Predictable Fluctuations in the Cross-Section and Time-Series of Asset Prices

by Keunbae Ahn

Thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy

under the supervision of Dr. Gerhard Hambusch

University of Technology Sydney
Faculty of Business

June 2021

Certificate of Original Authorship

I, Keunbae Ahn, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Finance Discipline Group at the University of Technology Sydney. This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution. This research is supported by the Australian Government Research Training Program.

Signature: Production Note: Signature removed prior to publication.

Date: 18 June. 2021

Acknowledgements

I express my deepest gratitude to my supervisory panel, including Dr. Gerhard Hambusch and Associate Professor Marco Navone, for their invaluable comments and suggestions. Under their supervision and guidance, I have been able to undertake three research projects during my Ph.D. candidature. It has been a great pleasure to work with them, and I have learned priceless lessons from their attitude towards research. My Ph.D. journey at the University of Technology Sydney (UTS) has been one of the most rewarding experiences.

I owe special thanks to the UTS Finance Discipline Group Ph.D. coordinator, Dr. Christina Nikitopoulos Sklibosios, who facilitated and guided my candidature's administrative tasks through three stage assessment presentations and the thesis submission. I would not have been able to complete this thesis without her continuous help. I am grateful for the financial support of UTS. Further, I thank numerous academic and administrative staff members in the Finance Discipline Group for their considerable contributions that enabled me and other Ph.D. students to focus on our research in a productive and collegial environment.

I also thank Professor Talis Putnins, Dr. Kihoon Jimmy Hong, several finance researchers and professionals from the network of the principal supervisor, two thesis examiners and two anonymous referees for their insightful comments and suggestions on the research projects in this thesis. Lastly, I am grateful for the thesis proofreading service delivered by a professional editor.

Table of Contents

List of Tables

List of Figures

Abstract

The purpose of this thesis is to examine predictable fluctuations in asset returns based on rational and irrational human behaviour in financial markets. The results presented in this thesis can inform retail and professional investors, as well as economic policy design, e.g., related to the better understanding and management of the effect of investor behaviour on capital markets. In this regard, this thesis intends to help achieving improved outcomes in capital markets to provide benefits for societies.

The first research project investigates household debt as a potential asset pricing factor. This research reveals that an increase in the level of household leverage places a strong and lasting negative effect on household consumption. The well-known consumption capital asset pricing model is modified to account for this negative association, and we show that leverage has a negative risk price using Fama-French test assets. Our results illustrate that the negative risk premium persists at the individual stock level. Further, we use traditional asset pricing factors and confirm that our leverage factor captures a risk premium, which is not explained by other known factors.

The second research project studies the effect of investor sentiment on international stock markets. To measure sentiment, we build composite sentiment indexes targeting global and regional markets. Our time-series results show that stocks are overpriced (underpriced) when investors are optimistic (pessimistic), whereas stock prices become more volatile and more correlated when investors are pessimistic. Our cross-sectional results indicate that most of our time-series results, except for sentiment-based underpricing, become more pronounced for securities with more exposure to sentiment or to market returns. This suggests that sentiment traders contribute to mispricing that affects the mean, variance and correlation of asset returns.

Our findings have important implications for understanding and managing the risk-return trade-off in capital markets.

The third research project focuses on how market participants respond to market-wide and firm-specific information. This research builds proxies for the respective information arrivals pertaining to the market or to specific firms. Our results suggest that investors underreact to market-wide information and overreact to firm-specific information such that these behavioural biases provide predictable variations in stock returns as well as in return variances over the short-term. Furthermore, this evidence is independent of arbitrage activities in the market. Our results have practical implications for investors who aim to time the market using historical data.

Chapter 1: Introduction

1.1. Motivation

Finance, as a social science, serves as a means to assist investors, including institutional and retail investors, in considering and seizing investment opportunities. Given uncertainties about markets and individual assets, the optimal allocation of scarce financial resources is perhaps the most important task in finance. Uncertainties often refer to challenges that make forecasting an exact state of the future rather difficult. Uncertainties require researchers to maximise the performance of investment strategies from the ex-ante perspective. For this reason, statistics takes on an important role in finance. Seminal studies of Eugene Fama and Paul Samuelson formalised the concept of uncertainties that pertain to asset prices. Fama (1965a, 1965b, 1970) suggested the efficient market hypothesis (EMH), arguing that changes in asset prices are unpredictable as long as asset prices reflect all relevant information. Samuelson (1965) offered a similar insight on motions in asset prices.

According to the EMH, it is impossible to earn profits from using information in an efficient market because trading of rational investors in competition reflects all available information in asset prices. Instead, investors must invest in assets that provide superior returns when the marginal value of their wealth or consumption is high to increase their expected returns. This is the implication of well-known asset pricing models: Sharpe’s (1964) capital asset pricing model (CAPM) and Lucas (1978) and Breeden’s (1979) consumption capital asset pricing model (CCAPM). These models show that risk-averse investors want to be compensated for holding assets that deliver inferior returns when their wealth or consumption decreases. Thus, in these models, an asset’s exposure to wealth or consumption determines the level of its risk and expected return.

The EMH has been criticised for its unrealistic assumption that investors are rational and hence immune to behavioural biases in their decision-making process. Previous studies suggest numerous instances of biases causing irrational behaviour.[1] Further, the criticism has resulted in subsequent studies on market participants' irrationalities that challenge the theoretical basis of the EMH. The literature shows that irrational investors cause predictable movements to emerge in capital markets. For example, asset prices moved upward together during the dot-com bubble period between 1995 and early 2000 before asset prices began to plummet as the bubble burst from March 2000. Such mispricing characterised by large rises and sharp falls of asset prices represents reversal patterns in asset returns, which should not occur according to the EMH.

In response to the critics, proponents of rational theories argue that sophisticated investors exploit arbitrage opportunities from mispricing to earn riskless profits which in turn results in efficient markets. However, theories based on irrational behaviour point out that arbitrage is not riskless. For instance, arbitrageurs must bear fundamental or noise trader risk. Suppose that an arbitrageur realises that an asset's market price has deviated from its fundamental value, and she decides to exploit this opportunity to earn profits. First, fundamental risk implies that the arbitrageur might have to bear losses if positive information about the asset emerges while she is waiting for the market price to converge to the fundamental value. Second, noise trader risk in De Long et al. (1990a) due to unpredictable irrational beliefs implies that, if noise traders aggravate mispricing after arbitrage positions are taken, it can lead to the arbitrageur needing to liquidate her positions at a loss before she can realise arbitrage profits.

[1] Prominent instances of behavioural biases in previous studies include anchoring (Tversky and Kahneman, 1974), loss aversion (Kahneman and Tversky, 1979), mental accounting (Thaler, 1985), representativeness (Tversky and Kahneman, 1974), conservatism (Edwards, 1962), optimism (Weinstein, 1980), overconfidence (Fischoff and Slovic, 1980) and herding (Huberman and Regev, 2001). These biases are known to hinder investors' rational decision-making.

Instead of arguing which theories are more sensible or developing a unique asset pricing model accommodating conflicting observations from financial markets, this thesis focuses on the examination of predictable fluctuations observed in the cross-section and in the time-series of asset prices based on rational or irrational behaviour. The research results in this thesis can make investing more efficient by helping investors to better manage uncertainties that they are exposed to.

1.2. Literature Review

The main goals that asset pricing models must accomplish, regardless of their specification, can be summarised as follows. First, regarding the time-series dimension, a model must be able to explain asset returns with a reasonable magnitude of preference parameters. The analysis of historical data on the U.S. market in previous studies shows that the mean and the variance of stock market returns are too high, whereas those of the risk-free rate are too low to correspond to the standard asset pricing model for which the preference parameters lie in the conventional range or for which the stochastic discount factor is stable over time (Campbell, 2003).[2] Second, regarding the cross-sectional dimension, a model must be able to describe the cross-sectional variation in asset returns based on exposure to the stochastic discount factor. For example, if the stochastic discount factor is the market excess return, the model indicates a positive risk-return relation when investors are risk-averse.

Most asset pricing studies that make the assumption that investors are rational have provided predictions related to the cross-section, rather than the time-series, of asset returns.[3] Previous

[2] Subsequent numerous asset pricing studies, e.g., Epstein and Zin (1991), Campbell and Cochrane (1999), Bansal and Yaron (2004), Constantinides and Duffie (1996), Brav, Constantinides and Geczy (2002) and Savov (2011), suggest alternative asset pricing models to provide explanations for puzzling empirical observations and to improve the performance of the CCAPM.

[3] There are previous studies providing theoretical and empirical evidence on the time-series of asset returns based on rational theories. For example, Lettau and Ludvigson (2001b), Lustig and Van Nieuwerburgh (2005), Santos

studies have shown that the representative agent is willing to hedge against the several state variables in the context of Merton's (1973) intertemporal capital asset pricing model (ICAPM), e.g., wealth (Sharpe, 1964), consumption (Lucas, 1978; Breeden, 1979), inflation (Chan, Chen and Hsieh, 1985; Stulz, 1986; Chen, Roll and Ross, 1986; Ferson and Harvey, 1991, 1993, 1994; Elton, Gruber and Blake, 1995), interest rate (Sweeney and Warga, 1986; Campbell, 1996; Brennan, Wang and Xia, 2004), investment (Cochrane, 1991) and income (Campbell, 1996; Jagannathan and Wang, 1996; Heaton and Lucas, 2000; Dittmar, 2002; Santos and Veronesi, 2006).[4]

Arguably, among the most important factors in describing the cross-section of asset returns are consumption and wealth, the determinants of the degree of agents' satisfaction (i.e., utility). These factors are located at the centre of rational theories. In many cases, other studies' models have suggested new factors because of their impact on consumption or wealth. The mechanism of how assets are priced in a model is simple, although some models are characterised by a high degree of complexity to reflect how investors or asset prices behave in the real-world. In general, it is assumed that investors want to hold assets providing superior returns when their wealth or consumption decreases. This implies that investors evaluate assets based on the assets' exposure to their wealth or consumption and that investors' demand for assets generates the cross-sectional dispersion in asset returns.

The existing asset pricing models based on rational behaviour have failed to account for most of the observed market anomalies. Some researchers ascribe the failure of the rational theories to fallacies in understanding how investors behave when determining their holding of securities. In their seminal research, Kahneman and Tversky (1979) proposed the prospect

---

and Veronesi (2006) and Piazzesi, Schneider and Tuzel (2007) investigate predictable fluctuations in the time-series of stock returns.

[4] Here, we have introduced selected macroeconomic forces with reference to the respective studies. It is important to note that other asset pricing factors have been put forward that are not mentioned here to provide a focus on the most important factors. For additional factors, we refer interested readers to Table 6 in Harvey, Liu and Zhu (2016) or online at http://faculty.fuqua.duke.edu/~charvey/Factor-List.xlsx.

theory which suggests that investors have a value function that differs from the one used in rational finance theories. Unlike the rational theories, which assume risk-averse investors in case of gains and losses, their experimental results showed that investor's value function is convex (i.e., investors are risk-seeking) when valuing losses and concave (i.e., investors are risk-averse) when valuing gains. In other words, investors exhibit irrational behaviour because their value function for losses and gains is asymmetric, i.e., convex for losses (risk-seeking) and concave for gains (risk-aversion). This is a fundamental difference compared to the rational behaviour assumption in traditional finance theories which implies that investors are risk-averse when facing gains and losses. Since then, behavioural studies have incorporated investors' irrational behaviour into their models through, e.g., a preference function, to resolve asset pricing puzzles. For example, using models based on irrational behaviour, Barberis, Huang and Santos (2001) explain the mean and variance of asset returns, and Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998, 2001) and Barberis and Huang (2001) describe the cross-section of asset returns. [5]

Based on the above-mentioned behavioural studies, the literature has presented extensive evidence of violations of the EMH. First, some studies have presented proxies that capture irrational behaviour. These studies show that the proxies have predictive power in the time-series or cross-section of asset returns, e.g., new share issuance (Loughran and Ritter, 1995; Baker and Wurgler, 2000; Pontiff and Woodgate, 2008), market share turnover (Jones, 2002; Baker and Stein, 2004), consumer confidence (Lemmon and Portniaguina, 2006; Schmeling, 2009), past returns (De Bondt and Thaler, 1985, 1987; Jegadeesh, 1990; Lehmann, 1990; Jegadeesh and Titman, 1993; Moskowitz, Ooi and Pedersen, 2012). The most influential research in this field is that of Baker and Wurgler (2006, 2007) examining the U.S. market and that of Baker, Wugler and Yuan (2012) analysing international markets. These studies propose

[5] See Barberis and Thaler (2003) for a summary of these studies.

a composite sentiment index and show evidence that appears to embrace empirical findings in previous behavioural studies. Furthermore, some of the more recent literature, e.g., Stambaugh and Yuan (2017) and Daniel, Hirshleifer and Sun (2020), suggest new pricing factors capturing mispricing to overcome the shortcomings of traditional asset pricing models in explaining market anomalies.

Second, behavioural studies argue that irrational investors affect variance and correlation of asset returns, however, previous studies have provided limited empirical evidence related to this claim. For example, Shiller (1981) and LeRoy and Porter (1981) demonstrate that an asset's market price is more volatile than its fundamental value from the present value model. Shiller (1989) and Pindyck and Rotemberg (1993) provide a similar observation on asset return comovements. Subsequent studies, e.g., Lee, Jiang and Indro (2002) (on excessive variance) and Vijh (1994), Barberis, Shleifer and Wurgler (2005), Kumar and Lee (2006), Ren (2017), and Frijns, Verschoor and Zwinkels (2017) (on excessive correlation) present that there are indeed nonfundamental fluctuations in asset returns causing the emergence of excessive variance and correlation.

1.3. Chapter 2: Investing in a Leveraged World

Chapter 2 examines an important topic in economics and finance, which is the role of household leverage in asset pricing. One observation contributing to the need for an improved understanding of the relation between debt and asset prices is the fact that the world has witnessed a dramatic increase in the level of household leverage in most modern economies over the past decades. This increase represents a fundamental shift in the basic structure of the economies and its consequences on asset prices are still understudied. Therefore, this research focuses on examining the relation between leverage and asset prices with implications for the mechanism of determining asset prices, the functioning of capital markets and the overall wealth in modern economies.

Households have a motive to hedge against their leverage to secure their consumption if households want to smoothen the path of consumption as suggested by the CCAPM. Historical evidence suggests that leverage places some negative effects on consumption as, e.g., observed in the Great Depression in the 1930s and in the subprime mortgage crisis in the 2000s. From this intuition, we draw a measurable asset pricing implication of leverage in the U.S. stock market.

Does household leverage hold back consumption? Past experiences provide a clue for the mechanism of how household balance sheets affect household consumption. During economic crisis periods, households confronted with unprecedented increases in their leverage ratio were forced to redeem a considerable amount of their interest and principal. Households must then choose to cut their spending to avoid default. Our empirical investigation on whether leverage holds back consumption involves a state-space model estimation using the Kalman filter which produces an efficient and unbiased estimator and a fourth-order vector autoregression (VAR) estimation. Our results present that leverage puts significant downward pressure on spending and the effect appears to persist for the subsequent 24 quarters.

Do households want to hedge against their leverage? Consulting the CCAPM, the model implies for the relation between leverage and consumption that leverage should be priced and that the sign of its risk price (or premium) should be negative. To examine whether household leverage is in fact priced, the research presented in Chapter 2 modifies the CCAPM. First, employing several sets of test assets capturing traditional anomalies such as size, value and momentum effects, we document that leverage is priced and the sign of the consumption risk price determines the sign of the leverage risk price. In most cases, consumption has a positive risk price and leverage has a negative risk price. Second, when we use individual stocks as test assets, a negative risk premium is confirmed in the post-2000 period but not in the pre-2000 period. This evidence might indicate that households' motive to hedge against their leverage using securities traded in financial markets was not sufficiently strong in the pre-2000 period.

Chapter 2 builds a connection between households' decisions on financing and spending. In general, households raise funds from financial institutions to cover their contemporaneous consumption, leading them to experience an increase in their leverage. This, in turn, affects consumption in the future because an increase in leverage accompanies the burden of debt redemption. The negative relation leads debt to have an influential force on the determination of asset prices. Our evidence has a nontrivial bearing on the theoretical model of Bansal and Yaron (2004) that provides a potential resolution of asset pricing puzzles. The motivation of the model is that investors care about a small, persistent and predictable component called long run risk (LRR) in consumption growth. Since LRR is not observable, our research suggests that household leverage might provide hints for the identification issue of LRR.

1.4. Chapter 3: Reversal Evidence from Investor Sentiment in International Stock Markets

Chapter 3 investigates sentiment-based mispricing. In the behavioural finance literature, investor sentiment is among the topics that have attracted the most researcher and practitioner interest. Based on the existing literature, it appears to be evident that sentiment incorporates nonfundamental fluctuations into asset prices, however, dispersions in the time-series and cross-section of the conditional moments due to sentiment are still understudied. To improve the understanding of the effect of sentiment on price movements in capital markets, Chapter 3 examines the relation between sentiment and the conditional moments of stock returns. To provide comprehensive evidence, we investigate several international stock markets in addition to the U.S. stock market.

First, we examine the contemporaneous relation of sentiment to moments of stock returns. Our time-series evidence indicates that (1) sentiment and stock returns move together in the same direction, i.e., a bullish (bearish) change in sentiment drives stock prices up (down) and (2) sentiment and the conditional moments (variance and correlation) move together but in the opposite direction, i.e., stocks become less (more) volatile and less (more) correlated with a bullish (bearish) change in sentiment. Moreover, our cross-sectional evidence indicates that the revealed relations tend to be more pronounced among securities more sensitive to sentiment or the market excess return.

Second, sentiment is utilised as a predictor of the moments of asset returns. Our time-series evidence presents that (1) stocks earn negative returns following optimism periods, whereas (2) the conditional variance and correlation decrease following pessimism periods. Once again, our cross-sectional evidence indicates that these reversal patterns tend to be more prominent among securities more sensitive to sentiment or the market excess return.

Chapter 3 provides novel results showing the existence of sentiment-driven movements in the conditional moments of asset returns. Stocks are overpriced in the presence of investors' optimism, while those exhibit higher levels of volatility and comovement when investors are pessimistic. These findings are important for investors to design investment strategies. For instance, investors can consider betting against the markets or individual stocks prone to sentiment in optimism periods. Alternatively, investors can consider increasing the weight of assets with high volatility in their portfolios during pessimism periods based on the expectation that financial markets will subsequently be less volatile.

Chapter 3 contributes to understanding asset pricing puzzles in financial markets. The previous literature (e.g., Campbell, 1987; Harvey, 2001) shows that the mean-variance relation is often negative, contradicting the prediction of the classic rational theories. Our results suggest that sentiment causes the negative relation because a shift in sentiment results in mean and variance changing in opposite directions. In addition, the previous literature (e.g., Fama and French, 1992; Frazzini and Pedersen, 2014) shows that the relation between the market beta and the expected return is flat or negative. Similarly, our results suggest that high market beta stocks earn lower expected returns due to investor sentiment. This suggests that the risk-return relation in the international financial markets included in our sample is inconsistent with the risk-return implications of the CAPM.

1.5. Chapter 4: Return Reversal and Continuation: Differential Response to Market-Wide and Firm-Specific Information

Chapter 4 investigates investor responses to market-wide and firm-specific information. Measuring information that investors trade on is challenging because information types and amounts used by investors are unobservable. The previous literature has attempted to extract information contents from individual transactions. However, in general, such attempts require large datasets and hence can be computationally demanding. In comparison, our method is simple and intuitive: we build separate proxies for market-wide and firm-specific information using individual stocks' trading volume series based on statistical properties of transactions pertaining to the respective information arrivals.

Following the previous studies on contrarian or momentum strategies, e.g., Moskowitz, Ooi and Pedersen (2012), we investigate how investors respond to information by examining the ability of historical returns to predict future returns conditional on the levels of information proxies. Our results present the existence of return reversal over the short-term and return continuation over the intermediate-term. Importantly, we show that market-wide information mitigates and firm-specific information reinforces the return reversal over the short-term. This result indicates that investors underreact to market-wide information and overreact to firm-specific information.

Our findings suggest another interesting research question related to the return variance because the serial correlation has a relation with variance in the stationary autoregressive process. Consistent with the implication of the revealed evidence, the market-wide information measure predicts a decrease in return variances, whereas the firm-specific information measure predicts an increase in return variances.

To provide a practical implication and to complement results obtained from the regression approach, we construct 18 equal-weighted portfolios using signals from excess returns and both of our information proxies. It is confirmed that profits from contrarian trading strategies, i.e., buying losers and selling winners, tend to decrease (increase) as exposure to market-wide (firm-specific) information increases. Individual stock's variances exhibit similar patterns, i.e., variances tend to decrease (increase) as exposure to market-wide (firm-specific) information increases.

Mispricing remains uncorrected when market conditions are not favourable for arbitrageurs as pointed out in the previous literature (e.g., Avramov, Chorida and Goyal, 2006). However, regardless of the market condition related to arbitrageurs' behaviour, our results demonstrate that firm-specific information triggers over-reaction. The portfolio formation analysis suggests that investors can enhance contrarian profits by controlling the exposure to market-wide and firm-specific information even if arbitrageurs trade actively.

Chapter 4 contributes to the literature that focuses on measuring information contents from trading volume. Our method to extract information contents from individual trading volumes is appealing to both researchers and practitioners because it is not vulnerable to the look-ahead bias. For example, building information proxies in month t requires employing observations in month t, and these can be used for investment strategies implemented in month $t+1$. Further, we provide a novel dimension of describing asset prices by showing that investor responses to information can be different depending on the coverage of information and, as a consequence, generates predictable movements in the time-series and cross-section of asset prices. Important for financial practitioners, Chapter 4 suggests investment strategies based on firm-specific and market-wide information arriving in the market.

1.6. Outline

This thesis has five chapters. Chapter 1 presents the research motivation, a literature review and brief summaries of research results and their contributions. Chapter 2 examines the role of household leverage in asset pricing in the U.S. stock market. Chapter 3 discusses the effect of sentiment on moments of asset returns in international stock markets. Chapter 4 studies investor responses to market-wide and firm-specific information in the U.S. stock market. Chapter 5 summarises empirical findings and concludes the thesis.

Chapter 2: Investing in a Leveraged World

2.1. Introduction

The increase in debt levels of the nonfinancial sector of most modern economies is one of the defining characteristics of the 21st century. The total credit to the nonfinancial sector in the U.S. was 187% of GDP at the beginning of this century, it is 249% in 2018. For advanced economies, the leverage of the nonfinancial sector has grown from 214% to 266% of GDP and from 110% to 183% for emerging market economies. The COVID-19 crisis has exacerbated these trends with a 1% growth of the U.S. household debt-to-GDP ratio in the first quarter of 2020 alone.[6] This dramatic increase in leverage for households, governments and nonfinancial corporations represents a fundamental shift in the basic structure of most economies with hard to predict implications for future economic growth. Even less understood are the consequences for asset prices and investment strategies.

This research focuses on exploring the implications of household leverage on asset pricing. Due to increasing household leverage levels, researchers, investors and policymakers have shown a great interest in better understanding leverage and its economic implications. In particular, the subprime mortgage crisis of 2007-2010, with its dramatic influence on global economies, triggered a wave of theoretical and empirical studies investigating phenomena related to economic shocks in the presence of high levels of leverage, e.g., job losses or the contraction in aggregate demand and income. These studies include theoretical studies that

[6] The referred statistics are obtained from Bank for International Settlements (BIS).

investigate the mechanism of excessive leverage and economic recession[7] and the causes of excessive leverage[8], as well as empirical studies[9].

Do household leverage dynamics have a significant effect on capital markets? This research investigates this question based on the relation between household leverage and consumption in the context of the consumption capital asset pricing model (CCAPM). Household leveraging is positively correlated with consumption. This association is trivial for consumer credit but generally holds for every form of household debt (e.g., real estate mortgages can be refinanced to support consumption). This positive association can be reversed when debt redemption (or deleveraging) reduces disposable income. The association is further complicated because of the fact that households can use debt to increase the stock of physical (e.g., buying a car) or human (e.g., paying for college) capital and permanently increase the trajectory of future consumption.

The association between household leverage and consumption provides an indication for a potential role of household leverage as a state variable in asset pricing. This research postulates that leverage affects consumption and therefore has measurable implications on asset pricing. In the CCAPM, the first-order condition for the investor optimisation problem indicates that risk-averse investors prefer to hold securities providing returns that are negatively correlated with consumption dynamics. If assuming that leverage decreases (increases) consumption, it follows that investors are willing to hold securities that provide superior returns when their leverage increases (decreases), i.e., when the marginal value of consumption is worth more. This economic rationale implies that household leverage has a negative (positive) risk price or

---

[7] See Hall (2011), Eggertsson and Krugman (2012), Korinek and Simsek (2016) and Guerrieri and Lorenzoni (2017). These studies show that leverage affects the whole of economies and conclude that leverage generates business fluctuations in economies.
[8] See Krueger and Perri (2006), Iacoviello (2008) and Kumhof, Ranciere and Winant (2015). These studies show that the cross-sectional dispersion in income across households is a determinant of leverage as well as financial soundness in the long run.
[9] See Dynan (2012), Mian, Rao and Sufi (2013) and Mian, Sufi and Verner (2017).

risk premium. To test this implication, and following Yogo (2006), we transform the asset pricing restriction taken from Epstein and Zin (1991) into the unconditional linear factor model using the first-order log-linear approximation. Then, we incorporate household leverage into the model. This research estimates the proposed model using the general method of moments (GMM) estimation procedure suggested in Hansen and Singleton (1982). For the estimation, we use six sets of standard test assets capturing market anomalies such as size, value and momentum effects.

As a next step, which also serves as a robustness test, we turn out attention to individual stocks. Following the method in Fama and MacBeth (1973), we run time-series regressions to estimate individual stocks' exposures to leverage and cross-sectional regressions to investigate the existence of the leverage risk premium. This research constructs portfolios according to the estimated exposures to leverage to investigate a pattern in the cross-section of stock returns. Furthermore, we build a factor capturing the leverage risk premium and examine its relation to prominent asset pricing factors.

Our research provides three important findings. First, household leverage growth predicts negative consumption growth. Furthermore, leverage growth leaves a strong and long-lived impact on consumption growth. The burden of debt redemption indeed changes households' spending plan. Second, we provide evidence of a negative risk price related to a covariance between asset returns and the growth rate of household leverage. We show that the sign of a consumption risk price determines the sign of a leverage risk price. In most cases, consumption has a positive risk price and leverage has a negative risk price, indicating that households are willing to accept lower expected returns when holding securities with returns positively related to household leverage dynamics because such securities provide a hedge against consumption losses.

Third, regarding individual stocks, our results obtained from the Fama-MacBeth regression and portfolio formation indicate that leverage had a negative risk premium in the post-2000 period. This result appears to suggest that the dramatic structural change from high leverage levels to lower leverage levels, which occurred around the subprime mortgage crisis period, in fact strengthened households' motive to hedge against the variation in indebtedness to protect their spending streams. This research further presents that the intercept in the regression of the leverage factor against Fama-French-Carhart (FFC) four factors is not statistically significant, indicating that leverage is not a redundant factor against other asset pricing factors in describing the cross-section of stock returns.

This chapter contributes to the economics literature by establishing a firm relation between household leverage and spending decisions. Our results suggest that the mechanism of how the interaction between household assets and liabilities repress consumption in crisis periods (see Mishkin, 1978; Olney, 1999; Dynan, 2012; Mian, Rao and Sufi, 2013) can persist in noncrisis periods. Second, this research provides novel empirical evidence that households' leveraging and deleveraging decisions can be a fundamental and influential force in determining asset prices. This is an important result as an increase in leverage for households is observed in most modern economies. Third, this chapter argues that household leverage might capture a small, persistent and predictable component called long run risk (LRR). Bansal and Yaron (2004) propose a theoretical model in which the LRR plays a critical role in replicating real-world financial market data. The disadvantage of their model is that the LRR is not observable. However, household leverage might provide hints to solve this identification problem.

The remainder of this chapter is organised as follows. Section 2.2 provides the literature review. Section 2.3 presents a state-space model of consumption to examine the effect of leverage on consumption. Section 2.4 presents the modified CCAPM to derive a testable asset pricing implication and estimates the model using sets of test assets capturing anomalies.

Section 2.5 examines the asset pricing evidence at the individual stock level and suggests a new pricing factor. Section 2.6 concludes this chapter.

2.2. Literature Review

This section provides an overview of the previous literature examining the role of leverage in economics and finance. Regarding the mechanism of how leverage affects consumption, Mishkin (1978) analyses data covering 1929 to 1941 and argues that a rise in the value of household liabilities increased debt service payments, while a decline in the value of household assets decreased the buffer of assets during the Great Depression. These exogenous changes in the household balance sheet increase the likelihood of financial distress and lead households to cut durable spending to avoid holding illiquid tangible assets.

Examining the same period, Olney (1999) argues that changes in the value of household assets are a result of changes in the value of household debt. During the Great Depression, the severe indebtedness gave rise to an extreme burden of instalment debt and seller-creditors repossessed their goods as instalment is missed. Households were forced to reduce non-durable spending to avoid default in turn.[10]

Several studies using household-level data argue that an analogous situation emerged during the subprime mortgage crisis (2007-2010). Dynan (2012) demonstrates that more leveraged homeowners experienced larger declines in spending between 2007 and 2009 compared to other less leveraged homeowners. The author argues that a rise in leverage resulting from the credit boom and subsequent housing price collapse accounts for the weakness in consumer spending. Mian, Rao and Sufi (2013) present that more leveraged households reduce their

[10] Olney (1999) shows that households reduced their spending in 1930, however, decided to default in 1938 as a legal alteration reduced the cost of default.

consumption more because their credit constraints become tighter than other less leveraged households. Combining the results from both studies suggests that a household debt overhang holds back consumption in times of crisis.

It is worth noting that the relative level of household liabilities to household assets (i.e., household leverage), rather than the absolute level of household liabilities, appears to have a negative effect on consumption during financial crises. In other words, changes to a households' debt-to-asset ratio (or leverage) over time are relevant to a household's consumption decision. Provided heterogenous wealth levels across households, and in line with the above-mentioned previous studies, our research's focus on the effect of leverage on consumption is sensible in economics and finance. To expand previous studies, we include crisis and noncrisis periods in our investigation.

Using a more recent sample of consumer and credit data for several developed countries, Bacchetta and Gerlach (1997) demonstrate that ex-ante consumer credit and mortgage growth positively predict consumption expenditure on non-durables and services. The authors also show that the predictive power of credit on consumption is stronger than that of disposable income in some cases. Using aggregate U.S. data on consumer credit as well as consumption, Ludvigson (1999) shows a positive effect of consumer credit growth on future consumption growth, independently of income growth. The author also establishes a theoretical framework for the association of consumption growth with predictable variation in credit and concludes that sufficient random variation in the credit ceiling should exist to account for the linkage between consumption and credit.

Household leverage has a significant influence on modern economies as a whole. On the theoretical side, the previous literature, e.g., Hall (2011), Eggertsson and Krugman (2012), Korinek and Simsek (2016), Guerrieri and Lorenzoni (2017) and Santos and Veronesi (2017) argue that household leverage is responsible for the economic recession during the subprime mortgage crisis (2007-2010).[11] On the empirical side, Mian, Sufi and Verner (2017) present that an increase in the debt-to-GDP (gross domestic product) ratio predicts lower future GDP growth, and Martin and Philippon (2017) establish a theoretical model to inspect the relation between leverage and economic recessions in the Eurozone based on endogenous (e.g., private leverage or funding cost) and exogenous factors (e.g., political bias or sudden stop in capital inflows).

Further, another stream of literature argues that debt affects investors' decision about asset allocation. Sharpe and Tint (1990) provide a framework that considers liabilities in the surplus optimisation. The authors show that the covariance between liabilities and assets can be an important and significant factor for investors who have liabilities. Elton and Gruber (1992), Waring and Whitney (2009) and Amenc et al. (2009) show that investors want to hold assets matching their liabilities. These studies suggest that debt is a state variable that investors seek to hedge against.

The following asset pricing studies suggest that financial intermediaries' leverage can also be a priced factor. He and Krishnamurthy (2013) present theoretical evidence that the leverage ratio of financial intermediaries predicts the cross-sectional asset returns. Adrian, Etula and Muir (2014) and He, Kelly and Manela (2017) confirm that financial intermediaries' leverage (or capital) ratio is a significant factor in asset pricing. These studies suggest that intermediaries' leverage can cause cross-sectional dispersions in asset returns.

[11] The previous literature including Hall (2011), Eggertsson and Krugman (2012), Korinek and Simsek (2016), Guerrieri and Lorenzoni (2017) highlights the role of the zero-lower bound on nominal interest rates, leading household balance sheets depressed aggregate demand during the crisis period. U.S. households were required to deleverage during the subprime mortgage crisis period, and this accompanies reduction in aggregate demand. To encourage spending, the interest rate had to fall, however, it was close to zero and thus most advanced economies plunged into demand-driven economic slumps. Meanwhile, Santos and Veronesi (2017) argue that leverage is a measure of risk aversion and therefore is related to consumption and asset prices based on the mean-reversion mechanism, e.g., a decrease in leverage is related to a decrease in consumption and asset prices.

2.3. Does Leverage Predict Consumption?

This research argues that consumption is the main channel that causes leverage to have an asset pricing implication. If investors' indebtedness affects their spending plan as suggested in the previous studies, leverage should be treated as an important state variable that investors hedge against. Thus, this section examines the relation between leverage and consumption to determine the role of leverage in asset pricing.

2.3.1. State-Space Model

This chapter models household consumption using the state-space modelling approach. Equation (2.1) presents household consumption as a function of household leverage and a latent variable:

$$\Delta c_{t+1} = \alpha + \beta \Delta d_t + \phi z_{t+1} + \sigma_e e_{t+1} \qquad (2.1)$$

where Δc_{t+1} is the natural logarithm of consumption growth, Δd_t is the natural logarithm of leverage growth and $e_{t+1} \sim N(0, 1)$. z_{t+1} in equation (2.1) is a latent variable that is assumed to follow a first-order autoregressive process:

$$z_{t+1} = \rho z_t + \sqrt{1-\rho^2}\, u_{t+1} \qquad (2.2)$$
$$\text{where } u_{t+1} \sim N(0, 1)$$

where $u_{t+1} \sim N(0, 1)$. To address the identification problem, we restrict ϕ in equation (2.1) to be positive.

This chapter uses the state-space model to avoid omitted variable bias. Previous studies have provided evidence that macroeconomic (e.g., disposable income) and financial (e.g., risk-free rate) variables determine consumption (see Flavin, 1981; Campbell and Mankiw, 1990; Bansal, Kiku and Yaron, 2007). Using the state-space model, researchers are not required to include potential omitted variables in their econometric model because it ensures the error term (e_{t+1}) to be independent to the regressors (Δd_t and z_{t+1}) through the recursive filtering algorithm (Kalman filter), assuming that the exact consumption function is linear and error terms have a Gaussian distribution.[12] In other words, the state-space model is a suitable and natural solution to the econometric problem.

Furthermore, another purpose of using the state-space modelling is related to asset pricing test. Most of the asset pricing studies have been criticised for not having a rigorous economic rationale for the proposed factors. In contrast, this research has a strong economic rationale. This research tests components decomposed from consumption using the state-space model and these components have a significant economic importance when investors determine their demands for assets in capital markets. Detailed discussions for each term included in equation (2.1) as an asset pricing factor is presented in Section 2.4. Overall, in contrast to the models suggested in the previous economics and finance literature, the state-space modelling approach enables us to achieve two goals at a time. First, we can estimate the unbiased relation between leverage and consumption. Second, we can test individual consumption components that have nontrivial economic implications as potential asset pricing factors.

[12] Using the maximum likelihood estimation (MLE) through the Kalman filter to estimate the state-space model provides an asymptotic unbiased and efficient estimator (see, Brogaard et al., 2014; Hendershott and Menkveld, 2014).

2.3.2. Data

Consumption data is obtained from U.S. Bureau of Economic Analysis's (BEA) 'National Income and Product Accounts Table 7.1'. Consumption is defined as the sum of real personal consumption expenditure on nondurables and services per capita. Quarterly consumption data are used because it is less prone to measurement error while providing a sufficient number of observations for statistical inference. Since consumption is not a point-in-time observation, we assume that consumption is measured at the end of the quarter.

We merge the consumption with household balance sheet data obtained from 'Household and Nonprofit Organizations Table B.101' on the Board of Governors of the Federal Reserve System's website. The seasonal variations in the time-series of the household balance sheet accounts are eliminated using the method of the U.S. Census Bureau referred to as X-11. The final dataset spans from 1952:Q2 to 2018:Q4.

Total liabilities (TL) of households consist primarily of consumer credit (CC) and home mortgages (HM). On average, CC and HM account for 24% and 65% of total liabilities over the sample period. In general, the duration of consumer credit is much shorter than that of home mortgages. Consumer credit is short- and intermediate-term credit for immediate purchase of goods and services, including cars and appliances. It covers credit card debt as well as secured or unsecured debt for automobiles, mobile homes, trailers and other purposes. Home mortgages are long-term credit secured on the properties of borrowers to purchase real estates. The rest of total liabilities are composed of depository institution loans not elsewhere classified (n.e.c.), other loans and advances, etc.

Total assets (TA) consist of financial assets (FA) and nonfinancial assets (NA), which make up 66% and 34% of total assets, on average, over the sample period. Financial assets are more liquid than nonfinancial assets. Financial assets include cash, stocks, bonds, mutual funds and bank deposits, while nonfinancial assets include land, properties and commodities. To avoid a potential selection bias, we conduct our empirical analysis using TL and TA as well as each of their two components, i.e., CC and HM from the right-hand side of household balance sheet and FA and NA from the left-hand side of household balance sheet. This research overlooks other components in total liabilities as some of components are not for households or account for a small fraction of total liabilities. The consideration of the nine leverage measures serves as a robustness test in addition to aiming at investigating similarities and differences relating to individual measure's contributions to price assets in capital markets.

Figure 2.1 plots all debt-to-asset ratios. For the ratio of TL and TA, values range from 6.39% to 19.22% with a value of 13.06% at the end of 2018. There are upward and downward trends in the pre- and post-subprime mortgage crisis periods, respectively, and these trends appear to be due to a significant leveraging and deleveraging in the mortgage market.

Table 2.1 reports descriptive statistics of the natural logarithm of one-quarter lagged debt-to-asset ratio growth and consumption growth and provides interesting results. First, the growth rate of the debt-to-asset ratio is lower albeit more volatile than the growth rate of consumption. Consumption growth has a mean of 0.48% and a standard deviation of 0.46% per quarter, while debt-to-asset ratio growth has a mean of 0.26% and a standard deviation of 1.39% per quarter. Second, a correlation coefficient between debt-to-asset ratio growth and consumption growth is negative, consistent with the literature introduced in the previous section (i.e., Mishkin, 1978; Olney, 1999; Dynan, 2012; Mian, Rao and Sufi, 2013).

Figure 2.2 plots the time-series of the one quarter lagged debt-to-asset ratio growth rate and the consumption growth rate and confirms the negative correlation coefficients presented in Table 2.1 (e.g., -0.11 for the case of household leverage computed using total liabilities and assets).

