfolios are rebalanced every 12 months (at the end of April) to form new portfolios each year. A firm is assigned to value portfolio or growth portfolio if the book-to-market ratio is above 70th percentile or below 30th percentile. A firm is assigned to the high intangibles-intensive portfolio or low intangibles-intensity portfolio if the m-VAIC rank measure is above 70th percentile or below 30th percentile. V-G represents the average monthly return differences between value portfolio and growth portfolios. H-L shows the average monthly return differences between high intangibles-intensive firms' portfolios and low intangibles-intensive portfolios. VH-GL shows average monthly return differences between portfolios of value-and-high-intangibles firms and growth-and-low-intangibles firms. VL-GH shows average monthly return differences between portfolios of value-and-low-intangibles firms and growth-and-high-intangibles firms. Monthly raw returns are calculated as the percentage difference of monthly total market performance index. Size-adjusted returns are measured by the net of return on its matched size decile return. Market-adjusted returns are measured as net returns on total monthly market returns.

Table 6: Common risk factors and misvaluation factor time series regression

	Full sample period		Earlier sample period		Later sample period	
	VH-GL	VL-GH	VH-GL	VL-GH	VH-GL	VL-GH
Return premium	1.23	-0.12	1.75	0.00	0.66	-0.26
Panel A: CAPM						
Alpha	0.01***	-0.00	0.01***	0.00	0.01**	-0.00
	(6.44)	(-0.70)	(4.36)	(0.13)	(3.05)	(-1.08)
MKT	-0.10*	-0.00	-0.19**	0.01	0.05	0.01
	(-2.29)	(-0.04)	(-3.46)	(0.19)	(0.87)	(0.12)
Panel B: Three-factor model with momentum factor						
Alpha	0.00**	-0.01***	0.00	-0.00	0.00	-0.01**
	(3.38)	(-4.06)	(1.81)	(-1.78)	(1.86)	(-3.09)
MKT	-0.08**	-0.01	-0.12**	0.03	-0.01	-0.05
	(-3.10)	(-0.26)	(-2.86)	(0.56)	(-0.18)	(-1.14)
SMB	0.60***	0.13	0.73***	0.15	0.39**	0.15
	(6.73)	(1.34)	(5.84)	(1.23)	(3.44)	(1.05)
HML	0.96***	0.80***	1.00***	0.66***	0.88***	0.99***
	(10.72)	(8.25)	(7.57)	(4.97)	(7.70)	(6.44)
WML	0.10	-0.10	0.15*	-0.26**	0.01	0.05
	(1.84)	(-1.66)	(2.01)	(-3.46)	(0.20)	(0.56)
Panel C: Five-factor model with momentum factor						

Alpha	0.00**	-0.00***	0.00	-0.00	0.00	-0.01**
	(2.96)	(-3.57)	(1.88)	(-1.57)	(1.81)	(-2.99)
MKT	-0.06*	-0.03	-0.07	-0.02	-0.01	-0.07
	(-2.29)	(-1.16)	(-1.56)	(-0.42)	(-0.18)	(-1.40)
SMB	0.70***	-0.01	0.87***	-0.02	0.42**	0.06
	(8.33)	(0.08)	(7.83)	(-0.22)	(3.51)	(0.37)
RMW	0.33***	-0.43***	0.44***	-0.47***	0.08	-0.22
	(5.36)	(-5.63)	(4.73)	(-5.45)	(0.90)	(-1.38)
CMA	0.23*	-0.27*	0.27	-0.42*	0.50	0.03
	(2.42)	(-2.52)	(1.76)	(-2.52)	(0.35)	(0.19)
HML	0.56***	1.28***	0.93	1.46***	0.82***	0.97***
	(4.16)	(9.07)	(1.95)	(7.46)	(4.52)	(4.37)
WML	0.07	-0.07***	0.00	-0.05	0.03	-0.01
	(1.16)	(-3.57)	(0.05)	(-0.56)	(0.42)	(-0.14)
Panel D: CAPM and misvaluation factor						
Alpha	0.01***	0.00**	0.00*	0.01*	0.00	0.00
	(3.83)	(3.43)	(2.47)	(2.62)	(1.75)	(1.85)
MKT	-0.06	-0.04	-0.13*	-0.05	0.04	0.02
	(-1.88)	(-1.28)	(-2.84)	(-1.16)	(0.83)	(0.54)
UMO	0.96***	-1.10***	0.96***	-0.97***	0.85***	-1.39***
	(10.45)	(-12.48)	(7.85)	(-8.32)	(6.59)	(-11.16)
Panel E: Three-factor model with momentum factor and misvaluation factor						

Alpha	-0.00	0.00	-0.00	0.00	-0.00	-0.00
	(-0.97)	(0.01)	(-0.45)	(0.96)	(-1.56)	(-0.51)
MKT	-0.06***	-0.03*	-0.08***	-0.01	-0.02	-0.02
	(-3.72)	(-2.32)	(-3.66)	(-0.50)	(-1.05)	(-1.44)
SMB	0.54***	0.20***	0.68***	0.21**	0.35***	0.21*
	(10.60)	(3.77)	(11.66)	(3.10)	(4.98)	(2.66)
HML	0.87***	0.91***	0.80***	0.87***	0.94***	0.90***
	(16.82)	(18.32)	(10.86)	(13.16)	(16.32)	(15.13)
WML	-0.01	0.03	-0.04	-0.04	-0.00	0.07
	(-0.43)	(0.86)	(-0.91)	(-0.95)	(-0.01)	(1.73)
UMO	0.95***	-1.11***	0.93***	-1.00***	0.96***	-1.30***
	(23.45)	(-25.06)	(16.96)	(-18.39)	(17.54)	(-18.83)
Panel F: Five-factor model with momentum factor and misvaluation factor						
Alpha	-0.00	-0.00	0.00	0.00	-0.00	-0.00
	(-0.67)	(-0.37)	(0.36)	(0.36)	(-1.54)	(-0.49)
MKT	-0.05*	-0.06**	-0.05*	-0.03	-0.02	-0.05*
	(-2.50)	(-3.30)	(-2.01)	(-1.20)	(-0.75)	(-2.40)
SMB	0.55***	0.17**	0.67***	0.19*	0.35***	0.15
	(11.13)	(3.19)	(11.57)	(2.81)	(5.22)	(1.76)
RMW	0.03	-0.08	0.08	-0.11	-0.01	-0.09
	(0.67)	(-1.73)	(1.19)	(-1.83)	(-0.17)	(-1.11)
CMA	-0.10	0.11	-0.22	0.08	-0.02	0.13

	(-1.34)	(1.82)	(-1.86)	(0.83)	(-0.21)	(1.36)
HML	0.96***	0.82***	0.98***	0.85***	0.97***	0.77***
	(12.18)	(9.98)	(7.99)	(7.39)	(8.45)	(6.48)
WML	0.01	-0.00	0.01	-0.06	-0.00	0.03
	(0.24)	(-0.03)	(0.18)	(-1.06)	(-0.02)	(0.68)
UMO	0.95***	-1.11***	0.95***	-0.97***	0.96***	-1.29***
	(23.05)	(-24.18)	(16.47)	(-16.76)	(17.28)	(-19.52)
Months-portfolio observations	300	300	156	156	144	144

* $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$

This table reports the results from time series regression to explain average return differences to VH-GL and VL-GH strategies. The return differences are regressed on market excess return (MKT), size factor (SMB), value factor (HML), profitability factor (RMW), investment factor (CMA), momentum factor (WML) and misvaluation factor (UMO). Panel A, B, and C provide CAPM, the three-factor model with momentum factor, and the five-factor model with a momentum factor. The panel D, E, and F reports result with the addition of a misvaluation factor. The VH-GL strategy takes a long position in value-and-high-intangibles stocks and a short position in growth-and-low-intangibles stocks. The VL-GH strategy takes a long position in value-and-low-intangibles stocks and a short position in growth-and-high-intangibles stocks. The table reports coefficient estimates and Newey-West adjusted t-statistics in parentheses along with the significance level.

Table 7: Sentiment analysis and lack of arbitrage capital analysis

Panel A: Regression on sentiment and noise factors for portfolio strategy						
	VH-GL			VL-GH		
Intercept	0.01***	0.01*	0.00	-0.00	-0.00	-0.00
	(6.13)	(2.26)	(1.07)	(-1.20)	(-1.76)	(-1.37)
Sentiment index	1.22***		1.32***	-0.35		-0.29
	(3.56)		(4.00)	(-1.20)		(-1.04)
Noise index		-0.20*	-0.24*		-0.13	-0.12
		(-2.02)	(-2.29)		(-1.72)	(-1.57)
Months portfolio observations	276	276	276	276	276	276

Panel B: Regression on sentiment and noise factors for portfolio forming strategy				
	VH	GL	VL	GH
Intercept	0.02***	0.02***	0.02***	0.02***
	(4.21)	(5.55)	(4.56)	(5.96)
Sentiment index	0.16	-1.15**	-0.43	-0.13
	(0.46)	(-3.42)	(-1.30)	(-0.41)
Noise index	-0.02	-0.26**	-0.12	-0.25
	(-0.10)	(-2.88)	(-1.02)	(-1.96)
Months-portfolio observations	276	276	276	276

* p < 0.050, ** p < 0.010, *** p < 0.001

Panel A reports the results from time-series regression to explain average return differences to VH-GL and VL-GH strategies. The return differences are regressed on Baker and Wurgler (2006) sentiment index and Hu et al., (2013) noise index The VH-GL strategy takes a long position in value-and-high-intangibles stocks and a short position in growth-and-low-intangibles stocks. The VL-GH strategy takes a long position in value-and-low-intangibles stocks and a short position in growth-and-high-intangibles stocks. Panel B shows the results of time-series regression of monthly returns of strategies comprising of VH-GL and VL-GH strategies on Baker and Wurgler (2006) sentiment index and Hu et al., (2013) noise index. The table reports coefficient estimates and Newey-West adjusted t-statistics in parentheses along with the significance level.

Table 8: Fama-MacBeth cross-sectional regression monthly buy-and-hold returns

	Full sample				Concurring sample				Conflicting sample			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Intercept	0.61***	1.01***	0.29***	0.14	0.88***	1.18***	-0.71**	0.08	0.18**	0.24**	0.15*	-0.55***
	(17.45)	(27.18)	(5.98)	(0.33)	(11.84)	(14.56)	(-3.42)	(0.14)	(2.60)	(3.34)	(2.09)	(-4.57)
BM ratio	1.29***		1.31***	1.81***	0.68***		1.74***	1.94***	1.71***		1.62***	1.05***
	(19.50)		(19.75)	(23.70)	(5.26)		(8.35)	(8.58)	(15.22)		(9.18)	(5.20)
m-VAIC rank measure		0.54***	0.62***	0.59***		0.18	1.98***	1.21***		1.85***	0.16	0.39***
		(8.63)	(9.84)	(8.86)		(1.51)	(9.31)	(5.25)		(15.08)	(0.79)	(5.95)
Firm size				-0.09***				-0.00**				0.06**
				(-6.34)				(-3.28)				(3.09)
Illiquidity				34.06				41.57				-7.44
				(1.11)				(0.47)				(-0.16)
Momentum				0.04***				0.05***				0.01
				(45.27)				(26.70)				(1.77)
Beta				0.00**				0.00*				-0.00***
				(3.26)				(2.23)				(-3.82)
Return weighted				0.00				0.00				0.54***
				(0.98)				(0.84)				(4.50)
Firms-year observations	30272	30272	30272	30272	5483	5483	5483	5483	5478	5478	5478	5478

* $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$

This table reports the results from Fama-MacBeth based time-series regression to explain the effects of BM ratio and intangibles-intensity on monthly total returns. The table reports the results of the full stocks sample, concurring indicators stock sample, and conflicting indicators stocks. Model 1 and 2 reports univariate regression and model 3 reports bivariate regression results. Model 4 reports multivariate regression by adding controls in model 3. The concurring sample consists of value stocks with high intangibles-intensity and growth stocks with low intangibles-intensity and conflicting sample consist of value stocks with low intangibles-intensity and growth stocks with high intangibles-intensity. The table reports coefficient estimates and Newey-West adjusted t-statistics in parentheses along with the significance level.

Table 9: Piotroski-So cross-sectional regression monthly buy-and-hold returns

			VAIC rank measure		ROTA rank measure	
Variable	Model 1	Model 2	Model 3	Model 4	Model 3	Model 4
Panel A: Cross-sectional regression						
Growth	1.19***	-1.61***	-1.58***	-1.62***	1.90***	-1.79***
	(23.33)	(-18.60)	(-17.71)	(17.16)	(-21.20)	(-19.07)
Value x HighFscore	-1.62***	-1.66***	-1.53***	-1.51***	-1.19***	-0.83**
	(-6.68)	(-6.89)	(-6.34)	(-6.25)	(-4.91)	(-3.28)
Growth x MidFscore	-0.25***	-0.14*	-0.12	-0.12	-0.10	-0.08
	(-3.70)	(-2.20)	(-1.84)	(-1.75)	(-1.55)	(-1.24)
Middle	1.27***	-1.24***	-1.17***	-1.22***	-1.36***	-1.35***
	(45.62)	(-18.71)	(-16.66)	(-16.17)	(-19.61)	(-18.44)
Value	-1.00***	-1.21***	-1.30***	-1.29***	-1.51***	-1.41***
	(-4.98)	(-6.05)	(-6.50)	(-6.47)	(-7.56)	(-6.95)
Value x MidFscore	-0.76***	-0.86***	-0.92***	-0.92***	-1.08***	-1.01***
	(-3.91)	(-4.49)	(-4.79)	(-4.78)	(-5.64)	(-5.23)
Value x HighFscore	2.32***	0.23	0.41*	0.52*	0.47*	0.27
	(12.38)	(1.22)	(2.13)	(2.59)	(2.42)	(1.34)
High intangibles-intensity (H)			0.05	0.14*	0.51***	0.49***
			(1.16)	(2.10)	(11.72)	(7.33)
Low intangibles-intensity (L)			-0.44***	-0.38***	-0.34***	-0.30***
			(-9.62)	(-5.53)	(-7.11)	(-4.43)

Growth stocks x high				0.01		-0.07
intangibles-intensity				(0.17)		(-0.70)
Growth stocks x low				-0.06		-0.61***
intangibles-intensity				(-0.55)		(-4.72)
Value stocks x high intangibles-				0.33**		0.15
intensity				(2.82)		(1.26)
Value stocks x low intangibles-				-0.18		0.19
intensity				(-1.55)		(1.77)
Firm size rank		-0.10***	-0.09***	-0.09***	-0.10***	-0.09***
		(-14.83)	(-13.38)	(-13.35)	(-13.68)	(-13.96)
Momentum rank		0.56***	-0.55***	0.56***	0.56***	0.56***
		(73.42)	(73.15)	(73.14)	(74.07)	(74.03)
Firms-year observations	30272	30272	30272	30272	30272	30272