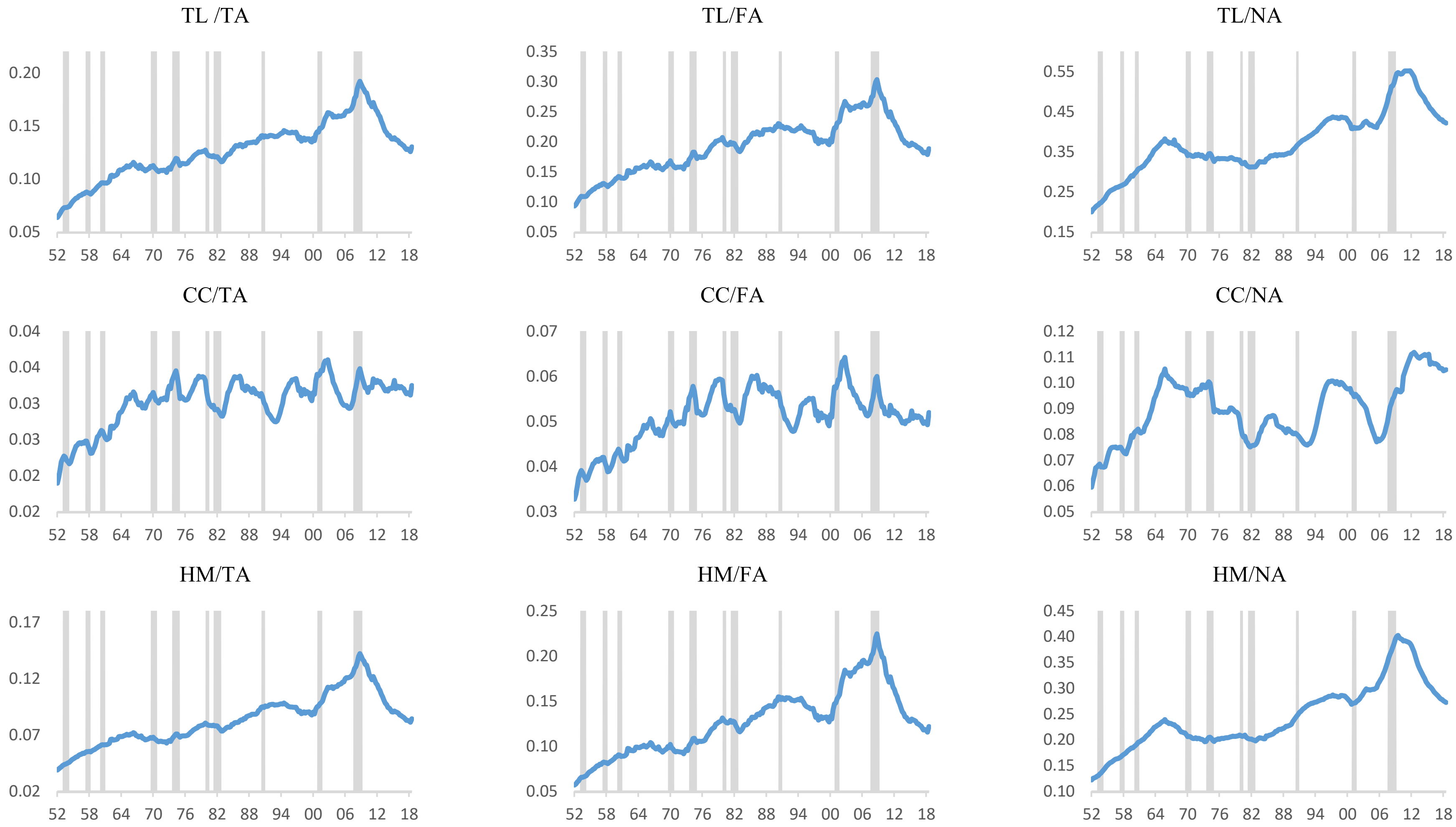

Figure 2.1. Level of Debt-to-Asset Ratio
The figure plots the time-series of the level of the U.S. household debt-to-asset ratio. The sample period spans from 1952:Q2 to 2018:Q4. Shaded areas represent NBER recessions. TL, CC and HM denote total liabilities, consumer credit and home mortgages. TA, FA and NA denote total assets, financial assets and nonfinancial assets. Each column heading denotes the leverage measure used.

Table 2.1. Descriptive Statistics

The table reports mean, standard deviation and correlation for the natural logarithm of one-quarter lagged U.S. household debt-to-asset ratio growth and consumption growth. The sample period spans from 1952:Q2 to 2018:Q4. CONS denotes consumption. TL, CC and HM denote total liabilities, consumer credit and home mortgages. TA, FA and NA denote total assets, financial assets and nonfinancial assets.

	Mean (%)	Std. Dev. (%)	Correlation									
			CONS	TL/TA	TL/FA	TL/NA	CC/TA	CC/FA	CC/NA	HM/TA	HM/FA	HM/NA
CONS	0.48	0.46	1									
TL/TA	0.26	1.39	-0.11	1								
TL/FA	0.25	1.90	-0.12	0.96	1							
TL/NA	0.29	1.07	-0.02	0.47	0.23	1						
CC/TA	0.20	1.78	-0.10	0.78	0.78	0.28	1					
CC/FA	0.19	2.25	-0.12	0.82	0.87	0.13	0.97	1				
CC/NA	0.23	1.44	-0.03	0.36	0.21	0.65	0.70	0.51	1			
HM/TA	0.29	1.50	-0.13	0.94	0.93	0.36	0.65	0.72	0.17	1		
HM/FA	0.28	2.03	-0.14	0.92	0.97	0.16	0.68	0.79	0.08	0.97	1	
HM/NA	0.31	1.09	-0.05	0.49	0.28	0.89	0.17	0.08	0.41	0.54	0.33	1

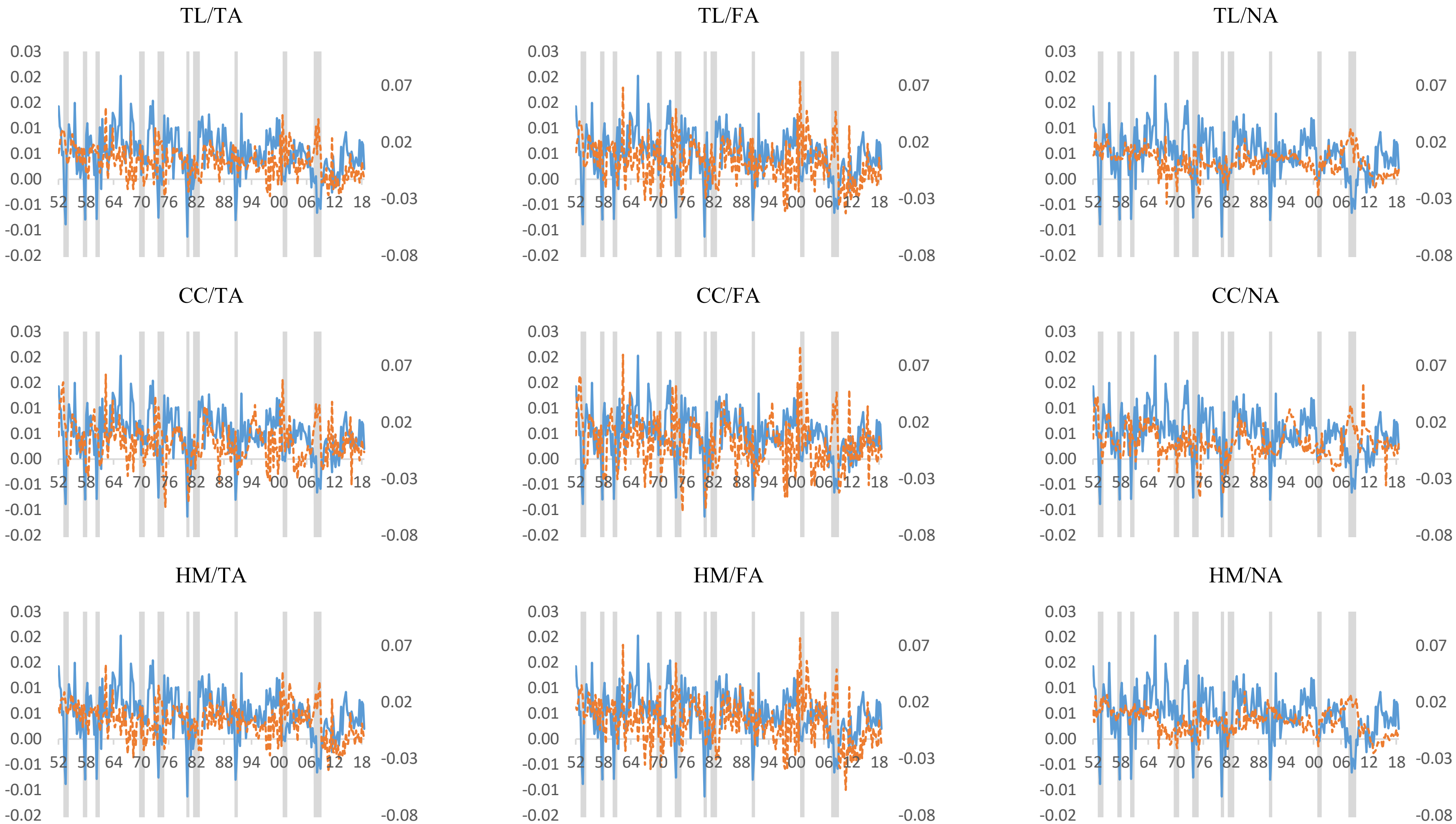

Figure 2.2. Debt-to-Asset Ratio Growth versus Consumption Growth

The figure plots the time-series of the natural logarithm of one-quarter lagged U.S. household debt-to-asset ratio growth and consumption growth. The data span from 1952:Q2 to 2018:Q4. Shaded areas represent NBER recessions. The solid line represents consumption growth, and the dashed line represents debt-to-asset ratio growth. The y-axis on the left-hand side shows consumption growth and the y-axis on the right-hand side shows debt-to-asset ratio growth. The x-axis shows time. TL, CC and HM denote total liabilities, consumer credit and home mortgages. TA, FA and NA denote total assets, financial assets and nonfinancial assets. Each column heading denotes the leverage measure used.

2.3.3. State-Space Model Estimation

Table 2.2 reports maximum likelihood estimates of the parameters in equation (2.1) and (2.2). First, the estimates show a negative and significant effect of leverage growth on future consumption growth, except for the cases of nonfinancial assets. Comparing the estimates in Panel A and B implies that the negative relation becomes stronger as omitted variable bias is corrected. For example, the coefficient on debt-to-asset ratio growth is -0.0369 ($t = -1.85$) in Panel A and -0.0524 ($t = -2.69$) in Panel B.

Second, the estimated effect of leverage on consumption is economically meaningful. For example, the estimate, -0.0524, expresses that a one standard deviation increase (1.39%) in the debt-to-asset ratio growth leads to a 0.07% (= 0.0524 × 1.39%) decrease in consumption growth per quarter. This corresponds to 16% of the standard deviation of consumption growth and, given the importance of consumption as an economic driver, we note that the negative effect of leverage on consumption is of economic significance.

The economic implications of the negative relation between debt and consumption are interesting. First, when households' income decreases because of, e.g., job transition or losses, they must reduce their consumption level. However, this change does not occur immediately because households are willing to maintain their spending habits (stickiness of consumption). Therefore, households increase their leverage to enable the transition to a lower consumption state.

Table 2.2. Maximum Likelihood Estimation of Consumption Function

The table reports maximum likelihood estimates of the parameters in consumption function along with the associated t-statistics in parentheses. Panel A reports estimates of the parameters in the following regression:

$$\Delta c_{t+1} = \alpha + \beta \Delta d_t + \sigma_\eta \eta_{t+1}$$

where Δc_{t+1} is the natural logarithm of consumption growth, Δd_t is the natural logarithm of debt-to-asset ratio growth and $Var(\eta_{t+1}) = 1$. Panel B reports estimates of the parameters in the following regression:

$$\Delta c_{t+1} = \alpha + \beta \Delta d_t + \phi z_{t+1} + \sigma_e e_{t+1}$$

where z_{t+1} is a latent component and where $e_{t+1} \sim N(0,1)$. z_{t+1} is assumed to have an AR (1) process:

$$z_{t+1} = \rho z_t + \sqrt{1-\rho^2} u_{t+1}$$

where $u_{t+1} \sim N(0,1)$. ϕ is restricted to have a positive value for the identification purpose. TL, CC and HM denote total liabilities, consumer credit and home mortgages. TA, FA and NA denote total assets, financial assets and nonfinancial assets. Each column heading denotes the leverage measure used in the estimation.

	TL/TA	TL/FA	TL/NA	CC/TA	CC/FA	CC/NA	HM/TA	HM/FA	HM/NA
Panel A: Biased Estimates									
α	0.0049	0.0049	0.0049	0.0049	0.0049	0.0049	0.0050	0.0049	0.0049
	(16.33)	(16.33)	(16.33)	(16.33)	(16.33)	(16.33)	(16.67)	(16.33)	(16.33)
β	-0.0369	-0.0292	-0.0066	-0.0266	-0.0236	-0.0104	-0.0400	-0.0304	-0.0228
	(-1.85)	(-2.01)	(-0.25)	(-1.72)	(-1.92)	(-0.54)	(-2.17)	(-2.24)	(-0.89)
σ_η	0.0045	0.0045	0.0045	0.0045	0.0045	0.0045	0.0045	0.0045	0.0045
	(22.50)	(22.50)	(22.50)	(22.50)	(22.50)	(22.50)	(22.50)	(22.50)	(22.50)
Panel B: Unbiased Estimates									
α	0.0050	0.0050	0.0049	0.0050	0.0050	0.0050	0.0051	0.0050	0.0049
	(8.28)	(8.16)	(8.38)	(8.11)	(7.99)	(8.48)	(8.32)	(8.18)	(8.46)
β	-0.0524	-0.0406	0.0043	-0.0487	-0.0391	-0.0276	-0.0540	-0.0403	-0.0081
	(-2.69)	(-3.00)	(0.15)	(-3.16)	(-3.37)	(-1.25)	(-2.85)	(-3.06)	(-0.25)
ϕ	0.0035	0.0034	0.0035	0.0035	0.0035	0.0035	0.0034	0.0034	0.0035
	(8.55)	(8.50)	(8.71)	(8.71)	(8.63)	(8.77)	(8.46)	(8.42)	(8.70)
ρ	0.7688	0.7752	0.7398	0.7716	0.7777	0.7418	0.7718	0.7772	0.7375
	(10.72)	(11.19)	(9.78)	(10.99)	(11.04)	(9.41)	(11.11)	(10.91)	(9.65)
σ_e	0.0029	0.0029	0.0029	0.0029	0.0029	0.0029	0.0030	0.0030	0.0029
	(10.74)	(10.99)	(9.90)	(10.75)	(10.90)	(9.70)	(10.92)	(10.95)	(9.83)

Second, the wealth effect in behavioural economics indicates that consumers spend more when their net wealth increases as they feel secure about their financial soundness. This implies that households reduce their spending when their net worth (or debt-to-asset ratio) decreases (increases).[13] Third, from the financial institutions' perspective, an accumulation of debt or a sharp increase in household leverage is not a desirable feature. During economic downturns, credit constraints keep highly levered households from borrowing additional funds. This forces households to cut their spending as described in previous studies, e.g., Dynan (2012) and Mian, Sufi and Rao (2013).[14]

Fourth, the burden of debt redemption reduces cash holdings. In most cases, interest and principal are paid as cash when redeeming outstanding debt, and consumers facing an unusual increase in their leverage have two choices: increase debt further or cut their spending. Even if financial institutions decide to provide additional funds to households in the interim, credit constraints will become binding when household debt eventually reaches the credit constraint threshold, at which point no further consumption can be funded with debt.

Our research results contradict the theoretical finding pertaining to the stochastic process of consumption presented in Hall (1978). The author argues that the level of consumption follows a random walk under the permanent income hypothesis (PIH) and its growth is unpredictable as a result.

[13] See Case, Quigley and Shiller (2005, 2013), Campbell and Cocco (2007), Greenspan and Kennedy (2008) and Carroll, Otsuka and Slacalek (2011) for further details about the wealth effect, particularly related to housing.
[14] If an increase in leverage results from a decrease in the value of assets (such as housing), households experience credit constraints because a decrease in the value of assets implies a devaluation of households' collateral.

2.3.4. Vector Autoregression

In general, debt redemption is slow, even for short-term debt such as credit card debt. This suggests a longer lasting effect of debt growth on future consumption. To measure the long-lived effect of leverage, we estimate a fourth-order vector autoregression (VAR) model of debt-to-asset ratio and consumption growth to assess how a one percent positive shock to leverage affects future consumption in the long run. Even though the first-order lag is considered in the state-space model, the actual relation between household leverage and consumption can span across higher-order lags based on the long-run effect of leverage on consumption. Unreported results show that the coefficient estimates for higher-order lags beyond the fourth-order lag are insignificant at the conventional significance level (5%). These results provide support for our order lag choice.

Table 2.3 presents maximum likelihood estimates of the parameters in the VAR model. The results in the consumption equation are consistent with the evidence presented in Table 2.2, indicating a negative and significant influence of leverage on future consumption. Furthermore, higher lags show that the negative effect is not reversed which leads leverage to have a long-lived impact on future consumption.

Figure 2.3 depicts the accumulated responses of consumption growth to a one percent shock to debt-to-asset ratio growth based on the VAR model. It implies that a one percent shock to debt-to-asset ratio growth predicts a 0.23% decrease in consumption growth over the next 24 quarters. We conclude that leverage puts a long-lasting negative effect on future consumption beyond its immediate effect presented in Table 2.2.

Table 2.3. Vector Autoregression

The table reports maximum likelihood estimates of the parameters in the fourth-order vector autoregression (VAR) model of debt-to-asset ratio growth (Δd_t) and consumption growth (Δc_t) along with the associated t-statistics in parentheses. Panel A reports estimates of the parameters in the consumption equation and Panel B reports those in the debt-to-asset ratio equation. TL, CC and HM denote total liabilities, consumer credit and home mortgages. TA, FA and NA denote total assets, financial assets and nonfinancial assets. Each column heading denotes the leverage measure used in the estimation.

	TL/TA	TL/FA	TL/NA	CC/TA	CC/FA	CC/NA	HM/TA	HM/FA	HM/NA
Panel A: Consumption Equation									
Intercept	0.0022	0.0021	0.0022	0.0019	0.0019	0.0021	0.0021	0.0021	0.0022
	(4.99)	(4.79)	(4.91)	(4.44)	(4.28)	(4.95)	(4.88)	(4.78)	(4.84)
Δc_{t-1}	0.3243	0.3199	0.3449	0.3172	0.3105	0.3405	0.3322	0.3274	0.3466
	(5.26)	(5.17)	(5.63)	(5.16)	(5.04)	(5.54)	(5.39)	(5.30)	(5.65)
Δc_{t-2}	0.1259	0.1276	0.0989	0.1269	0.1289	0.1020	0.1176	0.1202	0.0978
	(1.96)	(1.99)	(1.55)	(1.99)	(2.03)	(1.60)	(1.84)	(1.88)	(1.54)
Δc_{t-3}	0.2020	0.2069	0.2101	0.2212	0.2242	0.2118	0.2079	0.2104	0.2095
	(3.13)	(3.21)	(3.30)	(3.45)	(3.49)	(3.32)	(3.24)	(3.27)	(3.29)
Δc_{t-4}	-0.0754	-0.0641	-0.0985	-0.0462	-0.0352	-0.0877	-0.0820	-0.0726	-0.1008
	(-1.22)	(-1.03)	(-1.62)	(-0.74)	(-0.56)	(-1.43)	(-1.34)	(-1.18)	(-1.65)
Δd_{t-1}	-0.0508	-0.0414	0.0060	-0.0547	-0.0447	-0.0298	-0.0512	-0.0393	-0.0129
	(-2.56)	(-2.97)	(0.20)	(-3.45)	(-3.71)	(-1.32)	(-2.69)	(-2.96)	(-0.38)
Δd_{t-2}	0.0190	0.0112	0.0082	0.0132	0.0074	0.0122	0.0206	0.0121	0.0119
	(0.95)	(0.80)	(0.27)	(0.80)	(0.60)	(0.49)	(1.07)	(0.90)	(0.32)
Δd_{t-3}	-0.0034	-0.0038	-0.0028	-0.0068	-0.0066	-0.0035	0.0009	-0.0009	-0.0018
	(-0.17)	(-0.28)	(-0.10)	(-0.41)	(-0.54)	(-0.14)	(0.04)	(-0.07)	(-0.05)
Δd_{t-4}	-0.0274	-0.0186	-0.0307	-0.0211	-0.0163	-0.0217	-0.0148	-0.0116	-0.0122
	(-1.41)	(-1.37)	(-1.06)	(-1.38)	(-1.41)	(-0.98)	(-0.78)	(-0.88)	(-0.37)

Table 2.3. Vector Autoregression (continued)

	TL/TA	TL/FA	TL/NA	CC/TA	CC/FA	CC/NA	HM/TA	HM/FA	HM/NA
Panel B: Debt-to-Asset Ratio Equation									
Intercept	-0.0025	-0.0049	0.0011	-0.0045	-0.0073	-0.0005	-0.0027	-0.0048	0.0006
	(-1.87)	(-2.54)	(1.19)	(-2.72)	(-3.38)	(-0.42)	(-1.90)	(-2.38)	(0.74)
Δc_{t-1}	0.4052	0.4844	0.0946	0.5688	0.6255	0.3193	0.3016	0.4030	-0.0693
	(2.10)	(1.76)	(0.73)	(2.44)	(2.03)	(1.91)	(1.50)	(1.40)	(-0.62)
Δc_{t-2}	0.2830	0.4665	-0.0676	0.4959	0.7087	0.1164	0.2953	0.4736	-0.0342
	(1.41)	(1.64)	(-0.50)	(2.05)	(2.23)	(0.67)	(1.41)	(1.59)	(-0.29)
Δc_{t-3}	-0.0122	0.0829	-0.1293	-0.0653	0.0531	-0.1258	-0.0081	0.0743	-0.0839
	(-0.06)	(0.29)	(-0.96)	(-0.27)	(0.17)	(-0.73)	(-0.04)	(0.25)	(-0.72)
Δc_{t-4}	0.1122	0.3022	-0.0090	0.1254	0.3582	-0.1118	0.1980	0.3455	0.1464
	(0.58)	(1.09)	(-0.07)	(0.53)	(1.14)	(-0.67)	(0.99)	(1.20)	(1.31)
Δd_{t-1}	0.2005	0.1458	0.3154	0.2666	0.1896	0.4209	0.2306	0.1704	0.4698
	(3.23)	(2.35)	(5.12)	(4.44)	(3.15)	(6.85)	(3.71)	(2.74)	(7.66)
Δd_{t-2}	0.2049	0.1661	0.2433	0.1916	0.1555	0.2663	0.2524	0.2129	0.2100
	(3.26)	(2.66)	(3.82)	(3.06)	(2.51)	(3.98)	(3.99)	(3.39)	(3.11)
Δd_{t-3}	0.2182	0.1885	0.1648	0.1846	0.1749	0.0316	0.2391	0.2133	0.0832
	(3.50)	(3.06)	(2.61)	(2.98)	(2.88)	(0.47)	(3.80)	(3.43)	(1.26)
Δd_{t-4}	-0.1579	-0.1782	0.0083	-0.2551	-0.2590	-0.0474	-0.1272	-0.1454	0.0628
	(-2.59)	(-2.95)	(0.14)	(-4.40)	(-4.48)	(-0.79)	(-2.05)	(-2.36)	(1.04)

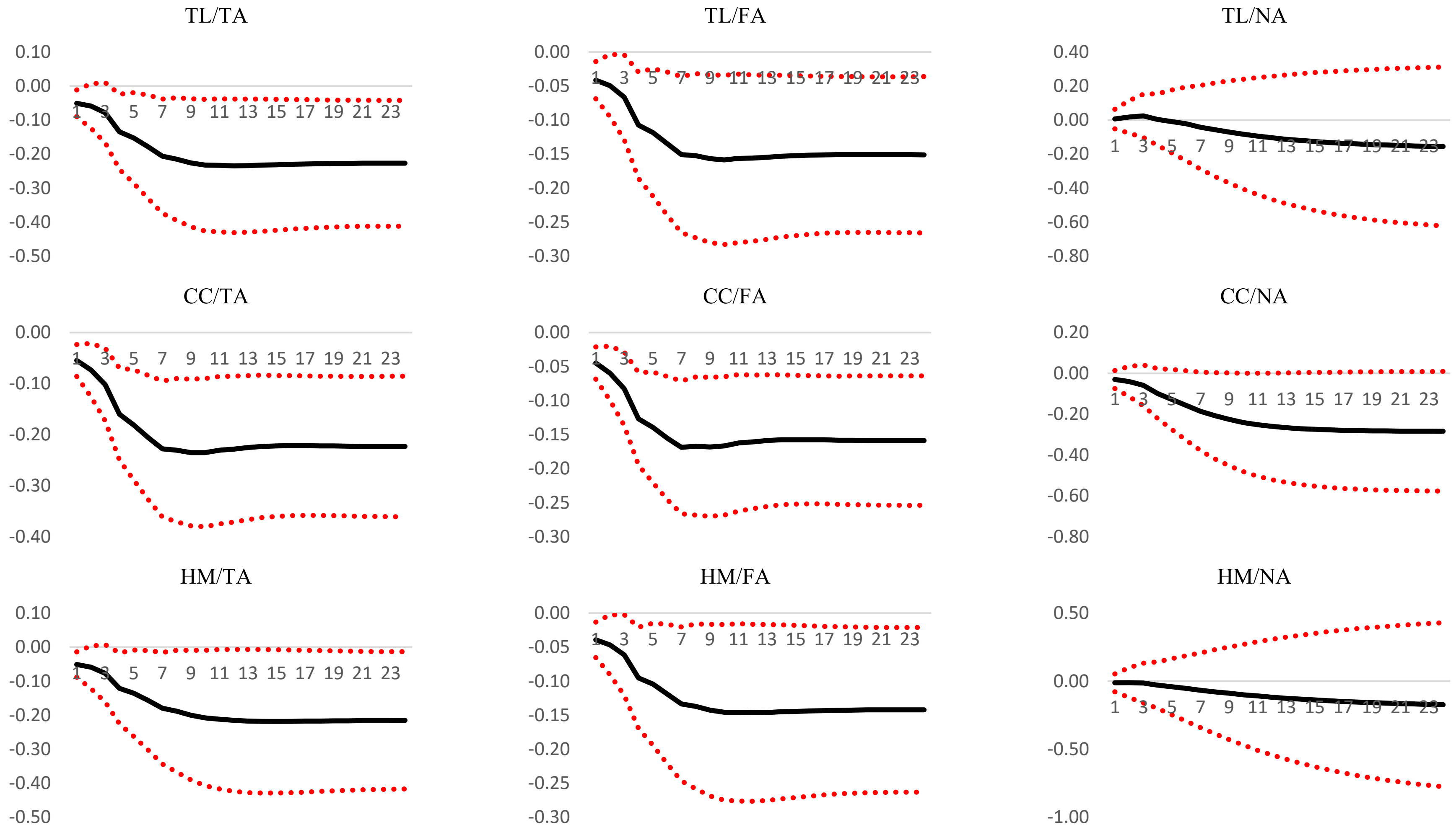

Figure 2.3. Cumulative Impulse Response Function

The figure plots the accumulated impulse response of consumption growth to a one percent positive shock to debt-to-asset ratio growth. The impulse response function is based on a fourth order vector autoregression (VAR) model of debt-to-asset ratio growth and consumption growth. The solid line represents the impulse response, and the dashed lines represent upper and lower boundaries of 95% confidence interval. The x-axis shows horizons (in quarters) and the y-axis shows the cumulative impulse response of consumption growth (in percentage terms). TL, CC and HM denote total liabilities, consumer credit and home mortgages. TA, FA and NA denote total assets, financial assets and nonfinancial assets. Each column heading denotes the leverage measure used.

2.4. Is Leverage Priced?

We have shown that shocks to household leverage have long-lasting effects on consumption growth. Expanding on this result, if households are interested in smoothing their consumption using the proceeds from their financial investments, they should be willing to pay a premium to hold assets whose returns are positively correlated with growth in their leverage. Therefore, we investigate whether this premium is reflected in asset prices.

2.4.1. Model

To derive asset pricing implications of leverage, we use Epstein and Zin's (1991) asset pricing restriction, which is the first-order condition of the investor's optimisation problem. Following Yogo (2006), we approximate the asset pricing restriction as an unconditional linear factor model and then replace consumption with its components in equation (2.1).[15] Under the specification, the approximation as an unconditional linear factor model provides:

$$E\left(R^e_{i,t+1}\right) = \beta\frac{\theta}{\psi}Cov\left(\Delta d_t, R^e_{i,t+1}\right) + \phi\frac{\theta}{\psi}Cov\left(z_{t+1}, R^e_{i,t+1}\right) + \frac{\theta}{\psi}Cov\left(e_{t+1}, R^e_{i,t+1}\right) + (1-\theta)Cov\left(r_{w,t+1}, R^e_{i,t+1}\right) \quad (2.3)$$

where $\theta \equiv (1-\gamma)/(1-1/\psi)$, $R^e_{i,t+1}$ is the excess return over risk-free rate on asset i, Δd_t is the growth rate of household leverage, z_{t+1} is a latent predictable component in consumption, e_{t+1} is an unpredictable component in consumption and $r_{w,t+1}$ is the real return on the agent's wealth. γ is the risk aversion (RA) parameter and ψ is the elasticity of intertemporal

[15] See Appendix 2.1 for details about the asset pricing restriction and unconditional linear factor model.

substitution (EIS) parameter. We estimate both the original model and the modified model, whereby the original model does not replace consumption with the consumption function shown in equation (2.1).

Similar to Epstein and Zin (1991), we assume that the agent's wealth is equivalent to the market portfolio and use the value-weighted market return obtained from the the Center for Research in Security Prices (CRSP) as the return on the market portfolio. Excess return is calculated using the risk-free rate series obtained from Kenneth R. French's website. Nominal term is converted to real term using Consumer Price Index (CPI) taken from Bureau of Labor Statistics (BLS).

Equation (2.3) implies that the sign and magnitude of the risk price of debt-to-asset ratio relies on the sign and magnitude of its effect on consumption (β), the RA parameter (γ) and the EIS parameter (ψ). Given the negative effect of leverage ($\beta < 0$), the risk price of leverage is negative either for $\gamma < 1$ and $\psi > 1$, or for $\gamma > 1$ and $\psi < 1$, while the risk price of leverage is positive either for $\gamma < 1$ and $\psi < 1$, or for $\gamma > 1$ and $\psi > 1$.[16] Previous studies like Mehra and Prescott (1985) argue that γ is greater than 10, and Hall (1988), Ogaki and Reinhart (1998) and Campbell (2003) contends that ψ is less than 1.[17] We treat coefficients in equation (2.3) as free parameters rather than as a function of the preference parameters, γ and ψ, because the purpose of this research is to examine whether household leverage, which is modelled as a component that determines future consumption, is priced rather than to examine and confirm the equilibrium model.

The terms of equation (2.3) offer associations with several important asset pricing models. The first and second terms on the right-hand side represent long run risk (LRR). Bansal and

[16] γ measures how the agent is reluctant to substitute her consumption between states of the world whereas ψ measures how the agent is reluctant to substitute her consumption between time periods (see Campbell, Lo and MacKinlay,1997).

[17] Yogo (2004) and Braun and Nakajima (2012) also report evidence that the EIS is less than 1. In contrast, Hansen and Singleton (1982), Attanasio and Weber (1989) and Gruber (2013) assert that the EIS is greater than 1.

Yaron (2004) present that LRR, which is a predictable, small and persistent component in consumption growth, is a crucial component in resolving asset pricing puzzles regarding the market risk premium and the risk-free rate. The third term represents the consumption risk implied in the traditional CCAPM since e_{t+1} has a statistical feature that satisfies the stochastic implication of Hall (1978). The fourth term represents the market risk from Sharpe's (1964) capital asset pricing model (CAPM). Overall, equation (2.3) offers a simple empirical set-up to examine whether household leverage is priced in the stock market when controlling for competing pricing factors derived from the CCAPM and CAPM.

To estimate equation (2.3), we use the two-step GMM estimation procedure of Hansen and Singleton (1982).[18] To assess the goodness-of-fit of the model, we use the J-statistic to test the null hypothesis that the pricing errors are jointly equal to zero across test assets. We use the mean absolute error (MAE) and Campbell and Vuloteenaho's (2004) R^2 to complement the J-statistic because, in the statistical sense, a higher J-statistic does not indicate better performance than a lower J-statistic as long as both statistics are simultaneously less or greater than the critical value on χ^2 distribution. The MAE is calculated as

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |\bar{e}_i| \qquad (2.4)$$

where $\bar{e}_i$ is the pricing error of the i^{th} asset and N is the number of assets used in the estimation. R^2 is computed as

$$R^2 = 1 - Var(\bar{e}_i)/Var(\bar{R}_i^e) \qquad (2.5)$$

[18] See Appendix 2.2 for details about the GMM estimation.

where $\bar{R}_i^e$ denotes the average excess return on the i^{th} asset. We compute the MAE and R^2 using residuals obtained from the first-stage estimation in which the weighting matrix is the same across models.

2.4.2. Factor Pricing

2.4.2.1. Size and B/M 25 Portfolios

Table 2.4 reports estimates of the risk price of the factors in the original and the modified linear factor models. The estimation is conducted using Size and B/M double-sorted 25 portfolios, obtained from Kenneth R. French's website, as a set of test assets. First, the estimate of the risk price for consumption, 227.93 (t = 14.10), is significant, with a magnitude similar to the estimation of other studies, e.g., Yogo (2006). Meanwhile, the estimate of the risk price for wealth, -0.07 (t = -0.14), is neither positive nor significant, which is inconsistent with the implication of the CAPM (Sharpe, 1964).

Second, when replacing consumption with its components, we observe that leverage has a negative and statistically significant risk price, regardless of how leverage is measured, except for one case. For instance, the estimate of the risk price for a debt-to-asset ratio computed with total liabilities and assets is -56.02 (t = -6.87). This implies that the leverage factor contributes to explaining the cross-sectional variation in stock returns, even if asset pricing factors derived from the CCAPM are controlled for.

The latent predictable component, z_{t+1}, has a positive risk price, which is consistent with the prediction of the LRR model. The error term, e_{t+1}, predominantly has a negative risk price, which is inconsistent with the prediction of the traditional CCAPM in which consumption is unpredictable. Furthermore, the replacement of consumption with our consumption function improves the model's performance. For example, MAE decreases from 0.29% to 0.21% and R^2 increases from 0.54 to 0.77.

Overall, the results in Table 2.4 are consistent with our expectation based on (1) the negative relation between leverage and consumption presented in Tables 2.2 and 2.3 and based on (2) the implications of the CCAPM. Our results suggest that investors perceive high debt-to-asset ratio periods as a bad state because they have to curtail consumption for debt redemption and thus investors are indeed willing to accept lower expected returns when holding securities that are good hedges against debt-to-asset ratio growth.

2.4.2.2. Other Test Assets

Benchmarking against Size and B/M double-sorted 25 portfolios has long been a staple in the asset pricing literature. Household leverage correlates with firm level leverage and therefore with firm characteristics for the priced factors since credit conditions affect financing decisions of both households and firms. To assess the full extent of household leverage as a novel asset pricing factor, this chapter estimates the factor model using other sets of test assets capturing traditional anomalies: (1) accrual (Sloan, 1996), (2) net stock issues (Daniel and Titman, 2006; Pontiff and Woodgate, 2008), (3) momentum (Jegadeesh and Titman, 1993), (4) short-term reversal (Jegadeesh, 1990; Lehmann, 1990) and (5) long-term reversal (De Bondt and Thaler, 1985, 1987). Each set of test assets is double-sorted on the corresponding variable along with Size, and data for these new test assets are obtained from Kenneth R. French's website. This chapter estimates both the original and modified CCAPM as in the previous section with sets of test assets capturing the above-mentioned anomalies.[19]

[19] While the above mentioned anomalies have challenged the efficient market hypothesis (EMH), recent research by Hou, Xue and Zhang (2020) shows that 65% of the 452 anomalies reported in the finance literature do not exhibit a significance level of 5% or better in their statistical test.

While presenting the entire results obtained from the estimation could be advantageous for understanding the factor model, our main research interest lies in determining the risk price for leverage based on its relation with consumption. Thus, to keep our result reporting focused, Table 2.5 reports signs of risk price estimates for consumption and leverage with an indication of statistical significance. The results show that investors hedge against leverage. First, most risk price estimates are statistically significant at the 5% significance level. Second, while a negative consumption risk price may surprise, the results in the table show that the leverage risk price depends on the consumption risk price. For most cases, household consumption (leverage) has a positive (negative) risk price.

Table 2.4. Estimation of Unconditional Linear Factor Model

The table reports estimates of the risk prices in the original and modified linear factor models along with the associated t-statistics in parentheses calculated based on the heteroskedasticity autocorrelation consistent (HAC) standard errors. Test assets are Size and B/M double-sorted 25 portfolios. The two-step GMM procedure is used in estimating the models. $r_{w,t+1}$ is the market portfolio return. Δc_{t+1} is consumption growth. Δd_t is debt-to-asset ratio growth. z_{t+1} is a latent predictable component in consumption. e_{t+1} is an unpredictable component in consumption. Statistics for goodness-of-fit of the model, mean absolute error (MAE), R^2 and the J-statistic, are reported. MAE and R^2 are computed from the first-stage estimation. The p-values for the J-statistics are presented in parentheses. TL, CC and HM denote total liabilities, consumer credit and home mortgages. TA, FA and NA denote total assets, financial assets and nonfinancial assets. Each column heading below the 'Modified CCAPM' column denotes the leverage measure used in the estimation.

	Original CCAPM	Modified CCAPM								
		TL/TA	TL/FA	TL/NA	CC/TA	CC/FA	CC/NA	HM/TA	HM/FA	HM/NA
$r_{w,t+1}$	-0.07	3.18	3.31	1.32	2.92	3.06	1.50	3.59	3.53	2.82
	(-0.14)	(5.58)	(5.71)	(2.12)	(5.04)	(5.23)	(3.09)	(6.50)	(6.25)	(4.68)
Δc_{t+1}	227.93									
	(14.10)									
Δd_t		-56.02	-35.26	70.04	-45.45	-31.66	-59.56	-41.90	-29.19	-85.47
		(-6.87)	(-6.41)	(8.38)	(-7.69)	(-7.07)	(-12.35)	(-6.27)	(-6.15)	(-11.17)
z_{t+1}		1.56	1.59	0.79	1.68	1.68	1.13	1.58	1.54	1.06
		(9.69)	(10.15)	(5.96)	(10.47)	(10.49)	(8.80)	(9.82)	(10.03)	(6.66)
e_{t+1}		-439.33	-374.67	148.37	-472.86	-403.41	-317.70	-361.74	-331.26	-310.50
		(-8.35)	(-8.01)	(3.30)	(-8.77)	(-8.14)	(-7.44)	(-7.79)	(-7.81)	(-5.85)
MAE (%)	0.29	0.21	0.17	0.24	0.25	0.22	0.25	0.22	0.18	0.23
R^2	0.54	0.77	0.80	0.69	0.69	0.74	0.70	0.74	0.81	0.72
J-statistic	624.51	419.76	373.45	404.36	299.50	290.62	596.39	351.29	357.50	408.19
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 2.5. Different Test Assets

The table presents the signs of the risk price estimates for the factors in the models and underlying estimate values are omitted for brevity. N denotes a negative risk price and P denotes a positive risk price. To estimate the models, the two-step GMM procedure is used. Sets of test assets capture the following anomalies: accrual, net stock issues, momentum, short-term reversal and long-term reversal. Each set of test assets are double-sorted on the corresponding variable along with Size. The consumption column reports the sign of consumption risk price and the debt-to-asset ratio columns report that of debt risk price. Bold font indicates that the risk price estimate retains the statistical significance at the 5% level. TL, CC and HM denote total liabilities, consumer credit and home mortgages. TA, FA and NA denote total assets, financial assets and nonfinancial assets. Each column heading below the 'Modified CCAPM' column denotes the leverage measure used in the estimation.

	Original CCAPM	Modified CCAPM								
		TL/TA	TL/FA	TL/NA	CC/TA	CC/FA	CC/NA	HM/TA	HM/FA	HM/NA
Accrual	**N**	**P**	P	**P**	**P**	P	**N**	P	P	**P**
Net Stock Issues	**P**	**N**	**N**	**N**	**N**	**N**	**N**	**N**	**N**	**P**
Momentum	**P**	**N**	**N**	**N**	**N**	**N**	**N**	**N**	**N**	**N**
Short-Term Reversal	**P**	**N**	**N**	**N**	**N**	**P**	**N**	**N**	**N**	**N**
Long-Term Reversal	**P**	**N**	**N**	**N**	**N**	**N**	**N**	**N**	**N**	**N**

2.5. Towards a New Pricing Factor

The previous section provides the empirical evidence that household leverage is priced using the portfolio level test assets. In this section, we examine asset pricing implications of leverage at the individual stock level.

2.5.1. Data

For our empirical analysis, we obtain data for all common stocks traded on the NYSE or AMEX from the Center for Research in Security Prices (CRSP). Following Boguth and Kuehn (2013), we exclude NASDAQ traded stocks to minimise the dominance of small- and micro-caps.[20] Data on accounting variables for the stocks included in the sample are obtained from COMPUSTAT.

For stocks included in the initial sample spanning from 1952 to 2018, the following variables are constructed: size (Size), book-to-market ratio (B/M) and momentum (MOM). Following Fama and French (1993), Size is the market capitalisation at the end of June of year t and B/M is calculated as book value of equity in year $t-1$ divided by market value of equity at the end of December of year $t-1$. Size and B/M are matched with excess returns from July of year t to June of year $t+1$. MOM is the cumulative excess return from month $t-12$ to month $t-2$ as in Fama and French (2016). Firms with missing values for the above-mentioned variables are excluded.

The level of leverage exhibits a gradually increasing trend during the period from 1952 to 2000. However, the speed of increase becomes more rapid from 2000 and the level of leverage

[20] As an alternative to excluding NASDAQ securities, one could also remove stocks with a price of less than $5 across all exchanges. However, in doing so, the dominance of small- and micro-caps. cannot be minimised in our regression approach.

starts to decrease from 2009. This structural change that emerges around 2000 in household leverage leads to separating the full sample period into pre- and post-2000 subsample periods. The motivation of this chapter is that investors are willing to hedge against their leverage to secure their consumption. If one assumes a constant relation between household leverage and consumption, the hedging motive against the leverage should become reinforced (eroded) as the leverage fluctuates more (less). This notion is consistent with the implication of the original CCAPM (i.e., investors are expected to not want to hedge against their consumption if a stream of their spending is constant over time). Hence, we divide the entire sample period into two subsample periods (pre- and post-2000) and repeat the same empirical analysis for these two periods to assess whether the leverage premium varies as the degree of fluctuation in household leverage changes.

2.5.2. Risk Loading

To estimate the exposure of individual stocks to the state variables implied in equation (2.3), we run the following time-series regression at the end of year t using quarterly observations over the past 8 years:

$$R^e_{i,t+1} = \beta^0_{i,t^*} + \beta^d_{i,t^*}\Delta d_t + \beta^z_{i,t^*} z_{t+1} + \beta^e_{i,t^*} e_{t+1} + \beta^w_{i,t^*} r_{w,t+1} + \epsilon_{i,t+1} \qquad (2.6)$$

where $t \in \{t^* - 31, t^*\}$ indexes quarters, $R^e_{i,t+1}$ is the excess return over risk-free rate on individual asset i, Δd_t is the growth rate of household leverage, z_{t+1} is a latent predictable component in consumption, e_{t+1} is an unpredictable component in consumption and $r_{w,t+1}$ is the value-weighted market return obtained from the Center for Research in Security Prices (CRSP). Firms are required to have at least 30 valid observations for the stable estimation, and the loadings at the end of year $t-1$ are matched with excess returns in year $t+1$. Because of the 32 (at least 30) quarters look-back period for estimating the risk loadings, the sample period spans from 1960 to 2018.

2.5.3. Fama-MacBeth Regression

This subsection investigates the impact of leverage on asset pricing at the individual stock level using the Fama-MacBeth regression method. We estimate the following cross-sectional regression of monthly excess returns on risk loading estimates and a set of control variables for known priced factors month-by-month:

$$R_{i,t+1}^{e} = \gamma_{t+1}^{0} + \gamma_{t+1}^{d}\hat{\beta}_{i,t}^{d} + \gamma_{t+1}^{z}\hat{\beta}_{i,t}^{z} + \gamma_{t+1}^{e}\hat{\beta}_{i,t}^{e} + \gamma_{t+1}^{w}\hat{\beta}_{i,t}^{w} + \gamma_{t+1}^{X}X_{i,t} + \eta_{i,t+1} \quad (2.7)$$

where $\hat{\beta}_{i,t}^{d}$, $\hat{\beta}_{i,t}^{z}$, $\hat{\beta}_{i,t}^{e}$ and $\hat{\beta}_{i,t}^{w}$ are estimates of risk loadings in equation (2.6) and $X_{i,t}$ is a vector of control variables including Size, B/M and MOM. Following Boguth and Kuehn (2013), the independent variables are normalised to have zero mean and unit variance at each month except for MOM. The purpose of this normalisation is as follows: it (1) prevents from obtaining the unusual size of coefficient estimates due to a dissimilar scale between the independent and dependent variables and (2) enables to assess the effect of a one standard deviation increase in the risk loading on the excess return as it leads the standard deviation of the risk loading to have an identical value over time.

Table 2.6. reports results obtained from the Fama-MacBeth regressions. The table shows that premiums for consumption and wealth are positive, however, the results lack statistical significance. In other words, both the CCAPM and CAPM fail to describe the cross-section of stock returns as shown in the previous literature (see Black, Jensen and Scholes, 1972; Mankiw

and Shapiro, 1986; Fama and French, 1992; Lettau and Ludvigson, 2001a; Boguth and Kuehn, 2013; Frazzini and Pedersen, 2014).

The results for household leverage lack significance for the full sample (Panel A) and the subsample ending 1999 (Panel B). However, and acknowledging the statistical significance differs across the leverage specifications, for the subsample covering the period 2000 onwards (Panel C), we observe that household leverage tends to emerge as a significant factor at the 5% significance level in four of nine leverage specifications. Meanwhile, traditional anomalies experience a decrease in statistical significance compared to the full and pre-2000 sample. The coefficient estimate, -0.13 (t = -2.03) indicates that a one standard deviation increase in the exposure to leverage predicts a 0.13% percentage points per month decrease in excess returns. Other consumption components, z_{t+1} and e_{t+1}, do not command a significant premium in the sample periods.

Looking at other specifications of household leverage, we observe that mortgage redemption risk appears to be an essential driver, indicating that the statistical significance is a result of the fast growth of the subprime mortgage market and the sharp deleveraging following the eruption of the crisis. This observation further supports our motivation for this subsample investigation, i.e., the build-up of the subprime mortgage market and the sharp leveraging and deleveraging around the time of the subprime mortgage crisis is an important component in understanding the leverage risk premium.

Table 2.6. Fama-MacBeth Regression

The table reports average coefficient estimates on risk loadings and firm characteristics in cross-sectional regressions of the percent excess return along with the associated Newey and West (1987) adjusted t-statistics in parentheses. Risk loadings are obtained from 8-year rolling time-series regressions of the excess return over consumption growth, Δc_{t+1} (β^c) and wealth growth, $r_{w,t+1}$ (β^w), in the case of the original model, and over leverage growth, Δd_{t+1} (β^d), a latent predictable component in consumption, z_{t+1} (β^z), an unpredictable component in consumption, e_{t+1} (β^e), and wealth growth, $r_{w,t+1}$ (β^w), in the case of the modified model. Firm characteristics include Size, B/M and MOM. Panel A reports results of the entire sample period and Panels B and C report those of the subsample periods. TL, CC and HM denote total liabilities, consumer credit and home mortgages. TA, FA and NA denote total assets, financial assets and nonfinancial assets. Each column heading below the 'Modified CCAPM' column denotes the leverage measure used in the estimation.

	Original CCAPM	Controls	Modified CCAPM								
			TL/FA	TL/FA	TL/NA	CC/TA	CC/FA	CC/NA	HM/TA	HM/FA	HM/NA
Panel A: Full Sample (196001 - 201812)											
β^c	0.03										
	(0.70)										
β^w	0.06		0.02	0.01	0.02	0.01	0.01	0.03	0.01	0.01	0.02
	(0.87)		(0.27)	(0.20)	(0.39)	(0.24)	(0.17)	(0.45)	(0.20)	(0.15)	(0.39)
β^d			-0.01	-0.01	0.02	0.00	-0.01	0.01	-0.02	-0.02	-0.02
			(-0.36)	(-0.41)	(0.51)	(0.02)	(-0.18)	(0.39)	(-0.85)	(-0.73)	(-0.61)
β^z			-0.02	-0.02	0.00	-0.02	-0.02	-0.01	-0.02	-0.02	0.00
			(-0.48)	(-0.46)	(-0.00)	(-0.40)	(-0.43)	(-0.17)	(-0.55)	(-0.47)	(0.08)
β^e			-0.01	-0.02	0.02	-0.01	-0.02	0.01	-0.02	-0.02	0.02
			(-0.28)	(-0.39)	(0.45)	(-0.36)	(-0.46)	(0.15)	(-0.44)	(-0.47)	(0.50)
ln(Size)		-0.12	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13
		(-1.95)	(-2.52)	(-2.49)	(-2.42)	(-2.51)	(-2.47)	(-2.51)	(-2.54)	(-2.50)	(-2.45)
ln(B/M)		0.13	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.11
		(3.19)	(3.14)	(3.11)	(3.09)	(3.17)	(3.14)	(3.23)	(3.17)	(3.14)	(3.06)
MOM		0.59	0.59	0.60	0.59	0.58	0.59	0.58	0.59	0.60	0.59
		(2.91)	(3.16)	(3.22)	(3.24)	(3.15)	(3.21)	(3.13)	(3.17)	(3.22)	(3.22)

Table 2.6. Fama-MacBeth Regression (continued)

	Original CCAPM	Controls	Modified CCAPM								
			TL/FA	TL/FA	TL/NA	CC/TA	CC/FA	CC/NA	HM/TA	HM/FA	HM/NA
Panel B: Subsample (196001 - 199912)											
β^c	0.03										
	(0.80)										
β^w	0.06		0.04	0.04	0.04	0.04	0.04	0.05	0.04	0.03	0.04
	(0.76)		(0.64)	(0.58)	(0.68)	(0.67)	(0.60)	(0.78)	(0.57)	(0.55)	(0.59)
β^d			0.05	0.03	0.06	0.04	0.03	0.05	0.03	0.03	0.04
			(1.38)	(1.15)	(1.50)	(1.12)	(0.90)	(1.20)	(1.15)	(0.96)	(1.36)
β^z			0.00	0.00	0.00	-0.01	-0.01	0.00	0.00	0.00	0.00
			(-0.09)	(-0.08)	(-0.08)	(-0.15)	(-0.18)	(0.03)	(-0.08)	(-0.05)	(-0.01)
β^e			0.04	0.04	0.04	0.04	0.03	0.04	0.03	0.03	0.04
			(0.89)	(0.84)	(0.91)	(0.80)	(0.77)	(0.85)	(0.77)	(0.77)	(0.89)
ln(Size)		-0.12	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13
		(-1.52)	(-1.91)	(-1.87)	(-1.94)	(-1.94)	(-1.88)	(-1.97)	(-1.89)	(-1.85)	(-1.90)
ln(B/M)		0.17	0.16	0.16	0.16	0.17	0.16	0.16	0.17	0.16	0.15
		(3.78)	(3.86)	(3.87)	(3.74)	(3.98)	(3.95)	(3.98)	(3.92)	(3.92)	(3.67)
MOM		0.97	0.96	0.96	0.95	0.93	0.94	0.93	0.96	0.96	0.98
		(5.31)	(5.98)	(5.96)	(5.99)	(5.81)	(5.86)	(5.82)	(5.98)	(5.95)	(6.16)

Table 2.6. Fama-MacBeth Regression (continued)

	Original CCAPM	Controls	Modified CCAPM								
			TL/FA	TL/FA	TL/NA	CC/TA	CC/FA	CC/NA	HM/TA	HM/FA	HM/NA
Panel C: Subsample (200001 - 201812)											
β^c	0.03										
	(0.24)										
β^w	0.07		-0.03	-0.04	-0.02	-0.05	-0.05	-0.02	-0.04	-0.05	-0.01
	(0.46)		(-0.28)	(-0.34)	(-0.18)	(-0.38)	(-0.40)	(-0.21)	(-0.33)	(-0.38)	(-0.09)
β^d			-0.13	-0.11	-0.06	-0.08	-0.08	-0.06	-0.14	-0.12	-0.15
			(-2.03)	(-1.80)	(-0.78)	(-1.25)	(-1.28)	(-0.92)	(-2.37)	(-1.98)	(-2.27)
β^z			-0.06	-0.06	0.01	-0.04	-0.04	-0.03	-0.07	-0.06	0.01
			(-0.58)	(-0.57)	(0.08)	(-0.42)	(-0.44)	(-0.26)	(-0.69)	(-0.61)	(0.13)
β^e			-0.12	-0.13	-0.03	-0.12	-0.13	-0.06	-0.13	-0.13	-0.02
			(-1.39)	(-1.50)	(-0.38)	(-1.43)	(-1.52)	(-0.77)	(-1.51)	(-1.57)	(-0.27)
ln(Size)		-0.12	-0.15	-0.14	-0.13	-0.14	-0.14	-0.14	-0.15	-0.15	-0.14
		(-1.27)	(-1.74)	(-1.74)	(-1.48)	(-1.67)	(-1.69)	(-1.60)	(-1.82)	(-1.79)	(-1.60)
ln(B/M)		0.03	0.02	0.02	0.02	0.02	0.01	0.02	0.02	0.02	0.03
		(0.45)	(0.25)	(0.22)	(0.33)	(0.21)	(0.18)	(0.31)	(0.25)	(0.21)	(0.41)
MOM		-0.22	-0.18	-0.15	-0.18	-0.15	-0.13	-0.16	-0.18	-0.15	-0.22
		(-0.46)	(-0.40)	(-0.34)	(-0.42)	(-0.33)	(-0.30)	(-0.36)	(-0.40)	(-0.33)	(-0.51)

2.5.4. Portfolio Formation

To further investigate the relation between assets' exposures to household leverage and the cross-section of asset returns, we build quintile portfolios sorted on leverage exposure. Stocks included in the sample are allocated to quintile groups based on their exposure to leverage at the beginning of year t and held until the end of year t, resulting in five equal-weighted portfolios.

Table 2.7 reports properties of the equal-weighted quintile portfolios. The results indicate that leverage commands a negative premium in the post-2000 period (Panel C) but not in the pre-2000 period (Panel B) and not in the 1960-2018 period (Panel A). In Panel C, the expected return tends to decrease from 1.00% to 0.70% per month as exposure to leverage increases. The difference between the bottom and top quintiles is 0.31% ($t = 1.95$) per month. There is no systematic pattern emerging in Size or B/M. This implies that the cross-sectional dispersion in Size or B/M is not a cause for leverage premium. MOM tends to decrease as exposure to leverage increases.

Table 2.7. Properties of Debt Beta Sorted Portfolios

The table reports properties of quintile portfolios sorted on leverage exposure. Stocks are assigned to quintile groups based on leverage exposure at the beginning of year t and held until the end of year t. This sort produces five equal-weighted portfolios. Properties reported include mean and standard deviation of the excess return on the quintile portfolios and firm characteristics including β^d (leverage beta), Size, B/M and MOM. The table also reports t-statistics for the mean excess returns. The column 'Low-High' shows results for a zero investment portfolio that is long in the bottom quintile and short in the top quintile. Panel A reports results pertaining to the full sample period and Panels B and C report results pertaining to subsample periods as indicated.

	1 (Low)	2	3	4	5 (High)	Low-High
Panel A: Full Sample (Jan-1960 - Dec-2018)						
			Return (%)			
Mean	0.79	0.79	0.74	0.78	0.74	0.05
Std. Dev.	5.90	5.06	4.76	4.82	5.62	2.22
t-stat.	3.58	4.17	4.11	4.29	3.52	0.59
			Firm Characteristics			
β^d	-3.99	-1.29	-0.05	1.15	3.76	
ln(Size)	12.31	13.03	13.18	13.17	12.58	
ln(B/M)	-0.35	-0.37	-0.38	-0.38	-0.34	
MOM (%)	15.74	13.18	12.48	12.10	12.44	
Panel B: Subsample (Jan-1960 - Dec-1999)						
			Return (%)			
Mean	0.69	0.74	0.69	0.76	0.77	-0.07
Std. Dev.	6.03	5.12	4.79	4.72	5.26	2.13
t-stat.	2.52	3.17	3.17	3.53	3.20	-0.77
			Firm Characteristics			
β^d	-4.33	-1.46	-0.16	1.04	3.38	
ln(Size)	11.57	12.28	12.48	12.57	12.06	
ln(B/M)	-0.23	-0.24	-0.26	-0.28	-0.27	
MOM (%)	15.44	13.77	13.15	12.76	12.53	
Panel C: Subsample (Jan-2000 - Dec-2018)						
			Return (%)			
Mean	1.00	0.91	0.82	0.81	0.70	0.31
Std. Dev.	5.64	4.95	4.70	5.03	6.32	2.39
t-stat.	2.69	2.76	2.64	2.44	1.66	1.95
			Firm Characteristics			
β^d	-3.27	-0.93	0.18	1.38	4.55	
ln(Size)	13.89	14.63	14.65	14.42	13.66	
ln(B/M)	-0.60	-0.67	-0.64	-0.60	-0.50	
MOM (%)	16.37	11.92	11.08	10.69	12.27	

2.5.5. New Pricing Factor

The results presented in Tables 2.6 and 2.7 suggest that the weakening of market anomalies coincides with the emergence of the leverage premium and that the leverage premium relates to momentum, raising the question about the relation between the leverage premium and other known premiums. To address this question, we take a zero investment portfolio, 'Low-High', from Table 2.7 that represents a long position in stocks with a low exposure to debt (in the bottom quintile) and short positions in stocks with a high exposure to debt (in the top quintile) and name it as 'DBT'. Then, we compare DBT with the Fama-French-Carhart (FFC) four factors that are designed to capture market (MKT), size (SMB), value (HML) and momentum (MOM) premiums.

The results in Panel A of Table 2.8 show that a mean of DBT is greater than those of SMB (0.25% per month), HML (0.27% per month) and MOM (0.21% per month), while the standard deviation of DBT is less than those of SMB (3.31% per month), HML (3.14% per month) and MOM (5.33% per month). The results in Panel B of Table 2.8 present that the correlation coefficient between DBT and MOM is equal to 0.35 and between DBT and SMB is equal to -0.27.

To examine the independence of the leverage premium and market-wide phenomena, we run spanning regressions that are similar to the ones used by Fama and French (2015) and Barillas and Shanken (2017), i.e., we regress each factor against a linear combination of the other factors. Results in Panel C of Table 2.8 show that small-cap firms or firms with poor past performance are more sensitive to the leverage factor, in line with the correlation coefficients reported for DBT, SMB and MOM.

Importantly, the intercept in the regression of DBT is statistically significant at the 5% level, whereas the intercepts in the regressions of SMB and MOM are statistically insignificant. The intercept in the regression of DBT is 0.33 (t = 2.32) and its magnitude is similar to that of the leverage premium presented in Panel A. Together, these results indicate that (1) DBT is not a by-product of other known priced factors and that (2) household leverage is a fundamental and significant force in determining the cross-section of asset returns.

Table 2.8. Factor Competition

The table presents properties of factor premiums. Panel A presents descriptive statistics of the market premium (MKT), size premium (SMB), value premium (HML), momentum premium (MOM) and leverage premium (DBT). DBT is a factor that buys stocks with a low exposure to debt and sells those with a high exposure to debt. See "Low-High" reported in Table 2.7. Panel B shows correlation coefficients between factors. Panel C shows coefficient estimates obtained from time-series regressions of the respective factors onto a combination of other pricing factors along with the associated t-statistics. The sample period spans from Jan-2000 to Dec-2018.

Panel A: Descriptive Statistics

	Mean (%)	Std. Dev. (%)	Min. (%)	Max. (%)	t-stat.
MKT	0.38	4.35	-17.23	11.35	1.33
SMB	0.25	3.31	-16.86	21.70	1.15
HML	0.27	3.14	-11.18	12.87	1.28
MOM	0.21	5.33	-34.39	18.36	0.60
DBT	0.31	2.39	-6.88	8.46	1.95

Panel B: Correlation

	MKT	SMB	HML	MOM	DBT
MKT	1	0.26	-0.06	-0.35	-0.16
SMB	0.26	1	-0.26	0.11	-0.27
HML	-0.06	-0.26	1	-0.17	-0.04
MOM	-0.35	0.11	-0.17	1	0.35
DBT	-0.16	-0.27	-0.04	0.35	1

Panel C: Factor Pricing

	Intercept	MKT	SMB	HML	MOM	DBT	R-Square
MKT	0.33		0.41	-0.07	-0.34	0.13	0.22
	(1.26)		(4.81)	(-0.81)	(-6.41)	(1.08)	
SMB	0.33	0.23		-0.21	0.19	-0.47	0.25
	(1.67)	(4.81)		(-3.37)	(4.52)	(-5.45)	
HML	0.39	-0.04	-0.23		-0.09	-0.09	0.09
	(1.90)	(-0.81)	(-3.37)		(-1.90)	(-0.91)	
MOM	0.07	-0.46	0.45	-0.19		0.81	0.30
	(0.25)	(-6.41)	(4.52)	(-1.90)		(6.18)	
DBT	0.33	0.04	-0.25	-0.04	0.18		0.22
	(2.32)	(1.08)	(-5.45)	(-0.91)	(6.18)		

2.6. Conclusion

The increase in leverage of the nonfinancial sector world-wide is one of the defining economic trends of the 21st centuries. The rapid leveraging and deleveraging of households around the subprime mortgage crisis show a negative and long-lived effect on subsequent spending. The asset pricing literature has shown that investors are willing to pay a premium for securities whose return allows the offset of negative influences on consumption, indicating that leverage should be a priced factor.

To investigate the relation between leverage and consumption, we use U.S. household data spanning from 1952 to 2018. Our evidence shows that leverage has a significant influence on the future consumption over the entire sample period, indicating that households take their debt redemption schedule into account when planning their spending schedule. Households cut their consumption on nondurables and services when their leverage ratio increases, a behaviour similar to that observed in the Great Depression in the 1930s.

This research infers an asset pricing implication of household leverage from its relation to consumption in the CCAPM. The CCAPM is modified to incorporate household leverage into the model. Using test assets capturing market anomalies, our results reveal that a premium is paid for purchasing securities that earn superior returns when consumption is depressed due to debt redemption. This indicates that investors want to hedge against their leverage to secure a stream of spending.

For a more in-depth confirmation of the asset pricing evidence, we expand our analysis to include individual stock returns. To this aim, and following Fama and MacBeth (1973), we run rolling time-series regressions at the end of each year using data over the past 32 quarters to estimate individual stocks' exposures to debt and month-by-month cross-sectional regressions to confirm the leverage risk premium. The results show that leverage has a negative risk premium in the post-2000 period.

Finally, we construct a debt risk factor, i.e., buying stocks with the low exposure to debt and selling those with the high exposure to debt, and show that this asset pricing implication is not captured by other well-known market anomalies and that in turn it can help to explain size and momentum factor returns in the post-2000 period.

We conclude that the consideration of the long-term effect of leveraging and deleveraging dynamics of the nonfinancial sector on asset prices is important for investment decisions and for policy making to anticipate, manage and respond to economic shocks and crises, especially when these shocks lead to output contraction which forces households to increase their leverage in order to smooth current consumption patterns.

Appendix 2.1. Consumption Based Asset Pricing Model

Asset Pricing Restriction

This chapter considers the agent with the Epstein and Zin (1991) recursive preferences. The authors present that the asset pricing restriction derived from the first-order condition of the maximisation problem for optimal consumption and portfolio choice faced by the agent is:

$$E_t\left[\delta^{\theta}\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}} R_{w,t+1}^{(\theta-1)} R_{i,t+1}^{e}\right] = 0 \qquad \text{(A2.1.1)}$$

where $\theta \equiv (1-\gamma)/(1-1/\psi)$, δ is the subjective discount factor, γ is the risk aversion (RA) parameter, ψ is the elasticity of intertemporal substitution (EIS) parameter, C_t is the agent's consumption and $R_{w,t+1}$ is the return on the agent's wealth.

Unconditional Linear Factor Model

Cochrane (2009) and Yogo (2006) show that the Euler equation can be transformed into the unconditional linear factor model. Suppose the following general form of the asset pricing restriction:

$$E\left(M_{t+1}R_{i,t+1}^{e}\right) = 0. \qquad \text{(A2.1.2)}$$

Using the following property of covariance, $Cov(X,Y) = E(XY) - E(X)E(Y)$, (A2.1.2) can be expressed as

$$E\left(R^e_{i,t+1}\right) = Cov\left(-\frac{M_{t+1}}{E(M_{t+1})}, R^e_{i,t+1}\right). \qquad \text{(A2.1.3)}$$

and a nonlinear term in (A2.1.3) can be approximated using the first-order log-linear approximation as

$$\frac{M_{t+1}}{E(M_{t+1})} \approx 1 - E(m_{t+1}) + m_{t+1}. \qquad \text{(A2.1.4)}$$

From equation (A2.1.1), the log of the stochastic discount factor in equation (A2.1.4) is

$$m_{t+1} = -\frac{\theta}{\psi}\Delta c_{t+1} + (\theta - 1)r_{w,t+1}.$$

and a non-linear term in equation (A2.1.3) is now expressed as

$$\frac{M_{t+1}}{E(M_{t+1})} \approx k - \frac{\theta}{\psi}\Delta c_{t+1} + (\theta - 1)r_{w,t+1}. \qquad \text{(A2.1.5)}$$

where $k = 1 + \frac{\theta}{\psi}E(\Delta c_{t+1}) + (1-\theta)E\left(r_{w,t+1}\right)$ is a constant. Substituting equation (A2.1.5) for a non-linear term in equation (A2.1.3) gives the unconditional linear factor model:

$$E\left(R^e_{i,t+1}\right) = \frac{\theta}{\psi}Cov\left(\Delta c_{t+1}, R^e_{i,t+1}\right) + (1-\theta)Cov\left(r_{w,t+1}, R^e_{i,t+1}\right). \qquad \text{(A2.1.6)}$$

and substituting consumption function for consumption in equation (A2.1.6) to place leverage in the model gives

$$E\left(R_{i,t+1}^{e}\right) = \beta\frac{\theta}{\psi}Cov\left(\Delta d_{t}, R_{i,t+1}^{e}\right) + \phi\frac{\theta}{\psi}Cov\left(z_{t+1}, R_{i,t+1}^{e}\right) + \frac{\theta}{\psi}Cov\left(e_{t+1}, R_{i,t+1}^{e}\right) + (1-\theta)Cov\left(r_{w,t+1}, R_{i,t+1}^{e}\right). \tag{A2.1.7}$$

Appendix 2.2. General Method of Moments (GMM) Estimation

We use Hansen and Singleton's (1982) two-step GMM procedure to estimate the unconditional linear factor models. The moment conditions for the unconditional linear factor model are as follows:

$$g_t = \sum_{t=1}^{T} \begin{bmatrix} R_t^e - R_t^e \left(f_t - \mu_f\right)' b \\ f_t - \mu_f \end{bmatrix} \otimes z_t \tag{A2.2.1}$$

where b is a vector of risk prices and z_t is a vector of instruments. The choice of instruments is a constant and the second lag of consumption growth. We use the following first-stage weighting matrix in Yogo (2006):

$$W = \begin{bmatrix} hI_N & 0 \\ 0 & diag\left(\hat{\Sigma}_{ff}^{-1}\right) \end{bmatrix}$$

where (A2.2.2)

$$\hat{\Sigma}_{ff} = E\left(\left(f_t - \mu_f\right)\left(f_t - \mu_f\right)'\right),$$

where $h > 0$ is a constant, I_N is N by N identity matrix and N is the number of test assets. The heteroscedasticity and autocorrelation consistent (HAC) covariance matrix of Andrew (1991) is computed for standard errors and t-statistics.

Hansen's (1982) J-statistic follows chi-square distribution with $M - P$, where M and P are the number of moment conditions and the parameters are calculated for the overidentifying restriction test. The test is similar to the asset pricing model test of Gibbons, Ross and Shanken (1989) (see Cochrane, 2009).

Chapter 3: Reversal Evidence from Investor Sentiment in International Stock Markets

3.1. Introduction

One of the most important building blocks in rational finance theories, the efficient market hypothesis (EMH), postulates that participants in financial markets exhibit rational behaviour, leading to each asset's market price being equal to its fundamental value (Fama, 1965a, 1965b, 1970). However, asset prices in real-world financial markets sometimes exhibit deviations from their fundamental value, implying that the EMH does not always hold true. Over the past decades, the tension between rational finance theories on the one side and empirical evidence of market anomalies on the other side has led to extensive research and continuing controversial debates on how to explain asset prices in financial markets.[21]

To better understand and explain market anomalies, e.g., value, size and momentum effects, researchers and practitioners have shown great interest in behavioural theories that examine how human behaviour affects economic decision-making. Regarding applications to financial models, behavioural finance theories suggest that participants in financial markets are not always or even rarely rational. Instead of depending on assumptions made in rational finance and economic theories to explain movements in asset prices, behavioural finance studies aim at explaining observed market anomalies through the lens of investors' irrational behaviour. Behavioural finance research has led to the identification of several behavioural biases that propose potential explanations for deviations from market participants' rational behaviour, e.g., confirmation bias and overconfidence.

[21] See Harvey, Liu and Zhu (2016) and Hou, Xue and Zhang (2020) for a review of empirical findings pertaining to numerous market anomalies.

One of the most debated behavioural biases in the recent literature is sentiment, which considers the influence of an investor's state of mind on her decision-making in financial markets. Optimism (pessimism) or high (low) sentiment has been put forward to explain bullish (bearish) consensus attitudes about expected upward (downward) asset price movements in capital markets (Baker and Wurgler, 2006; Baker, Wurgler and Yuan, 2012; Yu and Yuan, 2011; Stambaugh, Yu and Yuan, 2012, 2014).

Sentiment is an important research topic for financial practitioners and researchers alike, as evident from the recently increased number of related studies, to better understand how human behaviour affects asset prices and to optimise investment decision-making in capital markets. While sentiment has enjoyed growing research interest in finance, the effect of sentiment on the variance and correlation of asset returns remains understudied. This is due to previous studies' primary focus on exploring the effect of sentiment on the mean of asset returns. In particular, the extant literature has not analysed sentiment-based dispersions in the time-series and cross-section of higher or mixed asset return moments. Therefore, this research examines whether sentiment affects variance and correlation of asset returns.

The most important related concept in understanding the effect of sentiment on financial markets is that of noise traders, which refers to traders who act upon erroneous signals. In asset pricing, noise traders are known to create correlated noise, which is unrelated to intrinsic value, because noise traders' trading strategies are similar to each other. [22] In their seminal behavioural research, De Long et al. (1990a) establish a theoretical model and show that asset price deviations from fundamental value can cause excessive variance and correlation when noise traders who have erroneous and unpredictable beliefs crowd out arbitrageurs from the market (noise trader risk). Furthermore, Shleifer and Vishny (1997) highlight the differences between

[22] Behavioural studies, e.g., Baker and Wurgler (2006) in the U.S. market and Baker, Wurgler and Yuan (2012) in international markets, argue that the level of aggregate sentiment predicts negative stock returns. This indicates that noise traders tend to be optimistic (or pessimistic) around the same time such that their demands put an enormous effect on the entire capital market.

‘textbook arbitrage’ and ‘real-world arbitrage’ and present that noise traders contribute to mispricing in financial markets. Extending the existing theoretic research, our research uses an empirical method to further explore the effect of sentiment-based market participant’s decision-making on financial markets and provide practical implications for active investment strategies.

There is ample evidence that sentiment influences the attitude towards the processing of information and therefore decision-making. The psychological literature, e.g., Schwarz, Bless and Bohner (1991) and Sinclair and Mark (1995), argues that individuals’ mood has a strong effect when processing information. The authors’ experimental results indicate that subjects who exhibit a good (bad) mood tend to be less (more) accurate, less (more) detailed and less (more) elaborate. This evidence is consistent with the observed market anomalies reinforced (eroded) when investors are optimistic (pessimistic) (Baker and Wurgler, 2006; Stambaugh, Yu and Yuan, 2012). Further, Forgas (1998) suggests that positive (negative) mood increases (decreases) the likelihood of occurring the attribution error. Overall, these studies present that mood exerts a significant effect on individuals’ strategies for information processing and thus can be a factor in explaining movements in asset prices.[23]

The theoretical explanation for excessive variance and correlation in asset prices is similar to the one for mispricing. Consider a pricing function that contains a term for sentiment. It can be then shown that (1) the moments of asset returns deviate from those of fundamental returns, similar to results obtained by De Long et al. (1990a). The sentiment term in the pricing function accommodates noise traders’ demands based on their sentiment, i.e., optimistic or pessimistic opinions. In contrast, considering variance as a traditional risk metric, some variations in the variance can be due to changes in the expected return. For instance, when the expected return become lower due to sentiment-based overpricing, the variance can decrease to accommodate

[23] See Shu and Chang (2015) for a review of previous studies’ finding related to the effect of investor sentiment on decision-making, time preference, risk attitude and financial markets.

the change in the expected return (see Christie, 1982). While this explanation is not applicable to the correlation, it offers an indication that the relation between sentiment and the second moment of asset returns are perhaps not irrational in part.[24]

Following Baker and Wurgler (2006), we construct a composite index using proxies for measuring sentiment. Our research targets international markets for the following reasons. First, numerous market participants, e.g., institutional investors, have an intention of investing their funds in multiple international markets in addition to the domestic market, but the focus of the extant sentiment studies is limited to the U.S. market. Hence, extending the sentiment studies to several international markets will provide more practical implications on active investment strategies for investors in the U.S. market and other international markets. Second, the seminal sentiment research, Baker, Wurgler, and Yuan (2012), builds sentiment indexes for several international markets, however, their indexes are sampled at an annual frequency and therefore do not provide enough number of observations to make meaningful statistical inferences for investors who revise their strategies at each month. For this reason, this research aims at constructing sentiment indexes that offer an observation for each month in international markets to overcome this problem. We include the following regions in this research: Asia Pacific, Europe and North America. Guided by data availability, we build global and regional sentiment indexes.

The main fundamental challenge for sentiment studies is that it is not possible to determine the true fundamental value of an asset as a benchmark for the analysis of mispricing. Provided this constraint, previous studies have examined whether sentiment proxies predict the time-series or cross-section of asset returns. We use a similar empirical approach in this research. Specifically, we examine the contemporaneous relation of sentiment to mean, variance and

[24] However, it appears to be challenging to examine whether the variation in the variance series is due to changes in the expected return or due to shifts in sentiment because sentiment is expected to affect both the mean and variance.

correlation of stock returns to identify the direction of the effect of sentiment. Then, we predict asset return moments using sentiment to examine the presence of anticipatable movements due to the effect of sentiment. We expect sentiment to have some predictive power if its effect is not permanent but transient.

Our research focuses on the effect of sentiment on both the time-series and cross-section of asset return moments. We use market portfolios in the analysis of the time-series and sentiment beta sorted portfolios as well as market beta sorted portfolios in the analysis of the cross-section of asset returns. For these selected test assets, we calculate the equal-weighted excess return and then estimate the following conditional moments: (1) the conditional variance using the generalised autoregressive conditional heteroscedasticity (GARCH) model (Bollerslev, 1986) and (2) the conditional correlation using the dynamic equicorrelation (DECO) model (Engle and Kelly, 2012).

This research delivers three main findings related to the time-series of the moments of asset returns. First, investors' optimism (pessimism) causes overpricing (underpricing). Our results show that positive (negative) changes in sentiment are associated with increases (decreases) in market returns and that stock markets tend to experience negative (positive) returns following optimism (pessimism) periods. Second, investors' pessimism rather than optimism contributes to excessive variance. The results show that market returns become more volatile with negative changes in sentiment and that market returns become less volatile following pessimism periods. Third, analogous to the case of excessive variance, investors' pessimism generates excessive correlation. Our results present that stocks become more correlated with negative changes in sentiment and that stocks become less correlated following pessimism periods.

Further, from the cross-sectional evidence, we find that most of the empirical regularities revealed in the time-series evidence become more pronounced among assets more sensitive to sentiment. First, stocks more sensitive to sentiment are more overpriced when investors are optimistic. Second, stocks with more exposure to sentiment become both more volatile and more correlated when investors are pessimistic. In addition, our results show that high market beta stocks exhibit the similar conditional variations on sentiment.

Based on our results, we argue that sentiment causes conflicting observations in regard to the relation between risk and return. First, previous studies demonstrate the negative mean-variance trade-off (Campbell, 1987; Turner, Startz and Nelson, 1989; Nelson, 1991; Glosten, Jagannathan and Runkle, 1993; Harvey, 2001; Whitelaw, 1994; Lettau and Ludvigson, 2003; MacKinlay and Park, 2004; Brandt and Kang, 2004). Our evidence shows that a bullish (bearish) change in sentiment tends to increase (decrease) mean and decrease (increase) variance. These sentiment-based movements in mean and variance perhaps result in the negative mean-variance relation observed in the above-mentioned studies.

Second, previous studies report that the relation between market beta and expected returns is flat or negative (Black, Jensen and Scholes, 1972; Fama and French, 1992; Baker, Bradley and Wurgler, 2011; Frazzini and Pedersen, 2014). Our results show that high market beta stocks earn inferior returns following high sentiment periods. However, high market beta stocks do not earn superior returns following low sentiment periods. Such regularities lower expected returns on high market beta stocks and may lead the previous studies to conclude that the risk-return relation is distorted.

Our research offers several important practical implications for fund managers. First, mean, variance and covariance estimators used in the mean-variance optimisation should reflect information on the aggregate sentiment level. For example, consider a fund manager who tries to obtain the optimal weights on individual assets. If she relies on the estimators from the prediction using sentiment, the ex-post performance of the resultant asset allocation plan from the optimisation procedure will be improved as the precision of estimators increases. Second, the prediction of the conditional variance and correlation of stocks using sentiment increases the flexibility of a fund manager when budgeting risks. For example, when markets appear to be undervalued due to sentiment traders' pessimism, a fund manager can either allocate more funds to assets with higher risk or increase her leverage to enhance her performance based on the prediction that the variance and correlation of market and individual returns decrease in the near future.

Our research contributes to the existing literature in several ways. First, using an analogous approach used in previous studies on the effect of sentiment on stock returns, we uncover sentiment-driven variations in the time-series and cross-section of variance and correlation of asset returns. Given our finding that sentiment affects asset return moments, it follows that mean, variance and correlation of the observed asset returns differ from mean, variance and correlation of fundamental returns. Therefore, our findings improve the understanding of the mechanism by which sentiment distorts asset return distributions. In addition, our research offers a potential explanation for puzzling observations that contradict traditional finance theories, e.g., the negative relations between expected return and variance and between the expected return and market beta.

The remainder of this chapter is organised as follows. Section 3.2 reviews the related literature. Section 3.3 describes the method employed for constructing sentiment indices and examining the effect of sentiment. Section 3.4 presents results pertaining to the time-series and cross-sectional analyses of the relation between sentiment and mean, variance and correlation of stock returns. Section 3.5 tests the robustness of our results obtained. Section 3.6 summarises our findings.

3.2. Literature Review

There is a considerable number of previous studies on the relation between sentiment and asset returns. Previous studies demonstrate that sentiment proxies predict the time-series of stock returns. Using the Center for Research in Security Prices (CRSP) value-weighted index, Kothari and Shanken (1997) investigate the period spanning from 1926 to 1991 and show that the market-level book-to-market ratio predicts negative market returns. In their research, the book-to-market ratio proxies the degree of overvaluation or undervaluation. For example, if the market-level book-to-market ratio at a given time has a value above (below) its historical value, researchers or practitioners argue that the market is overvalued (undervalued).

Baker and Wurgler (2000) and Henderson, Jegadeesh and Weisbach (2006) present that market returns are negative following periods in which the relative preference of firms for issuing securities to raise funds is biased towards equities. Using U.S. new issues data obtained from the Federal Reserve Bulletin, Baker and Wurgler (2000) analyse the period from 1928 to 1997 and show that the ratio of equity issues to total issues predicts decreases in both the CRSP value- and equal-weighted indexes. Using international new issues data obtained from the Security Data Corporation (SDC), Henderson, Jegadeesh and Weisbach (2006) analyse the period from 1991 to 2001 and present similar results to those in Baker and Wurgler (2000) related to the U.S. stock market. In these studies, managers are assumed to exploit mispricing, i.e., managers who have better access to inside information have a motive to issue equities (debts) when their firms are overvalued (undervalued).

Schmeling (2009) argues that the consumer confidence index has a negative relation to subsequent market returns. Using stock market returns for 18 developed countries, the author shows that market returns tend to decrease following high sentiment periods across countries.

Interestingly, the author emphasises that the effect of sentiment becomes stronger in countries that are more prone to exhibit herding behaviour or that have inefficient regulatory institutions.