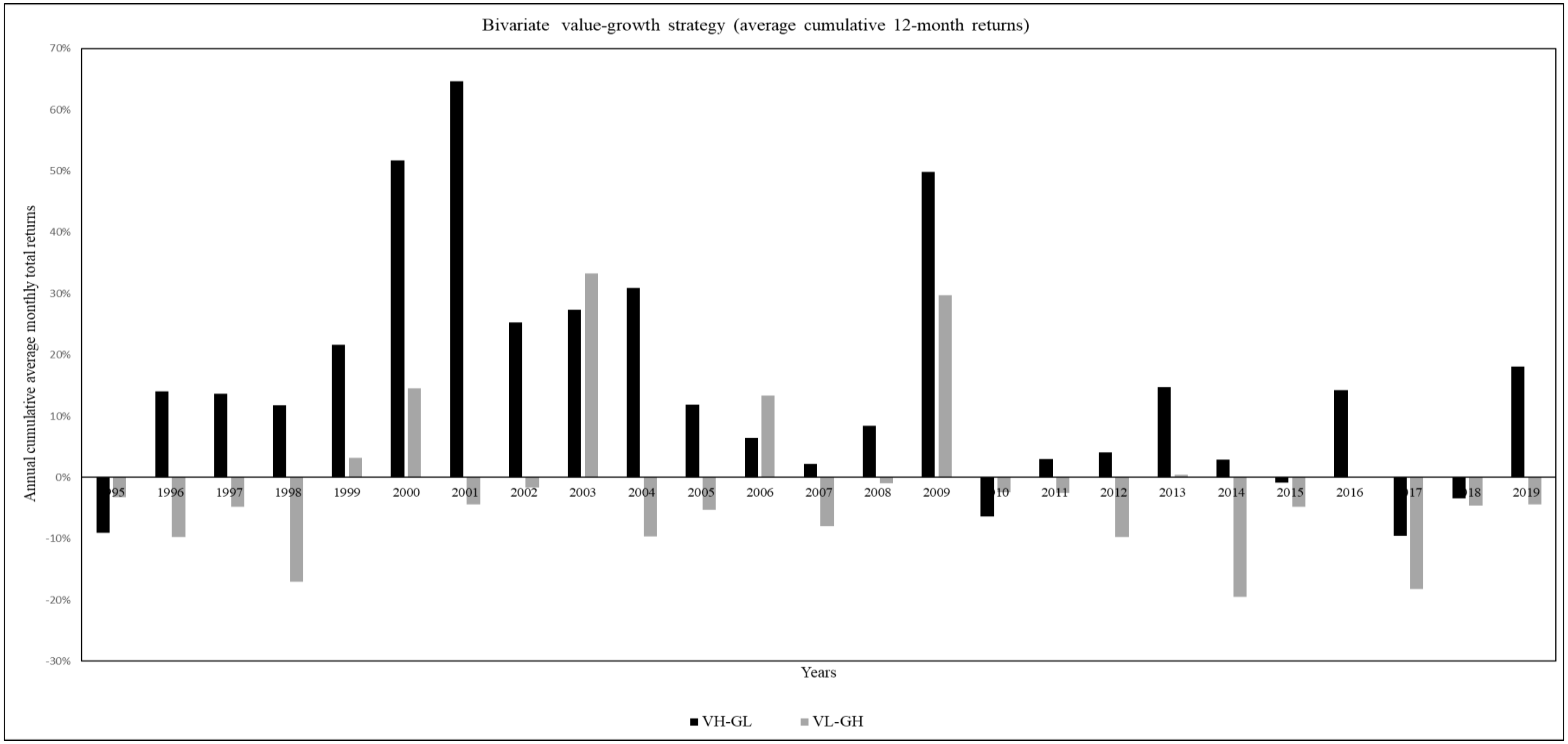
Panel B: Coefficient test						
Congruent strategy (Cong)	-2.19***	0.41	0.28	0.33	0.39	0.38
	(-10.57)	(1.89)	(1.32)	(1.50)	(1.80)	(1.75)
Incongurent strategy (Incong)	3.95***	1.89***	1.94***	2.03***	1.66***	1.10**
	(12.86)	(6.11)	(6.25)	(6.43)	(5.36)	(3.38)
Incong - Cong	6.14***	1.49**	1.65***	1.70***	1.27*	0.71*
	(13.31)	(3.14)	(3.48)	(3.55)	(2.67)	(1.99)

(Incong-Cong) x H - (Incong-Cong) x L	0.01**	0.01**	0.01*	0.01*
	(3.33)	(3.22)	(2.65)	(1.98)

* p < 0.050, ** p < 0.010, *** p < 0.001

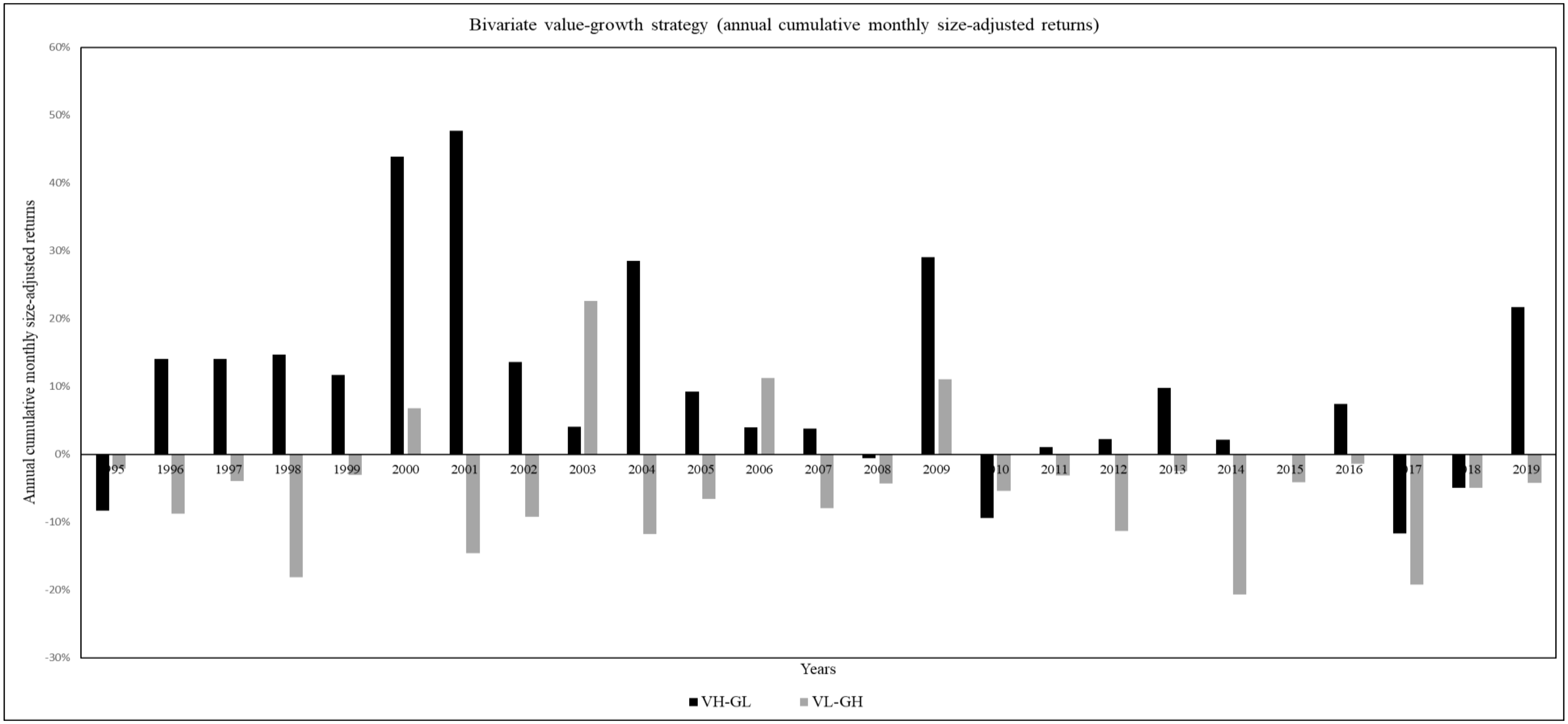
This table reports the results from Piotroski-So based time-series regression to explain buy-and-hold average monthly returns. Panel A provides one-month buy-and-hold estimates starting from May (t) to the end of next year April (t+1). For robustness, estimates are presented by using both intangibles-intensity measurements (i.e. m-VAIC rank measure and ROTA rank measure). The independent variables are measured as dummy variables. Model 1 and 2 reports return-predictability estimates of value stocks, growth stocks, and interaction terms as done by Piotroski and So (2012). Model 3 includes the effect of high and low intangibles-intensity. Model 4 additionally adds interaction terms between value/growth stocks and high/low intangibles-intensity. The table reports coefficient estimates and Newey-West adjusted t-statistics in parentheses along with the significance level. The coefficient test reports the differences between estimates of the main regression. The coefficient test reports return differences to Piotroski and So (2012) proposed congruent and incongruent strategies. The congruent strategy coefficient test reports the returns differences between value stocks with weak fundamentals and growth stocks with strong fundamentals, whereas incongruent strategy reports the returns differences between value stocks with strong fundamentals and growth stocks with weak fundamentals. The coefficient test also reports the difference between incongruent and congruent strategy and the difference between incongruent and congruent strategy across high and low intangibles-intensity.

Figure 1: Bivariate value-growth strategy (average total returns)



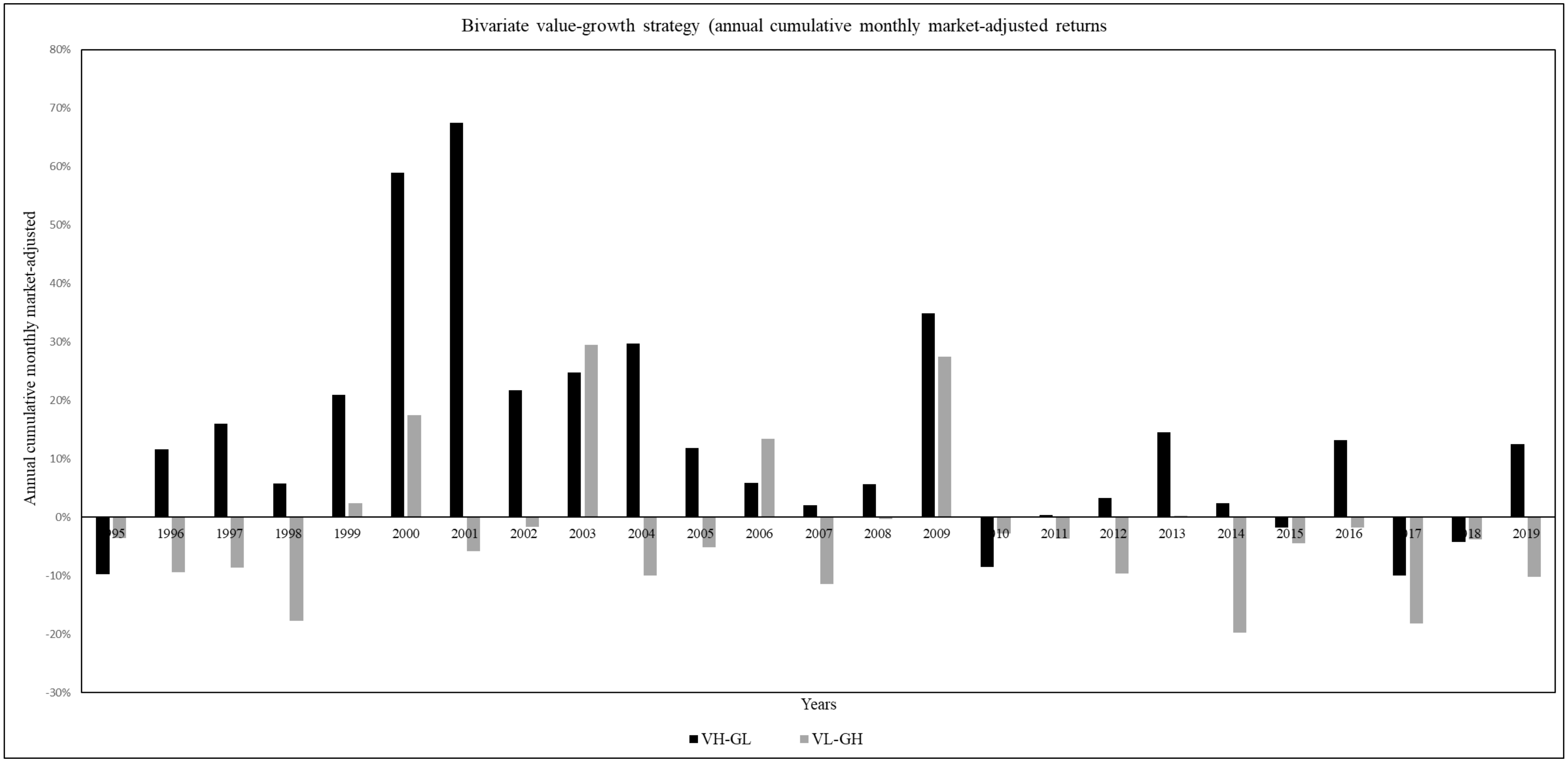
The figure shows 12-months cumulative monthly average returns of bivariate sort portfolios based on both book-to-market ratio and intangibles intensity (measured as the m-VAIC rank measure) formed at the end of April (t). Portfolios are rebalanced every 12 months (at the end of April) to form new portfolios each year. A firm is assigned to value portfolio or growth portfolio if the book-to-market ratio is above 70th percentile or below 30th percentile. A firm is assigned to the high intangibles-intensive portfolio or low intangibles-intensity portfolio if the m-VAIC rank measure is above 70th percentile or below 30th percentile. VH-GL shows average 12-month return differences between portfolios of value-and-high-intangibles firms and growth-and-low-intangibles firms. VL-GH shows average 12-month return differences between portfolios of value-and-low-intangibles firms and growth-and-high-intangibles firms.

Figure 2: Bivariate value-growth strategy (size-adjusted returns)



The figure shows 12-months cumulative monthly average size-adjusted returns of bivariate sort portfolios based on both book-to-market ratio and intangibles intensity (measured as the m-VAIC rank measure) formed at the end of April (t). Portfolios are rebalanced every 12 months (at the end of April) to form new portfolios each year. A firm is assigned to value portfolio or growth portfolio if the book-to-market ratio is above 70th percentile or below 30th percentile. A firm is assigned to the high intangibles-intensive portfolio or low intangibles-intensity portfolio if the m-VAIC rank measure is above 70th percentile or below 30th percentile. VH-GL shows average 12-month return differences between portfolios of value-and-high-intangibles firms and growth-and-low-intangibles firms. VL-GH shows average 12-month return differences between portfolios of value-and-low-intangibles firms and growth-and-high-intangibles firms.

Figure 3: Bivariate value-growth strategy (market-adjusted returns)



The figure shows 12-months cumulative monthly average market-adjusted returns of bivariate sort portfolios based on both book-to-market ratio and intangibles intensity (measured as the m-VAIC rank measure) formed at the end of April (t). Portfolios are rebalanced every 12 months (at the end of April) to form new portfolios each year. A firm is assigned to value portfolio or growth portfolio if the book-to-market ratio is above 70th percentile or below 30th percentile. A firm is assigned to the high intangibles-intensive portfolio or low intangibles-intensity portfolio if the m-VAIC rank measure is above 70th percentile or below 30th percentile. VH-GL shows average 12-month return differences between portfolios of value-and-high-intangibles firms and growth-and-low-intangibles firms. VL-GH shows average 12-month return differences between portfolios of value-and-low-intangibles firms and growth-and-high-intangibles firms.