Baker and Wurgler (2007) show for the U.S. stock market and Baker, Wurgler and Yuan (2012) show for international stock markets that their composite indexes of sentiment predict negative market returns. Baker and Wurgler (2007) construct their sentiment index using six sentiment proxies, including the closed-end fund discount, share turnover, the number of initial public offerings (IPOs), the average first-day returns of IPOs, the ratio of gross equity issuance to gross equity and debt issuance, and the dividend premium.[25] Analysing the period from 1966 to 2005, the authors show that their index predicts lower stock market returns. Similarly, Baker, Wurgler and Yuan (2012) construct sentiment indexes for six developed markets using four sentiment proxies, including the number of initial public offerings (IPOs), the average first-day returns of IPOs, share turnover and the variance premium. The authors investigate the period spanning from 1980 to 2005 and provide similar empirical findings to those in Baker and Wurgler (2007).

In addition, previous studies show that sentiment also predicts the cross-section of asset returns. Using two consumer confidence indexes obtained from the University of Michigan and the Conference Board, Lemmon and Portniaguina (2006) investigate the period from 1977 to 2002 and report that returns on small stocks are lower than those on large stocks following high consumer confidence periods.

Baker and Wurgler (2006) demonstrate for the period from 1962 to 2001 and Baker, Wurgler and Yuan (2012) demonstrate for the period from 1980 to 2005 that their composite sentiment indexes predict that stocks that are more difficult to value and stocks that are more difficult to arbitrage experience lower returns following high sentiment periods. The authors measure the

[25] Baker and Wurgler (2006) use the same proxies to construct a sentiment index for the U.S. market.

difficulties of arbitrage or valuation using firm characteristics, e.g., firm size, total risk, book-to-market ratio and sales growth.

Subsequent studies employ Baker and Wurgler's (2006) index to investigate the relation between sentiment and market anomalies. For instance, Stambaugh, Yu and Yuan (2012) report that market anomalies become stronger following high sentiment periods. Antoniou, Doukas and Subrahmanyam (2016) and Shen, Yu, and Zhao (2017) show that riskier firms experience negative returns following high sentiment periods.

In contrast, the relation between investor sentiment and variance of stock returns remains understudied. Shiller (1981) and LeRoy and Porter (1981) show that stock prices are more volatile than fundamental values obtained from the present value model. Specifically, Shiller (1981) shows that the S&P's composite price index is much more volatile than the present value of actual subsequent dividends over the period from 1871 to 1979. Similarly, LeRoy and Porter (1981) propose statistics to test for the implication obtained from the present value relation. The authors analyse the period from 1955 to 1973 and show that stock prices are too volatile to be consistent with the present value model.

To examine the effect of sentiment on the excess return and conditional variance, Lee, Jiang and Indro (2002) construct an index to measure investor sentiment using data obtained from Investors' Intelligence of New Rochelle, New York and incorporate their index into mean and variance equations for the GARCH-in-Mean model. For the sample period from 1973 to 1995, the authors report that positive changes in sentiment predict decreases in the market variance and increases in the market return. Furthermore, the authors argue that downward (upward) revisions in the market variance due to shifts in sentiment are related to higher (lower) future returns.

The effect of sentiment on the correlation of asset returns is examined in previous literature, however, its dispersion in the time-series and cross-section is still understudied. For the period from 1919 to 1987, Shiller (1989) compares stock prices and dividends between the U.S. and U.K. stock markets and concludes that stock prices are more correlated than dividends between the two countries. Similarly, Pindyck and Rotemberg (1993) analyse the period from 1969 to 1987 to examine comovements in individual stock returns. Using the present value model, the authors provide evidence of stock price movements that are not explained by changes in economic fundamentals that determine future earnings. This result leads the authors to conclude that excessive comovement in stock returns exits.

Vijh (1994) and Barberis, Shleifer and Wurgler (2005) report that stock returns become more sensitive to returns on S&P 500 index after inclusion in the index. For the period from 1986 to 1989, Vijh (1994) shows that market betas for stocks that are included in the S&P 500 are on average 0.125 higher than market betas for stocks that are not included in the S&P 500 index. Barberis, Shleifer and Wurgler (2005) extend Vijh's (1994) analysis to a longer sample period (1976-2000) and show that their bivariate regression test provides results consistent with friction- and sentiment-based explanations.

Kumar and Lee (2006) use retail investors' transaction data consisting of more than 1.85 million trades to investigate the relation between investor sentiment and return comovements. The authors investigate the period from 1991 to 1996 and report that the correlated retail investor-driven demand accounts for comovement in stock returns.

In more recent studies, excessive stock return comovements have been confirmed. Ren (2017) documents that stock returns are less (more) correlated following high (low) sentiment periods using Baker and Wurgler's (2006) sentiment index. Frijns, Verschoor and Zwinkels (2017) decompose stock returns into fundamental and nonfundamental components using the Gordon Growth Model and present that comovement in market-level stock returns between developed countries can be attributed to nonfundamental returns rather than fundamental returns.

3.3. Method

This section describes our empirical method used to measure sentiment and examine the impact of sentiment on financial markets.

3.3.1. Measuring Sentiment

To measure sentiment, we construct a composite index of sentiment in international stock markets using the method of Baker and Wurgler (2006). First, we build proxies for measuring sentiment based on implications from behavioural theories. Our choice of sentiment proxies differs from the previous research due to lack of data availability in selected countries. Our analysis uses the following proxies: the variance premium (PVAR), net stock issues (NSI) and dividend premium (PDIV).

The PVAR, as suggested in Baker, Wurgler and Yuan (2012), quantifies the valuation difference between high and low variance stocks. Since volatile stocks are harder to value and harder to arbitrage, these are rather unattractive to arbitrageurs and, as a consequence, prone to sentiment-based demand. This cross-sectional variation in the fundamental and arbitrage risk indicates that the valuation of high variance stocks is higher (lower) during high (low) sentiment periods compared to the valuation of low variance stocks.

The NSI gauges managers' behaviour in response to mispricing. Managers have a motive to issue (repurchase) stocks when they believe that their stocks are overpriced (underpriced). Daniel and Titman (2006) and Pontiff and Woodgate (2008) show that firms that issue stocks experience lower subsequent returns than firms that repurchase stocks. Other studies show that managers time the market (see Loughran, Ritter and Rydqvist, 1994; Loughran and Ritter, 1995;

Baker and Wurgler, 2000; Baker and Wurgler, 2002; Henderson, Jegadeesh and Weisbach, 2006).

The PDIV, as suggested in Baker and Wurgler (2006), measures the valuation difference between stocks that pay dividend (payers) and stocks that do not pay dividends (nonpayers). Fama and French (2001) show that nonpayers tend to be smaller and less profitable, and their growth opportunities are weaker than payers. These characteristics indicate that nonpayers are riskier. Given that noise traders increase their preference on riskier stocks, nonpayers are more overvalued (undervalued) than payers when investors are optimistic (pessimistic).

Second, we construct a monthly composite levels index of investor sentiment, building on the common variation in the constructed sentiment proxies. Following Baker and Wurgler (2006), a composite index is defined as the first principal component of the sentiment proxies standardised to have zero mean and unit variance:

$$S_t = aPVAR_t + bNSI_t + cPDIV_t \tag{3.1}$$

The loadings are rescaled for the index to have a unit variance.[26] The sentiment measurement approach proposed by Baker and Wurgler (2006), which we employ in this research, permits us to capture more of the common variation in the sentiment compared to the simple averaging of the sentiment proxies (see Brown and cliff, 2004; Baker and Wurgler, 2007).

To construct a changes index which measures the shift in investor sentiment, we take the first difference of the levels index (sampled at a monthly frequency) as follows:

$$\Delta S_t = S_t - S_{t-1} \tag{3.2}$$

[26] The further sentiment measure, turnover (TURN), from Baker and Wurgler (2006), can be included in equation (3.1) at the expense of the earlier sample period, however, the introduction of the new measure does not affect our empirical regularities.

It is important to note that both the changes and level indexes are standardised to have zero mean and unit variance. These statistical features enable us to a comparison of the effect of a one standard deviation increase in the sentiment indexes on asset return moments.

We measure sentiment for global and regional markets instead of country-level markets because the number of firms in the sample during the 1980s is too small to build a reliable country-level indexes.[27] We consider three regions (Asia Pacific, Europe and North America) and eight developed countries from these regions (Australia, Hong Kong and Japan from the Asia Pacific region; France, Germany and the United Kingdom from the European region; Canada and the United States from the North America region). These countries provide a sufficient number of firms traded in the stock exchanges and account for a substantial amount of market capitalisation for each region.

Second, we construct regional-specific (local) levels and changes indexes that capture the components of the regional sentiment indexes independent to the global index. Specifically, we run the following regressions:

$$S_t^R = aS_t^G + S_t^L \tag{3.3A}$$

$$\Delta S_t^R = a'\Delta S_t^G + \Delta S_t^L \tag{3.3B}$$

where S_t^R (ΔS_t^R) represents the regional levels (changes) index, S_t^G (ΔS_t^G) represents the global levels (changes) index and S_t^L (ΔS_t^L), the residual, is the local levels (changes) index. As before, we standardise the local indexes to have zero mean and unit variance.

[27] Baker, Wurgler and Yuan (2012) show that the common variation in sentiment across developed countries has predictive power in explaining the time-series and the cross-section of stock returns.

3.3.2. Econometric Model

We run the following regressions to examine the effect of sentiment traders' demands on moments of stock returns:

$$X_{i,t} = a + b\Delta S_{j,t}^{R} + u_{i,t} \quad (3.4A)$$

$$X_{i,t} = c + d\Delta S_{t}^{G} + e\Delta S_{j,t}^{L} + u_{i,t} \quad (3.4B)$$

$$\left(\frac{1}{k}\right)\sum_{h=1}^{k} X_{i,t+h} = a' + b'S_{j,t}^{R} + e_{i,t} \quad (3.5A)$$

$$\left(\frac{1}{k}\right)\sum_{h=1}^{k} X_{i,t+h} = c' + d'S_{t}^{G} + e'S_{j,t}^{L} + e_{i,t} \quad (3.5B)$$

where i indexes countries, j indexes regions that countries belong to, t indexes months and $X_{i,t}$ is either the excess return, the change in the conditional variance or the change in the conditional correlation for the test assets.[28]

We build one- and two-factor models. The one-factor models in equations (3.4A) and (3.5A) include the regional sentiment index. The two-factor models in equations (3.4B) and (3.5B) include the global and local indexes. These specifications aim at the identification of investors who drive the effect of sentiment, i.e., either investors investing in multiple international stock markets or investors investing in a single domestic stock market.[29]

[28] In contrast to the mean, the variance and the correlation have a strict constraint on the range of a value: the variance cannot have a negative value, and the correlation cannot have a value below -1 or above 1. If one uses the levels of variance and those of correlation when examining their relation with sentiment, it is possible that the econometric model provides some results that cannot be interpreted, such as a negative variance or a correlation coefficient outside the range of -1 to 1. Therefore, this research uses the change of the variance and the correlation rather than their levels to obtain feasible results from the econometric model.

[29] Baker, Wurgler and Yuan (2012) argue that the local sentiment index affects the cross-section of individual-level assets more than it does the time-series of market-level assets because of the following features. International investors are interested in market-level assets rather than individual-level assets. Meanwhile, local investors have more information on local firms. Furthermore, local investors prefer to invest in local firms as argued in previous studies, e.g., French and Poterba (1991).

Equation (3.4) investigates the contemporaneous relation between the change in sentiment and the moments of returns. It is well-known that sentiment and stock prices move together in the same direction, however, in which direction sentiment drives the variance and correlation has not yet been confirmed by previous studies. To answer this question, we determine the sign of parameter estimates of equation (3.4).

Equation (3.5) predicts movements in mean, variance and correlation from month $t+1$ to month $t+k$. If the effect of sentiment is not permanent but transient, sentiment should predict moments of returns. Similar to the case of equation (3.4), previous studies have shown that sentiment predicts negative stock returns, however, these studies do not examine how the return variance and correlation evolve following high or low sentiment periods. To answer this question, we determine the sign of parameter estimates of equation (3.5).

Unlike the previous sentiment studies that predict returns in month $t+1$ using sentiment in month t, i.e., k = 1, we choose k = 12 because variance and correlation are persistent such that it takes more time to test whether predictable variations from investor sentiment occur in the time-series.

Short-sale impediments might lead sentiment effects to become asymmetric across periods of optimism and pessimism.[30] To analyse this potential asymmetry, we estimate the following regressions:

$$X_{i,t} = a + b\Delta S_{j,t}^{R} N_{j,t}^{R} + c\Delta S_{j,t}^{R} P_{j,t}^{R} + u_{i,t} \tag{3.6A}$$

$$X_{i,t} = d + e\Delta S_{t}^{G} N_{t}^{G} + f\Delta S_{t}^{G} P_{t}^{G} + g\Delta S_{j,t}^{L} N_{j,t}^{L} + h\Delta S_{j,t}^{L} P_{j,t}^{L} + u_{i,t} \tag{3.6B}$$

[30] Overpricing should be more prominent than underpricing because of short-sale impediments as argued in Miller (1977) for several reasons: (1) Mutual funds are prohibited from shorting securities; (2) asset price is unpredictable until it converges to fundamental value and such price movements might cause steep margin calls (De Long et al., 1990a; Shleifer and Vishny, 1997); (3) borrowed securities can be recalled whenever a lender requires to and short sellers might have to close their position at a loss (Lamont, 2012); (4) some securities that have low institutional ownership, such as small- and micro-caps. securities, have low supplies of securities for lending (D'Avolio, 2002; Lamont, 2012).

$$\left(\frac{1}{k}\right)\sum_{h=1}^{k} X_{i,t+h} = a' + b'S_{j,t}^{R}L_{j,t}^{R} + c'S_{j,t}^{R}H_{j,t}^{R} + e_{i,t} \tag{3.7A}$$

$$\left(\frac{1}{k}\right)\sum_{h=1}^{k} X_{i,t+h} = d' + e'S_{t}^{G}L_{t}^{G} + f'S_{t}^{G}H_{t}^{G} + g'S_{j,t}^{L}L_{j,t}^{L} + h'S_{j,t}^{L}H_{j,t}^{L} + e_{i,t} \tag{3.7B}$$

where N_t^G, $N_{j,t}^R$ and $N_{j,t}^L$ (P_t^G, $P_{j,t}^R$ and $P_{j,t}^L$) are dummy variables for the period in which the value of the global, regional, and local changes indexes are negative (positive) and L_t^G, $L_{j,t}^R$ and $L_{j,t}^L$ (H_t^G, $H_{j,t}^R$ and $H_{j,t}^L$) are dummy variables for the period in which the value of the global, regional and local levels indexes are less (greater) than the median of the global, regional and local levels index, respectively. In this research, equations (3.4) and (3.5) are referred to as one-regime models and equations (3.6) and (3.7) are referred to as two-regime models. The econometric models illustrated in this section are similar to those in Baker, Wurgler and Yuan (2012) and Shen, Yu and Zhao (2017).

3.4. Empirical Findings

3.4.1. Data

We obtain several stock market variables from Datastream: unadjusted stock price (UP), total return index (RI), adjustment factor (AF) and number of shares outstanding (NOSH). In addition, the following variables for balance sheet and income statement are obtained from Worldscope: total assets (WC02999), total liabilities (WC03351), preferred stock (WC03451), date of fiscal year end (WC05350) and net income before preferred dividends (WC01651). All non-U.S. currency variables are U.S. dollar denominated to consider the viewpoint of U.S. investors. Excess returns are calculated using the risk-free rate series obtained from Kennth R. French's website.

We construct the following variables: size (Size), book-to-market ratio (B/M), return on equity (ROE), investment (INV) and momentum (MOM). Size is market capitalisation at the end of June of year t. B/M is calculated as book value of equity in year $t-1$ divided by market value of equity at the end of December of year $t-1$. ROE is calculated as net income in year $t-1$ divided by book value of equity in year $t-1$. INV is calculated as book value of asset in year $t-1$ divided by book value of asset in year $t-2$. These variables are matched with excess returns from July of year t to June of year $t+1$ as in Fama and French (1993). MOM is calculated as the cumulative excess return from month $t-12$ to month $t-2$ as in Fama and French (2016).

The sentiment proxies in the previous section are constructed as follows. The PVAR is the log of the ratio of the value-weighted average market-to-book ratio of high variance stocks to that of low variance stocks. To estimate the variance, we use trailing 12-month excess returns. Stocks with variance above (below) the 70^{th} (30^{th}) percentile of the variance are categorised as high (low) variance stocks. The NSI is the value-weighted average growth rate of the number of stock-split adjusted shares outstanding. We use a 12-month backward moving average for the NSI to remove noise from the proxy. The PDIV is the log of the ratio of the value-weighted average market-to-book ratio of payers to the value-weighted average market-to-book ratio of nonpayers.[31]

Similar to Fama and French (2001), in an abuse of monthly and year notation, the market-to-book ratio is calculated as market value of asset in month t of year t divided by book value of asset in year t. Book value of asset in year t minus book value of equity in year t plus market value of equity at the end of month t of year t is market value of asset in month t of year t.

[31] Following Baker and Wurgler (2004), firms with positive dividends are categorized as payers and as nonpayers otherwise.

3.4.2. Sentiment Index

Table 3.1 reports descriptive statistics of the sentiment proxies that spans from January 1984 to December 2019. First, the proxies are correlated to other proxies in the expected direction based on their motivation because the proxies share the common variation due to sentiment. Furthermore, the proxies enter in the sentiment index with the expected signs. Second, in order of the areas reported in the table, the indexes account for 61%, 50%, 65% and 67% of the variance of the sentiment proxies. These are comparable to those of the previous sentiment studies.[32] Third, the mean of PVAR (PDIV) is positive (negative) across the targeted areas. This implies that, on average, volatile stocks and dividend payers are traded at premium relative to their counterparts.

Table 3.2 reports correlations between indexes. First, the regional and global indexes appear to move together. In order of the regions presented in the table, the correlation coefficients for the levels (changes) indexes are 0.30, 0.91 and 0.84 (0.51, 0.41 and 0.61). This indicates that the global index captures the common variation that underlies the regional indexes. Second, the regional indexes as well as local indexes are correlated with each other to a certain extent, however, the correlation coefficients appear to be positive among the regional indexes and negative among the local indexes.

Figure 3.1 depicts the sentiment levels indexes. Our indexes capture the major fluctuation in sentiment in international stock markets. First, sentiment was peaked during the dot-com bubble period (1995-2000) and at the trough during the subprime mortgage crisis period. Second, sentiment in the Asia Pacific region was at its highest level during the asset price bubble period concentrated in the Japanese market (1986-1991), whereas it was at its lowest

[32] The corresponding figure in Baker and Wurgler (2006) is 49% for the U.S. and those in Baker, Wurgler and Yuan (2012) are 49% for Canada, 40% for France, 48% for Germany, 37% for Japan, 37% for the U.K. and 42% for the U.S. It is worth noting that their indexes are sampled at an annual frequency.

level during the Asian financial crisis period (1997-1999). We use these indexes to examine the effect of sentiment-based demands on asset prices in the subsequent subsection.

Table 3.1. Sentiment Proxies

The table reports descriptive statistics of sentiment proxies targeting the global market (Panel A) and the following regional markets: Asia Pacific (Panel B), Europe (Panel C) and North America (Panel D). The variance premium (PVAR) is the log of the ratio of the value-weighted average market-to-book ratio of high variance stocks to that of low variance stocks. Stocks with the variance above (below) the 70th (30th) percentile of the variance are high (low) variance stocks and the variance is estimated using trailing 12-month excess returns. The net stock issues (NSI) is the value-weighted average growth rate of the number of stock-split adjusted shares outstanding. To remove noise from the proxy, we use a 12-month backward moving average for the NSI. The dividend premium (PDIV) is the log of the ratio of the value-weighted average market-to-book ratio of payers to that of nonpayers. Firms with positive dividends are categorised as payers and as nonpayers otherwise. The sentiment levels index (S) is the first principal component of the standardised proxies to have zero mean and unit variance. The loadings on the proxies and a fraction of variance of the proxies explained by the sentiment levels index are reported. The sample period covers Jan-1984 to Dec-2018.

	Mean	Std. Dev.	Min.	Max.	Loading	Correlation				Explained Variance
						S	PVAR	NSI	PDIV	
Panel A: Global Levels Index										
PVAR	0.08	0.17	-0.27	0.72	0.55	0.74	1			
NSI	0.10	0.07	0.00	0.31	0.55	0.74	0.28	1		0.61
PDIV	-0.14	0.13	-0.59	0.18	-0.63	-0.85	-0.46	-0.47	1	
Panel B: Regional Levels Index - Asia Pacific										
PVAR	0.08	0.14	-0.45	0.60	0.50	0.61	1			
NSI	0.10	0.04	0.02	0.24	0.58	0.71	0.15	1		0.50
PDIV	-0.06	0.11	-0.41	0.23	-0.64	-0.79	-0.25	-0.34	1	
Panel C: Regional Levels Index - Europe										
PVAR	0.03	0.20	-0.25	0.94	0.60	0.84	1			
NSI	0.17	0.09	0.04	0.50	0.54	0.76	0.45	1		0.65
PDIV	-0.02	0.15	-0.78	0.33	-0.59	-0.82	-0.55	-0.42	1	
Panel D: Regional Levels Index - North America										
PVAR	0.13	0.23	-0.28	0.95	0.59	0.84	1			
NSI	0.08	0.09	-0.08	0.33	0.48	0.68	0.29	1		0.67
PDIV	-0.18	0.12	-0.67	0.03	-0.65	-0.91	-0.7	-0.47	1	

Table 3.2. Correlations of Sentiment Indexes

The table reports correlations between the sentiment indexes. Panel A shows correlations between the levels indexes and Panel B reports those between the changes indexes. The sentiment levels index is the first principal component of the standardised sentiment proxies to have zero mean and unit variance. To construct the changes index, we take the first difference of the levels index and standardise the differenced series to have zero mean and unit variance. Global, regional and local sentiment indexes are constructed, and local indexes are components of the regional index independent to the global index. The local index is standardised to have zero mean and unit variance. The following regions are considered: Asia Pacific Europe and North America. The following sentiment proxies are used. The variance premium (PVAR) is the log of the ratio of the value-weighted average market-to-book ratio of high variance stocks to that of low variance stocks. Stocks with the variance above (below) the 70th (30th) percentile of the variance are high (low) variance stocks and the variance is estimated using trailing 12-month excess returns. The net stock issues (NSI) is the value-weighted average growth rate of the number of stock-split adjusted shares outstanding. To remove noise from the proxy, we use a 12-month backward moving average for the NSI. The dividend premium (PDIV) is the log of the ratio of the value-weighted average market-to-book ratio of payers to that of nonpayers. Firms with positive dividends are defined as payers and as nonpayers otherwise. The sample period is from Jan-1984 to Dec-2018.

	Global Index	Regional Index			Local Index		
		Asia Pacific	Europe	North America	Asia Pacific	Europe	North America
Panel A: Level							
Asia Pacific	0.30	1			1		
Europe	0.91	0.31	1		0.10	1	
North America	0.84	-0.07	0.70	1	-0.62	-0.26	1
Panel B: Change							
Asia Pacific	0.51	1			1		
Europe	0.41	0.13	1		-0.10	1	
North America	0.61	0.15	0.13	1	-0.23	-0.16	1

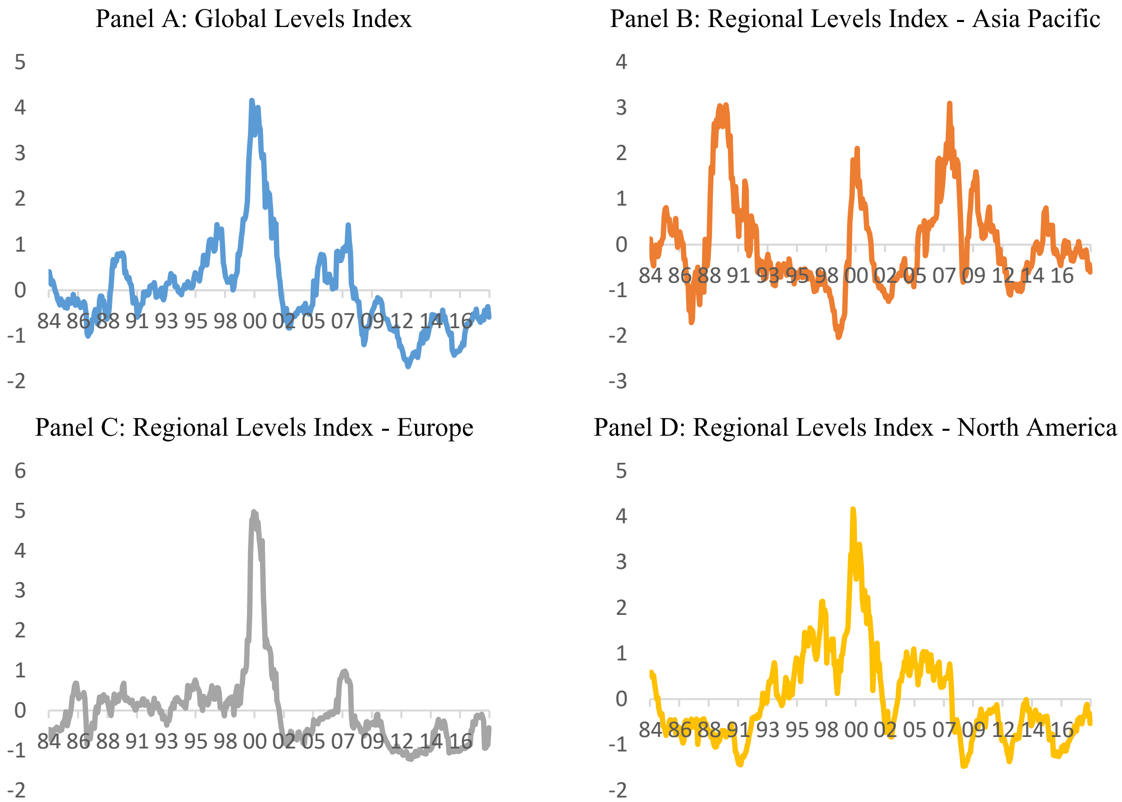

Figure 3.1. Sentiment Indexes

The figure plots the time-series of sentiment levels indexes for the global market (Panel A) and the following regional markets: Asia Pacific (Panel B), Europe (Panel C) and North America (Panel D). The sentiment levels index is the first principal component of the standardised sentiment proxies to have zero mean and unit variance. The following proxies are used. The variance premium (PVAR) is the log of the ratio of the value-weighted average market-to-book ratio of high variance stocks to that of low variance stocks. Stocks with the variance above (below) the 70th (30th) percentile of the variance are high (low) variance stocks and the variance is estimated using trailing 12-month excess returns. The net stock issues (NSI) is the value-weighted average growth rate of the number of stock-split adjusted shares outstanding. To remove noise from the proxy, we use a 12-month backward moving average for the NSI. The dividend premium (PDIV) is the log of the ratio of the value-weighted average market-to-book ratio of payers to the value-weighted average market-to-book ratio of nonpayers. Firms with positive dividends are categorised as payers and as nonpayers otherwise. The sample period is from Jan-1984 to Dec-2018.

3.4.3. Reversal Evidence

This subsection examines the time-series and cross-section of the effect of sentiment on mean, variance and correlation of stock returns. This chapter constructs two sets of test assets in the selected countries: market portfolios for the time-series test and sentiment beta sorted portfolios for the cross-sectional test.

For each market portfolio, we calculate the equal-weighted excess return of stocks included in the market. To construct sentiment beta sorted portfolios in each market, we proceed with the following procedure. First, to estimate individual stock's exposure to sentiment, we run a regression of the excess return on the change in the index using the past 36-month data at the end of year $t-1$:

$$R_{i,t} = a + \beta_{i,t^*}^{S} \Delta S_{j,t}^{R} + u_{i,t} \quad (3.8)$$

where i indexes individual stocks, j indexes regions that individual stocks belong to, $t \in \{t^* - 35, t^*\}$ indexes months and $r_{i,t}$ is the excess return. We exclude stocks with less than 24 valid observations. The loadings at the end of year $t-1$ are matched with excess returns in year t. Second, stocks are assigned to quintile groups based on the absolute value of the exposure to sentiment ($|\beta_{i,t^*}^{S}|$) at the beginning of year t and held during year t. We then calculate the equal-weighted excess return of stocks allocated to each group. To construct the test assets, we use the absolute value of the exposure, instead of the value of the exposure, because our interest lies in the test asset's variance and correlation.[33]

[33] In the following, we refer to this set of test assets as 'sentiment beta sorted portfolio'.

To estimate the conditional variance and correlation for the constructed test assets, we use the generalised autoregressive conditional heteroscedasticity (GARCH) model (Bollerslev, 1986) and dynamic equicorrelation (DECO) model (Engle and Kelly, 2012).[34] Each set of test assets is split into subordinate quintile groups when estimating the conditional correlation according to the absolute value of the exposure to sentiment.

3.4.3.1. Time-Series Evidence

3.4.3.1.1. Mean

Table 3.3. presents the parameter estimates for equations (3.4), (3.5), (3.6) and (3.7) in which X_t is the market excess return. First, the positive estimates for ΔS_t in Panel A suggest that sentiment and the market excess return move together in the same direction. For example, a one standard deviation increase in ΔS_t^G predicts 23.16 percentage points per annum (1.93 percentage points per month) higher market excess returns. Second, the negative estimates for S_t in Panel B suggest that the market excess return is reversed over the next 12 months. For example, a one standard deviation increase in S_t^G is associated with 8.64 percentage points per annum (0.72 percentage points per month) lower market excess returns.

The global sentiment index exhibits the highest level of economic significance, indicating that international investors contribute to mispricing in market-level assets, similar to Baker, Wurgler and Yuan (2012). Furthermore, considering the results from the two-regime models, mispricing appears to emerge regardless of whether investors are pessimistic or optimistic.

[34] See Appendix 3.1 and 3.2. for details about the GARCH and DECO models, respectively. The DECO model is particularly suitable for our research because it provides a single time-series of the conditional correlation for the given test assets by assuming that all pairs of returns have the same correlation.

Our results show that sentiment drives mispricing across developed countries. De Long et al. (1990a) suggest that mispricing emerges when noise traders' unpredictable beliefs crowd arbitrageurs out. Market correction arises in subsequent periods either as arbitrageurs return to the market or as noise traders realise that their own beliefs are incorrect. This mechanism leads sentiment to predict market excess returns as shown by this research and other previous studies, e.g., Schmeling (2009), Kothari and Shanken (1997), Henderson, Jegadeesh and Weisbach (2006), Baker and Wurgler (2006, 2007) and Baker, Wurgler and Yuan (2012).

Table 3.3. Market Return

The table reports parameter estimates in the regressions for the market returns. The dependent variable is the market excess return in month t in Panel A and the average of market excess returns from month $t+1$ to month $t+12$ in Panel B. The independent variables are as follows. The one-factor model includes the regional (R) sentiment levels or changes index in month t and the two-factor model contains the global (G) and local (L) sentiment levels or changes indexes in month t. The one-regime model contains the sentiment levels or changes index(es) in month t and the two-regime model consists of the interaction terms between the sentiment levels or changes indexes in month t and the following dummy variables in month t. N (P) is for the period in which the value of the changes index is negative (positive), and L (H) is for the period in which the value of the levels index is less (greater) than the median of the levels index. The table presents parameter estimates times 100. The associated p-values are calculated based on the Newey and West (1987) adjusted standard errors and reported in parentheses.

		One-Factor		Two-Factor			
		R		G		L	
Panel A: Contemporaneous Relation							
One-Regime		1.82	(0.00)	1.93	(0.00)	1.01	(0.00)
Two-Regime	N	2.08	(0.00)	2.77	(0.00)	0.81	(0.01)
	P	1.55	(0.00)	1.09	(0.00)	1.22	(0.00)
Panel B: Prediction							
One-Regime		-0.73	(0.00)	-0.72	(0.00)	-0.38	(0.00)
Two-Regime	L	-0.95	(0.00)	-0.57	(0.00)	-0.44	(0.01)
	H	-0.63	(0.00)	-0.81	(0.00)	-0.31	(0.02)

3.4.3.1.2. Variance

Table 3.4 reports the parameter estimates for equations (3.4), (3.5), (3.6) and (3.7) in which X_t is the change in the conditional variance of the market excess return. First, the negative estimates for ΔS_t in Panel A suggest that the stock market becomes more (less) volatile as the level of sentiment decreases (increases). For instance, a one standard deviation increase in ΔS_t^G predicts 35.76 bps per annum (2.98 bps per month) lower conditional market variance. Second, in Panel B, the estimates for S_t times L_t are positive and statistically significant, while those for S_t times H_t are close to zero. These indicate that the conditional market variance is reversed over the next 12 months following low sentiment periods but not following high sentiment periods. For example, a one standard deviation decrease in S_t^G predicts 17.76 bps per annum (1.48 bps per month) lower market variance. The higher levels of statistical and economic significance for the global index indicate that global sentiment is a prime driver for the relation between sentiment and the market return variance.

Our results indicate that a fraction of the time-series variation in the conditional market variance depends on sentiment, i.e., investors' pessimism generates nonfundamental variations in asset prices and excessive variance in turn. This confirms the prediction from the model of De Long et al. (1990a).

Investor sentiment bears a close relation to the speed of mean- reversion of the conditional variance.[35] Our evidence implies that variance persistence or clustering is perhaps related to bearish sentiment to a certain extent. In this regard, our results support the specification of stochastic variance models that include a term for investor sentiment in previous studies, e.g.,

[35] Kumari and Mahakud (2015) show that introducing sentiment into the variance equation affects the coefficient on the GARCH term which indicate that investor sentiment is related to variance persistence.

Lee, Jiang and Indro (2002), Kumari and Mahakud (2015) and Frijns, Verschoor and Zwinkels (2017).

Combining results in Tables 3.3 and 3.4 suggests that the mean-variance association can be negative as presented in previous literature, e.g., Campbell (1987), Nelson (1991) and Yu and Yuan (2011).[36] Based on our results, we argue that the market excess return tends to increase (decrease) with a bullish (bearish) change in sentiment, while the market return variance tends to increase (decrease) with a bearish (bullish) change in investor sentiment. These contrasting sentiment-based movements may have led previous literature to conclude the negative relation between mean and variance.[37]

Is there an intuitive economic rationale for this result? In the light of the leverage effect proposed in influential studies, e.g., Christie (1982), our results can be interpreted to reflect that investors' pessimism drags an asset's market price down, while its variance increases to accommodate an increase in the expected return.

[36] Meanwhile, previous studies including French, Schwert and Stambaugh (1987), Baillie and De Gennaro (1990), Campbell and Hentschel (1992), Ghysel, Santa-Clara and Valkanov (2005), Guo and Whitelaw (2006), Lundblad (2007) and Pastor, Sinha and Swaminathan (2008) show the positive mean-variance relation.

[37] Furthermore, Yu and Yuan (2011) show that sentiment erodes the mean-variance relation when investors are optimistic in particular.

Table 3.4. Market Variance

The table reports parameter estimates in the regressions for the changes in the conditional variances for the market excess returns. We use Bollerslev's (1986) generalised autoregressive conditional heteroscedasticity (GARCH) model to estimate the conditional market variance. The dependent variable is the change in the conditional market variance in month t in Panel A and the average of changes in the conditional market variance from month $t+1$ to month $t+12$ in Panel B. The independent variables are as follows. The one-factor model includes the regional (R) sentiment levels or changes index in month t and the two-factor model contains the global (G) and local (L) sentiment levels or changes indexes in month t. The one-regime model contains the sentiment levels or changes index(es) in month t and the two-regime model consists of the interaction terms between the sentiment levels or changes indexes in month t and the following dummy variables in month t. N (P) is for the period in which the value of the changes index is negative (positive), and L (H) is for the period in which the value of the levels index is less (greater) than the median of the levels index. The table presents parameter estimates times 10,000. The associated p-values are calculated based on the Newey and West (1987) adjusted standard errors and reported in parentheses.

		One-Factor		Two-Factor			
		R		G		L	
Panel A: Contemporaneous Relation							
One-Regime		-2.70	(0.01)	-2.98	(0.00)	-1.48	(0.18)
Two-Regime	N	-5.11	(0.01)	-3.23	(0.05)	-3.89	(0.06)
	P	-0.21	(0.83)	-2.69	(0.03)	1.08	(0.44)
Panel B: Prediction							
One-Regime		0.28	(0.09)	0.47	(0.00)	-0.14	(0.43)
Two-Regime	L	0.85	(0.04)	1.48	(0.00)	0.13	(0.66)
	H	0.03	(0.89)	0.06	(0.75)	-0.25	(0.42)

3.4.3.1.3. Correlation

Table 3.5 reports the parameter estimates for equations (3.4), (3.5), (3.6) and (3.7) in which X_t is the change in the conditional correlation of the market excess return. Overall, the results for the conditional correlation are analogous to those for the conditional variance. First, the negative estimates for ΔS_t in Panel A indicate that stock markets become more (less) correlated when aggregate market sentiment decreases (increases). For example, a one standard deviation increase in ΔS_t^G is associated with 0.0240 per annum (0.0020 per month) lower conditional market correlation.

Second, in Panel B, the estimates for S_t times L_t are positive and significant, whereas those for S_t times H_t are statistically insignificant, indicating that the conditional market correlation is reversed over the next 12 months following low sentiment periods but not following high sentiment periods. For example, a one standard deviation decrease in S_t^G predicts 0.0072 per annum (0.0006 per month) lower conditional market correlation.

Sentiment traders' pessimism contributes to excessive correlation in addition to excessive variance as those traders implement similar trading strategies, i.e., their opinions on the future cash flows from firms tend to be erroneous around the same time. Further, it is obvious that the excessive correlation causes a fraction of the excessive variance in Table 3.4. Our results reveal that a fraction of the time-series variation in the conditional correlation depends on sentiment traders' wrong beliefs, similar to the case of the conditional variance and contribute to the findings in the literature that comovements in assets' market prices can diverge from those in their fundamental values (Shiller, 1989; Pindyck and Rotemberg, 1993; Vijh, 1994; Barberis, Shleifer and Wurgler, 2005; Kumar and Lee, 2006; Frijns, Verschoor and Zwinkels, 2017; Ren, 2017).

Table 3.5. Market Correlation

The table presents parameter estimates in the regressions for the changes in the conditional correlations for the market excess returns. We use Engle and Kelly's (2012) dynamic equicorrelation (DECO) model to estimate the conditional market correlation. The dependent variable is the change in the conditional market correlation in month t in Panel A and the average of changes in the conditional market correlation from month $t+1$ to month $t+12$ in Panel B. The independent variables are as follows. The one-factor model includes the regional (R) sentiment levels or changes index in month t and the two-factor model contains the global (G) and local (L) sentiment levels or changes indexes in month t. The one-regime model contains the sentiment levels or changes index(es) in month t and the two-regime model consists of the interaction terms between the sentiment levels or changes indexes in month t and the following dummy variables in month t. N (P) is for the period in which the value of the changes index is negative (positive), and L (H) is for the period in which the value of the levels index is less (greater) than the median of the levels index. The table presents parameter estimates times 1,000. The associated p-values are calculated based on the Newey and West (1987) adjusted standard errors and reported in parentheses.

		One-Factor		Two-Factor			
		R		G		L	
Panel A: Contemporaneous Relation							
One-Regime		-1.80	(0.01)	-1.98	(0.00)	-0.80	(0.20)
Two-Regime	N	-1.75	(0.20)	-1.45	(0.08)	-0.76	(0.55)
	P	-1.85	(0.02)	-2.51	(0.00)	-0.85	(0.27)
Panel B: Prediction							
One-Regime		-0.04	(0.81)	-0.04	(0.77)	0.06	(0.65)
Two-Regime	L	0.84	(0.00)	0.62	(0.01)	1.30	(0.00)
	H	-0.41	(0.07)	-0.04	(0.89)	-0.87	(0.00)

3.4.3.2. Cross-Sectional Evidence

Next, we investigate the cross-section of asset return moments. Table 3.6 reports properties of sentiment beta sorted quintile portfolios. The results in the table account for all countries in the sample. First, stocks with more exposure to sentiment experience higher expected returns compared to those with less exposure to sentiment. This cross-sectional dispersion in the excess return might capture the premium for bearing the variation related to sentiment. It turns out that the sentiment premium is 0.47% (t = 4.90) per month which retains the economic and statistical significance. Second, the mean of the conditional variance tends to increase as the exposure to sentiment increases, as in the sentiment literature arguing that volatile firms are more prone to the shift in sentiment-based demands. Third, unlike the excess return and conditional variance, no interesting pattern emerges in the mean of the conditional correlation.

Table 3.6 confirms several arguments made in Baker and Wurgler (2006): stocks with more exposure to sentiment are smaller (Size) and less profitable (ROE). Besides, high sentiment beta stocks tend to experience higher recent performance (MOM) and asset growth (INV). However, B/M does not appear to be related to sentiment.