Appendix

Appendix A

Table A1: Effect of components and M-VAIC rank measures on return on assets

	ROA	ROA	ROA	ROA	ROA	ROA	ROA
Human capital efficiency rank	0.042*** (15.81)				0.05*** (16.63)		
Relational capital efficiency rank		0.03*** (8.57)			0.03*** (8.00)		
Innovation capital efficiency rank			0.01*** (7.05)		0.01*** (4.60)		
Capital employed rank				0.06*** (23.95)	0.06*** (24.69)		
m-VAIC rank measure						0.06*** (19.46)	
ROTA rank measure							0.16*** (36.50)
Control (log of size)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of observations	30272	30272	30272	30272	30272	30272	30272

* $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$

The table reports the effect of individual component rank measure of modified-Value Added Intellectual Coefficient (m-VAIC) and aggregate m-VAIC rank measure on return on assets (ROA) by controlling for firm size. The t-statistics values are in parentheses.

Table A2: Effect of components and M-VAIC rank measures on return on equity

	ROE	ROE	ROE	ROE	ROE	ROE	ROE
Human capital	0.24*				0.33*		
efficiency rank	(2.23)				(2.03)		
Relational capital		0.26***			0.33*		
efficiency rank		(2.72)			(2.22)		
Innovation capital			-0.05		-0.05		
efficiency rank			(-0.70)		(-0.81)		
Capital employed rank				0.14**	0.08*		
				(3.28)	(2.33)		
m-VAIC rank measure						0.18***	
						(5.22)	
ROTA rank measure							0.67***
							(4.60)
Control (log of size)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of observations	30272	30272	30272	30272	30272	30272	30272

* $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$
The table reports the effect of individual component rank measure of modified-Value Added Intellectual Coefficient (m-VAIC) and aggregate m-VAIC rank measure on return on equity (ROE) by controlling for firm size. The t-statistics values are in parentheses.

Table A3: Effect of components and M-VAIC rank measures on book-to-market ratio

	BM ratio	BM ratio	BM ratio	BM ratio	BM ratio	BM ratio	BM ratio
Human capital efficiency rank	-0.11*** (-13.21)				-0.08*** (-9.51)		
Relational capital efficiency rank		-0.12*** (13.08)			-0.16*** (-17.18)		
Innovation capital efficiency rank			-0.10*** (-12.05)		-0.06*** (-8.40)		
Capital employed rank				-0.23*** (-23.50)	-0.26*** (-26.30)		
m-VAIC rank measure						-0.12*** (-12.87)	
ROTA rank measure							-0.33*** (-31.19)
Control (log of size)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of observations	30272	30272	30272	30272	30272	30272	30272

* p < 0.050, ** p < 0.010, *** p < 0.001

The table reports the effect of individual component rank measure of modified-Value Added Intellectual Coefficient (m-VAIC) and aggregate m-VAIC rank measure on book-to-market ratio (BM) by controlling for firm size. The t-statistics values are in parentheses.

Appendix B

Table B1: Data items, codes and definitions as given in DataStream

Variable	Data item	Definition of variable
Book value of Common equity	WC03501	This represents common shareholders' investment in a company.
Cash flows from operations	WC04201	This represents the sum of net income and all non-cash charges or credits. It is the cash flow of the company.
Closing price	P	This represents the official closing price.
Common Shares Outstanding	WC05301	This represents common shareholders' investment in a company.
Cost of good sold	WC01051	This represents specific or direct manufacturing cost of material and labor entering in the production of finished goods. This represents the purchase price of items sold, as well as indirect overhead such as freight, inspecting, and warehouse costs. Service Organizations may refer to this as Cost of Services.
Depreciation, Depletion And Amortization	WC01151	This represents the process of allocating the cost of a depreciable asset to the accounting periods covered during its expected useful life to a business.
Earnings before interest and taxes	WC18191	This represent the earnings of a company before interest expense and income taxes.
Earnings before interest, tax,	WC18198	This represent the earnings of a company before interest expense, income taxes and depreciation.

depreciation and amortization		
Interest expense	WC01251	This represents the service charge for the use of capital before the reduction for interest capitalized.
Long term debt	WC03251	This represents all interest-bearing financial obligations, excluding amounts due within one year.
Material expense	WC18195	This represents the cost directly related to the purchase of raw materials and supplies used in the manufacture of a company's product.
Net income before extraordinary items	WC01551	This represents income before extraordinary items and preferred and common dividends, but after operating and non-operating income and expense, reserves, income taxes, minority interest and equity in earnings.
Property, Plant And Equipment Net	WC02501	This represents Gross Property, Plant and Equipment less accumulated reserves for depreciation, depletion and amortization.
Purchase of common and preferred stocks	WC04751	This represents funds used to increase the outstanding shares of common and/or preferred stock.
R&D	WC01201	This represents all direct and indirect costs related to the creation and development of new processes, techniques, applications and products with commercial possibilities.
Return index	RI	This shows a theoretical growth in value of a shareholding over a specified period, assuming that dividends are re-invested to purchase additional units of an equity or unit trust at the closing price applicable on the ex-dividend date.

Salaries and benefits expenses	WC01084	This represents wages paid to employees and officers of the company.
Sale of common and preferred stocks	WC04251	This represents funds used to decrease the outstanding shares of common and/or preferred stock.
Sales	WC01001	This represent gross sales and other operating revenue less discounts, returns and allowances.
Sales, marketing & distribution expenses	WC01101	This represents expenses not directly attributable to the production process but relating to selling, general and administrative functions.
Tax	WC01451	This represent all income taxes levied on the income of a company by federal, state and foreign governments.
Total assets	WC02999	This represent the sum of total current assets, long term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets.
Total current assets	WC02201	This represents cash and other assets that are reasonably expected to be realized in cash, sold or consumed within one year or one operating cycle.
Total current liabilities	WC03101	This represent debt or other obligations that the company expects to satisfy within one year.
Trading volume	VO	This shows the number of shares traded for a stock on a particular day.

Appendix C

Table C1: Common risk factors and misvaluation factor time series regression

	Full sample period		Earlier sample period		Later sample period	
	VH-GL	VL-GH	VH-GL	VL-GH	VH-GL	VL-GH
Panel A: CAPM and misvaluation factor						
Alpha	0.00***	0.00***	0.01*	0.01*	0.00	0.00
	(3.55)	(3.55)	(2.55)	(2.55)	(1.61)	(1.61)
MKT	-0.05	-0.05	-0.08*	-0.08*	0.03	0.03
	(-1.62)	(-1.62)	(-2.12)	(-2.12)	(0.71)	(0.71)
UMO	1.00***	-1.00***	1.05***	-0.95***	0.86***	-1.14***
	(13.42)	(-13.38)	(10.40)	(-9.41)	(8.31)	(-10.96)
Panel B: Three-factor model with momentum factor and misvaluation factor						
Alpha	-0.00	-0.00	0.00	0.00	-0.00	-0.00
	(-0.63)	(-0.63)	(0.28)	(0.28)	(-1.34)	(-1.34)
MKT	-0.05***	-0.05***	-0.05**	-0.05**	-0.02	-0.02
	(-4.46)	(-4.46)	(-2.98)	(-2.98)	(-1.61)	(-1.61)
SMB	0.38***	0.38***	0.45***	0.45***	0.29	0.29
	(10.36)	(10.36)	(9.78)	(9.78)	(5.67)	(5.67)
HML	0.89***	0.89***	0.83***	0.83***	0.93***	0.93***
	(22.02)	(22.02)	(15.05)	(15.05)	(20.68)	(20.68)
WML	0.01	0.01	-0.05	-0.05	0.03	0.03
	(0.24)	(0.24)	(-1.24)	(-1.24)	(1.05)	(1.05)
UMO	0.92***	-1.08***	0.97***	-1.03***	0.84***	-1.16***
	(35.33)	(-41.54)	(28.50)	(-30.09)	(21.80)	(-30.17)
Panel C: Five-factor model with momentum factor and misvaluation factor						
Alpha	-0.00	-0.00	0.00	0.00	-0.00	-0.00
	(-0.69)	(-0.69)	(0.48)	(0.48)	(-1.35)	(-1.35)
MKT	-0.05***	-0.05***	-0.04*	-0.04*	-0.03	-0.03
	(-4.13)	(-4.13)	(-2.14)	(-2.41)	(-1.80)	(-1.80)
SMB	0.37***	0.37***	0.43***	0.43***	0.27***	0.27***

	(10.01)	(10.01)	(8.82)	(8.82)	(4.75)	(4.75)
RMW	-0.02	-0.02	-0.01	-0.01	-0.04	-0.04
	(-0.59)	(-0.59)	(-0.27)	(-0.27)	(-0.73)	(-0.73)
CMA	0.00	0.00	-0.07	-0.07	0.04	0.04
	(0.986)	(0.986)	(-0.91)	(-0.91)	(0.54)	(0.54)
HML	0.89***	0.89***	0.92***	0.92***	0.88***	0.88***
	(14.51)	(14.51)	(9.99)	(9.99)	(9.45)	(9.45)
WML	0.00	0.00	-0.02	-0.02	0.01	0.01
	(0.15)	(0.15)	(-0.57)	(-0.57)	(0.39)	(0.39)
UMO	0.93***	-1.07***	0.99***	-1.01***	0.85***	-1.16***
	(34.40)	(-39.90)	(26.91)	(-27.40)	(22.58)	(-30.90)
Months-portfolio observations	300	300	156	156	144	144

* $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$

This table reports the results from time series regression to explain average return differences to VH-GL and VL-GH strategies. The return differences are regressed on market excess return (MKT), size factor (SMB), value factor (HML), profitability factor (RMW), investment factor (CMA), momentum factor (WML) and misvaluation factor (UMO). Panel A, B, and C provide CAPM, three-factor model with momentum factor, and five-factor model with momentum factor. The panel D, E, and F reports result with misvaluation factor. The VH-GL strategy takes a long position in value stocks with high intangibles-intensity and a short position in growth stocks with low intangibles-intensity. The VL-GH strategy takes a long position in value stocks with low intangibles-intensity and a short position in growth stocks with high intangibles-intensity. The table reports coefficient estimates and Newey-West adjusted t-statistics in parentheses along with the significance level.

Appendix D

Table D1: Fama-MacBeth cross-sectional regression monthly buy-and-hold returns

	Full sample				Concurring sample				Conflicting sample			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Intercept	0.61***	1.00***	-0.06	-0.03	0.18*	0.31**	-	-	0.88***	1.29***	0.75***	0.73
	(17.45)	(24.19)	(-1.18)	(-0.79)	(2.60)	(3.21)	0.41***	0.55***	(11.84)	(14.43)	(6.65)	(1.28)
							(-417)	(-4.60)				
BM	1.29***		1.51***	1.71***	1.70***		1.61***	2.07***	0.68***		0.72***	1.34***
	(19.50)		(22.29)	(26.34)	(15.22)		(14.00)	(9.28)	(5.26)		(5.46)	(9.17)
ROTA rank		0.55***	1.13***	1.46***		1.66***	1.28***	1.69***		-0.05	0.25	0.23
measure		(8.00)	(16.14)	(19.93)		(10.58)	(7.95)	(17.84)		(-0.31)	(1.49)	(1.26)
Size				-				0.00				-0.00**
				0.09***				(1.24)				(-2.95)
				(-6.91)								
Illiquidity				37.11				-3.22				48.80
				(1.19)				(-0.07)				(0.55)
Mom				0.04***				0.01				0.05***
				(45.37)				(1.79)				(27.02)
Beta				0.00***				-0.00**				0.00**
				(3.82)				(-3.17)				(2.85)
Return				0.00				0.53***				0.00
weighted				(0.99)				(-4.51)				(0.84)

Firms year observations	30272	30272	30272	30272	5483	5483	5483	5483	5478	5478	5478	5478

* $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$

This table reports the results from Fama-MacBeth based time series regression to explain the effect of BM ratio and intangibles-intensity on monthly total returns. The table reports the result of the full stocks sample, concurring indicators stock sample, and conflicting indicators stocks. Model 1 and 2 reports univariate regression and model 3 reports bivariate regression results. Model 4 reports multivariate regression by adding controls in model 3. The concurring sample consists of value stocks with high intangibles-intensity and growth stocks with low intangibles-intensity and conflicting sample consist of value stocks with low intangibles-intensity and growth stocks with high intangibles-intensity. The table reports coefficient estimates and Newey-West adjusted t-statistics along with a significant level. The coefficient test reports the differences between estimates of the main regression.

Chapter 5

Investor's Intrinsic Motives and the Valence of Word-of-Mouth in Sequential Decision-Making

Publication

This paper is published in the Journal of Behavioral Finance on 2nd May 2020.

Table of Contents

Investor's Intrinsic Motives and the Valence of Word-of-Mouth in Sequential Decision-Making

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Abstract

An escalation of commitment refers to an individual's decision to engage in greater risk-taking following prior losses than gains. This behavior was found to be preeminent in situations framed as portfolio decisions. However, there is a lack of evidence regarding the underlying mechanism behind an individual's decision to engage in later high (or low) risk-taking in a loss (or gain) domain. A model was developed based on the connections between prospect theory, self-determination theory and word-of-mouth to provide underlying mechanisms that activate investors' decisions to engage in later high (or low) risk-taking. We theorized that self- and/or social motives and negative word-of-mouth (NWoM) or positive word-of-mouth (PWoM) would double mediate the effect of prior low (high) risk-taking on later high (low) risk-taking in the loss (gain) domain. Results supported a double mediation effect and indicated that investors have different underlying self- and/or social motives, manifested in NWoM or PWoM, that activate later high (low) risk-taking in the loss (gain) domain. The findings have pertinent implications for advisors wishing to understand underlying self- and/or social motives in order to predict and manage client risk-attitude. The findings also help researchers and analysts to identify patterns in investor behavior that can predict market trends.

Keywords

Sequential decision-making, risk-attitude, word-of-mouth communication, self-motives, social motives, investor behavior

5.1. Introduction

Individuals engage in comparatively greater risk-taking following prior losses than following gains when making later decisions[1]; this is termed an escalation of commitment effect (Staw, 1976). Prospect theory suggests that prior losses and gains influence an individual's attitude to risk differently by inducing high or low risk-taking in later decisions. The mechanism guiding changes in an individual's attitude to risk following prior losses and gains is sparse. Literature in finance suggests the effect of an investor's desire to fulfill self-motives (e.g. Kirk et al., 2015), and the effect of social motives on stock market participation (e.g. Changwony et al., 2014; Patacchini & Rainone, 2017; Zhang et al., 2018). Socially active investors have been shown to engage in high risk-taking via participation in the stock market (e.g. Cai et al., 2015), and an investor's portfolio choices can be attributed to social interaction (Ivkovic & Weisbenner, 2007; Wuthisatian et al., 2017). The social interaction takes the form of traditional word-of mouth (WoM)[2] that allows individuals (investors) to share (investment) opinions and experiences with each other (Hennig-Thurau et al., 2004). However, the literature on WoM posits that the WoM sender's desire to fulfill self- and/or social motives leads to positive word-of-mouth (PWoM) and negative word-of-mouth (NWoM) (Alexandrov et al., 2013). Hence, we may presume that the WoM sender (investor) is motivated by self-desire to seek intrinsic motives (i.e. self- and/or social motives) manifested in NWoM or PWoM in the loss or gain domain before engaging in later high or low risk-taking. This implies that there is a missing link between prior and later risk-taking decisions, and it can be explained by examining the connections between prospect theory, self-determination theory and WoM. Self-determination theory asserts that an individual's intrinsic motives are the main driver of decision-making behavior and that the individual strives to achieve a higher degree of self-motivation and self-determination (Deci & Ryan, 2000). Thus, we ask the following question: How do losses or gains after prior

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[1] Sequential decision-making refers to situations where people analyse successive observations of prior decisions and their influence on changes in risk attitude in a series of later decisions. In this study, prior and later decision-making events are constituted by successive series of low and high risk-taking decisions. Here, prior losses refer to individual low risk-taking in the loss domain and prior gains constitute high risk-taking in the gain domain.