It is not surprising to observe that sentiment and market betas are correlated because changes in sentiment and market excess returns tend to move together as presented in Table 3.3. This relation may be a reason that previous studies did not succeed in confirming the implication of the CAPM (Sharpe, 1964): a positive relation between market beta and the excess return (Black, Jensen and Scholes, 1972; Fama and French, 1992; Frazzini and Pedersen, 2014).

Table 3.6. Properties of Sentiment Beta Sorted Portfolios

The table reports properties of sentiment beta sorted portfolios. Stocks are assigned to quintile groups based on the absolute value of the exposure to sentiment at the beginning of year t and held until the end of year t. Then, the equal-weighted excess return for each quintile portfolio is calculated. Individual stock's exposure to sentiment is estimated using a 3-year rolling time-series regression of individual excess returns over the regional changes index at the end of year t and matched with excess returns in year t. For the constructed portfolios, we use Bollerslev's (1986) generalised autoregressive conditional heteroscedasticity (GARCH) model to estimate the conditional variance and Engle and Kelly's (2012) dynamic equicorrelation (DECO) model to estimate the conditional correlation. Means and standard deviations of the excess returns, conditional variances and conditional correlations are reported, and the associated t-statistics are reported in parentheses. Reported firm characteristic include sentiment beta (β^S), market beta (β^M), size (Size), book-to-market ratio (B/M), return on equity (ROE), investment (INV) and momentum (MOM). β^M is estimated from a 3-year rolling time-series regression of the individual excess return over the market excess return. Size is market capitalisation at the end of June of year t. B/M is calculated as book value of equity in year $t-1$ divided by market value of equity at the end of December of year $t-1$. ROE is calculated as net income in year $t-1$ divided by book value of equity in year $t-1$. INV is calculated as book value of asset in year $t-1$ divided by book value of asset in year $t-2$. Size, B/M, ROE and INV are matched with excess returns from July of year t to June of year $t+1$. MOM is the cumulative excess return from month $t-12$ to month $t-2$.

	1 (Low)	2	3	4	5 (High)	High-Low
			Return (%)			
Mean	1.17	1.24	1.33	1.37	1.64	0.47
Std. Dev.	5.80	6.13	6.70	7.62	9.07	5.12
t.stat.	(10.84)	(10.81)	(10.63)	(9.63)	(9.69)	(4.90)
			Variance (%)			
Mean	0.40	0.42	0.45	0.51	0.60	0.20
Std. Dev.	0.35	0.36	0.40	0.46	0.61	0.37
t.stat.	(61.90)	(62.85)	(61.36)	(59.35)	(52.65)	(29.10)
			Correlation			
Mean	0.77	0.77	0.77	0.75	0.70	-0.07
Std. Dev.	0.13	0.14	0.14	0.15	0.17	0.08
t.stat.	(310.03)	(304.68)	(288.31)	(264.85)	(218.18)	(-49.00)
			Firm Characteristics			
$\beta^S \times 100$	0.19	0.65	1.19	2.00	4.14	
β^M	0.61	0.71	0.82	0.97	1.24	
ln(Size)	11.68	11.74	11.63	11.39	10.75	
B/M	1.00	1.01	1.03	1.00	0.93	
ROE (%)	2.11	2.04	-0.41	-4.49	-12.41	
INV (%)	22.63	20.97	22.58	27.07	39.09	
MOM (%)	13.73	14.74	15.82	18.15	31.36	

3.4.3.2.1. Mean

Table 3.7 reports the parameter estimates for equations (3.4), (3.5), (3.6) and (3.7) in which X_t is the sentiment beta sorted portfolio excess return. First, the positive estimates for ΔS_t in Panel A increase as the exposure to sentiment increases because the test assets are constructed according to the exposure to sentiment. For example, a one standard deviation increase in ΔS_t^G predicts that the highest quintile earns 16.44 percentage points per annum (1.37 percentage points per month) higher excess return than the lowest quintile. Second, the negative estimates for S_t times H_t (L_t) in Panel B decrease (increase) as the exposure to sentiment increases, which implies that stocks more prone to sentiment are (not) more overpriced (underpriced) due to investors' optimism (pessimism). For instance, a one standard deviation increase in S_t^G predicts that the highest quintile earns 10.44 percentage points per annum (0.87 percentage points per month) lower excess return than the lowest quintile. Further, international investors' sentiment appears to be a main culprit behind the relative overpricing in the cross-section as in Table 3.3.

Our evidence contributes to previous literature on the cross-sectional stock return variation due to sentiment traders' demands (see Lemmon and Portniagunia, 2006; Baker and Wurgler, 2006, 2007; Baker, Wurgler and Yuan, 2012; Stambaugh, Yu and Yuan, 2012; Antoniou, Doukas and Subrahmanyam, 2015; Shen, Yu and Zhao, 2017). These papers find that the cross-sectional dispersion in the effect of sentiment generates well-known traditional anomalies in financial markets.

Table 3.7. Sentiment Beta Sorted Portfolio Return

The table presents parameter estimates in the regressions for the sentiment beta sorted portfolio returns. The dependent variable is the portfolio excess return in month t in Panel A and the average of portfolio excess returns from month $t + 1$ to month $t + 12$ in Panel B. The independent variables are as follows. The one-factor model includes the regional (R) sentiment levels or changes index in month t and the two-factor model contains the global (G) and local (L) sentiment levels or changes indexes in month t. The one-regime model contains the sentiment levels or changes index(es) in month t and the two-regime model consists of the interaction terms between the sentiment levels or changes indexes in month t and the following dummy variables in month t. N (P) is for the period in which the value of the changes index is negative (positive), and L (H) is for the period in which the value of the levels index is less (greater) than the median of the levels index. The table presents parameter estimates times 100. The associated p-values are calculated based on the Newey and West (1987) adjusted standard errors and reported in parentheses.

			One-Factor		Two-Factor			
			R		G		L	
Panel A: Contemporaneous Relation								
One-Regime		1 (Low)	1.43	(0.00)	1.38	(0.00)	0.86	(0.00)
		2	1.55	(0.00)	1.51	(0.00)	0.92	(0.00)
		3	1.66	(0.00)	1.64	(0.00)	0.98	(0.00)
		4	2.14	(0.00)	2.10	(0.00)	1.26	(0.00)
		5 (High)	2.81	(0.00)	2.75	(0.00)	1.65	(0.00)
		H-L	1.38	(0.00)	1.37	(0.00)	0.79	(0.00)
Two-Regime	N	1 (Low)	1.73	(0.00)	1.99	(0.00)	0.84	(0.00)
		2	1.87	(0.00)	2.13	(0.00)	0.95	(0.00)
		3	1.94	(0.00)	2.38	(0.00)	0.87	(0.00)
		4	2.33	(0.00)	2.98	(0.00)	1.03	(0.00)
		5 (High)	2.84	(0.00)	3.86	(0.00)	1.18	(0.00)
		H-L	1.11	(0.00)	1.86	(0.00)	0.33	(0.08)
	P	1 (Low)	1.12	(0.00)	0.75	(0.00)	0.88	(0.00)
		2	1.21	(0.00)	0.87	(0.00)	0.89	(0.00)
		3	1.37	(0.00)	0.89	(0.00)	1.09	(0.00)
		4	1.93	(0.00)	1.21	(0.00)	1.50	(0.00)
		5 (High)	2.78	(0.00)	1.63	(0.00)	2.17	(0.00)
		H-L	1.66	(0.00)	0.87	(0.00)	1.29	(0.00)

Table 3.7. Sentiment Beta Sorted Portfolio Return (continued)

			One-Factor		Two-Factor			
			R		G		L	
Panel B: Prediction								
One-Regime		1 (Low)	-0.51	(0.00)	-0.52	(0.00)	-0.21	(0.01)
		2	-0.59	(0.00)	-0.60	(0.00)	-0.22	(0.01)
		3	-0.61	(0.00)	-0.60	(0.00)	-0.24	(0.01)
		4	-0.71	(0.00)	-0.71	(0.00)	-0.29	(0.01)
		5 (High)	-1.05	(0.00)	-1.01	(0.00)	-0.53	(0.00)
		H-L	-0.54	(0.00)	-0.50	(0.00)	-0.32	(0.00)
Two-Regime	L	1 (Low)	-0.84	(0.00)	-0.73	(0.00)	-0.15	(0.31)
		2	-0.95	(0.00)	-0.82	(0.00)	-0.12	(0.50)
		3	-0.96	(0.00)	-0.63	(0.00)	-0.12	(0.54)
		4	-1.10	(0.00)	-0.53	(0.02)	-0.16	(0.49)
		5 (High)	-1.33	(0.00)	-0.38	(0.12)	-0.38	(0.17)
		H-L	-0.49	(0.00)	0.36	(0.00)	-0.23	(0.13)
	H	1 (Low)	-0.36	(0.00)	-0.40	(0.00)	-0.29	(0.03)
		2	-0.43	(0.00)	-0.47	(0.00)	-0.36	(0.02)
		3	-0.45	(0.00)	-0.55	(0.00)	-0.35	(0.03)
		4	-0.54	(0.00)	-0.77	(0.00)	-0.38	(0.03)
		5 (High)	-0.92	(0.00)	-1.27	(0.00)	-0.58	(0.00)
		H-L	-0.56	(0.00)	-0.87	(0.00)	-0.29	(0.00)

3.4.3.2.2. Variance

Table 3.8 reports the parameter estimates for equations (3.4), (3.5), (3.6) and (3.7) in which X_t is the change in the conditional variance of the sentiment beta sorted portfolio excess return. First, the negative estimates for ΔS_t in Panel A tend to decrease with the exposure to investor sentiment, indicating that stocks more sensitive to sentiment become less (more) volatile than those less sensitive to sentiment with a bullish (bearish) change in sentiment. For example, a one standard deviation decrease in ΔS_t^G predicts that the conditional variance of the highest quintile is 36.48 bps per annum (3.04 bps per month) higher than that of the lowest quintile. However, the difference between the coefficients for the extreme quintile is not statistically significant at the 5% significance level for both optimistic and pessimistic periods.

Second, the estimates for S_t times L_t (H_t) in Panel B are (not) positive and (do not) tend to increase with the exposure to sentiment, indicating that the conditional variance for stocks that are more sensitive to sentiment undergoes severer reversal over the next 12 months following the period of pessimism but not following the period of optimism. For example, a one standard deviation decrease in S_t^G predicts that the conditional variance of the highest quintile is 7.20 bps per annum (0.60 bps per month) lower than that of the lowest quintile. Further, international investor sentiment rather than local investor sentiment appears to contribute to the emergence of the relative excessive variance, analogous to the previous evidence.

There are sentiment-based cross-sectional dispersions in predictable movements in the time-series of the conditional variance. First, our result suggests that the speed of mean-reversion of variance may depend on exposure to investor sentiment and support incorporating sentiment into the multivariate stochastic variance model. Our suggestion based on the results presented in this section is to assign a separate coefficient on sentiment for each asset to capture the cross-sectional difference. Second, our results indicate that the classic mean-variance relation can be more complicated for assets prone to investor sentiment because sentiment-based movements are stronger among these assets.

Table 3.8. Sentiment Beta Sorted Portfolio Variance

The table presents parameter estimates in the regressions for the changes in the conditional variances for the sentiment beta sorted portfolio excess returns. We use the generalised autoregressive conditional heteroscedasticity (GARCH) model developed by Bollerslev (1986) to estimate the conditional portfolio variance. The dependent variable is the change in the conditional portfolio variance in month t in Panel A and the average of changes in the conditional portfolio variance from month $t+1$ to month $t+12$ in Panel B. The independent variables are as follows. The one-factor model includes the regional (R) sentiment levels or changes index in month t and the two-factor model contains the global (G) and local (L) sentiment levels or changes indexes in month t. The one-regime model contains the sentiment levels or changes index(es) in month t and the two-regime model consists of the interaction terms between the sentiment levels or changes indexes in month t and the following dummy variables in month t. N (P) is for the period in which the value of the changes index is negative (positive), and L (H) is for the period in which the value of the levels index is less (greater) than the median of the levels index. The table shows parameter estimates times 10,000. The associated p-values are calculated based on the Newey and West (1987) adjusted standard errors and reported in parentheses.

			One-Factor		Two-Factor			
			R		G		L	
Panel A: Contemporaneous Relation								
One-Regime		1 (Low)	-2.88	(0.00)	-2.22	(0.00)	-2.08	(0.01)
		2	-2.78	(0.00)	-2.25	(0.00)	-1.93	(0.01)
		3	-3.29	(0.00)	-2.66	(0.00)	-2.31	(0.02)
		4	-4.16	(0.00)	-3.37	(0.00)	-2.88	(0.01)
		5 (High)	-5.72	(0.00)	-5.26	(0.00)	-3.55	(0.01)
		H-L	-2.84	(0.00)	-3.04	(0.01)	-1.46	(0.08)
Two-Regime	N	1 (Low)	-4.70	(0.00)	-2.43	(0.01)	-3.64	(0.02)
		2	-4.51	(0.00)	-2.58	(0.01)	-3.55	(0.02)
		3	-5.74	(0.00)	-3.25	(0.01)	-4.45	(0.03)
		4	-6.75	(0.00)	-3.91	(0.01)	-5.30	(0.01)
		5 (High)	-9.26	(0.00)	-6.69	(0.03)	-7.14	(0.01)
		H-L	-4.56	(0.01)	-4.26	(0.08)	-3.50	(0.02)
	P	1 (Low)	-0.93	(0.17)	-1.96	(0.01)	-0.35	(0.69)
		2	-0.92	(0.22)	-1.87	(0.01)	-0.13	(0.88)
		3	-0.66	(0.45)	-2.01	(0.04)	0.07	(0.95)
		4	-1.38	(0.18)	-2.77	(0.01)	-0.19	(0.87)
		5 (High)	-1.93	(0.24)	-3.72	(0.03)	0.45	(0.79)
		H-L	-1.00	(0.39)	-1.76	(0.15)	0.80	(0.45)

Table 3.8. Sentiment Beta Sorted Portfolio Variance (continued)

			One-Factor		Two-Factor			
			R		G		L	
Panel B: Prediction								
One-Regime		1 (Low)	0.22	(0.09)	0.31	(0.01)	-0.09	(0.51)
		2	0.27	(0.05)	0.35	(0.00)	-0.08	(0.60)
		3	0.33	(0.03)	0.41	(0.00)	-0.05	(0.76)
		4	0.41	(0.02)	0.47	(0.00)	-0.02	(0.91)
		5 (High)	0.36	(0.13)	0.48	(0.06)	-0.11	(0.65)
		H-L	0.14	(0.31)	0.17	(0.30)	-0.02	(0.90)
Two-Regime	L	1 (Low)	0.75	(0.02)	1.20	(0.00)	0.11	(0.63)
		2	0.83	(0.01)	1.29	(0.00)	0.12	(0.62)
		3	0.96	(0.01)	1.47	(0.00)	0.15	(0.57)
		4	1.00	(0.03)	1.70	(0.00)	0.09	(0.78)
		5 (High)	0.66	(0.32)	1.80	(0.00)	-0.34	(0.52)
		H-L	-0.08	(0.85)	0.60	(0.00)	-0.45	(0.19)
	H	1 (Low)	-0.01	(0.95)	-0.06	(0.70)	-0.15	(0.59)
		2	0.02	(0.93)	-0.05	(0.76)	-0.11	(0.68)
		3	0.05	(0.79)	-0.04	(0.83)	-0.08	(0.79)
		4	0.14	(0.54)	-0.07	(0.73)	0.06	(0.86)
		5 (High)	0.23	(0.46)	-0.20	(0.60)	0.29	(0.49)
		H-L	0.24	(0.14)	-0.14	(0.60)	0.44	(0.03)

3.4.3.2.3. Correlation

Table 3.9 reports the parameter estimates for equations (3.4), (3.5), (3.6) and (3.7) in which X_t is the change in the conditional correlation of the sentiment beta sorted portfolio excess return. First, the estimates for ΔS_t in Panel A are negative and tend to decrease with the exposure to sentiment, indicating that stocks more sensitive to sentiment become less (more) correlated with a bullish (bearish) change in sentiment. For example, a one standard deviation increase in ΔS_t^G predicts that the conditional correlation of the highest quintile is 0.0168 per annum (0.0014 per month) lower than that of the lowest quintile. Compared to results presented in Table 3.8, the statistical significance of the estimates for ΔS_t times N_t is lower.

Second, similar to the case of the conditional variance, the estimates for S_t times L_t in Panel B are positive and tend to increase as the exposure to sentiment increases, and the estimates for S_t times H_t in Panel B are not positive and do not tend to increase as the exposure to sentiment increases. This indicates that the conditional correlation for stocks more sensitive to sentiment decreases more than stocks less sensitive to sentiment over the next 12 months following low sentiment periods. For example, a one standard deviation decrease in S_t^G predicts that the conditional correlation of the highest quintile is 0.0180 per annum (0.0015 per month) lower than that of the lowest quintile.

While the level of statistical significance for the results from the two-regime models in Panel A is lower, the results presented in Table 3.9 provide evidence of the sentiment-based cross-sectional dispersion in predictable variations in the time-series of the conditional correlation, similar to the cross-sectional evidence on the conditional variance.[38] Furthermore, our results

[38] The lower statistical significance may suggest that the stochastic correlation model, which assumes that each pair of assets has an identical correlation, is less elaborate when compared to the stochastic variance model.

suggest that the cross-sectional dispersion in the excessive correlation may explain some level of the cross-sectional dispersion in the excessive variance.

Table 3.9. Sentiment Beta Sorted Portfolio Correlation

The table presents parameter estimates in the regressions for the changes in the conditional correlations for the sentiment beta sorted portfolio excess returns. We use the dynamic equicorrelation (DECO) model developed by Engle and Kelly (2012) to estimate the conditional portfolio correlation. The dependent variable is the change in the conditional portfolio correlation in month t in Panel A and the average of changes in the conditional portfolio correlation from month $t+1$ to month $t+12$ in Panel B. The independent variables are as follows. The one-factor model includes the regional (R) sentiment levels or changes index in month t and the two-factor model contains the global (G) and local (L) sentiment levels or changes indexes in month t. The one-regime model contains the sentiment levels or changes index(es) in month t and the two-regime model consists of the interaction terms between the sentiment levels or changes indexes in month t and the following dummy variables in month t. N (P) is for the period in which the value of the changes index is negative (positive), and L (H) is for the period in which the value of the levels index is less (greater) than the median of the levels index. The table presents parameter estimates times 1,000. The associated p-values are calculated based on the Newey and West (1987) adjusted standard errors and reported in parentheses.

			One-Factor		Two-Factor			
			R		G		L	
Panel A: Contemporaneous Relation								
One-Regime		1 (Low)	-2.02	(0.00)	-1.86	(0.00)	-1.23	(0.01)
		2	-2.24	(0.00)	-1.67	(0.00)	-1.59	(0.00)
		3	-2.66	(0.00)	-1.99	(0.00)	-1.87	(0.00)
		4	-2.48	(0.00)	-2.11	(0.00)	-1.65	(0.01)
		5 (High)	-4.20	(0.00)	-3.26	(0.00)	-2.98	(0.00)
		H-L	-2.17	(0.00)	-1.40	(0.01)	-1.75	(0.00)
Two-Regime	N	1 (Low)	-2.44	(0.01)	-1.18	(0.14)	-1.87	(0.04)
		2	-2.69	(0.00)	-1.12	(0.15)	-2.22	(0.03)
		3	-3.06	(0.00)	-1.28	(0.17)	-2.33	(0.03)
		4	-3.07	(0.02)	-1.18	(0.26)	-2.46	(0.08)
		5 (High)	-4.18	(0.01)	-2.08	(0.15)	-3.08	(0.04)
		H-L	-1.73	(0.06)	-0.90	(0.37)	-1.21	(0.19)
	P	1 (Low)	-1.57	(0.03)	-2.54	(0.00)	-0.53	(0.46)
		2	-1.76	(0.02)	-2.21	(0.01)	-0.89	(0.19)
		3	-2.22	(0.00)	-2.70	(0.00)	-1.37	(0.08)
		4	-1.85	(0.01)	-3.04	(0.00)	-0.74	(0.36)
		5 (High)	-4.22	(0.00)	-4.47	(0.00)	-2.87	(0.01)
		H-L	-2.65	(0.00)	-1.93	(0.04)	-2.34	(0.01)

Table 3.9. Sentiment Beta Sorted Portfolio Correlation (continued)

			One-Factor		Two-Factor			
			R		G		L	
Panel B: Prediction								
One-Regime		1 (Low)	-0.17	(0.27)	-0.22	(0.20)	0.07	(0.59)
		2	-0.13	(0.43)	-0.20	(0.26)	0.13	(0.40)
		3	-0.14	(0.42)	-0.22	(0.26)	0.14	(0.43)
		4	-0.11	(0.58)	-0.21	(0.35)	0.18	(0.38)
		5 (High)	0.02	(0.95)	-0.11	(0.72)	0.28	(0.23)
		H-L	0.18	(0.23)	0.11	(0.48)	0.21	(0.20)
Two-Regime	L	1 (Low)	0.50	(0.13)	0.61	(0.02)	0.73	(0.02)
		2	0.92	(0.01)	1.08	(0.00)	0.97	(0.01)
		3	1.15	(0.00)	1.21	(0.00)	1.04	(0.01)
		4	1.21	(0.01)	1.56	(0.00)	1.25	(0.01)
		5 (High)	1.16	(0.04)	2.07	(0.00)	1.48	(0.01)
		H-L	0.66	(0.05)	1.46	(0.00)	0.75	(0.04)
	H	1 (Low)	-0.47	(0.05)	-0.43	(0.14)	-0.40	(0.15)
		2	-0.60	(0.01)	-0.58	(0.07)	-0.45	(0.12)
		3	-0.72	(0.00)	-0.65	(0.05)	-0.48	(0.10)
		4	-0.70	(0.01)	-0.76	(0.05)	-0.54	(0.12)
		5 (High)	-0.50	(0.20)	-0.81	(0.11)	-0.49	(0.25)
		H-L	-0.03	(0.90)	-0.38	(0.13)	-0.08	(0.74)

3.5. Robustness

To retain robustness for the uncovered empirical regularities in the previous section, we employ another set of test assets. Noise traders are known to increase their preference on riskier assets when they are optimistic. It follows that high market beta stocks are more prone to the shift in sentiment as argued in Antonious, Doukas and Subrahmanyam (2016). Hence, we repeat the same set of cross-sectional empirical investigations in the current section using market beta sorted portfolios. These assets are constructed in the same manner as in the case of sentiment beta sorted portfolios.

Table 3.10 presents properties of market beta sorted portfolios. The results presented in the table consider all countries in the sample. First, the expected return on the highest quintile, 1.37% (t = 8.43) per month, is higher than that on the lowest quintile, 1.74% (t = 14.11) per month, and their difference, -0.37% (t = -3.93) per month, retains meaningful statistical and economic significance. This negative premium contradicts the implication of the CAPM. This is not surprising as previous studies, including Black, Jensen and Scholes (1972), Fama and French (1992), Baker, Bradley and Wurgler (2011) and Frazzini and Pedersen (2014), have shown that the relation between market beta and the expected return is flat or even negative in the U.S. stock market, and our evidence extends these studies' results to international stock market.

Second, the mean of the conditional variance tends to increase as market beta increases, indicating that riskier stocks are attractive to sentiment traders but unattractive to arbitrageurs. Meanwhile, the mean of the condition correlation of the highest quintile is higher than that of the lowest quintile. Looking at firm characteristics, companies in the extreme quintiles are less profitable and experience more rapid asset growth and better recent performance. The table confirms the positive relation between sentiment and market beta.

Table 3.10. Properties of Market Beta Sorted Portfolios

The table reports properties of market beta sorted portfolios. Stocks are assigned into quintile groups based on the market exposure at the beginning of year t and held until the end of year t. Then, the equal-weighted excess return for each quintile portfolio is calculated. Individual stock's market beta is estimated from a 3-year rolling time-series regression of individual excess returns against the market excess return at the end of year t and matched with excess returns in year t. For the constructed quintile portfolios, we use Bollerslev's (1986) generalised autoregressive conditional heteroscedasticity (GARCH) model to estimate the conditional variance. We use Engle and Kelly's (2012) dynamic equicorrelation (DECO) model to estimate the conditional correlation. Means and standard deviations of the excess returns, conditional variances and conditional correlations are presented, and the associated t-statistics are presented in parentheses. Firm characteristics, sentiment beta (β^S), market beta (β^M), size (Size), book-to-market ratio (B/M), return on equity (ROE), investment (INV) and momentum (MOM), are reported. β^S is estimated from a 3-year rolling time-series regression of individual excess returns over the regional sentiment changes index. Size is market capitalisation at the end of June of year t. B/M is calculated as book value of equity in year $t-1$ divided by market value of equity at the end of December of year $t-1$. ROE is calculated as net income in year $t-1$ divided by book value of equity in year $t'-1$. INV is calculated as book value of asset in year $t-1$ divided by book value of asset in year $t-2$. Size, B/M, ROE and INV are matched with excess returns from July of year t to June of year $t+1$. MOM is cumulative excess return from month $t-12$ to month $t-2$.

	1 (Low)	2	3	4	5 (High)	H-L
			Return (%)			
Mean	1.74	1.26	1.22	1.27	1.37	-0.37
Std. Dev.	6.73	6.02	6.46	7.34	8.86	5.17
t.stat.	(14.11)	(11.42)	(10.33)	(9.42)	(8.43)	(-3.93)
			Variance (%)			
Mean	0.44	0.44	0.48	0.54	0.65	0.21
Std. Dev.	0.42	0.37	0.42	0.48	0.59	0.38
t.stat.	(57.13)	(64.79)	(62.73)	(61.49)	(60.14)	(30.45)
			Correlation			
Mean	0.69	0.77	0.79	0.78	0.75	0.06
Std. Dev.	0.16	0.14	0.13	0.14	0.16	0.07
t.stat.	(232.61)	(305.25)	(332.86)	(311.40)	(252.09)	(46.57)
			Firm Characteristics			
$\beta^S \times 100$	0.28	0.94	1.41	2.02	3.52	
β^M	-0.13	0.51	0.81	1.15	1.97	
ln(Size)	10.56	11.51	11.86	11.90	11.46	
B/M	1.07	1.03	1.03	1.01	0.96	
ROE (%)	-2.67	3.40	2.52	0.00	-10.16	
INV (%)	29.02	19.77	18.82	22.72	32.85	
MOM (%)	20.58	16.33	16.97	18.25	27.15	

3.5.1. Mean

Table 3.11 reports the parameter estimates for equations (3.4), (3.5), (3.6) and (3.7) in which X_t is the market beta sorted portfolio excess return. First, the positive estimates for ΔS_t in Panel A tend to increase as market beta increases. For example, a one standard deviation increase in ΔS_t^G predicts 15.00 percentage points per annum (1.25 percentage points per month) higher excess returns for the highest quintile compared to the lowest quintile. This increasing pattern supports the argument in the sentiment literature introduced in the previous section that riskier stocks are more sensitive to sentiment.

Second, the negative estimates for S_t in Panel B tend to decrease as market beta decreases, but the difference between the coefficients for the extreme quintiles is not significant for the case of pessimism periods. This result suggests that the highest quintile earns lower excess return than the lowest quintile following high sentiment periods, however, the highest quintile does not earn higher excess return than the lowest quintile following low sentiment periods. For example, a one standard deviation increase in S_t^G predicts that the highest quintile yields 7.20 percentage points per annum (0.60 percentage points per month) lower excess returns than the lowest quintile.

Overall, the results presented in the Table 3.11 are similar to those in Table 3.7, i.e., the relative sentiment-based overpricing is confirmed in the cross-sectional dimension, while the relative sentiment-based underpricing is not. The consistent results across Tables 3.7 and 3.11 indicate that sentiment is a significant factor in explaining dispersions in the cross-sectional asset returns when investors are optimistic.

Our results suggest that the relation between market beta and the expected return can be negative due to investors' optimistic opinions. This finding speaks to the empirical evidence of Antonious, Doukas and Subrahmanyam (2016): the slope of the security market line (SML) is negative following high sentiment periods and positive following low sentiment periods. Therefore, to explain the cross-section of stock returns, a pricing factor capturing a premium for sentiment should be included in an asset pricing model to accommodate the effect of sentiment on the expected return.[39]

[39] More recent studies, e.g., Stambaugh and Yuan (2017) and Daniel, Hirshleifer and Sun (2020) propose a novel asset pricing model in order to consider the effect of mispricing on the cross-section of asset returns.

Table 3.11. Market Beta Sorted Portfolio Return

The table presents parameter estimates in the regressions for the market beta sorted portfolio returns. The dependent variable is the portfolio excess return in month t in Panel A and the average of portfolio excess returns from month $t+1$ to month $t+12$ in Panel B. The independent variables are as follows. The one-factor model includes the regional (R) sentiment levels or changes index in month t and the two-factor model contains the global (G) and local (L) sentiment levels or changes indexes in month t. The one-regime model includes the sentiment levels or changes index(es) in month t and the two-regime model contains the interaction terms between the sentiment levels or changes indexes in month t and the following dummy variables in month t. N (P) is for the period in which the value of the changes index is negative (positive), and L (H) is for the period in which the value of the levels index is less (greater) than the median of the levels index. The table presents parameter estimates times 100. The associated p-values are calculated based on the Newey and West (1987) adjusted standard errors and reported in parentheses.

			One-Factor		Two-Factor			
			R		G		L	
Panel A: Contemporaneous Relation								
One-Regime		1 (Low)	1.51	(0.00)	1.48	(0.00)	0.89	(0.00)
		2	1.50	(0.00)	1.42	(0.00)	0.90	(0.00)
		3	1.63	(0.00)	1.58	(0.00)	0.98	(0.00)
		4	1.92	(0.00)	1.94	(0.00)	1.11	(0.00)
		5 (High)	2.76	(0.00)	2.73	(0.00)	1.62	(0.00)
		H-L	1.25	(0.00)	1.25	(0.00)	0.73	(0.00)
Two-Regime	N	1 (Low)	1.60	(0.00)	1.97	(0.00)	0.85	(0.00)
		2	1.74	(0.00)	1.99	(0.00)	0.86	(0.00)
		3	1.98	(0.00)	2.31	(0.00)	0.96	(0.00)
		4	2.17	(0.00)	2.89	(0.00)	0.87	(0.01)
		5 (High)	2.80	(0.00)	3.82	(0.00)	1.10	(0.00)
		H-L	1.20	(0.00)	1.85	(0.00)	0.25	(0.14)
	P	1 (Low)	1.42	(0.00)	0.97	(0.00)	0.94	(0.00)
		2	1.24	(0.00)	0.84	(0.00)	0.95	(0.00)
		3	1.25	(0.00)	0.83	(0.00)	0.99	(0.00)
		4	1.66	(0.00)	0.97	(0.00)	1.38	(0.00)
		5 (High)	2.73	(0.00)	1.61	(0.00)	2.20	(0.00)
		H-L	1.30	(0.00)	0.65	(0.00)	1.26	(0.00)

Table 3.11. Market Beta Sorted Portfolio Return (continued)

			One-Factor		Two-Factor			
			R		G		L	
Panel B: Prediction								
One-Regime		1 (Low)	-0.61	(0.00)	-0.60	(0.00)	-0.24	(0.02)
		2	-0.52	(0.00)	-0.54	(0.00)	-0.17	(0.05)
		3	-0.63	(0.00)	-0.68	(0.00)	-0.20	(0.02)
		4	-0.70	(0.00)	-0.72	(0.00)	-0.27	(0.01)
		5 (High)	-0.95	(0.00)	-0.99	(0.00)	-0.38	(0.00)
		H-L	-0.34	(0.00)	-0.40	(0.00)	-0.14	(0.01)
Two-Regime	L	1 (Low)	-0.88	(0.00)	-0.46	(0.02)	-0.10	(0.66)
		2	-0.86	(0.00)	-0.61	(0.00)	-0.09	(0.64)
		3	-0.90	(0.00)	-0.69	(0.00)	-0.09	(0.62)
		4	-0.99	(0.00)	-0.63	(0.00)	-0.20	(0.31)
		5 (High)	-0.98	(0.00)	-0.41	(0.09)	-0.19	(0.38)
		H-L	-0.10	(0.51)	0.06	(0.64)	-0.09	(0.38)
	H	1 (Low)	-0.49	(0.00)	-0.62	(0.00)	-0.35	(0.04)
		2	-0.36	(0.00)	-0.48	(0.00)	-0.26	(0.08)
		3	-0.51	(0.00)	-0.65	(0.00)	-0.30	(0.05)
		4	-0.56	(0.00)	-0.74	(0.00)	-0.31	(0.06)
		5 (High)	-0.93	(0.00)	-1.22	(0.00)	-0.46	(0.01)
		H-L	-0.44	(0.00)	-0.60	(0.00)	-0.11	(0.20)

3.5.2. Variance

Table 3.12 reports the parameter estimates for equations (3.4), (3.5), (3.6) and (3.7) in which X_t is the change in the conditional variance of market beta sorted portfolio excess return. First, Panel A shows that the negative estimates for ΔS_t in Panel A decrease as market beta increases, indicating that the highest quintile becomes less (more) volatile than the lowest quintile with a bullish (bearish) shift in sentiment. For example, a one standard deviation decrease in ΔS_t^G predicts that the conditional variance of the highest quintile is 36.00 bps per annum (3.00 bps per month) higher than that of the lowest quintile.

Second, Panel B shows that the positive estimates for S_t times L_t in Panel B increase as market beta increases. This indicates that that the conditional variance of the highest quintile decreases more than that of the lowest quintile following low sentiment periods. For example, a one standard deviation decrease in S_t^G predicts that the conditional variance of the highest quintile is 15.36 bps per annum (1.28 bps per month) lower than the conditional variance of the lowest quintile.

Overall, the results presented in Table 3.12 are consistent with the ones discussed for Table 3.8. The influence of sentiment on the cross-section of the conditional variance appears to be similar or even greater, compared to the results in Table 3.8. The results further support the sentiment-based cross-sectional variation in the conditional variance and suggest that investors should take sentiment into account when budgeting or managing their risk in international markets.

Table 3.12. Market Beta Sorted Portfolio Variance

The table presents parameter estimates in the regressions for the changes in the conditional variances of the sentiment beta sorted portfolio excess returns. We use the generalised autoregressive conditional heteroscedasticity (GARCH) model developed by Bollerslev (1986) to estimate the conditional portfolio variance. The dependent variable is the change in the conditional portfolio variance in month t in Panel A and the average of the changes in the conditional portfolio variance from month $t+1$ to month $t+12$ in Panel B. The independent variables are as follows. The one-factor model includes the regional (R) sentiment levels or changes index in month t and the two-factor model contains the global (G) and local (L) sentiment levels or changes indexes in month t. The one-regime model contains the sentiment levels or changes index(es) in month t and the two-regime model consists of the interaction terms between the sentiment levels or changes indexes in month t and the following dummy variables in month t. N (P) is for the period in which the value of the changes index is negative (positive), and L (H) is for the period in which the value of the levels index is less (greater) than the median of the levels index. The table shows parameter estimates times 10,000. The associated p-values are calculated based on the Newey and West (1987) adjusted standard errors and reported in parentheses.

			One-Factor		Two-Factor			
			R		G		L	
Panel A: Contemporaneous Relation								
One-Regime		1 (Low)	-2.65	(0.00)	-2.00	(0.00)	-1.94	(0.02)
		2	-2.39	(0.00)	-1.77	(0.00)	-1.76	(0.02)
		3	-3.02	(0.00)	-2.36	(0.00)	-2.16	(0.01)
		4	-3.82	(0.00)	-3.39	(0.00)	-2.46	(0.02)
		5 (High)	-5.34	(0.00)	-4.99	(0.00)	-3.31	(0.02)
		H-L	-2.69	(0.00)	-3.00	(0.00)	-1.37	(0.10)
Two-Regime	N	1 (Low)	-4.16	(0.01)	-2.41	(0.01)	-3.39	(0.04)
		2	-4.07	(0.00)	-1.96	(0.02)	-3.34	(0.02)
		3	-5.28	(0.00)	-2.95	(0.01)	-4.10	(0.02)
		4	-6.76	(0.00)	-4.47	(0.01)	-5.03	(0.02)
		5 (High)	-9.39	(0.00)	-6.48	(0.01)	-7.54	(0.01)
		H-L	-5.23	(0.00)	-4.07	(0.04)	-4.15	(0.01)
	P	1 (Low)	-1.01	(0.21)	-1.53	(0.09)	-0.34	(0.72)
		2	-0.58	(0.41)	-1.54	(0.04)	-0.01	(0.99)
		3	-0.58	(0.48)	-1.72	(0.06)	0.00	(1.00)
		4	-0.66	(0.50)	-2.21	(0.03)	0.39	(0.74)
		5 (High)	-0.97	(0.51)	-3.36	(0.03)	1.38	(0.41)
		H-L	0.04	(0.97)	-1.83	(0.11)	1.72	(0.10)

Table 3.12. Market Beta Sorted Portfolio Variance (continued)

			One-Factor		Two-Factor			
			R		G		L	
Panel B: Prediction								
One-Regime		1 (Low)	0.17	(0.18)	0.27	(0.02)	-0.08	(0.56)
		2	0.30	(0.02)	0.38	(0.00)	-0.04	(0.79)
		3	0.43	(0.01)	0.51	(0.00)	-0.03	(0.86)
		4	0.56	(0.00)	0.65	(0.00)	0.00	(0.99)
		5 (High)	0.70	(0.00)	0.79	(0.00)	-0.02	(0.93)
		H-L	0.53	(0.00)	0.53	(0.00)	0.06	(0.66)
Two-Regime	L	1 (Low)	0.38	(0.24)	0.89	(0.00)	-0.02	(0.93)
		2	0.61	(0.05)	1.13	(0.00)	0.05	(0.81)
		3	0.79	(0.05)	1.43	(0.00)	0.04	(0.89)
		4	0.99	(0.05)	1.72	(0.00)	0.00	(1.00)
		5 (High)	1.04	(0.09)	2.17	(0.00)	-0.24	(0.58)
		H-L	0.66	(0.09)	1.28	(0.00)	-0.22	(0.39)
	H	1 (Low)	0.07	(0.67)	-0.01	(0.97)	-0.05	(0.85)
		2	0.16	(0.37)	0.05	(0.74)	-0.01	(0.96)
		3	0.27	(0.22)	0.10	(0.58)	0.04	(0.89)
		4	0.37	(0.14)	0.14	(0.51)	0.15	(0.67)
		5 (High)	0.54	(0.09)	0.09	(0.77)	0.38	(0.40)
		H-L	0.47	(0.02)	0.10	(0.61)	0.43	(0.09)

3.5.3. Correlation

Table 3.13 reports the parameter estimates for equations (3.4), (3.5), (3.6) and (3.7) in which X_t is the change in the conditional correlation of market beta sorted portfolio excess return. First, similar to the results presented in Table 3.9, the statistical significance of the estimates for ΔS_t presented in Panel A is quite low.

Second, and nonetheless, Panel B present that the estimates for S_t times L_t in Panel B are positive and tend to increase as market beta increases, indicating that the conditional correlation of riskier stocks decreases more following low sentiment periods. For instance, a one standard deviation decrease in S_t^G predicts that the conditional correlation of the highest quintile is 0.0093 per annum (0.0008 per month) lower than that of the lowest quintile. The results in general are consistent with the ones in Table 3.9. i.e., sentiment-based excessive correlation due to investors' pessimistic mood is confirmed.

Overall, our results on the relation between the moments of asset returns and sentiment are remarkably consistent and do not depend on the test asset considered. Our analysis suggests that investors' optimistic sentiment overvalues assets, while their pessimistic sentiment creates excessive variance and correlation. Such distortions in the moments of asset returns enable sentiment to anticipate capital market behaviour.

Table 3.13. Market Beta Sorted Portfolio Correlation

The table presents parameter estimates in the regressions for the changes in the conditional correlations of the sentiment beta sorted portfolio excess returns. We use the dynamic equicorrelation (DECO) model developed by Engle and Kelly (2012) to estimate the conditional portfolio correlation. The dependent variable is the change in the conditional portfolio correlation in month t in Panel A and the average of the changes in the conditional portfolio correlation from month $t+1$ to month $t+12$ in Panel B. The independent variables are as follows. The one-factor model includes the regional (R) sentiment levels or changes index in month t and the two-factor model contains the global (G) and local (L) sentiment levels or changes indexes in month t. The one-regime model contains the sentiment levels or changes index(es) in month t and the two-regime model consists of the interaction terms between the sentiment levels or changes indexes in month t and the following dummy variables in month t. N (P) is for the period in which the value of the changes index is negative (positive), and L (H) is for the period in which the value of the levels index is less (greater) than the median of the levels index. The table presents parameter estimates times 1,000. The associated p-values are calculated based on the Newey and West (1987) adjusted standard errors and reported in parentheses.

			One-Factor		Two-Factor			
			R		G		L	
Panel A: Contemporaneous Relation								
One-Regime		1 (Low)	-3.33	(0.00)	-2.34	(0.00)	-2.43	(0.00)
		2	-2.54	(0.00)	-1.69	(0.00)	-1.94	(0.00)
		3	-1.94	(0.00)	-1.46	(0.00)	-1.39	(0.00)
		4	-2.61	(0.00)	-2.19	(0.00)	-1.72	(0.00)
		5 (High)	-3.41	(0.00)	-3.01	(0.00)	-2.14	(0.00)
		H-L	-0.08	(0.87)	-0.67	(0.20)	0.29	(0.58)
Two-Regime	N	1 (Low)	-4.10	(0.01)	-2.04	(0.09)	-2.62	(0.09)
		2	-2.78	(0.00)	-0.44	(0.63)	-2.57	(0.01)
		3	-2.01	(0.02)	-0.73	(0.39)	-1.49	(0.10)
		4	-3.09	(0.01)	-1.25	(0.21)	-2.46	(0.03)
		5 (High)	-3.19	(0.03)	-1.62	(0.17)	-2.46	(0.08)
		H-L	0.91	(0.28)	0.42	(0.63)	0.16	(0.85)
	P	1 (Low)	-2.50	(0.01)	-2.64	(0.01)	-2.22	(0.03)
		2	-2.28	(0.00)	-2.96	(0.00)	-1.24	(0.09)
		3	-1.85	(0.00)	-2.21	(0.00)	-1.28	(0.04)
		4	-2.09	(0.01)	-3.14	(0.00)	-0.91	(0.30)
		5 (High)	-3.66	(0.00)	-4.42	(0.00)	-1.79	(0.06)
		H-L	-1.16	(0.20)	-1.79	(0.05)	0.44	(0.62)

Table 3.13. Market Beta Sorted Portfolio Correlation (continued)

		One-Factor		Two-Factor			
		R		G		L	
Panel B: Prediction							
One-Regime	1 (Low)	-0.17	(0.48)	-0.22	(0.39)	0.16	(0.51)
	2	-0.12	(0.49)	-0.20	(0.31)	0.13	(0.42)
	3	-0.20	(0.19)	-0.30	(0.06)	0.11	(0.45)
	4	-0.07	(0.67)	-0.14	(0.48)	0.18	(0.27)
	5 (High)	0.13	(0.56)	-0.03	(0.90)	0.35	(0.06)
	H-L	0.29	(0.00)	0.19	(0.03)	0.19	(0.06)
Two-Regime L	1 (Low)	1.27	(0.01)	1.36	(0.00)	1.67	(0.00)
	2	0.76	(0.06)	0.83	(0.01)	0.98	(0.01)
	3	0.73	(0.02)	0.68	(0.01)	0.78	(0.02)
	4	0.97	(0.01)	1.10	(0.00)	0.94	(0.02)
	5 (High)	1.51	(0.00)	2.14	(0.00)	1.56	(0.00)
	H-L	0.24	(0.32)	0.78	(0.00)	-0.11	(0.60)
Two-Regime H	1 (Low)	-0.82	(0.02)	-0.56	(0.22)	-0.99	(0.02)
	2	-0.52	(0.04)	-0.46	(0.19)	-0.49	(0.10)
	3	-0.62	(0.01)	-0.58	(0.04)	-0.37	(0.15)
	4	-0.55	(0.03)	-0.52	(0.14)	-0.33	(0.25)
	5 (High)	-0.50	(0.12)	-0.72	(0.10)	-0.44	(0.22)
	H-L	0.32	(0.01)	-0.16	(0.22)	0.55	(0.00)

3.6. Conclusion

This chapter analyses the effect of sentiment on the conditional moments of asset returns in international capital markets. Composite sentiment indexes are constructed targeting global and regional markets based on the method proposed by Baker and Wurgler (2006). Then, the effect of sentiment on the time-series and cross-section of mean, variance and correlation of asset returns is examined to determine whether sentiment traders' attitudes and moods create predictable variations. Our research contributes to the asset pricing literature by improving the understanding of the multivariate distribution of asset returns.

Using international stock market data spanning from 1984 to 2018, our analysis reveals important aspects of the relation between sentiment and moments of asset returns. First, a bullish (bearish) change in sentiment causes an increase (decrease) in asset prices, whereas a bearish change in sentiment result in an increase in the conditional variance and correlation. Further, investors' optimism (pessimism) predicts negative (positive) excess returns, whereas investors' pessimism anticipates a decrease in the conditional variance and correlation. Overall, our time-series evidence indicates that overpricing (underpricing) occurs during optimism (pessimism) periods and that excessive variance and excessive correlation occur during the pessimism periods. Second, even though underpricing evidence disappears, our cross-sectional results indicate that the empirical regularities in the time-series evidence are more pervasive among high market or sentiment beta stocks.

Our research suggests that investor sentiment is associated with puzzling observations in international financial markets. First, positive changes in sentiment create upward movements in mean, while positive changes in sentiment cause downward movements in variance. In line with previous studies, these sentiment-based movements lead to the conclusion that the mean-variance relation is negative. Second, high beta stocks are more overpriced in optimism periods and returns on high beta stocks become lower in subsequent periods, which means that the slope of the SML can be flat or negative, especially following high sentiment periods. We recommend utilising conditional mean, variance and covariance estimators on sentiment either to enhance ex-post performance when establishing asset allocation plans or to increase the flexibility of investment strategies when budgeting risks.

Appendix 3.1. Conditional Variance Model

This chapter uses the univariate GARCH model of Bollerslev (1986) to estimate conditional variance:

$$\epsilon_t = \sigma_t z_t \tag{A3.1.1}$$

$$h_t = \omega + \beta\epsilon_{t-1}^2 + \gamma h_{t-1} \tag{A3.1.2}$$

where ϵ_t is the demeaned daily excess return and h_t is the daily conditional variance. The conditional variance in month t is calculated as follows:

$$\sigma_t^2 = \frac{22}{N_t}\sum_{d=1}^{N_t} h_{t+d} \tag{A3.1.3}$$

where the subscript $t + d$ is the date t plus d days and N_t is the number of trading days in month t. We assume that the number of trading days in each month is 22.

Appendix 3.2. Conditional Correlation Model

This chapter uses the DECO model of Engle and Kelly (2012) to estimate the conditional correlation. The authors show that the conditional equicorrelation matrix of standardised excess returns in this model can be described as follows:

$$R_t = (1 - r_t)I_N + r_t J_{N\times N} \tag{A3.2.1}$$

where r_t is $\frac{2}{N(N-1)}\sum_{i>j}\frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}}$, I_N denotes the N-dimensional identity matrix and $J_{N\times N}$ is the $N \times N$ matrix of ones. $q_{i,j,t}$ is the i, jth element of Q_t and Q_t has the following dynamic process:

$$Q_t = \bar{Q}(1 - \beta - \gamma) + \beta \tilde{Q}_{t-1}^{\frac{1}{2}} Z_{t-1} Z_{t-1}' \tilde{Q}_{t-1}^{\frac{1}{2}} + \gamma Q_{t-1} \tag{A3.2.2}$$

where Z_t is the vector of standardised excess returns, Q_t is the covariance matrix of standardised excess returns and $\bar{Q}$ is the unconditional covariance matrix of standardised excess returns. $\tilde{Q}_t$ have zeros for the off-diagonal elements, and its main diagonal elements equal those of Q_t. Standardised excess returns are obtained from the univariate GARCH model. The conditional correlation in month t is calculated as follows:

$$\rho_t = \frac{1}{N_t}\sum_{d=1}^{N_t} r_{t+d} \tag{A3.2.3}$$

where the subscript $t + d$ is the date t plus d days and N_t is the number of trading days in month t.

Chapter 4: Return Reversal and Continuation: Differential Response to Market-Wide and Firm-Specific Information

4.1. Introduction

In February 2020, the COVID-19 crisis crushed capital markets worldwide and wiped \$1.7 trillion off the S&P500. By March 2020, the S&P500 and NASDAQ indices had lost more than 30% in market capitalisation, and it took the index levels almost half a year to recover from the collapse due to the COVID-19 crisis. While market indexes started increasing towards the pre-crisis level, the relative weights of index constituents experienced dramatic changes.[40] This exceptional event can be characterised as steep downward and upward motions in asset prices in response to the arrival of information pertaining to COVID-19. Provided such dramatic developments in financial markets, with significant impacts on economies and societies, this research examines how investors respond to information arriving in markets. In contrast to the previous literature that focuses solely on firm-specific information, we consider two separate information categories that are market-wide information and firm-specific information.

Individuals, including those who make trading decisions in financial markets, sometimes exhibit irrational behaviour when responding to new information. Numerous previous studies have analysed the relation between market participants' attitudes towards the processing of information and movements in asset prices. In their seminal research, Daniel, Hirshleifer and Subrahmanyam (1998) develop a model based on overconfidence and biased self-attribution and show that investors tend to overreact to private signals and underreact to public signals. Barberis, Shleifer and Vishny (1998) propose a model of sentiment based on conservatism and

[40] For example, the concentration of the S&P500's five biggest stocks grew to a staggering 21%, a 'modern-day record' according to U.S. investment bank Goldman Sachs.

the representativeness heuristic and argue that investors' reactions to the current information depends on the past information. Hong and Stein (1999) suggest a theoretical model based on newswatchers and momentum traders and argue that asset prices are expected to exhibit a trend related to under-reaction over the short run and over-reaction over the long run. These studies provide ample evidence that investors' reactions to information are irrational and cause some predictable variations in asset returns.

In this research, we characterise and quantify investor reactions to the arrival of market-wide and firm-specific information. We use trading volume data from the NYSE, AMEX and NASDAQ exchanges spanning the period from 1927 to 2019 to construct proxies that measure information flowing to the market pertaining to either the entire market or individual firms. We use a decomposition model to divide trading volume into market-relevant (i.e., market-wide) and market-irrelevant (i.e., firm-specific) components where the former (latter) captures trades that are correlated (uncorrelated). Our decomposition model is based on the following intuition: information pertaining to the entire market results in transactions that are correlated, whereas information pertaining to specific firms generates transactions that are not correlated.

Armed with measurements for the arrival of market-wide and firm-specific information, we analyse stock returns, return variance and profits based on contrarian strategies. Extending existing research that documents that how under- and over-reaction contribute to predictable variations in stock returns, we build a simple econometric model that includes our market-wide and firm-specific information proxies to assess whether these sorts of information drive return reversal (implying over-reaction) or return continuation (implying under-reaction). To examine whether market-wide and firm-specific information predicts stock return variance, we run Fama-MacBeth regressions that incorporate our information measures. To measure the impact of each of our information measures on contrarian profits, we examine cross-sectional and time-series contrarian strategies. Furthermore, we investigate whether the return predictability and contrarian profits are conditional on arbitrageurs' activities in the market.

Our research provides several interesting results. First, in relation to return predictions using historical returns, and consistent with Novy-Marx (2012), we confirm the existence of return reversal over the short-term (i.e., months from $t-1$ to $t-6$) and return persistence over the intermediate-term (i.e., months from $t-7$ to $t-12$). Further, assuming that the prediction relation is a function of the information proxies, we demonstrate that market-wide information attenuates the return reversal, and that firm-specific information reinforces the return reversal. In light of the contrarian and momentum literature, our empirical findings appear to suggest under-reaction to market-wide information and over-reaction to firm-specific information. Our results further present that the effect of firm-specific information is stronger than the effect of market-wide information. Provided that individual stocks' returns are reversed over the short-term, consider the example of the one-month look-back period: when the market-wide information measure is equal to zero and the firm-specific information measure is equal to its mean value, the predicted response of the return is large and negative. In contrast, for the opposite case of the firm-specific information measure equal to zero and the market-wide information measure equal to its mean value, the predicted response of the return is close to zero.

Second, we present that our information proxies can be used to forecast return variance. To be more specific, an increase in the measure level for market-wide (firm-specific) information predicts a decrease (an increase) in the variance of individual stock returns. This result is important and suggests, in conjunction with our findings pertaining to return predictions, that mispricing results in the actual stochastic process for individual stock returns to have similar properties to the autoregressive process.

Third, we present that profits from contrarian strategies can be enhanced by controlling exposure to market-wide or firm-specific information. In particular, using our market-wide and firm-specific information proxies for portfolio construction reveals that contrarian profits in the cross-section tend to increase (decrease) through exposure to firm-specific (market-wide) information.

Fourth, we investigate whether our results related to return prediction and contrarian profits depend on arbitrage activities. To this aim, we use illiquidity (Pastor and Stambaugh, 2003) and sentiment (Baker and Wurgler, 2006) indexes to gauge the willingness of arbitrageurs to engage in arbitrage trades. Consistent with previous studies (e.g., Avramov, Chordia and Goyal, 2006; Chordia, Roll and Subrahmanyam, 2008), we show that the ability of historical returns to predict future returns is greater in markets where arbitrageurs are reluctant to submit their orders. Further, we show that return reversal due to over-reaction to firm-specific information persists regardless of arbitrage activities, however, return continuation due to under-reaction to market-wide information does not. Nonetheless, arbitrage activities do not have a significant impact on the role that our market-wide and firm-specific information proxies can play to enhance contrarian strategies' profits.

Our results have several important implications. First, our finding that under-reaction (over-reaction) to market-wide (firm-specific) information can emerge within the same period has important timing implications for investors implementing momentum or contrarian strategies. Provided the knowledge of the type of information (market-wide or firm-specific) arriving in the market, our empirical findings can be used to improve investment strategies based on return continuation or return reversal.

Regarding the variance of stock returns, our results present that under- and over-reaction contribute to the predictable fluctuation in the cross-section of the return variance. This finding provides market participants and financial market regulators with the improved understanding of financial markets, in particular at the individual stock-level. Given that retail investors tend to take risky bets on individual stocks based on attitudes and moods in expectation of higher-than-average returns, this research can assist market regulators to design policies that protect retail investors who suffer from behavioural biases and from losses caused by information asymmetries in capital markets.

Our results pertaining to contrarian trading strategies reveal that contrarian profits appear to stem from long positions (i.e., losers) rather than the short positions (i.e., winners). This finding indicates that investor responses to negative information have a larger impact compared to responses to positive information. Hence, controlling exposure to negative firm-specific and market-wide information is important for contrarian traders because the major proportion of the enhanced profits comes from taking long contrarian positions rather than short contrarian positions. These results can also benefit long-only investors, such as retail investors or mutual funds, who can consider using investment strategies suggested in this research.

Our research contributes to the asset pricing literature by analysing market-wide and firm-specific information flows and investor behaviour in capital markets. This research extends the existing literature in several ways. First, previous studies have shown that aggregate market-level returns tend to be continued (Moskowitz, Ooi and Pedersen, 2012), while individual stock returns tend to be reversed (Lehmann, 1990; Jegadeesh, 1990). We investigate the implications of these results presented in the literature and show that stock market returns and individual stock returns exhibit different dynamics because of investor responses to the arrival of different information types.

Second, in the market microstructure literature, it has long been a staple to infer information contents from individual transactions (e.g., Easley et al., 1996; Nyholm, 2002; Lei and Wu, 2005; Easley, Lopez de Prado and O'Hara, 2012; Rzayev and Ibikunle, 2019; Chang, Chang and Wang, 2014). These studies' methods require large datasets and advanced computational resources. To propose a less resources demanding alternative solution, this research uses a simple econometric model and builds proxies for market-wide and firm-specific information based on the statistical properties of market-wide and firm-specific information.

Third, we contribute to the literature that examines how market conditions drive mispricing. Avramov, Chordia and Goyal (2006) and Chordia, Roll and Subrahmanyam (2008) show that mispricing is more pronounced when markets are illiquid because arbitrageurs are less inclined to submit orders. Further, Baker and Wurgler (2007) and Baker, Wurgler and Yuan (2012) show that their composite sentiment index is negatively related to future market excess returns, which indicates that mispricing emerges when investors are either optimistic or pessimistic. Given these findings, we investigate whether market conditions related to liquidity or sentiment have an impact on observed under- and over-reaction phenomena.

The remainder of the paper is organised as follows. The next section provides an overview of the related literature. Section 4.3 presents the development of proxies for measuring market-wide and firm-specific information and an econometric model used to examine investors' responses to the arrival of different types of information to the market. Section 4.4 presents the empirical analysis of under- and over-reactions. Section 4.5 examines the effect of arbitrage trades on our empirical results and Section 4.6 concludes.

4.2. Related Literature

Our research builds on the previous literature that argues that the variation in transactions captures the arrival of information to the market and suggests theoretical models that relate moments of asset returns to trading volume or moments of asset returns and trading volume to information flow. Early studies propose that stock return is a subordinate to a mixing variable, which is trading volume (Clark, 1973; Epps and Epps, 1976). Subsequent studies argue that stock return and trading volume are subordinates to an unobservable mixing variable, which is information flow (Tauchen and Pitts, 1983; Andersen, 1996; Fleming, Kirby and Ostdiek, 2006). Similarly, Foster and Viswanathan (1990, 1995) suggest market microstructure models that connect stock return to trading volume. These models account for the stochastic dependence between stock return and trading volume and fall into the class of the mixture of distributions model (MDM).

Previous studies have provided empirical evidence supporting the MDM (See Clark, 1973; Harris, 1986, 1987; Lamoureux and Lastrapes, 1990, 1993; Gallant, Rossi and Tauchen, 1992). In addition, Richardson and Smith (1994) suggest a direct test of the MDM. They show that the restrictions on the joint moments of stock returns and trading volume imposed by the MDM can be tested using the generalised method of moments procedure of Hansen (1982). Overall, the theoretical and empirical evidence on the MDM confirms that an increment in trading volume measures information flow and therefore causes movements in stock prices.

Besides, Covrig and Ng (2004) argue that the autocorrelation in trading volume increases as the rate of information arrivals increases and this relation becomes more pronounced as institutional ownership increases. Rzayev and Ibikunle (2019) use a state-space modelling approach to measure trading activities of informed and uninformed traders. Specifically, in their research, the authors model trading volume as a function of permanent (noninformation) and transient (information) components.

Several studies investigate empirical mispricing evidence and suggests under- and over-reaction instances. On the one hand, previous studies demonstrate that contrarian strategies are profitable and argue that investors tend to overreact to firm-specific information. Lehmann (1990) and Jegadeesh (1990) use the performance in the previous month and De Bondt and Thaler (1985, 1987) use the performance over the previous 60 months to implement contrarian strategies. Even though Lo and MacKinlay (1990) argue that the cross-autocorrelation between individual stock returns is the main explanation for contrarian profits, the negative return autocorrelation in individual stock returns remains to be the main challenge for rational finance theories that assume a nonstationary process for asset prices.

On the other hand, Jegadeesh and Titman (1993) show that momentum strategies are profitable using the performance over the previous 12 months. However, the profits of their momentum strategies tend to be continued in the intermediate-term (i.e., months from $t + 1$ to $t + 12$) and reversed in the long-term (i.e., months from $t + 13$ onwards). While debatable and controversial, nonetheless, these results are consistent with initial under-reaction and belated over-reaction in behavioural theories. Moskowitz, Ooi and Pedersen (2012) provide similar results to those in Jegadeesh and Titman (1993). In contrast to traditional momentum studies including Jegadeesh and Titman (1993), the momentum strategies examined in Moskowitz, Ooi and Pedersen (2012) are based on the absolute performance in the time-series rather than on the relative performance in the cross-section. The most notable distinction between cross-sectional and time-series momentum strategies relates to the signal from historical returns that determines the composition of the portfolio. In cross-sectional momentum strategies, investors compare the performance of securities in the cross-section (e.g., the relative performance of individual securities in comparison to other securities at a point in time). In contrast, time-series momentum strategies build on securities' own performance (e.g., the absolute performance of individual securities over time).

There is a stream of literature examining investor reactions to public or private information. On the under-reaction side, previous studies have provided evidence of return drifts related to, e.g., (1) dividend initiations or omissions (Michaely, Thaler and Womack, 1995), (2) share repurchases (Ikenberry, Lakonishok and Vermaelen, 1995), (3) earnings (Pritamani and Singal, 2001) and (4) stock splits (Ikenberry and Ramnath, 2002). On the over-reaction side, return reversals have been confirmed, related to, e.g., (1) media pessimism (Tetlock, 2007), (2) stock recommendation (Barber and Loeffler, 1993; Beltz and Jennings, 1997; Keasler and McNeil, 2010; Engelberg, Sasseville and Williams, 2012), (3) stale information (Tetlock, 2011) and (4) drug approvals (Manela, 2014). In addition, several studies provide comprehensive evidence of both under-reaction and over-reaction: (1) Chan (2003) shows that investors underreact to public information and overreact to extreme movements in asset prices; (2) Savor (2012) shows that information-based price changes cause return drifts, while other prices changes generate return reversals; (3) Frank and Sanati (2018) show that information-based positive (negative) price changes cause return reversals (drifts). The research closest to this chapter is the one by Chan (2003) and Savor (2012) that provide similar empirical regularities to those revealed in this research.

The important relation between the return autocorrelation and trading volume has previously been studied in the literature. Campbell, Grossman and Wang (1993) show that the return serial correlation has a negative relation with trading volume using daily returns on value-weighted indexes for the NYSE and AMEX exchanges for the period 1962 to 1988. The authors argue that market makers require to be compensated with a higher expected return when accommodating uninformed traders' unusual trading volume. For the period from 1977 to 1991, Sias and Starks (1997) show, using daily returns of securities traded on the NYSE exchange as well as using daily returns of the equal-weighted NYSE index, that the return autocorrelation increases with increases in institutional stock ownership. The authors argue that their results are driven by the fact that institutional investors increase the speed at which information is incorporated into stock prices.

Analysing data on the Stockholm Stock Exchange (SSE) for the period from 1980 to 1995, Säfvenblad (2000) reports that the return autocorrelation has a negative relation with trading volume. The author shows that this holds true for market and individual stock returns and argues that retail investors' trading patterns such as feedback trading serves as the primary driver for the negative relation between autocorrelation and trading volume reported in the study.

4.3. Empirical Framework

In this section, we illustrate an empirical framework to develop proxies for market-wide and firm-specific information and an econometric model to examine how investors respond to the respective information types.

4.3.1. Information Proxies

This chapter uses trading volume to make inferences on information contents that investors act upon. Our intuition is as follows: (1) Transactions occur as new information arrives in the market because investors revise their positions as a response to the new information, consistent with the above-mentioned previous studies employing mixture of distributions models (MDM). This implies that the variation in trading volume captures information flow. (2) Transactions to trade on market-wide information are correlated because, by definition, market-wide information influences the entire market. However, transactions to trade on firm-specific information are not correlated because, by definition, firm-specific information influences a specific firm. (3) While market-wide information pertains to the entire market, its effects on different industries and companies varies.

Extracting market-wide and firm-specific information requires to divide observed trading volume into correlated and uncorrelated components. To determine the components from the observed trade series, we model individual stock's trading volume as a function of market trading volume:

$$v_{i,t+d} = \omega_i + \theta_{i,t} v_{m,t+d} + \epsilon_{i,t+d} \tag{4.1}$$

where i indexes individual firms, t indexes months, d indexes days, $v_{i,t+d}$ is the natural logarithm of split-adjusted trading volume, $v_{m,t+d}$ is the natural logarithm of market trading volume. Market trading volume is defined as the equal-weighted average of split-adjusted individual volumes. We assume that $\theta_{i,t} v_{m,t+d}$ captures the correlated component and $\epsilon_{i,t+d}$ captures the uncorrelated component.

Equation (4.1) builds on previous studies on return comovements including Morck, Yeung and Yu (2000) and Piotroski and Roulstone (2004). The authors regress individual securities' returns on the market return and define R^2 as a comovement measure. The intuition behind this measure is that the component related to the market return captures the correlated variation, whereas the component unrelated to the market return captures the uncorrelated variation. This research extends the above-mentioned studies by employing trading volume to build proxies for market-wide and firm-specific information.

Equation (4.1) is estimated using daily observations at the end of month t to decompose the trading volume and stocks with less than 15 observations are excluded. This research defines the proxies for market-wide and firm-specific information that flows into the market in month t as the variance of the market-wide and firm-specific components:

$$m_{i,t} = \theta_{i,t}^2 Var_t\left(v_{m,t+d}\right) \tag{4.2}$$

$$f_{i,t} = Var_t\left(\epsilon_{i,t+d}\right) \tag{4.3}$$

where $m_{i,t}$ and $f_{i,t}$ serve as proxies for market-wide and firm-specific information, respectively.

Market microstructure studies have used the second moment of trading volume to measure trading activities. For example, Chordia, Subrahmanyam and Anshuman (2001) use the second moment of dollar trading volume to measure related trading activities. Furthermore, Rzayev and Ibikunle (2019) decompose their individual trading volume series into transient and permanent components using state-space modelling and define the proxies for informational and noninformational trading activities as the second moment of the respective components. Similar to these studies, we use the second moment of the correlated (uncorrelated) components as a measure for trading activities that result from the arrival of market-wide (firm-specific) information.

4.3.2. Investor Response

Following previous studies on under- and over-reaction (Lehmann, 1990; Jegadeesh, 1990, Jegadeesh and Titman, 1993; Moskowitz, Ooi and Pedersen, 2012; Novy-Marx, 2012), we examine predictable variations in returns using historical returns to investigate how investors respond to market-wide and firm-specific information, where return continuation is related to under-reaction and return reversal is related to over-reaction. If there is under- or over-reaction to market-wide or firm-specific information, the ability of historical returns to predict future returns should vary subject to varying information proxy levels.

First, we run a regression of the excess return in month t on the excess return in month $t-k$ to examine the unconditional predictability:

$$r_{i,t} = \alpha_k + \beta_k r_{i,t-k} + u_{i,t} \tag{4.4}$$

where i indexes individual firms, t indexes months, k indexes the orders of a lag and $r_{i,t}$ is excess return. While various arguments for the sign and magnitude of β_k can be put forward, we follow the seminal time-series momentum research, Moskowitz, Ooi and Pedersen (2012), that interprets the positive (negative) sign of β_k as under-reaction (over-reaction).

Second, to examine the conditional predictable patterns in stock returns on market-wide and firm-specific information, we assume that the coefficient, β_k, in equation (4.4), is a function of the proxies for information, m_{t-k} and f_{t-k}:

$$\beta_{k,t} = \beta_k + \gamma_k m_{i,t-k} + \phi_k f_{i,t-k} \tag{4.5}$$

Substituting the right-hand side of equation (4.5) for β_k in equation (4.4) yields:

$$r_{i,t} = \alpha_k + \beta_k r_{i,t-k} + \gamma_k m_{i,t-k} r_{i,t-k} + \phi_k f_{i,t-k} r_{i,t-k} + u_{i,t} \tag{4.6}$$

In equation (4.6), and similar to the case of β_k in equation (4.4), γ_k has a positive (negative) sign in case of under-reaction (over-reaction) to market-wide information and ϕ_k has a positive (negative) sign in case of under-reaction (over-reaction) to firm-specific information. Following Moskowitz, Ooi and Pedersen (2012), we run pooled regressions to estimate the parameters in equation (4.4) and (4.6). Regarding the time horizon, this research defines the short-term as the period from month $t-1$ to month $t-6$ and the intermediate-term as the period from month $t-7$ to month $t-12$.

4.4. Empirical Evidence

4.4.1. Dataset

NYSE, AMEX and NASDAQ listed common stocks obtained from the Center for Research in Security Prices (CRSP) are included in the sample covering the period from January 1927 to December 2019.[41] Trading volume is multiplied by the cumulative adjustment factor for shares to adjust stock split. Excess return is calculated using the risk-free rate obtained from Kenneth R. French's website.

Table 4.1 reports descriptive statistics of the resultant measures for market-wide and firm-specific news. The table shows that m_t has a mean of 0.21 and f_t has a mean of 2.66. This indicates that market transactions are based on a greater amount of firm-specific information than market-wide information in general. This result appears consistent with the notion that the amount of information that pertains to the entire market is smaller than the amount information that pertains to specific firms. Further, the table reports the correlation coefficient between m_t and f_t to be nontrivial at a level of 0.40. One possible explanation relates to common factors that influence trading decisions and that might drive the covariation in the proxies.

[41] This research suggests the use of novel information proxies in addition to using historical returns in order to explain asset returns. Consequently, our approach requires a sufficient number of securities to be included in our sample, in particular, when building portfolios sorted on (1) the market-wide information measure, (2) the firm-specific information measure and (3) historical returns. Therefore, we consider securities traded in NYSE, AMEX and NASDAQ. Nonetheless, we note that the empirical results presented in this chapter are robust to the exclusion of NASDAQ stocks in general.

Table 4.1. Descriptive Statistics

The table reports descriptive statistics of information proxies, m_t and f_t, for market-wide and firm-specific information arriving in the market in month t. The proxies are constructed based on the following procedure. First, individual firms' trading volume is modelled as a function of market trading volume as follows:

$$v_{i,t+d} = \omega_i + \theta_{i,t} v_{m,t+d} + \epsilon_{i,t+d} \quad (4.1)$$

where i indexes individual firms, t indexes months, d indexes days, $v_{i,t+d}$ is the natural logarithm of trading volume, $v_{m,t+d}$ is the natural logarithm of market trading volume. Market trading volume is the equal-weighted average of split-adjusted individual volumes. Equation (4.1) is estimated at the end of month t using observations in month t. Second, proxies for market-wide and firm-specific information in month t are calculated as the variances of the second and third components in equation (4.1):

$$m_{i,t} = \theta_{i,t}^2 Var_t(v_{m,t+d}) \quad (4.2)$$
$$f_{i,t} = Var_t(\epsilon_{i,t+d}) \quad (4.3)$$

$m_{i,t}$ and $f_{i,t}$ are proxies for market-wide and firm-specific information incorporated into firm i's stock prices.

	Mean	Std. Dev.	P25	P50	P75	Correlation	
						m_t	f_t
m_t	0.21	0.49	0.01	0.05	0.17	1	0.40
f_t	2.66	3.88	0.28	0.70	3.78	0.40	1

4.4.2. Return

Table 4.2 presents the parameter estimates for equations (4.4) and (4.6). The negative parameter estimates for the excess returns from months $t-1$ through $t-6$ indicate return reversal, whereas the positive parameter estimates for the excess returns from months $t-7$ through $t-12$ (except $t-8$) indicate return continuation. This evidence is consistent with the previous studies on contrarian trading (e.g., Lehmann, 1990; Jegadeesh, 1990) and momentum trading (e.g., Jagadeesh and Titman, 1993; Novy-Marx, 2012).

The positive parameter estimates related to market-wide information for months $t-1$ and $t-2$ indicate return continuation, while the negative parameter estimates associated with firm-specific information for months $t-1$ through $t-5$ indicate return reversal. This confirms the prediction based on the autocorrelation of market returns and that of individual stocks' returns: investors underreact to market-wide information and overreact to firm-specific information. Interestingly, the results indicate that some level of return persistence can coincide with return reversal.

Table 4.2 shows that market-wide (firm-specific) information attenuates (reinforces) return reversal. For example, in the case of the first lag, when both m_{t-1} and f_{t-1} are equal to zero, the predicted response of the excess return is -0.0054; when m_{t-1} is equal to zero and f_{t-1} has a value of its mean, 2.66, the predicted response of the excess return is -0.0136; when m_{t-1} equals its mean, 0.21, and f_{t-1} has a value of zero, the predicted response of the excess return is -0.0033, which is close to zero. Similar instances can be identified for higher order lags.

Our empirical evidence suggests that investors' responses to market-wide and firm-specific information are differential. Since this research does not intend to establish a theoretical model on the behavioural bias pertaining to information arrivals, we relate our empirical findings to previous studies' theoretical findings that provide potential explanations for investors' under-and over-reaction. On the one hand, under-reaction emerges due to the gradual diffusion of information (Hong and Stein, 1999) or conservatism (Barberis, Shleifer and Vishny, 1998). On the other hand, over-reaction occurs because of positive feedback trading (De Long et al., 1990b; Hong and Stein, 1999), the representativeness heuristic (Barberis, Shleifer and Vishny, 1998), overconfidence and biased self-attribution (Daniel, Hirshleifer and Subrahmanyam, 1998), herding (Bikhchandani, Hirshleifer and Welch, 1992) or sentiment (Baker and Wurgler, 2006).

Our results perhaps reflect behavioural differences between institutional and retail investors. It is well-known that, in general, the composition of institutional investors' holdings is similar to that of the market portfolio, whereas retail investors often limit their holdings to a few individual securities. Thus, on average, institutional investors are more sensitive to market-wide information, while retail investors are more sensitive to firm-specific information. In this regard, one possible explanation for our empirical findings presented in this section can be that institutional investors underreact to market-wide information, while retail investors overreact to firm-specific information.[42] The slow revision in positions because of, e.g., organisational investment policy constraints can cause institutional investors' under-reaction. In contrast, the rapid revision in positions due to, e.g., overconfidence or herding, can result in retail investors' over-reaction.

[42] The actual compositions of individual institutional investors' holdings are heterogenous. However, on average, the aggregated composition of institutional holdings likely becomes analogous to the composition of the market portfolio. In this regard, institutional investors' behaviour, which can be inferred from historical data, is likely similar to the behaviour of those who invest in the market portfolio.

Table 4.2. Unconditional and Conditional Return Predictability

The table reports parameter estimates for equations (4.4) and (4.6) along with the associated t-statistics in parentheses. Equations (4.4) and (4.6) are as follows:

$$r_{i,t} = \alpha_k + \beta_k r_{i,t-k} + u_{i,t} \tag{4.4}$$

$$r_{i,t} = \alpha_k + \beta_k r_{i,t-k} + \gamma_k m_{i,t-k} r_{i,t-k} + \phi_k f_{i,t-k} r_{i,t-k} + u_{i,t} \tag{4.6}$$

where i indexes individual firms, t indexes months, k indexes the orders of a lag, $r_{i,t}$ is the excess return, $m_{i,t-k}$ is market-wide information measure and $f_{i,t-k}$ is firm-specific information measure. Pooled OLS estimations are conducted to estimate the parameters in the above equations. The t-statistics are calculated based on the Newey and West (1987) adjusted standard errors. The table reports parameter estimates times 100. The sample period spans from Jan-1927 to Dec-2019.

k	Eq. (4.4)	Eq. (4.6)		
	β_k	β_k	γ_k	ϕ_k
1	-1.38	-0.54	1.01	-0.31
	(-12.35)	(-3.72)	(4.98)	(-8.58)
2	-0.60	-0.38	0.49	-0.10
	(-5.83)	(-3.05)	(2.96)	(-4.54)
3	-0.46	-0.22	-0.40	-0.03
	(-4.63)	(-1.84)	(-1.69)	(-1.18)
4	-0.69	-0.44	0.15	-0.08
	(-7.13)	(-3.80)	(0.96)	(-3.12)
5	-0.26	-0.06	0.05	-0.06
	(-2.69)	(-0.46)	(0.19)	(-2.53)
6	-0.42	-0.51	-0.77	0.09
	(-3.38)	(-4.29)	(-2.92)	(1.72)
7	0.58	0.91	-0.30	-0.07
	(5.93)	(7.74)	(-1.75)	(-2.63)
8	-0.22	-0.35	0.07	0.03
	(-2.18)	(-2.84)	(0.38)	(1.05)
9	0.40	0.02	0.00	0.11
	(3.75)	(0.14)	(-0.02)	(3.26)
10	0.61	0.61	-0.01	0.00
	(5.94)	(5.01)	(-0.09)	(0.06)
11	0.69	0.82	0.09	-0.05
	(6.91)	(6.95)	(0.53)	(-1.87)
12	1.41	1.17	0.06	0.07
	(14.28)	(9.99)	(0.40)	(2.68)

4.4.3. Variance

The results presented in Table 4.2 have implication for serial correlation of individual stocks' returns. One of the well-known statistical properties of the autoregressive process is that its variance increases as the absolute value of the serial correlation approaches 1 from 0. Provided that the unconditional return autocorrelation is negative as implied in Table 4.2, we can extend our research to incorporate the stock return variance where the market-wide (firm-specific) information measure is expected to predict a decrease (increase) the stock return variance.

To confirm our prediction, we test whether our information proxies can predict the return variance. Unlike the previous empirical investigation on the return prediction, this subsection focuses on the cross-section because of the stickiness of the stochastic return variance. Based on the seminal studies, Engle (1982) and Bollerslev (1986), previous studies have provided evidence that the stochastic variance tends to be persistent, i.e., clustered. From a practical perspective, this implies that the variance prediction in the time-series have a rather trivial implication than the one in the cross-section. For this reason, we run the following Fama-MacBeth regression:

$$\sigma_{i,t}^2 = a_{k,t} + b_{k,t}\sigma_{i,t}^2 + c_{k,t}m_{i,t-k} + d_{k,t}f_{i,t-k} + u_{i,t} \tag{4.7}$$

where i indexes individual firms, t indexes months, k indexes the orders of a lag and $\sigma_{i,t}^2$ is variance of excess returns. We estimate equation (4.7) month-by-month and report averages of parameter estimates along with the associated t-statistics as in Fama and MacBeth (1973).

Table 4.3 presents the parameter estimates in equation (4.7). The table implies that under- and over-reaction contribute to predictable fluctuations in the cross-section of the return variance. First, the negative estimates for market-wide information are associated with a decrease in the variance. For example, a one standard deviation increase in m_{t-1} predicts 0.48 (= 0.49 × 0.98) bps per month decrease in the return variance. Second, the positive estimates for firm-specific information are associated with an increase in the variance. For example, a one standard deviation increase in f_{t-1} predicts 3.14 (= 3.88 × 0.81) bps per month increase in the return variance. Overall, the evidence confirms our prediction that the differential investor response to market-wide and firm-specific information affects the return autocorrelation which enables us to forecast the return variance.

Table 4.3. Fama-MacBeth Regression

The table reports Fama-MacBeth regression results along with the associated t-statistics in parentheses. We consider the following cross-sectional regression:

$$\sigma_{i,t}^2 = a_{k,t} + b_{k,t}\sigma_{i,t}^2 + c_{k,t}m_{i,t-k} + d_{k,t}f_{i,t-k} + u_{i,t} \quad (4.7)$$

where i indexes individual firms, t indexes months, k indexes the orders of a lag, $\sigma_{i,t}^2$ is the variance of excess returns, $m_{i,t-k}$ is the market-wide information measure and $f_{i,t-k}$ is the firm-specific information measure. The return variance is estimated using observations within month t and multiplied by 100. Equation (4.7) is estimated month-by-month and the average coefficients and their t-statistics are calculated. The t-statistics are calculated based on the Newey and West (1987) adjusted standard errors. The table reports parameter estimates times 100. The sample period spans from Jan-1927 to Dec-2019.

k	b_k	c_k	d_k
1	49.59	-0.98	0.81
	(38.93)	(-2.52)	(9.53)
2	46.86	-1.30	0.91
	(34.51)	(-2.90)	(8.99)
3	46.94	-1.04	0.87
	(30.75)	(-1.86)	(8.23)
4	46.92	-1.09	0.88
	(28.46)	(-2.47)	(8.64)
5	46.58	0.02	0.76
	(28.73)	(0.02)	(7.56)
6	47.13	-1.55	0.90
	(27.18)	(-3.57)	(8.24)
7	46.85	-0.78	0.88
	(24.57)	(-2.03)	(9.69)
8	46.08	-1.22	0.89
	(25.07)	(-2.80)	(8.18)
9	44.78	-1.21	0.94
	(25.53)	(-2.08)	(7.17)
10	44.85	-1.00	0.82
	(25.63)	(-2.04)	(7.69)
11	45.74	-0.60	0.83
	(24.08)	(-1.21)	(8.17)
12	45.46	-0.76	0.82
	(22.60)	(-1.76)	(7.02)

4.4.4. Portfolio Construction

To examine a practical implication embedded in our evidence on predictable fluctuations in the return and its variance due to irrational response to information, we construct loser and winner portfolios that have dissimilar exposures to information. To do so, we use independent $2 \times 3 \times 3$ sorts to isolate the effect of market-wide and firm-specific information. Using signals from the excess return and information proxies over the look-back period, we independently sort stocks into two return groups, three market-wide information groups and three firm-specific information groups at the beginning of month t and hold them during the holding period. Then, we calculate the excess return and variance for stocks allocated to the respective groups. To keep our analysis focused, we use one-month look-back and holding periods.