[2] WoM as a communication process involves both sender and receiver. The WoM sender shares investment opinions and experiences, whereas the WoM-receiver seeks information about portfolio choices. Hereafter, investors sharing WoM are referred to as WoM senders, and investors seeking information are referred to as WoM-receivers. The valence of WoM is defined as Negative-WoM (NWoM) and Positive-WoM (PWoM). The NWoM (PWoM) association represents negative (or positive) opinions and experiences related to prior portfolio decisions.

decisions impact later risk-taking by investors having different underlying self- and/or social motives acquired through NWoM or PWoM?

This study integrates prospect theory with self-determination theory and WoM to identify the mechanisms underlying sequential decision-making in the context of portfolio decisions. Specifically, we propose a double serial mediation effect of intrinsic motives (i.e. self- and/or social motives) and NWoM or PWoM on the relationship between prior and later decisions. We conducted two online experiments to empirically validate the proposed double serial mediation effect. Results suggested that losses (or gains) in prior risk-taking stimulate investor decisions to engage in NWoM (or PWoM), leading to relatively high (or low) risk-taking in later decisions (Hypotheses 1a & 1b). Investors engage in NWoM (PWoM) following prior losses (gains) to self-affirm themselves (or self-enhancement) (Hypotheses 2a & 2b) or to strengthen (or develop) social interaction ties, relational trust and shared vision (or shared vision) (Hypotheses 3a & 3b). Finally, results confirmed a double serial mediation effect by indicating that investors seek to self-affirm (or self-enhance) themselves by engaging in NWoM (or PWoM), following prior losses (gains) (Hypotheses 4a & 4b). Investors also seek to strengthen (develop) social interaction ties and/or relational trust and/or shared vision (relational trust and/or shared vision) manifested in NWoM (PWoM) following prior losses (gains) (Hypotheses 5a & 5b).

We contribute to two strands of literature. First, we extend the literature on intrinsic motives and investor behavior in two ways (Rau, 2017). We assert that prior decisions affect investors' need to support underlying self- and/or social motives as manifested in NWoM or PWoM and consequently change investor's risk attitude as reflected in later high or low risk-taking. Additionally, we argue that investors spend a substantial amount of time on planning and sharing posts on Social Networking Sites (SNSs) to fulfill self- and/or social motives as manifested in shared opinions. Furthermore, we add to the literature on sequential decision-making by integrating individual intrinsic motives as manifested in the valence of WoM and argue that different underlying mechanisms activate an escalation of commitment effect in the context of portfolio decision-making. This implies that investors are not only interested in gaining economic benefits but also seek the self- and/or social motives associated with investment.

This study also underscores significant implications for financial advisors in understanding the underlying self- and/or social motives manifested in NWoM or PWoM that can change a client's preferences towards risk-taking. It can also help advisors manage a client's attitude to risk by framing investment decisions by highlighting associated self- and/or social motives. Additionally, analysts and researchers can identify patterns in investor behaviors (manifested in market sentiments) to predict market movements and the performance of investment decisions.

In the remainder of the paper, section 2 comprises theory and hypothesis development. Section 3 provides details on study 1 and study 2 and a brief description of the data collection process and methodology. Section 4 reports the results of study 1 and study 2. In a subsequent section (i.e. section 5), we discuss the main findings, managerial implications, limitations and future research directions.

5.2. Theory development and hypotheses

Five hypotheses were developed to establish the double serial mediation effect of investors' intrinsic motives and NWoM or PWoM on the relationship between prior and later decisions. The first set of hypotheses proposed the indirect effect of prior decisions on later decisions via NWoM or PWoM by integrating the valence of WoM in the prospect theory-based explanation of escalation of commitment. The second set of hypotheses drew its theoretical framing from prospect theory, self-determination theory and the literature on WoM. The next two hypotheses established the indirect effect of prior decisions on NWoM or PWoM via self-motives (hypothesis 2) and/or social motives (hypothesis 3). The last two hypotheses proposed a double serial mediation effect of prior decisions on later decisions via self-motives and NWoM or PWoM (hypothesis 4), and via social motives and NWoM or PWoM (hypothesis 5). The complete model is presented in Figure 1.

5.2.1. Indirect effects of prior decisions on later decisions via NWoM or PWoM

The literature on sequential decision-making posits that investors exhibit a tendency to engage in relatively greater risk-taking following prior losses than following gains, which is termed an escalation of commitment (Staw, 1976). A representative escalation of commitment situation is one where investors have faced prior losses but tend to hold expected losers and sell expected winners. This situation is called a disposition effect by Shefrin and Statman (1985) and

Weber and Camerer (1998). In addition, investors prefer to buy additional shares of losers (perceived high risk-taking) relatively more than winners (perceived low risk-taking) (Odean, 1998). This implies that investors exhibit less (high) risk aversion behavior following prior losses (gains) under the influence of optimistic (pessimistic) expectations associated with the expected outcome. However, the reverse effect is also true; individuals are more willing to take high risks following prior gains than losses, which is termed the house money effect (Thaler & Johnson, 1990). Weber and Zuchel (2005) elucidated this contradiction by proposing that an escalation of commitment is predominant in situations framed as an investment, whereas the house money effect is prevalent in situations framed as gambling.

Escalation of commitment can be explained by using the prospect theory value function and the self-justification theory. Self-justification theory proposes that investors do not feel the need to provide justification and rationale for prior decisions (Staw, 1976). There are three main characteristics of the prospect theory value-function: first, it is defined in terms of losses and gains in relation to a reference-point; second, it is concave (i.e. high risk aversion) for gains, and convex (i.e. low risk aversion) for losses; and third, it is comparatively steeper for losses than for gains. This suggests that the reference level is the important characteristic of the value function. Different assumptions by investors related to reference level can produce a different level of risk-taking following prior losses or gains. Assuming that initial starting wealth is a reference point for the investor, in the case of loss it will fall below the reference point in the convex region (i.e. loss domain), implying that the investor should take a high risk to (partly) offset the prior losses. This implies that subsequent losses hurt less than subsequent gains because they (partly) offset the prior losses. In terms of gains, investors move into the concave region (i.e. gain domain), which may increase risk aversion.

Prospect theory predicts that investors become less risk-averse and seek a higher return to (partly) offset prior losses in the loss domain. They rebalance their portfolio by incorporating additional high-risk stocks in anticipation of overdue events (i.e. gains). Investors spread NWoM to justify their bad outcomes by blaming market conditions, luck, and destiny (Aydemir & Aren, 2017). They persist or reinvest in markets perceived as high-risk, losing stock. As a result, investors defend their self-image without providing a justification or rationale for prior investment choices (Staw, 1976). Hence, we presume that investors engaged in prior low risk-taking who experience losses will share their opinion via NWoM to defend their investment strategy. Additionally, investors exhibit positive expectations that losses in prior portfolio decisions are more likely to be followed by subsequent gains (i.e. gambler fallacy). Consequently, they engage in high risk-taking to (partly) offset prior losses (Shefrin, 2007). Hence,

Hypothesis 1a: The decision to engage in NWoM positively mediates the effects of prior low risk-taking on later high risk-taking.

According to prospect theory, investors exhibit high risk aversion and reinvest in perceived low-risk winning stocks to maintain a stream of positive returns (i.e. hot hand fallacy) (Shefrin, 2007), following prior gains. Investors attempt to engage in PWoM to associate a good performance with one's self-ability, knowledge, and experience. In so doing, they seek to enhance their positive self-image and recommend that others follow their investment strategy. Hence, we suggest that investors who engage in high risk-taking share PWoM and exhibit optimistic expectations regarding the continuation of positive returns and that they reinvest in low-risk winning stocks. Therefore,

Hypothesis 1b: The decision to engage in PWoM positively mediates the effects of prior high risk-taking on later low risk-taking.

5.2.2. Indirect effects of prior decisions on NWoM or PWoM via self- and/or social motives

Self-determination theory highlights the tendencies or efficiencies of intrinsic motivation in explaining the selection of choices rather than extrinsic motivation. It asserts that intrinsic motivation is more dominant in explaining individual behavior than extrinsic motivation, implying that individual behavior is shaped by a higher degree of self-motivation and self-determination. Three major psychological needs – namely, competence, autonomy and relatedness – induce individual to engage in a specific behavior (Deci & Ryan, 2000). Competence is the individual's belief they can control the outcome and the ability to achieve their desired objectives. Autonomy is one's desire to control one's own behavior, which is in their best self-interest (Vallerand & Ratelle, 2002). Relatedness is an individual's desire to interact, connect and care for others (Deci & Ryan, 2000).

In the context of stock market investment, SNSs provide autonomy to express one's investment opinion based on one's experience without external influences. Given that the WoM sender has no vested interest in sharing investment opinions, the WoM receiver is more likely to accept the information as reliable, thereby improving the WoM sender's belief in their own competence and relatedness. WoM is a two-way communication process and requires acceptance of the opinion credibility on the part of the WoM receiver. The greater the acceptance on the part of the WoM receiver, the more motivated the WoM sender is to follow their need for intrinsic motivation. Consequently, investors are motived by self-desire to seek self-motives and/or social benefits via sharing investment opinion on SNSs.

The two main self-motives that individuals seek to fulfill by sharing the valence of WoM are self-enhancement and self-affirmation. Self-enhancement is defined as seeking constant positive evaluation and a flattering view of oneself to feel good. Self-enhancers want to achieve high perceived status among group affiliates by confirming, increasing and maintaining self-satisfaction, self-esteem, personal worth and effectiveness (Sedikides & Gregg, 2008). To do so, they take credit for gains and forfeit their responsibility for losses (Campbell & Sedikides, 1999). However, self-affirmation is used as a self-defense mechanism to sustain one's self-integrity and self-image (Sherman & Cohen, 2006). Self-affirmers defend their perceived status by disclaiming responsibility for a negative outcome and presenting it as a consequence of bad luck. In this way, they reaffirm their competence, knowledge, and expertise to sustain their self-image.

Investors tend to renounce prior losses and associate negative reinforcement with bad luck. In doing so, they employ self-affirmation as a self-defense mechanism and engage in NWoM to self-affirm and claim that losses are not due to any flaw in their abilities but rather due to other uncontrollable factors. In this way, investors employ NWoM to seek the benefit of self-affirmation in order to sustain their self-image and ego (Alicke & Sedikides, 2009). In addition, self-affirmation also helps to reduce cognitive dissonance (Steele & Liu, 1983). Therefore, we argue that investors use self-affirmation as a self-defense mechanism by attributing prior losses to external factors and luck, resulting in NWoM. Hence,

Hypothesis 2a: The need for self-affirmation positively mediates the effects of prior low risk-taking on the decision to engage in NWoM.

Investors espouse prior good performance as positive reinforcement and tend to affiliate prior gains with self-abilities in order to enhance their self-image and self-desirability in their social circle. Consequently, investors engage in PWoM to associate prior good performance with self-abilities and thus reap the benefits of self-enhancement (Krik et al., 2015). In other words, we suggest that investors have a tendency to engage in PWoM in order to seek the benefits of self-enhancement, following prior gains.

Hypothesis 2b: The need for self-enhancement positively mediates the effects of prior high risk-taking on the decision to engage in PWoM.

Individuals (investors) seek to obtain social benefits by developing and accumulating a set of social resources (Burt, 2000) embedded in three social dimensions: structural, relational and cognitive (Chiu et al., 2006). The structural dimension takes the form of social interaction ties, the relational dimension refers to relational trust and the cognitive dimension is a shared vision.

The extent of knowledge exchange, frequency of exchange, time spent, emotional connectedness, reciprocity and the strength of the relationship among SNS members is called social interaction ties (Chiu et al., 2006). Social interaction ties facilitate the rapid spread of and easy access to a wide range of knowledge resources. This helps improve and expand social relationships, the spread of information, and the scope and intensity of the information exchanged (Steinfield et al., 2008). Most information is costly and hard to access but social interaction ties can allow access to information in a cost-effective way. Members on SNSs exchange and combine information in expectation of achieving benefits. Along the same lines, investors on SNSs or in social circles exchange and seek information to make informed investment decisions. Thus, social interaction ties facilitate the dissemination of the valence of WoM and influence risk-taking on the part of WoM receivers (Bansal & Voyer, 2000). Investors are interested in understanding common investment interests, sharing prior experience and possible future portfolio choices as topics of social discussion (Choi et al., 2017). In this way, investors seek emotional support and invest in the same stocks as other community members (Brown et al., 2008). This leads to a strong sociability effect with higher market participation (Changwony et al., 2015; Hong et al., 2004; Georgarakos & Pasini, 2011).

Relational trust refers to convenience when accessing the opinion of others and the availability of emotional support. Investors consider an opinion from social interaction ties more credible and trustworthy than that from unknown sources. In this context, the norm of reciprocity suggests that shared information is of mutual interest and subject to a rewarding response from network ties. A similar argument is supported by Bougheas et al., (2013) and Patacchini and Rainone (2017), namely that the perceived level of trust results in peer-influenced risk-taking. Similarly, households are found to invest in the same stocks as those of their siblings thanks to higher perceived trust (Tokuoka, 2017). In addition, investors exhibiting a high level of perceived trust are more likely to exhibit high risk-taking by participating in the stock market and to hold a higher proportion of stocks (Balloch et al., 2014; Guiso et al., 2008).

A shared vision indicates that individuals develop shared values and a sense of affiliation and collective identity with other network ties. Individuals with strong shared vision affiliation have high self-esteem and set high self-goals. However, individuals with low levels of self-esteem try to establish a self-identity in a social group by setting goals with reference to the group's shared vision (Choi et al., 2017). For instance, small investors are more interested in stocks that are common among peers and in the community because it provides a sense of affiliation with the social group, an investment goals setting, and an opportunity to talk about stocks in order to develop or enhance social resources (e.g. Brown et al., 2004, 2008). Additionally, investors are motivated by social learning and perceived social utility to invest in peer-owned stocks (e.g. Hvide & Östberg, 2015; Kaustia & Knüpfer, 2012).