To assess robustness, we take both the cross-sectional and time-series trading strategies into account. The return breakpoint is the median excess return in the cross-sectional strategies, while it is zero in the time-series trading strategies. Losers (winners) are defined as stocks with the excess return below (above) the return breakpoint. The information breakpoints are 30$^{\text{th}}$ and 70$^{\text{th}}$ percentiles of the information proxies. This approach enables us to compare the mean and variance of returns on losers and winners according to the exposure to market-wide and firm-specific information.

To ensure that our evidence on over- and under-reaction is not attributable to the risk-return trade-off in the CAPM (Sharpe, 1964) or ICAPM (Merton, 1973), we regress the excess returns of the constructed portfolios over the well-known asset pricing factors capturing market, size, value and momentum premiums:

$$r_{i,t} = a_i + b_i MKT_t + c_i SMB_t + d_i HML_t + e_i MOM_t + u_{i,t} \qquad (4.8)$$

where i indexes portfolios, t indexes months, $r_{i,t}$ is excess return, MKT_t is the market factor, SMB_t is the size factor, HML_t is the value factor and MOM_t is the momentum factor. The factor data are obtained from Kenneth R. French's website.

4.4.4.1. Cross-Sectional Strategies

Table 4.4 reports the average equal-weighted returns and variances for 18 portfolios from the independent $2 \times 3 \times 3$ sorts for the cross-sectional strategies. First, profits from the contrarian strategies, i.e., buying losers and selling in winners, increase as the exposure to market-wide (firm-specific) information decrease (increase). For example, contrarian profits decrease from 0.71% (t = 5.76) to 0.29% (t = 1.80) per month within the 'Low' firm-specific information group (FSI_Low), while contrarian profits increase from 0.71% (t = 5.76) to 1.28% (t = 8.97) per month within the 'Low' market-wide information group (MWI_Low). We observe similar results across other market-wide or firm-specific information groups. Our results further show that the observed increasing or decreasing patterns in contrarian profits stem from losers (i.e., long positions) rather than winners (i.e., short positions). These results suggest that investors react more severely to negative information compared to positive information.

Second, the return variance tends to increase as the exposure to market-wide (firm-specific) information decreases (increases). For example, the return variance decreases from 17.69 bps (t = 7.85) to 11.54 bps (t = 17.43) per month within the 'Low' firm-specific information group (FSI_Low), while the return variance increases from 17.69 bps (t = 7.85) to 28.65 bps (t = 14.38) per month within the 'Low' market-wide information group (MWI_Low). The decreasing pattern associated with market-wide information is not confirmed within the 'High' firm-specific information group (FSI_High). Overall, the results presented in Table 4.4 confirm the regression results presented in the previous section.

Table 4.4. Cross-Sectional Strategies

The table reports average equal-weighted abnormal returns and variances for stocks allocated to 18 groups from independent $2 \times 3 \times 3$ sorts for cross-sectional strategies. Using three signals from excess returns and proxies for firm-specific and market-wide information in month $t-1$, stocks are independently sorted into two return groups (Losers and Winners), three market-wide information groups (MWI_Low, MWI_Mid, MWI_High) and three firm-specific information groups (FSI_Low, FSI_Mid, FSI_High) at the beginning of month t and held until the end of month t. The return breakpoint is the median excess return, and the information breakpoints are the 30th and 70th percentiles of the proxies. To estimate the abnormal return, the following regression is estimated:

$$r_{i,t} = a_i + b_i MKT_t + c_i SMB_t + d_i HML_t + e_i MOM_t + u_{i,t} \tag{4.8}$$

where i indexes portfolios, $r_{i,t}$ is the excess return, MKT_t is the market factor, SMB_t is the size factor, HML_t is the value factor and MOM_t is the momentum factor. The intercept estimate in the regression is defined as the abnormal return. The associated Newey-West (1987) adjusted t-statistics are reported in parentheses. The sample period spans from Jan-1927 to Dec-2019.

	FSI_Low			FSI_Mid			FSI_High		
	MWI_Low	MWI_Mid	MWI_High	MWI_Low	MWI_Mid	MWI_High	MWI_Low	MWI_Mid	MWI_High
					Abnormal Return (%)				
Losers	0.45	0.17	0.14	0.73	0.63	0.43	0.94	0.89	0.84
	(3.95)	(2.07)	(1.24)	(5.99)	(5.76)	(4.29)	(7.87)	(8.46)	(8.79)
Winners	-0.26	-0.23	-0.16	-0.39	-0.33	-0.34	-0.34	-0.31	-0.28
	(-4.25)	(-4.25)	(-1.49)	(-4.54)	(-4.61)	(-4.58)	(-3.51)	(-3.36)	(-3.43)
Losers-Winners	0.71	0.40	0.29	1.13	0.95	0.77	1.28	1.20	1.12
	(5.76)	(3.79)	(1.80)	(7.61)	(7.76)	(6.30)	(8.97)	(9.53)	(10.45)
					Variance (bps)				
Losers	17.69	10.91	11.54	22.38	19.49	17.75	28.65	29.18	28.44
	(7.85)	(16.96)	(17.43)	(12.12)	(13.49)	(15.94)	(14.38)	(12.38)	(13.91)
Winners	13.47	7.83	8.39	15.76	14.00	12.69	20.13	19.15	20.19
	(6.15)	(16.65)	(19.41)	(10.77)	(11.26)	(16.73)	(15.46)	(17.04)	(15.61)
Losers-Winners	4.22	3.08	3.10	6.62	5.48	5.06	8.52	10.03	8.25
	(3.67)	(9.69)	(8.32)	(8.44)	(7.27)	(9.03)	(7.63)	(6.36)	(7.16)

4.4.4.2. Time-Series Strategies

Table 4.5 reports the average equal-weighted returns and variances for stocks allocated to 18 groups from independent 2 × 3 × 3 sorts for the time-series strategies. First, contrarian profits have a negative (positive) association with exposure to market-wide (firm-specific) information. For example, contrarian profits decrease from 0.98% (t = 6.94) to 0.33% (t = 2.20) per month within the 'Low' firm-specific information group (FSI_Low) and increase from 0.98% (t = 5.76) to 1.19% (t = 8.18) per month within the 'Low' market-wide information group (MWI_Low). However, the decreasing pattern associated with market-wide information is not observed within the 'High' firm-specific information group (FSI_High). Considering the nontrivial correlation between the information proxies, one explanation may be that the effect of firm-specific information might dominate that of market-wide information.

Second, the return variance has a negative (positive) relation with the exposure to market-wide (firm-specific) information. For example, the return variance decreases from 18.60 bps (t = 6.61) to 11.68 bps (t = 17.62) per month within the 'Low' firm-specific information group (FSI_Low) and increases from 18.60 bps (t = 6.61) to 28.25 bps (t = 14.59) per month within the 'Low' market-wide information group (MWI_Low). Similar to the contrarian profit case, the decreasing pattern associated with market-wide information in the return variance are not observed for the 'High' firm-specific information group (FSI_High).

Overall, Table 4.4 and 4.5 provide important implications for investors who use historical data to implement market-timing strategies. Complementing results from previous studies that have recommended to buy losers and sell winners to time the market over the short-term, and in order to further increase profits from contrarian trading, our results suggest to (1) buy losers that recently experienced firm-level negative events and to (2) sell winners that have little exposure to market-wide information. Furthermore, our results suggest using strategies based on relative performance (i.e., cross-sectional strategies) rather than using strategies based on absolute performance (i.e., time-series strategies). Second, in unreported results, we find that no interesting pattern in portfolio-level return variances emerges, and this suggests that the predictable variation in the return variance is indeed attributable to idiosyncratic components in stock returns. Hence, our empirical results serve as a diversification reminder, i.e., holding only a small number of securities in a contrarian strategy portfolio might lead to a greater level of portfolio volatility.

Table 4.5. Time-Series Strategies

The table reports average equal-weighted abnormal returns and variances for stocks allocated to 18 groups from independent $2 \times 3 \times 3$ sorts for time-series strategies. Using three signals from excess returns and proxies for firm-specific and market-wide information in month $t-1$, stocks are independently sorted into two return groups (Losers and Winners), three market-wide information groups (MWI_Low, MWI_Mid, MWI_High) and three firm-specific information groups (FSI_Low, FSI_Mid, FSI_High) at the beginning of month t and held until the end of month t. The return breakpoint is zero, and the information breakpoints are the 30th and 70th percentiles of the proxies. To determine the abnormal return, the following regression is estimated:

$$r_{i,t} = a_i + b_i MKT_t + c_i SMB_t + d_i HML_t + e_i MOM_t + u_{i,t} \tag{4.8}$$

where i indexes portfolios, $r_{i,t}$ is the excess return, MKT_t is the market factor, SMB_t is the size factor, HML_t is the value factor and MOM_t is the momentum factor. The intercept estimate in the regression is defined as the abnormal return. The associated Newey-West (1987) adjusted t-statistics are reported in parentheses. The sample period spans from Jan-1927 to Dec-2019.

	FSI_Low			FSI_Mid			FSI_High		
	MWI_Low	MWI_Mid	MWI_High	MWI_Low	MWI_Mid	MWI_High	MWI_Low	MWI_Mid	MWI_High
					Abnormal Return (%)				
Losers	0.58	0.29	0.20	0.70	0.74	0.53	0.78	0.87	1.12
	(4.57)	(3.43)	(1.73)	(5.61)	(5.89)	(4.99)	(6.15)	(7.13)	(5.83)
Winners	-0.40	-0.20	-0.17	-0.42	-0.36	-0.47	-0.40	-0.43	-0.35
	(-4.69)	(-3.25)	(-1.65)	(-4.00)	(-4.22)	(-4.55)	(-3.51)	(-3.60)	(-3.28)
Losers-	0.98	0.49	0.33	1.12	1.11	1.01	1.19	1.30	1.47
Winners	(6.94)	(4.69)	(2.20)	(7.20)	(8.07)	(6.99)	(8.18)	(8.96)	(7.11)
					Variance (bps)				
Losers	18.60	11.64	11.68	22.58	19.90	18.16	28.25	28.02	29.21
	(6.61)	(14.31)	(17.62)	(12.81)	(14.08)	(16.37)	(14.59)	(14.01)	(12.69)
Winners	13.67	8.41	7.98	15.56	14.88	13.49	20.69	19.42	19.21
	(6.79)	(8.60)	(19.88)	(11.23)	(8.45)	(10.46)	(12.37)	(15.66)	(16.51)
Losers-	4.93	3.15	3.61	7.01	5.01	4.68	7.78	8.60	9.97
Winners	(2.61)	(4.62)	(9.56)	(8.84)	(4.63)	(4.37)	(5.60)	(6.86)	(6.88)

4.5. Further Evidence

As a next step, we investigate whether the level of willingness of arbitrageurs to engage in arbitrage trades affects the empirical regularities related to investor responses to market-wide and firm-specific information. First, arbitrageurs are known to be reluctant to submit their orders when the market is illiquid and hence psychological biases (e.g., overconfidence or conservatism) are more likely to have a greater impact on stock prices during illiquid periods (Avramov, Chordia and Goyal, 2006; Chordia, Roll and Subrahmanyam, 2008). This raises the question of whether the return predictability due to investors' over- and under-reaction to information arriving in the market may depend on the ability of a market to process a large number of trades without profound price impacts related to a lack of liquidity.

Second, sentiment has been put forward to be one of the most eminent causes of mispricing. Previous studies show that stock prices are overvalued (undervalued) when investors are optimistic (pessimistic) (see Baker and Wurgler, 2006; Baker, Wurgler and Yuan, 2012; Shen, Yu and Zhao, 2017). Arbitrageurs might be less inclined to submit their orders during optimism or pessimism periods because of noise trader risk identified by De Long et al. (1990a). This raises the question of whether the return predictability due to under- and over-reaction is associated with the level of investor sentiment in the market.

To investigate this issue, we use Pastor and Stambaugh's (2003) aggregate illiquidity index (LIQ) from and Baker and Wurgler's (2006) aggregate sentiment index (SNT). Both indexes are obtained from the respective authors' websites.

Figure 4.1 plots the time-series of the LIQ spanning from August 1962 to December 2019 and that of the SNT spanning from July 1965 to December 2018. The figure shows that both indexes do not exhibit significant covariation. For the overlapping period, the coefficient of correlation between the indexes is 0.0960.

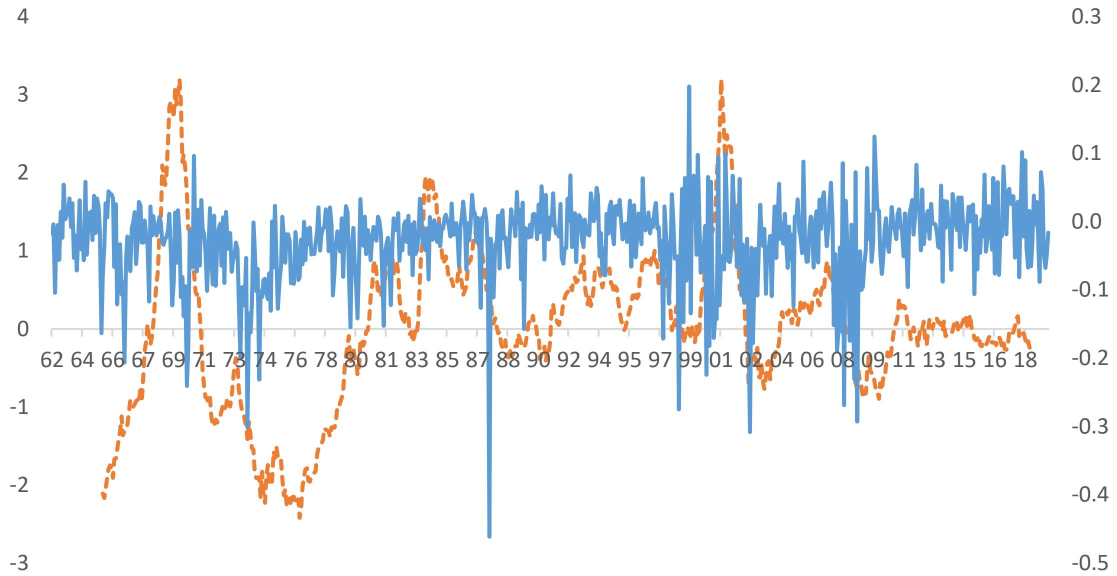

Figure 4.1. Illiquidity and Sentiment Indexes

The figure plots the illiquidity index (solid line) developed by Pastor and Stambaugh (2003) and the sentiment index (dashed line) developed by Baker and Wurgler (2006). The y-axis on the left-hand side shows the value of sentiment index and the y-axis on the right-hand side shows the value of the illiquidity index. The x-axis shows times (in months). The illiquidity index spans from Aug-1962 to Dec-2019 and the sentiment index spans from Jul-1965 to Dec-2018.

4.5.1. Two-Regime Regression

To examine the role of arbitrageurs in determining the unconditional and conditional ability of historical return to predict future returns, we transform the one-regime equation presented in equation (4.4) into the two-regime equation:

$$r_{i,t} = \alpha_k + \beta_{j,k}^{IL} r_{i,t-k} D_{j,t-k}^{IL} + \beta_{j,k}^{IH} r_{i,t-k} D_{j,t-k}^{IH} + u_{i,j,t} \tag{4.9}$$

and equation (4.6) is transformed into:

$$\begin{aligned} r_{i,t} = \alpha_k + \beta_{j,k}^{IL} r_{i,t-k} D_{j,t-k}^{IL} + \beta_{j,k}^{IH} r_{i,t-k} D_{j,t-k}^{IH} + \gamma_{j,k}^{IL} m_{i,t-k} r_{i,t-k} D_{j,t-k}^{IL} + \\ \gamma_{j,k}^{IH} m_{i,t-k} r_{i,t-k} D_{j,t-k}^{IH} + \phi_{j,k}^{IL} f_{i,t-k} r_{i,t-k} D_{j,t-k}^{IL} + \phi_{j,k}^{IH} f_{i,t-k} r_{i,t-k} D_{j,t-k}^{IH} + u_{i,j,t} \end{aligned} \tag{4.10}$$

where t indexes months, k indexes the orders of a lag, $j \in \{LIQ, SNT\}$ and $D_{j,t-k}^{IL}$ ($D_{j,t-k}^{IH}$) is a dummy variable for the periods in which the value of the index is less (greater) than the median of the series of the index. These equations enable us to evaluate how the return predictability varies as the inclination of arbitrageurs to submit their orders or the level of information proxies.

Table 4.6 reports parameter estimates for equations (4.9) and (4.10) specified with LIQ in Panel A. First, Panel A shows that the speed of market correction is faster during liquid periods, consistent with Avramov, Chorida and Goyal (2006). Specifically, the estimate for the excess return in month $t-1$ is -0.51 (t = -3.01) for liquid periods, which is closer to zero than the one for illiquid periods, -2.08 (t = -17.83), indicating that arbitrageurs trade more actively to benefit from over-reaction when the market is liquid.

Second, the estimate associated with market-wide information for month $t-1$ is not statistically significant regardless of whether the market is liquid, indicating that the persistence in stock returns due to under-reaction to market-wide information disappears. Meanwhile, the estimate associated with firm-specific information for month $t-1$ is statistically significant in both liquid and illiquid periods, indicating that over-reaction to firm-specific information is strong enough to remain persistent for some time even in the presence of arbitrageurs' trading.

For example, when both m_{t-1} and f_{t-1} are equal to zero, the predicted response of the excess return is 0.0052 (-0.0202) in liquid (illiquid) periods; when m_{t-1} is equal to zero and f_{t-1} has a value of its mean, 2.66, the predicted response of the excess return is -0.0038 (-0.0255) in liquid (illiquid) periods.

Table 4.6 reports the parameter estimates for equations (4.9) and (4.10) specified with SNT in Panel B. The results in Panel B provide several interesting observations. First, the estimates for the excess returns from months $t-1$ ($t-6$) through $t-4$ ($t-12$) tend to be negative (positive) in optimism periods. These estimates capture return reversal (continuation) over the short-term (intermediate-term). In contrast, the estimates for the excess returns from months $t-1$ ($t-6$) through $t-4$ ($t-12$) tend to be insignificant in pessimism periods, indicating that both return reversal and continuation disappear. Our evidence suggests that sentiment traders' optimism contributes to return reversal and persistence as sentiment traders erroneous and unpredictable beliefs crowd out arbitrageurs from the market.

Second, Panel B shows that market-wide information-triggered under-reaction does not exist, while firm-specific information-triggered over-reaction exists, regardless of whether investors are optimistic or pessimistic. In both optimism and pessimism periods, the estimate related to market-wide information for month $t-1$ is not statistically significant, while the estimate related to firm-specific information for month $t-1$ is statistically significant. Thus, these results do not confirm evidence of under-reaction to market-wide information but do confirm evidence of over-reaction to firm-specific information.

For example, when both m_{t-1} and f_{t-1} are equal to zero, the predicted response of the excess return is -0.0142 (0.0072) in optimism (pessimism) periods. For the case where m_{t-1} is equal to zero and f_{t-1} has a value equal to its mean of 2.66, the predicted response of the excess return is -0.0230 (-0.0021) in optimism (pessimism) periods.

Table 4.6. Two-Regime Regression

The table reports parameter estimates in two-regime equations (4.9) and (4.10) together with the associated t-statistics in parentheses. Equation (4.9) and (4.10) are as follows:

$$r_{i,t} = \alpha_k + \beta_{j,k}^{IL} r_{i,t-k} D_{j,t-k}^{IL} + \beta_{j,k}^{IH} r_{i,t-k} D_{j,t-k}^{IH} + u_{i,j,t} \quad (4.9)$$

$$r_{i,t} = \alpha_k + \beta_{j,k}^{IL} r_{i,t-k} D_{j,t-k}^{IL} + \beta_{j,k}^{IH} r_{i,t-k} D_{j,t-k}^{IH} + \gamma_{j,k}^{IL} m_{i,t-k} r_{i,t-k} D_{j,t-k}^{IL} + \gamma_{j,k}^{IH} m_{i,t-k} r_{i,t-k} D_{j,t-k}^{IH} + \phi_{j,k}^{IL} f_{i,t-k} r_{i,t-k} D_{j,t-k}^{IL} + \phi_{j,k}^{IH} f_{i,t-k} r_{i,t-k} D_{j,t-k}^{IH} + u_{i,j,t} \quad (4.10)$$

where i indexes individual firms, t indexes months, k indexes the orders of a lag, $j \in \{LIQ, SNT\}$, $r_{i,t}$ is excess return, $m_{i,t-k}$ is market-wide information measure, $f_{i,t-k}$ is firm-specific information measure and $D_{j,t-k}^{IL}$ ($D_{j,t-k}^{IH}$) is a dummy variable for the periods in which the value of the index is less (greater) than the median of the index. Pooled OLS estimations are conducted to estimate the parameters in the above equations. The t-statistics are calculated based on the Newey and West (1987) adjusted standard errors. The differences between the parameter estimates for illiquid and liquid periods or for optimism and pessimism periods are reported along with the chi-squared statistics in parentheses. Estimates in Panel A are from the equation specified with the illiquidity index (LIQ) developed by Pastor and Stambaugh (2003) and those in Panel B are from the equation specified with the sentiment index (SNT) developed by Baker and Wurgler (2006). The table reports parameter estimates times 100. The sample period with the LIQ spans from Aug-1962 to Dec-2019 and that with the SNT spans from Jul-1965 to Dec-2018.

k	Eq. (4.9)			Eq. (4.10)								
	$\beta_{j,k}^{IL}$	$\beta_{j,k}^{IH}$	$\beta_{j,k}^{IH} - \beta_{j,k}^{IL}$	$\beta_{j,k}^{IL}$	$\beta_{j,k}^{IH}$	$\beta_{j,k}^{IH} - \beta_{j,k}^{IL}$	$\gamma_{j,k}^{IL}$	$\gamma_{j,k}^{IH}$	$\gamma_{j,k}^{IH} - \gamma_{j,k}^{IL}$	$\phi_{j,k}^{IL}$	$\phi_{j,k}^{IH}$	$\phi_{j,k}^{IH} - \phi_{j,k}^{IL}$
Panel A: j = LIQ												
1	-0.51	-2.80	-2.29	0.52	-2.02	-2.54	0.44	0.22	-0.22	-0.34	-0.20	0.14
	(-3.01)	(-17.83)	(98.86)	(2.37)	(-10.25)	(74.76)	(1.36)	(0.78)	(0.26)	(-5.22)	(-4.57)	(2.66)
2	-2.69	1.58	4.27	-3.17	2.84	6.01	0.61	-0.46	-1.07	0.10	-0.27	-0.37
	(-17.30)	(10.34)	(376.57)	(-17.12)	(16.04)	(537.59)	(2.06)	(-1.97)	(8.07)	(2.81)	(-7.93)	(55.97)
3	-0.65	0.51	1.16	-0.58	0.84	1.42	0.23	-0.19	-0.42	-0.04	-0.07	-0.03
	(-4.39)	(3.44)	(30.48)	(-3.30)	(4.83)	(32.73)	(0.44)	(-0.67)	(0.50)	(-0.96)	(-1.62)	(0.20)
4	-0.35	-0.64	-0.29	-0.08	-0.40	-0.32	-0.12	-0.01	0.11	-0.07	-0.06	0.01
	(-2.40)	(-4.50)	(2.09)	(-0.46)	(-2.45)	(1.83)	(-0.47)	(-0.05)	(0.10)	(-2.05)	(-1.54)	(0.09)
5	-0.17	-0.36	-0.19	0.11	-0.31	-0.42	0.34	0.20	-0.14	-0.11	-0.03	0.08
	(-1.30)	(-2.35)	(0.89)	(0.69)	(-1.44)	(2.49)	(1.33)	(0.37)	(0.05)	(-3.25)	(-0.79)	(2.99)
6	0.26	-0.96	-1.22	0.36	-1.40	-1.76	-0.24	-0.23	0.01	-0.01	0.13	0.14
	(1.91)	(-3.95)	(19.18)	(2.20)	(-7.73)	(52.46)	(-0.97)	(-0.49)	(0.00)	(-0.35)	(1.39)	(2.02)
7	-0.09	1.10	1.19	-0.06	1.81	1.87	0.31	-0.50	-0.81	-0.03	-0.15	-0.12
	(-0.66)	(7.03)	(34.17)	(-0.39)	(9.72)	(59.68)	(1.16)	(-1.81)	(4.53)	(-1.02)	(-3.51)	(4.93)

Table 4.6. Two-Regime Regression (continued)

k	Eq. (4.9)			Eq. (4.10)								
	$\beta_{j,k}^{IL}$	$\beta_{j,k}^{IH}$	$\beta_{j,k}^{IH}-\beta_{j,k}^{IL}$	$\beta_{j,k}^{IL}$	$\beta_{j,k}^{IH}$	$\beta_{j,k}^{IH}-\beta_{j,k}^{IL}$	$\gamma_{j,k}^{IL}$	$\gamma_{j,k}^{IH}$	$\gamma_{j,k}^{IH}-\gamma_{j,k}^{IL}$	$\phi_{j,k}^{IL}$	$\phi_{j,k}^{IH}$	$\phi_{j,k}^{IH}-\phi_{j,k}^{IL}$
8	-0.68	-0.39	0.29	-0.67	-0.53	0.14	0.03	-0.05	-0.08	-0.01	0.04	0.05
	(-5.29)	(-2.50)	(2.11)	(-4.44)	(-2.66)	(0.29)	(0.09)	(-0.16)	(0.03)	(-0.23)	(0.86)	(0.71)
9	-1.73	1.11	2.84	-2.24	1.33	3.57	-0.45	-0.24	0.21	0.20	-0.04	-0.24
	(-11.14)	(7.66)	(177.84)	(-12.32)	(8.01)	(208.74)	(-1.24)	(-0.99)	(0.24)	(3.45)	(-1.05)	(12.10)
10	0.56	0.12	-0.44	0.67	0.17	-0.50	-0.38	0.21	0.59	0.00	-0.03	-0.03
	(4.02)	(0.74)	(4.58)	(4.00)	(0.89)	(3.90)	(-1.46)	(0.86)	(2.72)	(-0.07)	(-0.87)	(0.26)
11	1.40	0.17	-1.23	1.57	0.21	-1.36	-0.28	0.45	0.73	-0.03	-0.05	-0.02
	(8.82)	(1.24)	(34.77)	(8.77)	(1.26)	(31.21)	(-0.91)	(1.64)	(3.14)	(-0.67)	(-1.46)	(0.10)
12	1.30	1.57	0.27	0.55	1.82	1.27	0.85	-0.35	-1.20	0.17	-0.04	-0.21
	(9.04)	(10.53)	(1.78)	(3.02)	(10.41)	(25.60)	(3.07)	(-1.40)	(10.40)	(3.24)	(-1.16)	(11.12)

Table 4.6. Two-Regime Regression (continued)

k	Eq. (4.9)			Eq. (4.10)								
	$\beta_{j,k}^{IL}$	$\beta_{j,k}^{IH}$	$\beta_{j,k}^{IH}-\beta_{j,k}^{IL}$	$\beta_{j,k}^{IL}$	$\beta_{j,k}^{IH}$	$\beta_{j,k}^{IH}-\beta_{j,k}^{IL}$	$\gamma_{j,k}^{IL}$	$\gamma_{j,k}^{IH}$	$\gamma_{j,k}^{IH}-\gamma_{j,k}^{IL}$	$\phi_{j,k}^{IL}$	$\phi_{j,k}^{IH}$	$\phi_{j,k}^{IH}-\phi_{j,k}^{IL}$
Panel B: j = SNT												
1	-0.29	-2.31	-2.02	0.72	-1.42	-2.14	0.47	0.20	-0.27	-0.35	-0.23	0.12
	(-1.54)	(-15.78)	(69.97)	(3.01)	(-7.54)	(49.48)	(1.24)	(0.79)	(0.37)	(-5.02)	(-5.28)	(2.23)
2	0.07	-1.14	-1.21	0.19	-0.86	-1.05	0.66	-0.26	-0.92	-0.09	-0.05	0.04
	(0.40)	(-8.13)	(30.47)	(0.99)	(-5.02)	(16.60)	(2.17)	(-1.14)	(5.85)	(-2.15)	(-1.82)	(0.75)
3	1.71	-1.31	-3.02	2.34	-1.56	-3.90	-0.38	0.21	0.59	-0.17	0.05	0.22
	(9.93)	(-9.78)	(188.69)	(11.38)	(-9.61)	(218.14)	(-0.90)	(0.56)	(1.09)	(-2.40)	(1.57)	(7.66)
4	-0.40	-0.39	0.01	-0.12	-0.07	0.05	-0.01	-0.12	-0.11	-0.09	-0.07	0.02
	(-2.48)	(-2.92)	(0.00)	(-0.65)	(-0.45)	(0.04)	(-0.03)	(-0.50)	(0.08)	(-1.52)	(-2.48)	(0.07)
5	-0.63	-0.08	0.55	-0.08	-0.14	-0.06	-0.57	0.74	1.31	-0.13	-0.04	0.09
	(-4.13)	(-0.57)	(7.44)	(-0.42)	(-0.78)	(0.05)	(-2.00)	(1.50)	(5.29)	(-2.73)	(-1.35)	(2.67)
6	-2.04	0.86	2.90	-2.37	1.01	3.38	0.21	-0.55	-0.76	0.09	0.00	-0.09
	(-12.78)	(4.49)	(134.82)	(-12.43)	(6.31)	(183.73)	(0.56)	(-1.31)	(1.83)	(2.09)	(0.05)	(0.92)
7	0.28	0.72	0.44	0.43	1.24	0.81	-0.60	0.09	0.69	0.00	-0.14	-0.14
	(1.72)	(5.36)	(4.41)	(2.18)	(7.72)	(10.34)	(-1.92)	(0.39)	(3.12)	(0.05)	(-3.99)	(6.44)
8	0.44	-1.18	-1.62	0.53	-1.42	-1.95	-0.11	0.00	0.11	-0.02	0.06	0.08
	(2.82)	(-8.71)	(62.13)	(2.92)	(-8.43)	(61.98)	(-0.24)	(0.02)	(0.05)	(-0.56)	(1.56)	(2.21)
9	-0.01	-0.72	-0.71	-0.21	-1.04	-0.83	-0.09	-0.40	-0.31	0.07	0.11	0.04
	(-0.08)	(-5.06)	(11.18)	(-1.19)	(-6.20)	(11.67)	(-0.25)	(-1.55)	(0.51)	(1.41)	(2.74)	(0.39)
10	-0.08	0.63	0.71	-0.18	0.86	1.04	-0.29	0.16	0.45	0.06	-0.07	-0.13
	(-0.50)	(4.66)	(11.12)	(-0.92)	(5.09)	(16.50)	(-1.11)	(0.64)	(1.57)	(1.18)	(-2.18)	(4.88)
11	0.62	0.86	0.24	0.32	1.28	0.96	-0.30	0.37	0.67	0.13	-0.14	-0.27
	(3.80)	(6.17)	(1.31)	(1.70)	(7.68)	(15.07)	(-0.95)	(1.33)	(2.51)	(2.13)	(-5.12)	(16.65)
12	1.80	1.12	-0.68	1.39	0.89	-0.50	0.31	0.13	-0.18	0.11	0.05	-0.06
	(11.20)	(8.13)	(10.55)	(7.66)	(5.40)	(4.05)	(0.97)	(0.54)	(0.21)	(2.35)	(1.64)	(1.19)

4.5.2. Conditional Abnormal Return

In this section, we expand our analysis by calculating the abnormal returns for 18 equal-weighted portfolios constructed in the previous section for liquid and illiquid periods or for pessimism and optimism periods. As before, we use the median breakpoint of the illiquidity or sentiment index to divide the sample into subsample periods. Then, to estimate the abnormal return for the respective periods, we run the following regression:

$$r_{i,t} = a_{i,j}^{IL} D_{j,t-1}^{IL} + a_{i,j}^{IH} D_{j,t-1}^{IH} + b_i MKT_t + c_i SMB_t + d_i HML_t + e_i MOM_t + u_{i,t} \tag{4.11}$$

The intercept estimate $\alpha_{i,j}^{IL}$ in equation (4.11) represents the abnormal return for the periods in which the value of the index in month $t-k$ is less than the median of the index. Similarly, the intercept estimate $\alpha_{i,j}^{IH}$ represents the abnormal return for the periods in which the value of the index in month $t-k$ is greater than the median of the index.

4.5.2.1. Cross-Sectional Strategies

Table 4.7 reports the conditional abnormal returns for 18 equal-weighted portfolios from independent $2 \times 3 \times 3$ sorts for the cross-sectional strategies. First, Panel A indicates that, regardless of whether the market is liquid, contrarian profits tend to decrease as the exposure to market-wide information increases, except within the 'High' firm-specific information group (FSI_High). For example, within the 'Low' firm-specific information group (FSI_Low), contrarian profits decrease from 0.66% (t = 3.78) to 0.22% (t = 0.94) per month in liquid periods and from 0.52% (t = 2.40) to 0.39% (t = 2.22) per month in illiquid periods. Even though market-wide information-triggered under-reaction is not confirmed in Table 4.6, the contrarian profit still varies with changes in the exposure to market-wide information. Meanwhile, contrarian profits increase as the exposure to firm-specific information increases. For example, within the 'Low' market-wide information group (MWI_Low), contrarian profits increase from 0.66% (t = 3.78) to 1.21% (t = 5.52) per month in liquid periods and from 0.52% (t = 2.40) to 0.69% (t = 3.35) per month in illiquid periods.

Second, Panel B presents results analogous to Panel A. The exposure to market-wide and firm-specific information tends to determine contrarian profits regardless of whether investors are optimistic (or pessimistic). For example, within the 'Low' firm-specific information group (FSI_Low), contrarian profits decrease from 0.50% (t = 3.01) to 0.17% (t = 0.78) per month in pessimism periods and from 0.68% (t = 3.07) to 0.42% (t = 1.88) per month with the exposure to market-wide information in optimism periods. By contrast, within the 'Low' market-wide information group (MWI_Low), contrarian profits increase from 0.50% (t = 3.01) to 1.07% (t = 4.60) per month in pessimism periods and from 0.68% (t = 3.07) to 0.88% (t = 3.84) per month with the exposure to firm-specific information in optimism periods.

Overall, the results in Table 4.7 indicate that the unconditional results still hold. Investors can in fact time the market using contrarian strategies and enhance their performance by using our information proxies when selecting stocks, irrespective of arbitrageurs' willingness to trade in the market against mispricing.

Table 4.7. Conditional Abnormal Return for the Cross-Sectional Strategies

The table presents the conditional average abnormal returns for 18 equal-weighted portfolios from independent 2 × 3 × 3 sorts for cross-sectional strategies. Using three signals from excess returns and proxies for firm-specific and market-wide information in month $t-1$, stocks are independently sorted into two return groups (Losers and Winners), three market-wide information groups (MWI_Low, MWI_Mid, MWI_High) and three firm-specific information groups (FSI_Low, FSI_Mid, FSI_High) at the beginning of month t and held until the end of month t. The return breakpoint is the median excess return, and the information breakpoints are 30th and 70th percentiles of the proxies. To determine the conditional abnormal return, the following regression is estimated:

$$r_{i,t} = a_{i,j}^{IL} D_{j,t-1}^{IL} + a_{i,j}^{IH} D_{j,t-1}^{IH} + b_i MKT_t + c_i SMB_t + d_i HML_t + e_i MOM_t + u_{i,t} \tag{4.11}$$

where i indexes portfolios, t indexes months, $j = \{LIQ, SNT\}$, $r_{i,t}$ is excess return, MKT_t is the market factor, SMB_t is the size factor, HML_t is the value factor and MOM_t is the momentum factor. $D_{j,t-k}^{IL}$ ($D_{j,t-k}^{IH}$) is a dummy variable for the periods in which the value of the index is less (greater) than the median of the index. The intercept estimates, $a_{i,j}^{IL}$ and $a_{i,j}^{IH}$, are defined as the abnormal returns, depending on which index is used for the regression, for liquid and illiquid periods, respectively, or pessimism and optimism periods, respectively. The equation for Panel A is specified using the illiquidity index (LIQ) developed by Pastor and Stambaugh (2003) and that for Panel B is specified using the sentiment index (SNT) developed by Baker and Wurgler (2006). The associated Newey-West (1987) adjusted t-statistics are reported in parentheses. The sample period with the LIQ spans from Aug-1962 to Dec-2019 and that with the SNT spans from Jul-1965 to Dec-2018.

		FSI_Low			FSI_Mid			FSI_High		
		MWI_Low	MWI_Mid	MWI_High	MWI_Low	MWI_Mid	MWI_High	MWI_Low	MWI_Mid	MWI_High
Panel A: j = LIQ										
Liquid Periods	Losers	0.36	0.30	0.14	0.79	0.63	0.41	0.92	0.79	0.85
		(2.37)	(2.11)	(0.76)	(5.18)	(4.56)	(2.90)	(4.49)	(3.93)	(4.64)
	Winners	-0.30	-0.18	-0.08	-0.22	-0.30	-0.28	-0.29	-0.26	-0.31
		(-3.36)	(-2.25)	(-0.53)	(-1.69)	(-2.45)	(-2.17)	(-1.65)	(-1.41)	(-1.73)
	Losers-Winners	0.66	0.48	0.22	1.01	0.93	0.68	1.21	1.05	1.15
		(3.78)	(2.67)	(0.94)	(5.59)	(5.68)	(3.53)	(5.52)	(5.62)	(6.54)
Illiquid Periods	Losers	0.29	0.10	0.10	0.48	0.38	0.22	0.67	0.81	0.81
		(1.32)	(0.70)	(0.68)	(1.88)	(1.68)	(1.24)	(3.31)	(4.53)	(4.86)
	Winners	-0.23	-0.33	-0.29	-0.23	-0.30	-0.32	-0.02	-0.12	-0.13
		(-3.00)	(-4.44)	(-2.37)	(-2.52)	(-3.77)	(-3.15)	(-0.14)	(-0.87)	(-0.92)
	Losers-Winners	0.52	0.43	0.39	0.71	0.68	0.54	0.69	0.93	0.93
		(2.40)	(2.61)	(2.22)	(2.84)	(2.99)	(3.02)	(3.35)	(5.21)	(6.88)

Table 4.7. Conditional Abnormal Return for the Cross-Sectional Strategies (continued)

		FSI_Low			FSI_Mid			FSI_High		
		MWI_Low	MWI_Mid	MWI_High	MWI_Low	MWI_Mid	MWI_High	MWI_Low	MWI_Mid	MWI_High
Panel B: j = SNT										
Pessimism Periods	Losers	0.31	0.27	0.25	0.77	0.64	0.41	0.98	1.00	1.09
		(2.08)	(2.03)	(1.46)	(4.84)	(4.44)	(2.89)	(4.63)	(5.10)	(6.05)
	Winners	-0.19	-0.17	0.08	-0.13	-0.22	-0.19	-0.09	-0.21	-0.19
		(-2.40)	(-2.22)	(0.58)	(-1.09)	(-1.98)	(-1.38)	(-0.45)	(-1.09)	(-0.98)
	Losers-Winners	0.50	0.44	0.17	0.89	0.87	0.60	1.07	1.20	1.28
		(3.01)	(2.77)	(0.78)	(5.02)	(5.05)	(3.18)	(4.60)	(5.80)	(6.90)
Optimism Periods	Losers	0.35	0.10	0.00	0.55	0.38	0.24	0.68	0.62	0.58
		(1.58)	(0.66)	(-0.01)	(2.19)	(1.73)	(1.37)	(3.19)	(3.14)	(3.24)
	Winners	-0.33	-0.34	-0.42	-0.34	-0.37	-0.37	-0.20	-0.14	-0.21
		(-3.35)	(-3.95)	(-3.32)	(-2.91)	(-3.31)	(-3.64)	(-1.25)	(-0.88)	(-1.35)
	Losers-Winners	0.68	0.44	0.42	0.89	0.75	0.61	0.88	0.76	0.79
		(3.07)	(2.31)	(1.88)	(3.36)	(3.11)	(3.05)	(3.84)	(4.25)	(5.36)

4.5.2.2. Time-Series Strategies

Table 4.8 reports the conditional abnormal returns for 18 equal-weighted portfolios from the independent 2 × 3 × 3 sorts for the time-series strategies. The table shows results that are somewhat similar to those in Table 4.7. Panel A shows that contrarian profits tend to vary with the exposure to market-wide and firm-specific information in both liquid and illiquid periods. For example, within the ‘Low’ firm-specific information group (FSI_Low), contrarian profits decrease from 1.03% (t = 5.77) to 0.29 (t = 1.13) per month in liquid periods and from 0.69% (t = 3.23) to 0.33% (t = 1.75) per month in illiquid periods. By contrast, within the ‘Mid’ market-wide information group (MWI_Mid), contrarian profits increase from 0.43% (t = 2.46) to 1.20% (t = 6.09) per month in liquid periods and from 0.57% (t = 3.64) to 1.17% (t = 6.62) per month in illiquid periods.