Investors interact with network ties to seek emotional support and confirmation of their investment decisions. In addition, perceived credibility and trustworthiness of network ties significantly influence the WoM sender's intentions to share information and the WoM-receiver's intentions to engage in investment decisions (e.g. Bougheas et al., 2013; Madrian & Shea, 2000; Patacchini & Rainone, 2017). Consequently, investors with mutual interests share negative experiences or opinions manifested in NWoM to learn from, advise and help others, while PWoM is shared with social interaction ties to enhance social desirability and seek investment-related information. Pan and Chiou (2011) have argued that negative information is trusted more and that it facilitates trust development, enhances a sense of connectedness and strengthens shared vision among network ties. Furthermore, individuals share their negative experiences with others to defend their self-image and ego. In this way, they achieve cognitive clarity and reduce stress to overcome cognitive dissonance (Steele & Liu, 1983). Specifically, negative outcomes are considered more urgent than positive outcomes and require immediate action. Hence, we argue that investors share NWoM to share negative investment opinions and validate their investment strategy. In doing so, they strengthen social interaction ties, relational trust and shared vision within a social group.

Hypothesis 3a: The need to strengthen (i) social interaction ties, (ii) relational trust, and (iii) shared vision positively mediate the impact of prior low risk-taking on the decision to engage in NWoM.

In contrast, investors capitalize on gains (positive experience) by engaging in PWoM to reflect their competence, knowledge, intelligence and experience, to improve their social desirability by extending social interaction ties and developing relational trust and shared vision.

Hypothesis 3b: The need to develop (i) social interaction ties, (ii) relational trust, and (iii) shared vision positively mediates the impact of prior high risk-taking on the decision to engage in PWoM.

5.2.3. Indirect effect of prior low risk-taking on later risk-taking via both self- and/or social motives and NWoM or PWoM

Based on the above arguments, investor self-motives and/or social motives and NWoM or PWoM (hypotheses 1, 2 and 3) are integrated into prior and later decisions (baseline assumptions). Specifically, hypothesis 1 illustrates the indirect effect of the NWoM or PWoM on the association between prior and later decisions, and hypotheses 2 and 3 propose the indirect effect of self-motives (i.e. self-affirmation and self-enhancement) and social motives (i.e. social interaction ties, relational trust, and shared vision) on the relationship between prior decisions and NWoM or PWoM. Hence, it can be presumed that investors engaged in prior low (or high) risk-taking will seek to confirm motives of self-affirmation (self-enhancement) manifested in NWoM (or PWoM), which will lead to later high (or low) risk-taking. Therefore,

Hypothesis 4a: The need for self-affirmation and the decision to engage in NWoM positively mediate the effect of prior low risk-taking in later high risk-taking.

Hypothesis 4b: The need for self-enhancement and the decision to engage in PWoM positively mediate the effect of prior high risk-taking in later low risk-taking.

Moreover, following prior losses (gains) investors will seek to strengthen (develop) social interaction ties, relational trust, and shared vision by sharing NWoM (PWoM) in a social community, which will translate into later high (low) risk-taking. Hence,

Hypothesis 5a: The need to strengthen (i) social interaction ties, (ii) relational trust, and (iii) shared vision and decisions to engage in NWoM positively mediate the effect of prior low risk-taking in later high risk-taking.

Hypothesis 5b: The need to develop (i) social interaction ties, (ii) relational trust, and (iii) shared vision and decisions to engage in PWoM positively mediate the effect of prior high risk-taking in later low risk-taking.

------------- Insert figure 1 -------------

5.3. Data and method

We conducted two experiments to validate the underlying mechanism behind a WoM sender's decision to engage in later high or low risk-taking following prior losses or gains.

5.3.1. Data collection

The data was collected using Amazon's Mechanical Turk, a relatively new web-based crowdsourcing platform to collect quality data for research. It provides a mechanism for inexpensive and rapid recruitment of participants from a large diverse pool, thereby ensuring the reliability and quality of data (Buhrmester et al., 2011). Studies like Antonetti and Maklan (2018), and Shanahan et al., (2019) have used Amazon Mechanical Turk for data collection. Two experiments were conducted, and all participants willingly participated in the experiment. By following Sokolowska and Makowiec (2017) two treatments that are bearish and bullish market settings were used in each experiment to induce pessimistic and optimistic expectations, respectively. A bearish market setting refers to a downward trend of prices and a bullish market setting suggests an upward trend of prices on the stock market (Preis & Stanley, 2011). The participants were randomly distributed among the two treatments for each experiment. Participants were expected to engage in prior low (high) risk-taking because of high (low) perceived risk, low (high) perceived return and high (low) risk attitude in the bearish (bullish) market settings (Silvapulle & Granger, 2001). Each participant received compensation of $0.30 after completion of the exercise. The two experiments (each experiment consisted of two treatments) were uploaded online at different times and participants were restricted to participating in only one treatment to avoid possible multiple submissions. The data collection spanned two months from 1st October 2018 to 25th November 2018. The detailed description of each experiment with the market setting was provided, along with clear instructions that the investment selection exercise was only for participants having prior stock market investment experience and SNS accounts[3]. The market setting information consist of a clear, explicit and limited economic description of bullish and bearish market settings. The economic description was represented by GDP, unemployment, interest rate, and stock market performance.[4]

Unlike university student samples, the current study's respondents had stock market experience, implying greater ecological validity and generalizability of findings (Weber et al., 2012). The two treatments were successfully induced and tested by Sokolowska and Makowiec (2017) but we also conducted pilot studies to validate treatments when setting prior low and high risk-taking tendencies in participants. Two pilot studies were conducted, and those results are not reported in this article.

5.3.2. Experiment 1

5.3.2.1. Participants

The responses initially collected for bearish and bullish treatments of experiment 1 were 188 and 180 respectively. Before analysis, a few data checks were used to extract usable data. Overall, 19 and 23 respondents were dropped due to the following reasons: no stock market experience or SNS accounts (i.e. 9 and 11), wrong responses to treatment-related checks (i.e. 3 and 4), and completion of the survey in less than five minutes (i.e. 7 and 8), in bearish and bullish treatments respectively. As a result, a total of 169 and 157 responses were used for, respectively, experiment 1's bearish and bullish treatments. The age of respondents ranged from

[3] The uses and gratification theory suggest that individuals seek a specific type of media that can fulfill their needs in a timely and efficient manner (Ko et al., 2005). Currently, SNSs are used for opinion sharing because they provide broader reach, instant response and an opportunity to expand social resources. Therefore, this study considered WoM senders sharing prior investment opinions (NWoM or PWoM) on SNSs as the settings for this study.

[4] The bearish and bullish market settings are available online at: https://impresaluiss.eu.qualtrics.com/jfe/form/SV_bO9UoXeoav2T1fn and https://impresaluiss.eu.qualtrics.com/jfe/form/SV_1Gj7uO6c11WrCWV

20 to 60 for both treatments. The bearish treatment participants were 68.64% male and 31.36% female. The mean age of respondents was 33.22 years (SD = 8.93). The age distribution was right-skewed with 56.8% of respondents younger than mean age. A total of 85.50% participants reported having bachelor's or higher degrees as their highest educational level. Notably, bullish treatment final participants were 63.69% male and 36.31% female. The mean age of participants was 34.80 years (SD = 10.53). The age distribution was right-skewed with 57.3% of participants towards the left of the mean age. A total of 87.50% participants reported having bachelor's or higher degree as their highest degree earned. The data collected from experiment 1 was fairly normally distributed because all latent variables indicated lower skewness and kurtosis values than three times the respective standard error values (Sposito et al., 1983).

5.3.2.2. Materials and measures

Risk-taking is a function of expected return, expected variance (volatility), and risk-attitude (Markowitz, 1952). The risk-attitude is the trade-off between expected return and volatility, which represents optimal combinations of expected return and volatility, known as the efficient market frontier. Note that investors may have different subjective estimates of risk and return (i.e. risk perception and return expectations). The subjective measures and objective measures (i.e. expected return and volatility) of risk and return are not perfectly correlated and former – subjective measures – account better for changes in investor's risk taking than latter – objective measure. The risk attitude remains stable with a change in market events but risk perception and return expectations significantly correspond to change in market conditions (Weber et al., 2012). Investors tend to have different risk preferences in different market settings (i.e. bearish and bullish market). They frequently chose a riskier portfolio in the bullish market then bearish market. However, this was found valid for both subjective and objective measures of risk and return (Sokolowska and Makowiec, 2017).

The return expectations show less deviations and are more strongly related to expected return than risk perception. The historical volatility strongly corresponds to risk perception but drastically differs if assets are known (Weber & Zuchel, 2005). So, return expectations and risk perception strongly corresponds to market settings and risk attitude remains stable in different market settings. The investor's risk taking is affected by expected return, volatility and market settings. In these lines, we manipulate market settings to induce pessimistic (optimistic) expectations in investors via exhibition of high (low) perceived risk, low (high) return expectations, and high (low) risk attitude in bearish (bullish) market treatment.

Following the above findings, we constructed two stock portfolios and provided participants simple and limited information about portfolios to reduce the difference between subjective and objective measures of risk and return. Each portfolio consisted of firm A and firm B stocks in a known proportion, where firm A stocks were always high-risk and high-return and firm B stocks were always low-risk and low-return. For each portfolio, participants were provided with portfolio returns, portfolio standard deviations, and the proportion of stocks A and B in portfolio. Firm A and firm B were real firms, but the names of firms were unknow to participants. The portfolio returns and portfolio standard deviation was calculated by using 15-year historical prices. The portfolio standard deviation was calculated from equation 1.

$$\text{Standard deviation of portfolio}_n = \sqrt{} \; W_A^2 * \sigma_A^2 + W_B^2 * \sigma_B^2 + 2 * W_A W_B(\rho_{A,B} * \sigma_A * \sigma_B) \qquad (1)$$

Where W_A and W_B were the proportion of firm A and firm B stocks, σ_A and σ_B were the standard deviations of firm A and firm B stocks respectively, and $\rho_{A,B}$ was the correlation between firm A and firm B stocks. Participants were required to select one portfolio from a set of four portfolios with an increasing rate of portfolio return and standard deviation. Portfolio 1 was the least risky portfolio with 100% of firm B stocks. Portfolio 2 included 20% of firm A and 80% of firm B stocks. Portfolio 3 comprised 80% of firm A and 20% of firm B stocks. Portfolio 4 was the riskiest portfolio with 100% of firm A stocks. The likelihood of a naïve investment strategy was minimized by excluding the portfolio with an equal proportion of firm A and firm B stocks (Hedesstrom et al., 2006). The correlation and covariance between both stocks were close to zero and all portfolios were efficient in terms of Markowitz portfolio theory. Participants were also presented with 15 years of historical returns in a graphical format with an emphasis on inducing greater volatility expectations in the bullish market and lower volatility expectations in the bearish market (Weber et al., 2012).

Three sets of portfolios were constructed for bearish and bullish market. The construction of three sets of portfolios was such that the baseline portfolio was in common and two sets of portfolios were rescaled version of baseline portfolios by a factor of 0.5 and 0.3 for the bearish market, and 1.5 and 1.2 for the bullish market. Three sets of portfolios were presented in random order but with the same order (i.e. from a lower to a higher rate of return and risk) within each set of portfolios. The baseline portfolio was given in appendix A1.

Prior risk-taking in bearish and bullish treatments was measured as the proportion of investment in low-risk stocks (i.e. stock B) and high-risk stocks (i.e. stock A) respectively (Weber et al., 2012). The average of three selected portions of low-risk and high-risk stocks were used, respectively, as prior low and high risk-taking measures. PWoM and NWoM scales were adapted from Alexandov et al., (2013) to measure the likelihood of sharing NWoM and PWoM by using three items for each construct, ranging from "1-extremely unlikely" to "7-extremely likely". The Cronbach's alpha values for NWoM and PWoM were 0.871 and 0.866 respectively. Later portfolio decision-making was measured as a binary item on reinvestment decisions in high- or low-risk portfolios for bearish and bullish market settings respectively. The descriptive statistics of bearish and bullish treatment responses were presented in the appendix A2 and A3.

5.3.2.3. Procedure

At the beginning of the experiment, participants were provided with market descriptions (either bearish or bullish market settings). Participants were informed that the experiment consisted of two parts: a portfolio selection exercise, followed by a few survey questions[5].

In the first part, participants were instructed to select one portfolio each from three sets of portfolios and provide the perceived riskiness level they associated with each portfolio. Afterwards, participants were presented with actual returns earned by their selected portfolios. In each set of portfolios, the first portfolio provided a negative actual return, the second portfolio's actual return was lower than the expected return, and the third and fourth portfolios provided higher than expected actual returns. It was expected that participants might first select lower risk portfolios (i.e. portfolio 1 or 2; low risk-taking) and later switch to portfolios 3 or 4 (high risk-taking) under the bearish market. In contrast, participants in bullish market settings were expected to select portfolios 4 or 3 (high risk-taking) and later change to portfolios 3 or 2 or 1 (relatively low risk-taking).

The second part of the study consisted of four questions related to NWoW or PWoM and later portfolio decision-making. In the bearish treatment, participants were asked three questions

[5] Experiment 1 is available online at: https://impresaluiss.eu.qualtrics.com/jfe/form/SV_bO9UoXeoav2T1fn

on the likelihood of sharing NWoM, while participants in the bullish treatment were presented with three questions on PWoM.

5.3.3. Experiment 2

5.3.3.1. Participants

The responses initially collected for the bearish and bullish treatments of experiment 2 were 260 and 278, respectively. As in experiment 1, four data checks were made and a total of 228 and 251 responses for the bearish and bullish market settings were used in the final analysis[6]. For both treatments, respondent ages ranged from 20 to 60 years. The final responses for the bearish treatment included 59.2% male and 40.8% female respondents with a mean age of 35.71 years (SD = 10.56). The age distribution was right-skewed with 61.4% respondents towards the left side of the mean value. A total of 85.55% reported having a bachelor’s or higher degree as their highest education level. The final participants in the bullish treatment were 57.4% male and 42.6% female with a mean age of 33.98 years (SD = 10.08). The distribution of age was right-skewed with 58.2% of respondents younger than mean age. A total of 81.3% participants reported having a bachelor’s or higher degree as their highest educational qualification. Data for both treatments was fairly normally distributed, as was evident from skewness and kurtosis values lower than three times the respective standard error values for all indicators (Sposito et al., 1983).

5.3.3.2. Materials and measures

In the first part of the experiment, an autobiographical emotional memory task was used to induce negative or positive emotions in the participants. In an emotional induction task, participants are required to share the desired emotional experience in a short essay. This method is quite popular in inducing desired emotions because of its easy implementation and applicability in both laboratory and real-world settings. Furthermore, it does not require expert writing skills and can be completed in less than 10 minutes. There are some doubts regarding the validity of an emotional induction task to induce the desired emotions without also inducing other incidental emotions. For instance, Mills and D’Mello (2014) argued that autobiographical

[6] Overall, 32 and 27 respondents were discarded by using the same data checks as experiment 1: no prior stock market experience or SNS accounts (i.e. 10 and 14), incorrect answers to treatment related questions (i.e. 9 and 8), and the completion of the survey within five minutes (i.e. 13 and 8) in bearish and bullish treatments, respectively.

emotional memory tasks successfully induce the desired emotion, but the effect of incidental emotions was also significant. This doubt was not relevant in experiment 2, however, because the objective in this case was to induce negative (NWoM) or positive (PWoM) emotions, not incidental emotions of the same valence like anger, fear, happiness or joy. Participants were instructed to share their prior loss (gain) investment experiences in bearish (bullish) market settings to induce negative (positive) emotions.

The measures for experiment 2 were derived from the existing literature and adapted to the context of portfolio decision-making. Prior risk-taking was measured as a proportion of the total wealth that participants invested in shared investment experience (Weber et al., 2012). Like experiment 1, the proportion of total wealth invested in shared losses (gains) experienced in bearish (bullish) treatments was used as measure of low (high) risk-taking. The measures of self-enhancement and self-affirmation were based on Yun et al., (2007) and Napper et al., (2009) and consisted of six and five items respectively. The three dimensions of social motives were based on Chiu et al., (2006). Social interaction ties, relational trust, and shared vision consisted of four, five and three items, respectively. The scale for all measures was measured via a 7-item Likert scale ranging from “strongly disagree” to “strongly agree”. The NWoM, PWoM, and later portfolio decisions were measured in the same way as in study 1. The descriptive statistics of both treatment responses are given in the appendix A4 and A5.

5.3.3.3. Procedure

As in experiment 1, participants were provided with an economic description of a bearish and a bullish market. Participants were informed that the study was divided into two parts. In the first part, participants were instructed to share a brief description of their experience of either prior losses or gains in a stock market investment in the context of the bearish (or bullish) market. Afterwards, they were required to state the proportion of their total wealth they had invested in the investment choice mentioned.

In the second part of the experiment, participants were instructed to respond to survey questions while keeping the above-mentioned stock market investment experience in mind. All questions were the same in the bearish and bullish market treatments except the likelihood of sharing NWoM and PWoM. The likelihood of sharing NWoM was measured in the bearish treatment and the likelihood of sharing PWoM was measured in the bullish treatment[7].

5.4. Results

Experiment 1 data was used to test the baseline assumption and hypotheses 1a and 1b by using PROCESS model 4 analysis (a model allowing for the indirect effect of multiple mediators in parallel, Hayes (2013). Experiment 2 data was used to validate parallel serial mediation hypotheses 2a, 2b, 3a, and 3b by using PROCESS model 4 analysis, and double serial mediation hypotheses 4a, 4b, 5a, and 5b by using PROCESS model 6 analysis (a model allowing for the serial indirect effect of multiple mediators; Hayes, 2013). The empirical results of experiment 1 and 2 are reported in table 1. The direct effects used to establish hypothesized indirect effects are given in appendix A6.

-------------- Insert table 1 --------------

5.4.1. Experiment 1 results

The study 1 data was used to test the baseline assumption – prior low (high) risk-taking positively affects an investor's tendency to engage in later high (low) risk-taking – and the indirect effect of low (high) risk-taking on high (low) risk-taking via NWoM (PWoM) (Hypotheses 1a &1b). The results given in table 1 confirmed the baseline assumption in both treatments by providing a statistically significant positive direct effect of prior low risk-taking on later high risk-taking in a bearish treatment ($\beta = 5.5066$, p-value < 0.001, 95% CI = 3.2428, 7.7703) and a positive direct effect of prior high risk-taking on later low risk-taking in a bullish treatment ($\beta = 2.0950$, p-value < 0.05, 95% CI = 0.0356, 4.1543). This suggests that prior low (high) risk-taking enhances an investor's tendency to engage in later relatively high (low) risk-taking in loss (gain) domains. We also find that the slopes of risk-taking in both bearish and bullish treatments were significantly different from each other (t-value = 3.7305, p-value < 0.001), confirming that an investor's tendency to engage in later high-risk stocks in the loss domain was significantly higher than in the gain domain.

The results confirmed a significant indirect positive effect of prior low risk-taking on later high risk-taking via NWoM (ab[8] = 2.4340, 95% CI = 1.0195, 4.3457), a positive indirect

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[7] Experiment 2 is available online at: https://impresaluiss.eu.qualtrics.com/jfe/form/SV_1Gj7uO6c11WrCWV
[8] From here on, "ab" represents the indirect effect coefficient.

effect of prior high risk-taking on later low risk-taking via PWoM (ab = 3.8868, 95% CI = 2.4316, 5.9151). The bootstrapping confidence interval confirmed the significance of both indirect effects at the confidence interval of 95%. This validates hypotheses 1a and 1b, suggesting that prior low (high) risk-taking enhances an investor's tendency to exhibit later high (low) risk-taking via the decision to engage in NWoM (PWoM).

5.4.2. Experiment 2 results

In this sub section, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were first used to assess the dimensionality, reliability, and the convergent and discriminant validity of observed variables to measure underlying theoretical phenomena for both bearish and bullish treatments. Afterward, proposed mediation hypotheses were tested.

The EFA used the maximum likelihood method to assess 26 items designed to measure six constructs (i.e. self-affirmation, self-enhancement, social interaction ties, relational trust, shared vision, and PWoM or NWoM). For each treatment, corresponding NWoM or PWoM items were included. The maximum likelihood method extracted six expected underlying factors for both treatments with the extraction commonalities of each item well above the threshold of 0.3. The KMO (Kaiser-Meyer-Olkin measure) and cumulative explained variance for bearish and bullish treatments were 0.894 and 66.682%, and 0.894 and 67.509%, respectively. The pattern matrix indicated factor loadings greater than 0.5 for all observed variables and the factor correlation matrix provided no correlation between six factors (i.e. correlation lower than 0.7). Cronbach's alpha for all constructs was greater than 0.70, which was higher than the threshold value of 0.60, demonstrating the reliability of factors. Convergent validity is demonstrated by respective observed variables loading on related factors, as indicated by the pattern matrix. In addition, discriminant validity was confirmed by no cross-loadings or correlation among factors. Therefore, no item was dropped from the analysis and all items were used in CFA to assess the consistency of each observed variable to measure the respective construct and fit in the measurement model.

In CFA, the measurement model was developed by using six constructs. The measurement model for each treatment indicated a perfect fit with loading for each item greater than 0.7, with the exception of one item of self-enhancement having a loading of 0.694. As the loading value was close to 0.7, the item was therefore retained for further analysis (see table 2).

The model fit statistics for the bearish treatment were: χ^2 = 432.495, df = 364, root mean square error of approximation (RMSEA) = .029, standardized root mean square residual (SRMR) = 0.0382, normed fit index (NFI) = 0.909, and comparative fit index (CFI) = 0.984. The model fit statistics for the bullish treatment were: χ^2 = 381.082, df = 364, RMSEA = 0.014, SRMR = 0.0345, NFI = 0.922, and CFI = 0.996. The convergent and discriminant validity for both treatments was demonstrated by the average variance extracted (AVE) for each construct being greater than 0.5 and the square root of AVE being greater than correlation. In addition, composite reliability (CR) is evident from constructs CR value being greater than 0.7, which ranged from 0.767 to 0.936 for the bearish treatment and 0.850 to 0.929 for the bullish treatment.

-------------- Insert table 2 --------------

The common method bias was checked by using Harman's single factor approach by forcing all items to load on a single factor (Podsakoff & Organ, 1986). The cumulative variance explained by one factor was 29.57% for the bearish treatment and 25.19% for the bullish treatment, suggesting that most of the cumulative variance is not explained by a single factor. Additionally, the current study did not include a marker like a social desirability scale in experiment 2. Therefore, the common latent factor was used to test the common method bias (Podsakoff et al., 2003). It hypothesized that shared variance by a common latent factor is not different from zero in the constrained and unconstrained measurement model (Gaskin, 2017). For the bearish treatment, we failed to reject the null hypothesis that a shared difference between the models is not different from zero (i.e. unconstrained model χ^2 = 392.5, df = 334, constrained model χ^2 = 432.5, df = 364, $\Delta\chi^2$ = 40, Δdf = 30, p-value = 0.105), indicating that there is no problem of common method bias. For the bullish treatment, we also failed to reject the null hypothesis and concluded that there is no problem of common method bias (i.e. unconstrained model χ^2 = 342.7, df = 334, constrained model χ^2 = 381.1, df = 364, $\Delta\chi^2$ = 38.4, Δdf = 30, p-value = 0.140). Hence, the common latent factor was not retained in the models, and factors were imputed for hypothesis testing without the common latent factor.

The imputed variables were used to test the indirect effect of self- and/or social motives on the relationship between prior low (high) risk-taking and NWoM (PWoM) in a parallel mediation model. The results supported a significant positive indirect effect of prior low risk-taking on NWoM via self-affirmation (ab = 0.5088, 95% CI 0.2480, 0.7985) in the bearish treatment and a significant indirect effect of high risk-taking on PWoM via self-enhancement (ab = 2.1717, 95% CI = 1.6324, 2.7414) in the bullish treatment, confirming hypotheses 2a and 2b. Both indirect effects were confirmed by bootstrapping at a confidence interval of 95%. It is important to note that we did not find an indirect effect of self-enhancement (self-affirmation) on the relationship between prior low (high) risk-taking and NWoM (PWoM) in the bearish (bullish) treatment (see appendix A7). It confirms that investors engage in NWoM (PWoM) after low (high) risk-taking in order to seek the benefits of self-affirmation (self-enhancement), and not self-enhancement (self-affirmation) in the loss (gain) domain.

The results in table 1 supported a significant positive indirect effect of social interaction ties (ab = 0.2564, 95% CI = 0.0595, 0.4824), relational trust (ab = 0.5352, 95% CI = 0.3451, 0.7806), and shared vision (ab = 0.2826, 95% CI = 0.1161, 0.4938) on the relationship between prior low risk-taking and NWoM in the bearish treatment. The results also showed a significant positive indirect effect of high risk-taking on PWoM via shared vision (β = 0.2450, 95% CI = 0.0204, 0.5072) in the bullish treatment. Hence, this confirmed the hypotheses in 3a (i, ii & iii) and 3b (iii). The bootstrapping confirmed the significance of four indirect effects at a confidence interval of 95%. This indicated that investors engage in NWoM to strengthen social interaction ties, relational trust and shared vision in the loss domain, while investors engage in PWoM to develop social resources via a shared vision in the gain domain.

The results confirmed hypotheses 4a and 4b by showing a significant double serial mediation effect of self-affirmation and NWoM (ab = 2.4411, 95% CI = 0.7384, 5.5957) on the relationship between prior low risk-taking and later high risk-taking in the bearish treatment, and self-enhancement and PWoM (ab = 2.3853, 95% CI = 1.1775, 3.8568) on the relationship between prior high risk-taking and later low risk-taking in the bullish treatment. In addition, we did not find a serial mediation effect of self-enhancement (self-affirmation) and NWoM (PWoM) on the relationship between prior low (high) risk-taking and later high (low) risk-taking in the bearish (bullish) treatments (see appendix A7). This confirmed that an investor's decision to engage in later high risk-taking is activated by self-affirmation manifested in NWoM in the loss domain. In contrast, an investor's decision to engage in later low risk-taking is motivated by self-enhancement reflected in PWoM in the gain domain.

Finally, results confirmed the double serial mediation effect of the three dimensions of social motives and NWoM on the relationship between prior low risk-taking and later high risk-taking. The results showed a significant serial mediation effect of social interaction ties and NWoM (ab = 1.5027, 95% CI = 0.6501, 2.8498), relational trust and NWoM (ab = 2.3185, 95% CI = 1.2755, 3.7472) and shared vision and NWoM (ab = 1.4828, 95% CI = 0.6569, 2.7566), confirming hypotheses 5a (i, ii & iii). However, results only partially confirmed the hypotheses in 5b (ii & iii) in the bullish treatment and showed a significant positive serial mediation effect of relational trust and PWoM (ab = 0.2243, 95% CI = 0.0597, 0.5317), and of shared vision and PWoM (ab = 0.8810, 95% CI = 0.4884, 1.4595), on the relationship between prior high risk-taking and later low risk-taking. This indicated that investors' motives to strengthen their social resources by engaging in NWoM activate decisions to invest in high-risk stocks in the loss domain. On the other hand, investors' motives to develop social resources by developing relational trust and shared vision manifested in PWoM activate decisions to engage in later low-risk investments in the gain domain.

5.5. Discussion and conclusion

An escalation of commitment suggests that individuals engage in relatively higher risk-taking in the loss domain than in the gain domain and this behavior is prominent in situations framed as stock selection. This concept is explained by prospect theory as an individual behaving differently in loss and gain domains by engaging in high or low risk-taking. There is a lack of evidence on the underlying mechanism that guides changes in individual risk attitudes in the loss (gain) domain. We integrated insights from the literature on self-determination theory and WoM with prospect theory to propose a double serial mediation effect to explain the underlying mechanism behind changes in individual risk attitudes. This study provided an understanding that individuals seek different self- and/or social motives manifested in NWoM or PWoM to engage in later high (low) risk-taking in loss (gain) domains. The data was collected online by using two experiments (each experiment with two treatments) from participants with stock market investment experience and ages ranging from 20 to 60 years old. This implies a higher ecological validity and generalizability of results than university student samples.

Overall, out of 10 sub-hypotheses, 8 were completely supported and 2 were partially supported. Two important conclusions were drawn from the results. First, results confirmed that later high and low risk-taking was activated by a different underlying mechanism which consisted of the investor's self- and/or social motives manifested in the NWoM or PWoM. Secondly, in the loss domain, investors exhibit less risk aversion and their tendency to engage in high-risk taking increases relatively more than investors in the gain domain. These findings were consistent with the results of existing studies. For example, Weber and Zuchel (2005) found that participants engage in high risk-taking following prior losses when the situation is framed as a portfolio decision. Aydemir and Aren (2017) argued that investors are psychologically distinct from one another and have a different underlying mechanism that explains risk-taking. Kirk et al., (2015) argued that non-conscious goals induce investors to exhibit psychological ownership of investment choices and engender self-enhancement, resulting in an intention to engage in WoM. In addition, investors refuse to acknowledge ownership of bad investment outcomes and justify losses by blaming market conditions, luck and destiny (Aydemir & Aren, 2017). We also replicate findings on the effect of social interaction (Changwony et al., 2015; Hong et al., 2004), relational trust (Tokuoka, 2017; Guiso et al., 2008) and shared vision (Brown et al., 2004; Brown et al., 2008; Ivkovic & Weisbenner, 2007; Zhang et al., 2018) on investors' portfolio decisions.

We find our results are consistent with the extant literature on an escalation of commitment (Staw, 1976). In the loss domain, investors are more willing to engage in high risk-taking to (partly) offset the prior loss, parallel to investors investing in winning stocks in the gain domain. Investors become less risk-averse because subsequent loss hurts less as compared to gain whereas investors become more risk-averse to maintain the positive return streams in the gain domain (Hens & Vlcek, 2011). It further suggests that investor risk attitudes depend on the initial starting wealth (reference point) following prior losses or gains. In addition, results further confirm that investors are more likely to commit additional funds to high-risk stocks in anticipation of a high return to (partly) cover prior losses in the loss domain (Odean, 1998). However, investors are more likely to reinvest in winning stocks to take short-term advantage of market conditions, resulting in relatively low risk-taking.

The main finding of this study is to underscore the underlying mechanism that induces investors to commit additional funds to losing stocks (high risk-taking) in the loss domain and reinvestment in winning stocks in the gain domain. The results suggest that different self- and/or social motives manifested in NWoM or PWoM drive investors' later portfolio decisions. The underlying mechanism differs for loss and gain domains. In terms of self-motives, investors seek to self-affirm by sharing NWoM to shift the blame for their losses on market condition, luck, and destiny (Aydemir & Aren, 2017). By doing so, the investor uses self-affirmation as a defence mechanism to attempt to show that losses are not due to their bad investment strategies but rather are a result of other external uncontrollable factors. It further confirms the self-justification hypothesis by suggesting that investors feel no need to justify their investment strategies and decide to engage in high risk-taking to offset prior losses (Staw, 1976) and sustain self-satisfaction and self-esteem. In the case of the gain domain, investors associate good performance with self-abilities and want to self-enhance by sharing PWoM and continue to reinvest in winning stocks to enhance a positive self-image. In this way, investors express psychological ownership of winning decisions and suggest others follow their investment strategies (Kirk et al., 2015).

The social motives (i.e. social interaction ties, relational trust, and shared vision) mediate the association between prior losses and later high risk-taking decisions through NWoM. The negative information is perceived as more credible and trustworthy (Pan & Chiou, 2011). It highlights the very important function of social resources: investors try to strengthen existing relationships through strong interaction ties, relational trust, and shared vision by sharing negative experiences manifested in NWoM. It helps investors to seek emotional support (Brown et al., 2008), advice, and confirmation of information to achieve cognitive clarity by reducing cognitive dissonance (Steele & Liu, 1983). In this way, investors persist with their investment strategy and engage in high risk-taking. In the gain domain, investors share PWoM to gain social desirability (Alexandrov et al., 2013) in the form of developing relational trust and shared vision in the community. Investors wish to improve their social standing by reciprocating the intention to exchange opinion, and to provide emotional support and develop shared values by sharing a positive investment experience as manifested in PWoM. To improve their positive standing, investors continue to invest relatively more in winning stocks in order to maintain positive streams of returns that reflect their competence and intelligence.

The serial mediation effect also explains investors' efforts to spend a significant amount of time on planning and sharing investment-related experiences and opinions on SNSs. The NWoM is shared on SNSs to further strengthen social resources, and to seek emotional support and information confirmation. It also helps to strengthen network ties by improving relational trust and shared vision. On the other hand, PWoM is shared on SNSs to enlarge network ties by communicating positive self-information to SNS members. In this way investors try to attract other members to follow their investment strategy and improve their social desirability. The results confirmed that self- and/or social motives are the main underlying drivers for sharing NWoM or PWoM, while previous literature had highlighted the "helping others perspective" of WoM between market participants (e.g. Hong et al., 2004). Hence, it can be argued that investors are more interested in confirming their own self- and/or social motives when sharing NWoM or PWoM during sequential decision-making than in inducing risk-taking behavior in WoM-receivers.

The results suggest that most investors follow a similar predictable pattern during portfolio decision-making, consistent with findings of other experimental studies (e.g. disposition effect; e.g. Odean, 1998; Shefrin & Statman, 1985; Weber & Camerer, 1998). Three similar possible alternative explanations related to investor's cognitive processes can be drawn from the findings. In the loss domain, investors are relatively more willing to engage in high risk-taking relative to investors in the gain domain. It is because of investor's overreliance on heuristics that make them overweigh the overdue event that has not occurred in recent times. Such cognitive processes make investors susceptible to gambler fallacy (Shefrin, 2007). In contrast, investors predict the continuation of recent performance and take advantage of the upward market trend in the gain domain. Such a belief gives rise to recency bias and hot hand fallacy (Shefrin, 2007). For example, consider bearish market settings of study 1, participants selected 55%, 56.8%, and 42.6% of either portfolio 1 or 2 from first, second, and third sets of portfolios, respectively. It suggests that participant's risk-attitude is shifted towards an overdue event i.e. high risk-taking (portfolio 3 or 4) in anticipation of gains to (partly) offset prior losses. However, participants selected 65.5%, 62%, and 57.2% of risky investment (i.e. portfolio 3 or 4) from first, second and third set of portfolios in the bullish market settings, respectively. It provides that participants reinvested a relatively higher proportion in perceived low-risk stocks than high-risk stocks to assure the continuation of positive return.

Another possible explanation is based on equity mispricing. The loss in specific stock involves price decrease that translates into an investor's pessimistic expectations (Lakonishok, Shleifer & Vishny, 1994). It pushes the prices further downward (undervalued), resulting in three possible effects: first, it provides an opportunity to buy good quality undervalued stock (i.e. fundamentally strong companies) that can revert to intrinsic value (Kok, Ribando & Sloan, 2017). Study 1 confirmed this argument that investors invest additional wealth in losing stocks (for bearish market settings). Second, expert investors with a rational investment strategy may persist with current losing stocks in anticipation of a high return on price reversion (Kok et al., 2017). This is confirmed by study 2 results by suggesting that investors share their negative experience and seek validation and confirmation from community members and persist with the investment strategy. Finally, it also provides an opportunity for naïve portfolio rebalancing to maintain the proportion of portfolio risk by purchasing losing stocks after selling winning stocks. The gain in stocks translates into investor's optimistic expectations, pushing prices upward (i.e. overvalued). The intelligent investors take advantage of the upward market trend by investing in overvalued stocks to a certain limit and withdraw funds in anticipation of price reversion. However, novice investors continue to invest in overvalued winning stocks (Fenton-O'Creevy, Soane, Nicholson & Willman, 2011) to sustain social desirability.

The most important alternative explanation is based on textual sentiment analysis. Recently, a growing body of literature in finance has started to explore the effect of investor sentiments extracted from textual messages posted on SNSs in predicting stock market returns. Most of the existing studies have used a textual dataset of messages posted on StockTwits to predict market return at monthly, weekly, and intraday level by using investor's sentiments (e.g. Sun, Najand, & Shen, 2016; Renault, 2017). The results suggest that investors reflect their self- or social-motives through NWoM or PWoM associated with prior portfolio decisions that can be used to predict investor's tendency to select the same or similar stocks in later decisions. It can be used by an analyst to predict market sentiments towards a specific set of stocks and associated direction of market price movement. It further suggests that messages on SNSs can help to predict the type of self- or social-motives gained by investors via investing in specific stocks. For example, socially responsible investors may share their personal positive, ethical, and moral reflections to improve social status via self-enhancement by sharing PWoM after investing in socially responsible firms' stocks.

The findings of this study also provide significant managerial implications for financial advisors and analysts. Normative investment models suggest that stock market investments only have economic benefits for investors. However, our findings suggest that investment reveals economic as well as self- and/or social motives. The self- and/or social motives have a strong impact on changing an investor's risk attitude. Clients are more likely to invest in specific stock to gain particular self- and/or social benefits. It is important for advisors to understand the underlying motives that sometimes make clients less and sometimes more risk-averse in the loss or gain domain. Financial advisors should be aware of the trade-off between different sets of self- and/or social motives and how these motives influence a client's risk attitude. By doing so, advisors can change the risk attitude of clients to protect them from sticking with losing stocks and can frame investment decisions with reference to self- and/or social motives that clients can achieve by modifying their portfolios. For instance, advisors can frame investment decisions in a way that strengthens social motives and validation from other advisors in order to change a client's risk attitude from more risk-averse to less risk-averse (i.e. escalation of commitment). On the other hand, advisors can change a client's risk attitude to high risk-averse behavior to prevent reinvestment in overvalued stocks by framing investment decision as a lowering of self-enhancement and a weakening of social resources.

The other implication is related to decision models for assessing risk attitude and investment performance. Our findings confirmed that investors are psychologically and sociologically distinct from one another and have different underlying mechanisms that explain later risk-taking. We argue that decision models based on normative theories do not consider investors' self- and/or social motives and cannot predict and explain investors' risk attitude. Therefore, the main parameters used in decision models should refer to self- and/or social motives that shape investor risk attitudes. In addition, investment decision assessment models should also consider the self- and/or social motives of investors when assessing the performance of the investment decision. Finally, our findings suggest that analysts can consider investors less risk-averse in the loss domain and more risk-averse in the gain domain. This can help predict systematic patterns in market movements and help in modelling asset pricing.

There are also a few limitations of this study. Firstly, the literature mentions other factors that constitute self- and/or social motives. For example, self-verification involves one's ability to drive one's self-concept, and self-improvement highlights one's efforts to better one's self-image, norms of reciprocity and identification. This study used only those self- and social motives that were previously examined in finance literature. Future studies may incorporate other self- and/or social motives to provide further detailed insight into the underlying motives of investors. Secondly, we induced negative and positive emotions in participants to share prior experiences of losses or gains. There is a possibility that investors may be more emotionally attached to one specific industry or company stock than others. Hence, it can be claimed that investors could be more emotionally prone to invest in certain industries or firms. Thus, controlling for industry or firm could further reveal these emotional affiliations. Along the same lines, financial advisors can further understand the emotional attachment of clients to specific industries and firms. It could also help them manage client risk attitudes. In addition, future studies could test how the self- and/or social motives proposed by this study may be used by advisors to manage the risk attitudes of clients following prior losses and gains.

Thirdly, Alexandrov et al., (2013) argued that self-motives mediate the valence of WoM via social motives. This study indicates that self- and/or social motives mediate the relationship between prior decisions and NWoM or PWoM in a parallel manner. Future studies may establish the mediating role of social motives on the relationship between self-motives and NWoM or PWoM. This could be done by using intentional models like the theory of planned behavior or reasoned actions, arguing that investors achieve self-motives by first analysing their social implications in terms of strengthening or developing social resources. Fourth, emotions of the same valence are fundamentally different in cognitive appraisals and predisposition preferences (Lerner & Keltner, 2000, 2001). One could argue that these emotions also have different underpinning self- and social motives (Lemay et al., 2012). It would be interesting to investigate what underlying mechanisms and investor motives lie behind the desire to share different categories of emotions, which is reflected in the valence of WOM. Finally, we used an online platform to conduct experiments, one might argue that compensation provided to participants is lower than the opportunity cost and lack of control over participants. We suggest future studies to replicate the finding of our study by using different samples via laboratory-based experiments or collaborate with financial institutions or brokers to conduct experiments from their clients, as done by Weber et al., (2012).

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List of tables and figures

Table 1: Test of research hypotheses

Hypothesis		Bearish treatment	Bullish treatment
		β, 95% [LLCI, ULCI]	β, 95% [LLCI, ULCI]
Experiment 1			
Baseline assumption	LRT→HRT	***5.5066 [3.2428, 7.7703]***	
Baseline assumption	HRT→LRT		***2.0950 [0.0356, 4.1543]***
H1a	LRT→NWoM→HRT	**2.4340 [0.0195, 4.3457]**	
H1b	HRT→PWoM→LRT		**3.8868 [2.4316, 5.9151]**
Experiment 2			
H2a	LRT→SA→NWoM	**0.5088 [0.2480, 0.7985]**	
H2b	HRT→SE→PWoM		**2.1717 [1.6324, 2.7414]**
H3a(i)	LRT→SIT→NWoM	**0.2564 [0.0595, 0.4824]**	
H3a(ii)	LRT→T→NWoM	**0.5352 [0.3451, 0.7806]**	
H3a(iii)	LRT→SV→NWoM	**0.2826 [0.1161, 0.4938]**	
H3b(i)	HRT→SIT→PWoM		0.0320 [-0.0925, 0.1734]
H3b(ii)	HRT→T→PWoM		0.0479 [-0.0214, 0.1762]
H3b(iii)	HRT→SV→PWoM		**0.2450 [0.0204, 0.5072]**
H4a	LRT→SA→NWoM→HRT	**2.4411 [0.7384, 5.0144]**	
H4b	HRT→SE→PWoM→LRT		**2.3853 [1.1775, 3.8568]**
H5a(i)	LRT→SIT→NWoM→HRT	**1.5027 [0.6501, 2.8498]**	
H5a(ii)	LRT→T→NWoM→HRT	**2.3185 [1.2755, 3.7472]**	
H5a(iii)	LRT→SV→NWoM→HRT	**1.4828 [0.6569, 2.7566]**	

H5b(i)	HRT→SIT→PWoM→L RT	0.0475 [-0.1421, 0.2768]
H5b(ii)	HRT→T→PWoM→LRT	**0.2243 [0.0597, 0.5317]**
H5b(iii)	HRT→SV→PWoM→L RT	**0.8810 [0.4884, 1.4595]**

In the table, LRT stands for low risk-taking, HRT for high risk-taking in later decision-making, NWoM for negative word-of-mouth, PWoM for positive word-of-mouth, SA for self-affirmation, SE for self-enhancement, SIT for social interaction ties, T for relational trust, and SV for shared vision.
β is the direct effect coefficient, and ab is the indirect effect coefficient.
LLCI is the lower level of confidence interval, and ULCI is the upper level of confidence interval.
95% confidence interval to test the significance of all indirect effects.
Significant indirect effects are given in bold font and significant direct effects in bold italics.
All hypotheses were tested by controlling for age and gender.

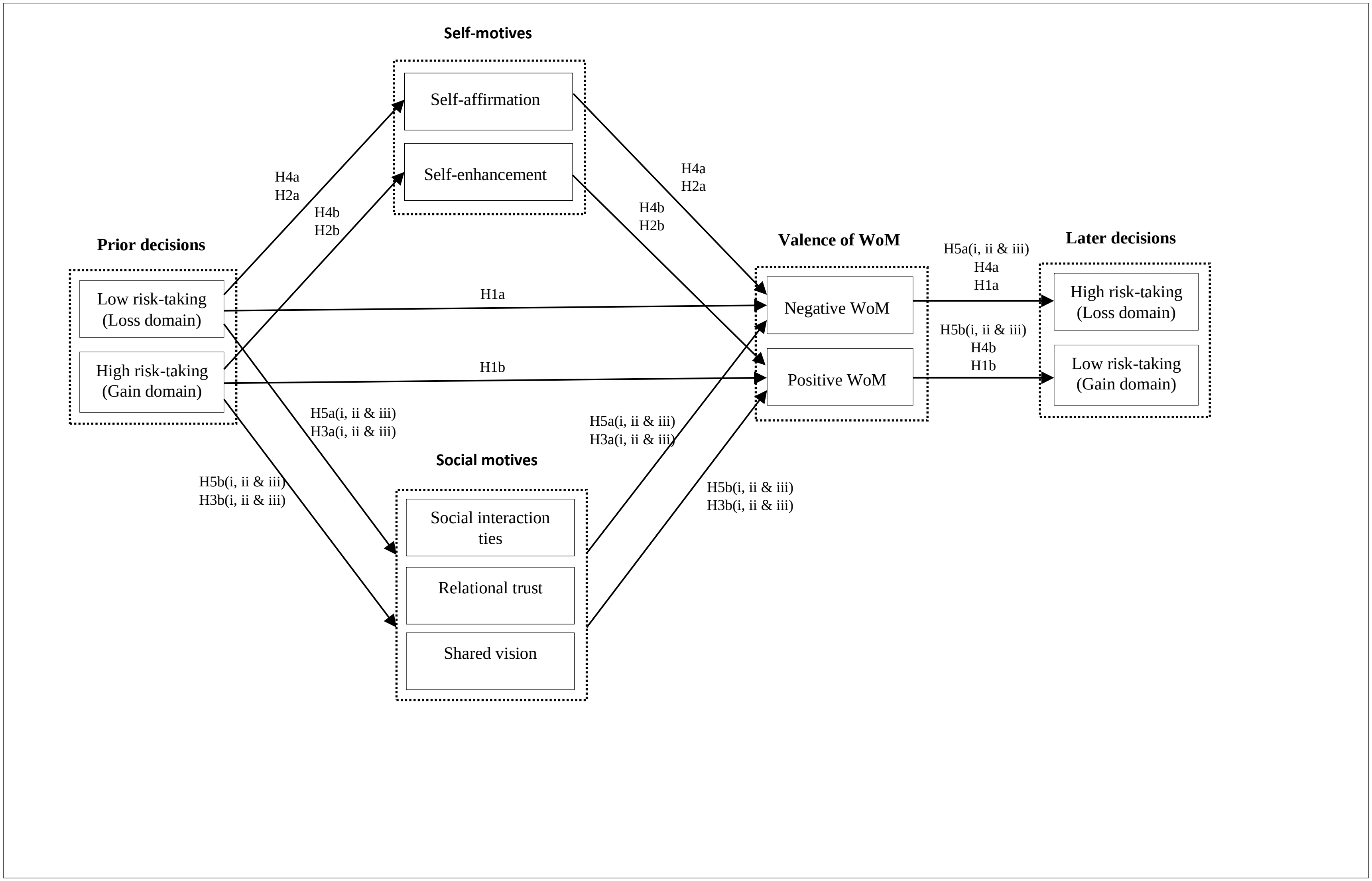
Table 2: Confirmatory factor analysis

	Bearish treatment	Bullish treatment
NWoM	0.767, 0.524, 0.724	
NWoM1	0.712	
NWoM2	0.73	
NWoM3	0.728	
PWoM		0.903, 0.756, 0.870
PWoM1		0.841
PWoM2		0.888
PWoM3		0.879
SA	0.936, 0.746, 0.863	0.914, 0.680, 0.825
SA1	0.881	0.803
SA2	0.856	0.828
SA3	0.868	0.791
SA4	0.853	0.856
SA5	0.859	0.844
SE	0.886, 0.566, 0.752	0.909, 0.685, 0.828
SE1	0.704	0.839
SE2	0.791	0.843
SE3	0.813	0.846
SE4	0.694	0.8
SE5	0.71	0.813
SE6	0.792	0.823
SIT	0.896, 0.684, 0.827	0.858, 0.603, 0.776
SIT1	0.862	0.802
SIT2	0.801	0.763
SIT3	0.846	0.695
SIT4	0.798	0.837
T	0.923, 0.705, 0.839	0.897, 0.635, 0.797
T1	0.886	0.786
T2	0.844	0.838

T3	0.818	0.768
T4	0.805	0.785
T5	0.841	0.804
SV	0.873, 0.696, 0.834	0.850, 0.654, 0.809
SV1	0.849	0.79
SV2	0.861	0.782
SV3	0.791	0.853

In the table, NWoM stands for negative word-of-mouth, PWoM for positive word-of-mouth, SA for self-affirmation, SE for self-enhancement, SIT for social interaction ties, T for relational trust, and SV for shared vision.
Items of a respective factor are represented by factor symbol and number, while the numbers for each item provide its loadings on the respective factor with p-value < 0.001.
For each factor, three numbers provide composite reliability, average variance extracted and shared variance.

Figure 1: Theoretical process model



Appendix

Appendix A

Table A1: Base portfolio

Portfolio	Percentage of Stock A	Percentage of Stock B	Portfolio expected return	Portfolio expected standard deviation
1	0%	100%	4.93%	9.31%
2	20%	80%	13.59%	15.48%
3	80%	20%	39.55%	54.97%
4	100%	0%	48.21%	68.73%

Table A2: Descriptive statistics Experiment 1 (Bearish treatment)

	Mean	SD	LRT	NWoM	HRT
LRT	0.48	0.30	1.00		
NWoM	3.86	1.44	.705**	1.00	
HRT	0.53	0.50	.683**	.631**	1.00

In the table, LRT stands for low risk-taking, NWoM for negative word-of-mouth, and HRT for high risk-taking in later decision-making.
** $p < 0.010$

Table A3: Descriptive statistics Experiment 1 (Bullish treatment)

	Mean	SD	HRT	WOM	LRT
HRT	0.59	0.25	1.00		
WOM	4.16	1.52	.498**	1.00	
LRT	0.61	0.49	.474**	.688**	1.00

In the table, LRT low stands for risk-taking, PWoM for positive word-of-mouth, and HRT for high risk-taking in later decision-making.
** $p < 0.010$

Table A4: Descriptive statistics Experiment 2 (Bearish treatment)

	Mean	SD	LRT	NWoM	SA	SE	SIT	T	SV	HRT
LRT	0.58	0.26	1.00							
NWoM	3.71	0.96	0.67**	1.00						
SA	4.32	1.48	0.66**	0.65**	1.00					
SE	2.78	0.98	-0.28**	-0.28**	-0.23**	1.00				
SIT	4.05	1.45	0.54**	0.55**	0.44**	-0.27**	1.00			
T	4.83	1.48	0.46**	0.65**	0.43**	-0.21**	0.46**	1.00		
SV	4.81	1.26	0.44**	0.57**	0.52**	-0.19**	0.29**	0.46**	1.00	
HRT	0.55	0.50	0.77**	0.76**	0.79**	-0.35**	0.59**	0.55**	0.52**	1.00

In the table, LRT stands for low risk-taking, HRT for high risk-taking in later decision-making, NWoM for negative word-of-mouth, SA for self-affirmation, SE for self-enhancement, SIT for social interaction ties, T for relational trust, and SV for shared vision.
** $p < 0.010$

Table A5: Descriptive statistics Experiment 2 (Bullish treatment)

	Mean	SD	HRT	PWoM	SA	SE	SIT	T	SV	LRT
HRT	0.47	0.25	1.00							
PWoM	4.00	1.24	0.55**	1.00						
SA	4.17	1.22	-0.08	0.05	1.00					
SE	4.02	1.28	0.74**	0.72**	-0.01	1.00				
SIT	4.23	1.21	0.03	0.28**	0.43**	0.08	1.00			
T	3.59	1.20	0.17**	0.34**	0.12*	0.27**	0.39**	1.00		
SV	3.76	1.07	0.43**	0.53**	0.12	0.57**	0.24**	0.35**	1.00	
LRT	0.62	0.49	0.56**	0.63**	0.00	0.65**	0.15*	0.39**	0.41**	1.00

In the table, LRT stands for low risk-taking, HRT for high risk-taking in later decision-making, PWoM for positive word-of-mouth, SA for self-affirmation, SE for self-enhancement, SIT for social interaction ties, T for relational trust, and SV for shared vision.
* p < 0.050, ** p < 0.010

Table A6: Direct effects

Experiment 1			
	NWoM	PWoM	HRT
LRT (Bearish)	3.4106***		
LRT (Bullish)		3.0137***	
NWoM			0.7134**
PWoM			1.2897***

Experiment 2									
Direct effect									
	SA	SE	SIT	T	SV	NWoM	PWoM	HRT (Bearish)	HRT (Bullish)
LRT (Bearish)	3.8325***	-1.0789***	3.0598***	2.6745***	2.1886***	0.9369***		9.1103***	
LRT (Bullish)	-0.3680	3.7589***	0.1543	0.8273**	1.8338***		0.1945		2.9642*
SA						0.1328***	-0.0392	1.9020***	0.0234
SE						-0.0261	0.5778***	-0.0955**	0.5415*
SIT						0.0838*	0.2074***	0.3534	0.0628
T						0.2001***	0.0579	-0.0136	0.7501***

SV	0.1291***	0.1336*	0.4227	-0.037
NWoM			2.7130***	
PWoM				0.9372***

In the table, LRT stands for low risk-taking, HRT for high risk-taking, SA for self-affirmation, SE for self-enhancement, SIT for social interaction ties, T for relational trust, and SV for shared vision.
* $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$
95% level of confidence for all confidence intervals.
All hypotheses are tested by controlling for age and gender.
The above results provide direct effects that are not hypothesized in this study but used to establish indirect effects.

Table A7: Indirect effects

	ab, 95% [LLCI, ULCI]
LRT→SE→NWoM	0.0282 [-0.0626, 0.1332]
LRT→SA→PWoM	0.0144 [-0.0153, 0.1011]
LRT→SE→NWoM→HRT	0.3083 [-0.0416, 0.8890]
LRT→SA→PWoM→HRT	-0.0458 [-0.2133, 0.0152]

ab is the indirect effect coefficient.
In the table, LRT stands for low risk-taking, HRT for high risk-taking, NWoM for negative word-of-mouth, PWoM for positive word-of-mouth, SA for self-affirmation, SE for self-enhancement, SIT for social interaction ties, T for relational trust, and SV for shared vision.
LLCI is the lower level of confidence interval, and ULCI is the upper level of confidence interval.
95% confidence interval to test significance of all indirect effects.
All hypotheses were tested by controlling for age and gender.
The table includes indirect effects that are not hypothesized in this study, but results are provided to confirm that no indirect effect was found for these variables.

Chapter 6

Conclusion, implications, and future research directions

Table of Contents

Conclusion, implications, and future research directions

The literature in value premium mainly attempted to either support or contradict risk-based explanation or mispricing explanation. However, this dissertation attempted to provide insight into the value premium from an individual investor's perspective and aggregate market behavior. Chapter two of this dissertation explored the role of investor's cognition (decision-making process), and emotion (emotional regulation strategies) to predict the selection of value versus growth stocks. Chapter three provided the impact of investors' attention towards firms-related fundamental and other critical information on the dynamics of the value premium. Consistent with chapter three, chapter four employed intangibles as a critical firm's strategy resource and analyzed the impact of investor attention to intangibles information on the superior returns to interaction strategy between high/low book-to-market ratio and high/low intangibles. Chapter five provided differences in underlying mechanism that induces investors to engage in reinvestment decisions following prior losses (high risk-taking) or prior gains (low risk-taking). In this section main findings, implications, and future research directions of this dissertation are discussed.

Consistent with economic behavior literature, we find the impact of the decision-making process that are Type 1 processing and Type 2 processing, and emotional regulation that are expressive suppression and cognitive reappraisal on the investor's preferences towards the selection of value stocks and growth stocks. Chapter two findings confirmed that investors with higher reliance on Type 1 (or Type 2) processing and cognitive reappraisal (or expressive suppression) have lower (or higher) preferences towards value versus growth stocks. These findings contributed by suggesting that investors first select emotion-induced intuition-based growth stocks and later engage in the rethinking process to select Type 2 based value stocks. We add by confirming that emphasized instructions and additional information debiased intuitive-based stocks selection and induced Type 2 processing. Findings suggested that investors with strong control over emotions and the ability to reappraise emotions and divert attentional deployment towards expected positive emotions. Such investors do not rely on standalone value-to-market ratios, instead engage in thorough investment analysis to analyze available fundamental information. These findings have significant practical implications. Investors can avoid the selection of emotion-driven overvalued stocks by reappraising negative emotions and engage in the cognitive-deliberative process. Investors can develop a list of fundamental indicators or heuristics to prevent the selection of Type 1 processing induced weak fundamentals growth stocks.

Chapter two has some theoretical and methodological weaknesses that can be considered in future research. First, theoretical framing overlooked the role of personality traits in determining an investor's ability to engage in Type 1 processing, Type 2 processing, cognitive reappraisal, and expressive suppression. Literature in economic behavior provides a significant effect of personality on the selection of economic choices. Thereby, future studies can investigate the mediating or moderating effect of personality traits on the association between decision-making process and emotional regulation. On the methodological side, we only manipulate Type 1-based thinking and Type 2-based thinking and not emotions. Hence, future studies can manipulate emotions and account for an individual's response to different emotions via emotional regulation strategy and their subsequent effect on the selection of economic choices.

Chapter three confirmed that investor attention influences the dynamics of the value premium. Results confirmed that value stocks with low investor attention outperformed growth stocks with low investor attention. This is consistent with the investor-recognition hypothesis that investors persistence with less visible neglected value stocks and avoid investing attention-induced overvalued growth stocks, leading to superior returns to value stocks with low attention on price reversal. We argue that superior returns to value stocks with low attention are mainly attributed to the negative price pressure on previously high attention growth stocks that on a reversal of biased market expectations lose significant market value. Findings imply that true investors can use other investors' neglect and inattentiveness to value stocks to generate superior returns. Specifically, investors can take a long position in value socks with low investor attention and short position in growth stocks with low investor attention to earn superior returns. In doing so, true value investors can take advantage of growth investors neglect towards fundamental information.

Chapter four confirmed investors limited attention hypothesis and use investor attention towards firms' intangibles-intensity and its effect on return differences between interaction strategy of value/growth firms and high/low intangibles-intensity. Results confirmed superior return difference between values stocks with high intangibles-intensity and growth stocks with low intangibles-intensity than standard value-growth strategy. These superior returns are primarily attributed to low returns to growth stocks with low intangibles-intensity. Findings further confirm that intangibles signals mispricing. The value-to-market ratio and intangibles-intensity combinedly provide a stronger indicator to identify mispricing. These findings also have important implications for investors. Investors should assess firms' current competitive position by using intangibles-intensity as a competitive moat to select firms for investment. Intangibles-intensity with fundamental analysis heuristics like F-score can help investors to identify strong fundamentals high intangibles-intensive value firms that can generate superior returns. Based on findings of chapter three and chapter four, future studies can identify fundamental factors that signal to mispricing and investigate their individual and combined effect with value-to-market ratios to develop profitable investment strategy than standard value-growth strategy.

Chapter five proposed a model based on the integration of sequential decision-making, prospect theory, intrinsic motives, and word-of-mouth to investigate the underlying mechanism behind investor's decision to engage in high (or low) risk-taking following prior gains (or losses). Results indicated that different underlying self- and/or social motives, manifested in negative word-of-mouth or positive word-of-mouth, that activate later high (low) risk-taking in the loss (gain) domain. This indicates that investors are not only interested in the economic benefits of investment but also seek to gain self-motive and social motives manifested in the valence of word-of-mouth. The findings of chapter five can be used by financial advisors to modify the risk-attitude of clients by presenting investment choices that satisfy the client's self-motives and social-motives. This can help advisors to prevent the selection of biased investment choices, predict the systematic patterns in market prices, and model asset pricing.

There are also some theoretical and methodological limitations of chapter five. First, we used self-affirmation and self-enhancement as the main predictor of self-motives, but literature also identifies other factors as self-motives like self-verification. Future studies can build on the proposed theoretical model and test the impact of other self-motives on an investor's ability to engage in reinvestment decisions. Second, investors might have an affiliation or emotional attachment with a specific sector or firm. Chapter five does not take into consideration the effect of a specific type of firm or sector. Hence, future studies can investigate the underlying mechanism in a specific sector or multiple sector scenario. Third, evidence suggests that self-motives mediate the valence of word-of-mouth through social motives (e.g. Alexandrov, Lilly & Babakus, 2013). Hence, the proposed theoretical model can be modified by establishing a mediating role of social motives on the relationship between self-motives and the valence of word-of-mouth. Fourth, Lerner and Keltner (2000, 2001) argued that emotions of the same valence are different in cognitive appraisals and predisposition preferences and may have different underlying self-motives or social motives. Hence, future studies can investigate the underlying mechanism behind different emotions of the same valence. Finally, data were collected by using Amazon Mechanical Turk and one can argue that there is a lack of control on participants. Also, the opportunity cost of participants might be higher than the compensation amount. Future studies can overcome these problems by using real-time investor's data via brokers (e.g., Weber, Weber & Nosić, 2012) or can conduct controlled laboratory experiments.

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