Panel B indicate the negative (positive) relation of contrarian profits with the exposure to market-wide (firm-specific) information in both pessimism and optimism periods. For instance, within the ‘Low’ firm-specific information group (FSI_Low), contrarian profits decrease from 0.86% (t = 5.04) to 0.15 (t = 0.75) per month in pessimism periods and from 0.90% (t = 3.97) to 0.40% (t = 1.57) per month in optimism periods. By contrast, within the ‘Mid’ market-wide information group (MWI_Mid), contrarian profits increase from 0.45% (t = 3.13) to 1.49% (t = 6.99) per month in pessimism periods and from 0.56% (t = 2.93) to 0.89% (t = 4.88) per month in optimism periods.

Table 4.8. Conditional Abnormal Return for the Time-Series Strategies

The table presents the conditional average abnormal returns for 18 equal-weighted portfolios from independent $2 \times 3 \times 3$ sorts for time-series strategies. Using three signals from excess returns and proxies for firm-specific and market-wide information in month $t-1$, at the beginning of month t, stocks are independently sorted into two return groups (Losers and Winners), three market-wide information groups (MWI_Low, MWI_Mid, MWI_High) and three firm-specific information groups (FSI_Low, FSI_Mid, FSI_High) and held until the end of month t. The return breakpoint is zero, and the information breakpoints are 30th and 70th percentiles of the proxies. To determine the conditional abnormal return, the following regression is estimated:

$$r_{i,t} = a_{i,j}^{IL} D_{j,t-1}^{IL} + a_{i,j}^{IH} D_{j,t-1}^{IH} + b_i MKT_t + c_i SMB_t + d_i HML_t + e_i MOM_t + u_{i,t} \tag{4.11}$$

where i indexes portfolios, t indexes months, $j = \{LIQ, SNT\}$, $r_{i,t}$ is excess return, MKT_t is the market factor, SMB_t is the size factor, HML_t is the value factor and MOM_t is the momentum factor. $D_{j,t-k}^{IL}$ ($D_{j,t-k}^{IH}$) is a dummy variable for the periods in which the value of the index is less (greater) than the median of the index. The intercept estimates, $a_{i,j}^{IL}$ and $a_{i,j}^{IH}$, are defined as the abnormal returns, depending on which index is used for the regression, for liquid and illiquid periods, respectively, or pessimism and optimism periods, respectively. The equation for Panel A is specified using the illiquidity index (LIQ) developed by Pastor and Stambaugh (2003) and that for Panel B is specified using the sentiment index (SNT) developed by Baker and Wurgler (2006). The associated Newey-West (1987) adjusted t-statistics are reported in parentheses. The sample period with the LIQ spans from Aug-1962 to Dec-2019 and that with the SNT spans from Jul-1965 to Dec-2018.

		FSI_Low			FSI_Mid			FSI_High		
		MWI_Low	MWI_Mid	MWI_High	MWI_Low	MWI_Mid	MWI_High	MWI_Low	MWI_Mid	MWI_High
Panel A: j = LIQ										
Liquid Periods	Losers	0.55	0.31	0.19	0.80	0.66	0.38	0.81	0.73	0.84
		(3.81)	(2.27)	(0.95)	(5.03)	(4.30)	(2.73)	(3.79)	(3.56)	(4.08)
	Winners	-0.48	-0.13	-0.12	-0.26	-0.39	-0.24	-0.31	-0.47	-0.49
		(-4.04)	(-1.19)	(-0.67)	(-1.83)	(-2.82)	(-1.42)	(-1.59)	(-2.07)	(-2.57)
	Losers-Winners	1.03	0.43	0.29	1.06	1.05	0.62	1.12	1.20	1.33
		(5.77)	(2.46)	(1.13)	(5.69)	(6.17)	(2.98)	(5.31)	(6.09)	(7.26)
Illiquid Periods	Losers	0.37	0.17	0.05	0.47	0.48	0.33	0.69	0.97	0.89
		(1.65)	(1.22)	(0.32)	(1.84)	(2.16)	(1.81)	(3.34)	(5.06)	(5.11)
	Winners	-0.32	-0.40	-0.28	-0.20	-0.32	-0.34	0.00	-0.20	-0.13
		(-4.13)	(-5.14)	(-2.09)	(-2.21)	(-3.92)	(-3.21)	(0.03)	(-1.42)	(-0.93)
	Losers-Winners	0.69	0.57	0.33	0.67	0.80	0.67	0.69	1.17	1.02
		(3.23)	(3.64)	(1.75)	(2.69)	(3.60)	(3.71)	(3.36)	(6.62)	(7.35)

Table 4.8. Conditional Abnormal Return for the Time-Series Strategies (continued)

		FSI_Low			FSI_Mid			FSI_High		
		MWI_Low	MWI_Mid	MWI_High	MWI_Low	MWI_Mid	MWI_High	MWI_Low	MWI_Mid	MWI_High
Panel B: j = SNT										
Pessimism Periods	Losers	0.50	0.32	0.32	0.78	0.75	0.46	0.97	1.06	1.16
		(3.48)	(2.71)	(1.85)	(4.67)	(5.02)	(3.34)	(4.33)	(5.20)	(5.62)
	Winners	-0.37	-0.13	0.16	-0.13	-0.32	-0.15	-0.14	-0.43	-0.36
		(-3.90)	(-1.38)	(0.99)	(-1.02)	(-2.55)	(-0.98)	(-0.70)	(-1.87)	(-1.72)
	Losers-Winners	0.86	0.45	0.15	0.91	1.07	0.61	1.11	1.49	1.52
		(5.04)	(3.13)	(0.75)	(4.85)	(6.46)	(3.23)	(5.04)	(6.99)	(8.04)
Optimism Periods	Losers	0.45	0.18	-0.08	0.54	0.42	0.28	0.61	0.65	0.60
		(2.02)	(1.09)	(-0.42)	(2.11)	(1.88)	(1.51)	(2.70)	(3.10)	(3.02)
	Winners	-0.45	-0.38	-0.49	-0.35	-0.38	-0.36	-0.16	-0.23	-0.24
		(-3.52)	(-3.91)	(-3.05)	(-2.74)	(-3.21)	(-3.24)	(-0.99)	(-1.24)	(-1.49)
	Losers-Winners	0.90	0.56	0.40	0.89	0.81	0.64	0.78	0.89	0.84
		(3.97)	(2.93)	(1.57)	(3.39)	(3.34)	(3.14)	(3.43)	(4.88)	(5.19)

4.6. Conclusion

This research studies investors' responses to market-wide and firm-specific information. To quantify the arrival of each information type, we construct information proxies based on trading volumes. To do so, we model individual stocks' trading volumes as a single-factor model using the equal-weighted market trading volume. Extending results from contrarian and momentum studies, we investigate the conditional ability of historical returns to predict future returns on the constructed information proxies to analyse how investors respond to market-wide and firm-specific information.

Our empirical analysis provides several important results. First, stock returns tend to be reversed over the short-term and continued over the intermediate-term, confirming previous studies' findings. Further, market-wide (firm-specific) information attenuates (amplifies) the return reversal over the short-term which indicates that investors tend to underreact (overreact) to market-wide (firm-specific) information. Second, market-wide (firm-specific) information predicts a decrease (increase) in the return variance. Third, contrarian strategies that buy losers and sell winners become more profitable when the exposure to market-wide (firm-specific) information decreases (increases). Fourth, predictable patterns in stock returns become more distinct when markets are less attractive to arbitrageurs. In the arbitrage context, our results suggest that market-wide information-triggered under-reactions disappear, while firm-specific information-triggered over-reactions persist, regardless of whether arbitrageurs are willing to trade in markets. However, contrarian profits can still be enhanced by controlling the exposure to market-wide (firm-specific) information.

Our results have important implications for practitioners who aim at timing the market and for regulators who benefit from an improved understanding of mispricing dynamics to design policies that improve the functioning of capital markets.

Chapter 5: Conclusion

This thesis analyses the time-series and cross-section of asset returns using predictions based on market participants' rational or irrational behaviour. The three research studies in this thesis provide investors with practical implications to improve and manage their investment strategies. In addition, the empirical results presented can serve financial regulators to design and adjust capital market policies based on the improved understanding of market participants' behaviour related to the use of debt (Chapter 2), effects of investors' attitudes and moods (Chapter 3) and the mechanism of how information that pertains to the entire market or individual firms impacts trading activities (Chapter 4).

As a general motivation for the research presented in this thesis, all three research studies aim at improving the understanding of the actual characteristics of investors' decision-making in financial markets based on leverage (in Chapter 2), sentiment (in Chapter 3) and information flows (in Chapter 4). These research studies expand the existing literature by using rigorous econometric analyses to investigate the effect of rational and irrational human behaviour on financial markets which leads to novel results and insights that can be employed by financial practitioners to improve their investment outcomes and by financial regulators to improve their policies for economies and societies.

The findings in this thesis contribute to the literature of asset pricing. This area of research is not only important because of the roles that financial economics and financial markets play in social sciences, but it is also characterised by the ongoing controversy about how market participants make decisions. While numerous previous studies have contributed to the debate to address the tension between finance theories based on rational and irrational behaviour, the battle between both camps appears to be far from over. Based on these streams of the literature, this thesis shows novel insights into predictable variations in asset returns based on rational or irrational behaviour.

5.1. Summary of Findings

The first research investigates the cross-section of stock returns based on the association between household indebtedness and consumption on the one side and related effects on asset prices on the other side. Our empirical analysis uses U.S. household data spanning from 1952 to 2018, and the results indicate that leverage has a significant and long-lasting negative repercussion on consumption. Using various sets of test assets capturing traditional anomalies presented in previous studies, we show that the risk price for household leverage is negative, indicating that households are willing to accept lower expected returns on securities with returns negatively related to the households' leverage dynamics. Importantly, the extension of the analysis to individual stocks shows that the leverage risk premium is not explained by well-known risk factors.

The second research investigates sentiment-based movements in the time-series and cross-section of stock returns using data from several developed markets covering the period 1984 to 2018. We construct global and regional sentiment indexes and show that investors' optimism is related to upward movements in asset returns, while investors' pessimism is associated with upward movements in the return variance and correlation. These findings of sentiment-based movements in stock markets lead to the conclusion, contrary to traditional finance theories, that sentiment predicts financial market dynamics. Specifically, stocks tend to earn negative returns following high sentiment (optimism) periods, while stock returns become less volatile and less correlated following low sentiment (pessimism) periods. Moreover, the results from the cross-sectional analysis show that the effect of sentiment is more pronounced among high sentiment or market beta stocks.

The third research explores market participants' responses to market-wide and firm-specific information using U.S. stock market data spanning from 1927 to 2019. Our research proposes an empirical model to construct proxies for the respective information arrivals. Armed with proxies for market-wide and firm-specific information, we investigate the question whether historical returns can predict future returns and show that investors underreact to market-wide information and overreact to firm-specific information. In addition, we find that the differential investor responses to market-wide and firm-specific information are related to the cross-section of return variances. Specifically, we document that the arrival of market-wide (firm-specific) information is related to a decrease (an increase) in individual stocks' return variances. Our results are particularly important for investors who implement contrarian investment strategies and suggest that these investors should increase their exposure to firm-specific information and decrease their exposure to market-wide information.

5.2. Implications of the Thesis

The findings have important implications for anybody with a relation to financial markets. For example, provided that most of members of societies around the world rely on capital markets, e.g., to invest their savings for retirement, the results presented in this thesis offer several far-reaching implications pertaining to the design of investment strategies and the better understanding of securities' return and risk characteristics in the light of rational and irrational behaviour.

For investors, this thesis suggests various implications for investment strategies. In Chapter 2, we show that investment strategies should be established by considering macroeconomic aspects related to household leverage. Our results imply that the effect of household leverage on financial markets becomes stronger as households' motive to hedge against their leverage for a smooth trajectory of their consumption is strengthened. Thus, market participants should pay close attention to the effect of household leverage on financial markets, particularly during economic downturns or crises. Recent economic phenomena such as the subprime mortgage crisis between 2007 and 2010 or the COVID-19 crisis in 2020 highlight the importance of the research results presented in Chapter 2.

In Chapter 3, we find that sentiment is a predictor not only of the mean of stock returns but also of the variance and correlation of stock returns. Therefore, our research improves the knowledge and understanding of effects related to investors' attitudes and moods and, therefore, increase the flexibility of investors when budgeting and managing risks (that are measured as the second moment of asset returns).

In Chapter 4, our research shows that investors respond differentially and irrationally to market-wide and firm-specific information. These results enhance a critical ability required by investors, which is to predict future stock returns and return volatility. Specifically, our results show that investors can improve their investment outcomes without taking further systematic risk using our information proxies.

For financial regulators, this thesis provides tools to understand and predict financial market dynamics. In Chapter 2, we find that the level of household leverage affects the cross-section of stock returns particularly during periods when households are forced to deleverage. This suggests that financial regulators should pay close attention to household balance sheets to understand developments in financial markets pertaining to asset pricing.

Undoubtedly, the volatility of financial markets is of great interest for financial regulators. The findings presented in Chapters 3 and 4 improve financial regulators' ability to predict the volatility of individual stock returns and stock market returns. Overall, our findings permit those who watch over markets from a policy design perspective to make better decisions to design better policy rules, regulations and laws which will increase the stability of financial markets.

5.3. Suggestions for Future Research

This thesis offers several suggestions for future research. To shed additional light on the relation between debt and asset prices, future research on the role of leverage in asset pricing could consider focusing on the determinants that trigger or reinforce households' hedging motive against households' leverage. In particular, the extended research of consumption in investment contexts may be of additional value in order to improve the understanding of the cross-sectional dispersion of stock returns subject to important economic circumstances, such as crisis or periods of economic recession.

Future research on the effect of investor sentiment should continue to strive for the provision of theoretical and empirical explanations for the asymmetric influence of sentiment traders' optimistic or pessimistic beliefs on moments of asset returns and on product moments of asset returns. Such research studies will enhance the understanding of multivariate distributions of asset returns conditional on sentiment.

Future research on investor responses to information arrivals to the market could consider investigating the association between the coverage of information and investors' responses to information. Such research would extend the research presented in this thesis because the findings in Chapter 4 indicate that investors' responses to information might be able to be fractionised according to the coverage of the information.

References

Adrian, Tobias, Erkko Etula, and Tyler Muir, 2014, Financial intermediaries and the cross-section of asset returns, *Journal of Finance* 69, 2557-2596.

Amenc, Noël, Lionel Martellini, Vincent Milhau, and Volker Ziemann, 2009, Asset-liability management in private wealth management, *Journal of Portfolio Management* 36, 100-120.

Andersen, Torben G., 1996, Return volatility and trading volume: An information flow interpretation of stochastic volatility, *Journal of Finance* 51, 169-204.

Andrews, Donald W. K., 1991, Heteroskedasticity and autocorrelation consistent covariant matrix estimation, *Econometrica* 59, 817-858.

Antoniou, Constantinos, John A. Doukas, and Avanidhar Subrahmanyam, 2016, Investor sentiment, beta, and the cost of equity capital, *Management Science* 62, 347-367.

Attanasio, Orazio P., and Guglielmo Weber, 1989, Intertemporal substitution, risk aversion and the euler equation for consumption, *Economic Journal* 99, 59-73.

Avramov, Doron, Tarun Chordia, and Amit Goyal, 2006, Liquidity and autocorrelations in individual stock returns, *Journal of Finance* 61, 2365-2394.

Bacchetta, Philippe, and Stefan Gerlach, 1997, Consumption and credit constraints: International evidence, *Journal of Monetary Economics* 40, 207-238.

Baillie, Richard T., and Ramon P. De Gennaro, 1990, Stock returns and volatility, *Journal of Financial and Quantitative Analysis* 25, 203-214.

Baker, Malcolm, Brendan Bradley, and Jeffrey Wurgler, 2011, Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly, *Financial Analysts Journal* 67, 40-54.

Baker, Malcolm, and Jeremy C. Stein, 2004, Market liquidity as a sentiment indicator, *Journal of Financial Markets* 7, 271-299.

Baker, Malcolm, and Jeffrey Wurgler, 2000, The equity share in new issues and aggregate stock returns, *Journal of Finance* 55, 2219-2257.

Baker, Malcolm, and Jeffrey Wurgler, 2002, Market timing and capital structure, *Journal of Finance* 57, 1-32.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61, 1645-1680.

Baker, Malcolm, and Jeffrey Wurgler, 2007, Investor sentiment in the stock market, *Journal of Economic Perspectives* 21, 129-152.

Baker, Malcolm, Jeffrey Wurgler, and Yu Yuan, 2012, Global, local, and contagious investor sentiment, *Journal of Financial Economics* 104, 272-287.

Bansal, Ravi, Dana Kiku, and Amir Yaron, 2007, Risks for the long run: Estimation and inference, Working Paper (University of Pennsylvania).

Bansal, Ravi, and Amir Yaron, 2004, Risks for the long run: A potential resolution of asset pricing puzzles, *Journal of Finance* 59, 1481-1509.

Barber, Brad M., and Douglas Loeffler, 1993, The "dartboard" column: Second-hand information and price pressure, *Journal of Financial and Quantitative Analysis* 28, 273-284.

Barberis, Nicholas, and Ming Huang, 2001, Mental accounting, loss aversion, and individual stock returns, *Journal of Finance* 56, 1247-1292.

Barberis, Nicholas, Ming Huang, and Tano Santos, 2001, Prospect theory and asset prices, *Quarterly Journal of Economics* 116, 1-53.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307-343.

Barberis, Nicholas, Andrei Shleifer, and Jeffrey Wurgler, 2005, Comovement, *Journal of Financial Economics* 75, 283-317.

Barillas, Francisco, and Jay Shanken, 2017, Which alpha?, *Review of Financial Studies* 30, 1316-1338.

Beltz, Jess, and Robert Jennings, 1997, "Wall street week with louis rukheyser" recommendations:Trading activity and performance, *Review of Financial Economics* 6, 15-27.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch, 1992, A theory of fads, fashion, custom, and cultural change as informational cascades, *Journal of Political Economy* 100, 992-1026.

Black, Fischer, Michael C. Jensen, and Myron S. Scholes, 1972, The capital asset pricing model: Some empirical tests, in Michael C. Jensen, ed.: *Studies in the theory of capital markets* (Praeger Publishers Inc., New York).

Boguth, Oliver, and Lars-Alexander Kuehn, 2013, Consumption volatility risk, *Journal of Finance* 68, 2589-2615.

Bollerslev, Tim, 1986, Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics* 31, 307-327.

Brandt, Michael W., and Qiang Kang, 2004, On the relationship between the conditional mean and volatility of stock returns: A latent var approach, *Journal of Financial Economics* 72, 217-257.

Braun, R. Anton, and Tomoyuki Nakajima, 2012, Making the case for a low intertemporal elasticity of substitution, Working Paper (FRB).

Brav, Alon, George M. Constantinides, and Christopher C. Geczy, 2002, Asset pricing with heterogeneous consumers and limited participation: Empirical evidence, *Journal of Political Economy* 110, 793-824.

Breeden, Douglas T., 1979, An intertemporal asset pricing model with stochastic consumption and investment opportunities, *Journal of Financial Economics* 7, 265-296.

Brennan, Michael J., Ashley W. Wang, and Yihong Xia, 2004, Estimation and test of a simple model of intertemporal capital asset pricing, *Journal of Finance* 59, 1743-1776.

Brogaard, Jonathan, Terrence Hendershott, and Ryan Riordan, 2014, High-frequency trading and price discovery, *Review of Financial Studies* 27, 2267-2306.

Brown, Gregory W., and Michael T. Cliff, 2004, Investor sentiment and the near-term stock market, *Journal of Empirical Finance* 11, 1-27.

Campbell, John Y., 1987, Stock returns and the term structure, *Journal of Financial Economics* 18, 373-399.

Campbell, John Y., 1996, Understanding risk and return, *Journal of Political Economy* 104, 298-345.

Campbell, John Y., 2003, Consumption-based asset pricing, in George M. Constantinides, Milton Harris, and René M. Stulz, eds.: *Handbook of the economics of finance* (Elsevier, North Holland, Amsterdam).

Campbell, John Y., and João F. Cocco, 2007, How do house prices affect consumption? Evidence from micro data, *Journal of Monetary Economics* 54, 591-621.

Campbell, John Y., and John H. Cochrane, 1999, By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107, 205-251.

Campbell, John Y., Sanford J. Grossman, and Jiang Wang, 1993, Trading volume and serial correlation in stock returns, *Quarterly Journal of Economics* 108, 905-939.

Campbell, John Y., and Ludger Hentschel, 1992, No news is good news: An asymmetric model of changing volatility in stock returns, *Journal of Financial Economics* 31, 281-318.

Campbell, John Y., Andrew W. Lo, and A. Craig MacKinlay, 1997. *The econometrics of financial markets* (Princeton University Press, Princeton, New Jersy).

Campbell, John Y., and N. Gregory Mankiw, 1990, Permanent income, current income, and consumption, *Journal of Business & Economic Statistics* 8, 265-279.

Campbell, John Y., and Tuomo Vuolteenaho, 2004, Bad beta, good beta, *American Economic Review* 94, 1249-1275.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Carroll, Christopher D., Misuzu Otsuka, and Jiri Slacalek, 2011, How large are housing and financial wealth effects? A new approach, *Journal of Money, Credit and Banking* 43, 55-79.

Case, Karl E., John M. Quigley, and Robert J. Shiller, 2005, Comparing wealth effects: The stock market versus the housing market, *B.E. Journal of Macroeconomics* 5.

Case, Karl E., John M. Quigley, and Robert J. Shiller, 2013, Wealth effects revisited 1978-2009, Working Paper (NBER).

Chan, K. C., Nai-fu Chen, and David A. Hsieh, 1985, An exploratory investigation of the firm size effect, *Journal of Financial Economics* 14, 451-471.

Chan, Wesley S., 2003, Stock price reaction to news and no-news: Drift and reversal after headlines, *Journal of Financial Economics* 70, 223-260.

Chang, Sanders S., Lenisa V. Chang, and F. Albert Wang, 2014, A dynamic intraday measure of the probability of informed trading and firm-specific return variation, *Journal of Empirical Finance* 29, 80-94.

Chen, Nai-Fu, Richard Roll, and Stephen A. Ross, 1986, Economic forces and the stock market, *Journal of Business* 59, 383-403.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2008, Liquidity and market efficiency, *Journal of Financial Economics* 87, 249-268.

Chordia, Tarun, Avanidhar Subrahmanyam, and V. Ravi Anshuman, 2001, Trading activity and expected stock returns, *Journal of Financial Economics* 59, 3-32.

Christie, Andrew A., 1982, The stochastic behavior of common stock variances: Value, leverage and interest rate effects, *Journal of Financial Economics* 10, 407-432.

Clark, Peter K., 1973, A subordinated stochastic process model with finite variance for speculative prices, *Econometrica* 41, 135-155.

Cochrane, John H., 1991, Production-based asset pricing and the link between stock returns and economic fluctuations, *Journal of Finance* 46, 209-237.

Cochrane, John H., 2009. *Asset pricing: Revised edition* (Princeton University Press, Princeton, New Jersy).

Constantinides, George M., and Darrell Duffie, 1996, Asset pricing with heterogeneous consumers, *Journal of Political Economy* 104, 219-240.

Covrig, Vicentiu, and Lilian Ng, 2004, Volume autocorrelation, information, and investor trading, *Journal of Banking and Finance* 28, 2155-2174.

D'avolio, Gene, 2002, The market for borrowing stock, *Journal of Financial Economics* 66, 271-306.

Daniel, Kent D., David Hirshleifer, and Avanidhar Subrahmanyam, 2001, Overconfidence, arbitrage, and equilibrium asset pricing, *Journal of Finance* 56, 921-965.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under-and overreactions, *Journal of Finance* 53, 1839-1885.

Daniel, Kent, David Hirshleifer, and Lin Sun, 2020, Short- and long-horizon behavioral factors, *Review of Financial Studies* 33, 1673-1736.

Daniel, Kent, and Sheridan Titman, 2006, Market reactions to tangible and intangible information, *Journal of Finance* 61, 1605-1643.

De Bondt, Werner F. M., and Richard Thaler, 1985, Does the stock market overreact?, *Journal of Finance* 40, 793-805.

De Bondt, Werner F. M., and Richard H. Thaler, 1987, Further evidence on investor overreaction and stock market seasonality, *Journal of Finance* 42, 557-581.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990a, Noise trader risk in financial markets, *Journal of Political Economy* 98, 703-738.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990b, Positive feedback investment strategies and destabilizing rational speculation, *Journal of Finance* 45, 379-395.

Dittmar, Robert F., 2002, Nonlinear pricing kernels, kurtosis preference, and evidence from the cross section of equity returns, *Journal of Finance* 57, 369-403.

Dynan, Karen, 2012, Is a household debt overhang holding back consumption?, *Brookings Papers on Economic Activity* 299-362.

Easley, David, Nicholas M. Kiefer, Maureen O'Hara, and Joseph B. Paperman, 1996, Liquidity, information, and infrequently traded stocks, *Journal of Finance* 51, 1405-1436.

Easley, David, Marcos M. López de Prado, and Maureen O'Hara, 2012, Flow toxicity and liquidity in a high-frequency world, *Review of Financial Studies* 25, 1457-1493.

Edwards, Ward, 1982, Conservatism in human information processing, in Amos Tversky, Daniel Kahneman, and Paul Slovic, eds.: *Judgment under uncertainty: Heuristics and biases* (Cambridge University Press, Cambridge).

Eggertsson, Gauti B., and Paul Krugman, 2012, Debt, deleveraging, and the liquidity trap: A fisher-minsky-koo approach, *Quarterly Journal of Economics* 127, 1469-1513.

Elton, Edwin J, and Martin J Gruber, 1992, Optimal investment strategies with investor liabilities, *Journal of Banking and Finance* 16, 869-890.

Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake, 1995, Fundamental economic variables, expected returns, and bond fund performance, *Journal of Finance* 50, 1229-1256.

Engelberg, Joseph, Caroline Sasseville, and Jared Williams, 2012, Market madness? The case of mad money, *Management Science* 58, 351-364.

Engle, Robert F., 1982, Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation, *Econometrica* 50, 987-1007.

Engle, Robert, and Bryan Kelly, 2012, Dynamic equicorrelation, *Journal of Business & Economic Statistics* 30, 212-228.

Epps, Thomas W., and Mary Lee Epps, 1976, The stochastic dependence of security price changes and transaction volumes: Implications for the mixture-of-distributions hypothesis, *Econometrica* 44, 305-321.

Epstein, Larry G., and Stanley E. Zin, 1991, Substitution, risk aversion, and the temporal behavior of consumption and asset returns: An empirical analysis, *Journal of Political Economy* 99, 263-286.

Fama, Eugene F., 1965a, Random walks in stock market prices, *Financial Analysts Journal* 21, 55-59.

Fama, Eugene F., 1965b, The behavior of stock market prices, *Journal of Business* 38, 34-105.

Fama, Eugene F., 1970, Efficient capital markets: A review of theory and empirical work, *Journal of Finance* 25, 383-417.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427-465.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F., and Kenneth R. French, 2001, Disappearing dividends: Changing firm characteristics or lower propensity to pay?, *Journal of Financial Economics* 60, 3-43.

Fama, Eugene F., and Kenneth R. French, 2016, Dissecting anomalies with a five-factor model, *Review of Financial Studies* 29, 69-103.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607-636.

Ferson, Wayne E., and Campbell R. Harvey, 1991, The variation of economic risk premiums, *Journal of Political Economy* 99, 385-415.

Ferson, Wayne E., and Campbell R. Harvey, 1993, The risk and predictability of international equity returns, *Review of Financial Studies* 6, 527-566.

Ferson, Wayne E., and Campbell R. Harvey, 1994, Sources of risk and expected returns in global equity markets, *Journal of Banking and Finance* 18, 775-803.

Fischhoff, Baruch., and Paul. Slovic, 1980, A little learning...: Confidence in multicue judgment tasks, in Raymond S. Nickerson, ed.: *Attention and performance viii* (Hillsdale, Erlbaum, New Jersy).

Flavin, Marjorie A., 1981, The adjustment of consumption to changing expectations about future income, *Journal of Political Economy* 89, 974-1009.

Fleming, Jeff, Chris Kirby, and Barbara Ostdiek, 2006, Stochastic volatility, trading volume, and the daily flow of information, *Journal of Business* 79, 1551-1590.

Forgas, Joseph P, 1998, On being happy and mistaken: Mood effects on the fundamental attribution error, *Journal of Personality and Social Psychology* 75, 318.

Foster, F Douglas, and Sean Viswanathan, 1990, A theory of the interday variations in volume, variance, and trading costs in securities markets, *Review of Financial Studies* 3, 593-624.

Foster, F Douglas, and Sean Viswanathan, 1995, Can speculative trading explain the volume–volatility relation?, *Journal of Business & Economic Statistics* 13, 379-396.

Frank, Murray Z., and Ali Sanati, 2018, How does the stock market absorb shocks?, *Journal of Financial Economics* 129, 136-153.

Frazzini, Andrea, and Lasse Heje Pedersen, 2014, Betting against beta, *Journal of Financial Economics* 111, 1-25.

French, Kenneth R., and James M. Poterba, 1991, Investor diversification and international equity markets, *American Economic Review* 81, 222-226.

French, Kenneth R., G. William Schwert, and Robert F. Stambaugh, 1987, Expected stock returns and volatility, *Journal of Financial Economics* 19, 3-29.

Frijns, Bart, Willem F. C. Verschoor, and Remco C. J. Zwinkels, 2017, Excess stock return comovements and the role of investor sentiment, *Journal of International Financial Markets, Institutions and Money* 49, 74-87.

Gallant, A. Ronald, Peter E. Rossi, and George Tauchen, 1992, Stock prices and volume, *Review of Financial Studies* 5, 199-242.

Ghysels, Eric, Pedro Santa-Clara, and Rossen Valkanov, 2005, There is a risk-return trade-off after all, *Journal of Financial Economics* 76, 509-548.

Gibbons, Michael R., Stephen A. Ross, and Jay Shanken, 1989, A test of the efficiency of a given portfolio, *Econometrica* 57, 1121-1152.

Glosten, Lawrence R., Ravi Jagannathan, and David E. Runkle, 1993, On the relation between the expected value and the volatility of the nominal excess return on stocks, *Journal of Finance* 48, 1779-1801.

Greenspan, Alan, and James Kennedy, 2008, Sources and uses of equity extracted from homes, *Oxford Review of Economic Policy* 24, 120-144.

Gruber, Jonathan, 2013, A tax-based estimate of the elasticity of intertemporal substitution, *Quarterly Journal of Finance* 03, 1350001.

Guerrieri, Veronica, and Guido Lorenzoni, 2017, Credit crises, precautionary savings, and the liquidity trap, *Quarterly Journal of Economics* 132, 1427-1467.

Guo, Hui, and Robert F. Whitelaw, 2006, Uncovering the risk–return relation in the stock market, *Journal of Finance* 61, 1433-1463.

Hall, Robert E., 1978, Stochastic implications of the life cycle-permanent income hypothesis: Theory and evidence, *Journal of Political Economy* 86, 971-987.

Hall, Robert E., 1988, Intertemporal substitution in consumption, *Journal of Political Economy* 96, 339-357.

Hall, Robert E., 2011, The long slump, *American Economic Review* 101, 431-69.

Hansen, Lars Peter, 1982, Large sample properties of generalized method of moments estimators, *Econometrica* 50, 1029-1054.

Hansen, Lars Peter, and Kenneth J. Singleton, 1982, Generalized instrumental variables estimation of nonlinear rational expectations models, *Econometrica* 50, 1269-1286.

Harris, Lawrence, 1986, Cross-security tests of the mixture of distributions hypothesis, *Journal of Financial and Quantitative Analysis* 21, 39-46.

Harris, Lawrence, 1987, Transaction data tests of the mixture of distributions hypothesis, *Journal of Financial and Quantitative Analysis* 22, 127-141.

Harvey, Campbell R., 2001, The specification of conditional expectations, *Journal of Empirical Finance* 8, 573-637.

Harvey, Campbell R., Yan Liu, and Heqing Zhu, 2016, … and the cross-section of expected returns, *Review of Financial Studies* 29, 5-68.

He, Zhiguo, Bryan Kelly, and Asaf Manela, 2017, Intermediary asset pricing: New evidence from many asset classes, *Journal of Financial Economics* 126, 1-35.

He, Zhiguo, and Arvind Krishnamurthy, 2013, Intermediary asset pricing, *American Economic Review* 103, 732-70.

Heaton, John, and Deborah Lucas, 2000, Portfolio choice and asset prices: The importance of entrepreneurial risk, *Journal of Finance* 55, 1163-1198.

Hendershott, Terrence, and Albert J. Menkveld, 2014, Price pressures, *Journal of Financial Economics* 114, 405-423.

Henderson, Brian J., Narasimhan Jegadeesh, and Michael S. Weisbach, 2006, World markets for raising new capital, *Journal of Financial Economics* 82, 63-101.

Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading, and overreaction in asset markets, *Journal of Finance* 54, 2143-2184.

Hou, Kewei, Chen Xue, and Lu Zhang, 2020, Replicating anomalies, *Review of Financial Studies* 33, 2019-2133.

Huberman, Gur, and Tomer Regev, 2001, Contagious speculation and a cure for cancer: A nonevent that made stock prices soar, *Journal of Finance* 56, 387-396.

Iacoviello, Matteo, 2008, Household debt and income inequality, 1963–2003, *Journal of Money, Credit and Banking* 40, 929-965.

Ikenberry, David L., and Sundaresh Ramnath, 2002, Underreaction to self-selected news events: The case of stock splits, *Review of Financial Studies* 15, 489-526.

Ikenberry, David, Josef Lakonishok, and Theo Vermaelen, 1995, Market underreaction to open market share repurchases, *Journal of Financial Economics* 39, 181-208.

Jagannathan, Ravi, and Zhenyu Wang, 1996, The conditional capm and the cross-section of expected returns, *Journal of Finance* 51, 3-53.

Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881-898.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Jones, Charles M., 2002, A century of stock market liquidity and trading costs, Working Paper (Columbia Business School).

Kahneman, Daniel, and Amos Tversky, 1979, Prospect theory: An analysis of decision under risk, *Econometrica* 47, 263-291.

Keasler, Terrill R., and Chris R. McNeil, 2010, Mad money stock recommendations: Market reaction and performance, *Journal of Economics and Finance* 34, 1-22.

Korinek, Anton, and Alp Simsek, 2016, Liquidity trap and excessive leverage, *American Economic Review* 106, 699-738.

Kothari, Smitu P., and Jay Shanken, 1997, Book-to-market, dividend yield, and expected market returns: A time-series analysis, *Journal of Financial Economics* 44, 169-203.

Krueger, Dirk, and Fabrizio Perri, 2006, Does income inequality lead to consumption inequality? Evidence and theory, *Review of Economic Studies* 73, 163-193.

Kumar, Alok, and Charles M. C. Lee, 2006, Retail investor sentiment and return comovements, *Journal of Finance* 61, 2451-2486.

Kumari, Jyoti, and Jitendra Mahakud, 2015, Does investor sentiment predict the asset volatility? Evidence from emerging stock market india, *Journal of Behavioral and Experimental Finance* 8, 25-39.

Kumhof, Michael, Romain Rancière, and Pablo Winant, 2015, Inequality, leverage, and crises, *American Economic Review* 105, 1217-45.

Lamont, Owen A., 2012, Go down fighting: Short sellers vs. Firms, *Review of Asset Pricing Studies* 2, 1-30.

Lamoureux, Christopher G., and William D. Lastrapes, 1990, Heteroskedasticity in stock return data: Volume versus garch effects, *Journal of Finance* 45, 221-229.

Lamoureux, Christopher G., and William D. Lastrapes, 1993, Forecasting stock-return variance: Toward an understanding of stochastic implied volatilities, *Review of Financial Studies* 6, 293-326.

Lee, Wayne Y., Christine X. Jiang, and Daniel C. Indro, 2002, Stock market volatility, excess returns, and the role of investor sentiment, *Journal of Banking and Finance* 26, 2277-2299.

Lehmann, Bruce N., 1990, Fads, martingales, and market efficiency, *Quarterly Journal of Economics* 105, 1-28.

Lei, Qin, and Guojun Wu, 2005, Time-varying informed and uninformed trading activities, *Journal of Financial Markets* 8, 153-181.

Lemmon, Michael, and Evgenia Portniaguina, 2006, Consumer confidence and asset prices: Some empirical evidence, *Review of Financial Studies* 19, 1499-1529.

LeRoy, Stephen F., and Richard D. Porter, 1981, The present-value relation: Tests based on implied variance bounds, *Econometrica* 49, 555-574.

Lettau, Martin, and Sydney Ludvigson, 2001a, Resurrecting the (c) capm: A cross-sectional test when risk premia are time-varying, *Journal of Political Economy* 109, 1238-1287.

Lettau, Martin, and Sydney Ludvigson, 2001b, Consumption, aggregate wealth, and expected stock returns, *Journal of Finance* 56, 815-849.

Lettau, Martin, and Sydney Ludvigson, 2003, Measuring and modeling variation in the risk-return trade-off, Working Paper (New York University).

Lo, Andrew W., and A. Craig MacKinlay, 1990, When are contrarian profits due to stock market overreaction?, *Review of Financial Studies* 3, 175-205.

Loughran, Tim, and Jay R. Ritter, 1995, The new issues puzzle, *Journal of Finance* 50, 23-51.

Loughran, Tim, Jay R. Ritter, and Kristian Rydqvist, 1994, Initial public offerings: International insights, *Pacific-Basin Finance Journal* 2, 165-199.

Lucas Jr., Robert E., 1978, Asset prices in an exchange economy, *Econometrica* 46, 1429-1445.

Ludvigson, Sydney, 1999, Consumption and credit: A model of time-varying liquidity constraints, *Review of Economics and Statistics* 81, 434-447.

Lundblad, Christian, 2007, The risk return tradeoff in the long run: 1836–2003, *Journal of Financial Economics* 85, 123-150.

Lustig, Hanno N., and Stijn G. Van Nieuwerburgh, 2005, Housing collateral, consumption insurance, and risk premia: An empirical perspective, *Journal of Finance* 60, 1167-1219.

MacKinlay, Andrew C., and J. W. Park, 2004, The relationship between expected risk premium and conditional permanent and transitory volatility, Working Paper (University of Pennsylvania).

Manela, Asaf, 2014, The value of diffusing information, *Journal of Financial Economics* 111, 181-199.

Mankiw, N. Gregory, and Matthew D. Shapiro, 1986, Risk and return: Consumption beta versus market beta, *Review of Economics and Statistics* 68, 452-459.

Martin, Philippe, and Thomas Philippon, 2017, Inspecting the mechanism: Leverage and the great recession in the eurozone, *American Economic Review* 107, 1904-37.

Masao Ogaki, and Carmen M. Reinhart, 1998, Measuring intertemporal substitution: The role of durable goods, *Journal of Political Economy* 106, 1078-1098.

Mehra, Rajnish, and Edward C. Prescott, 1985, The equity premium: A puzzle, *Journal of Monetary Economics* 15, 145-161.

Merton, Robert C., 1973, An intertemporal capital asset pricing model, *Econometrica* 41, 867-887.

Mian, Atif, Kamalesh Rao, and Amir Sufi, 2013, Household balance sheets, consumption, and the economic slump, *Quarterly Journal of Economics* 128, 1687-1726.

Mian, Atif, Amir Sufi, and Emil Verner, 2017, Household debt and business cycles worldwide, *Quarterly Journal of Economics* 132, 1755-1817.

Michaely, Roni, Richard H. Thaler, and Kent L. Womack, 1995, Price reactions to dividend initiations and omissions: Overreaction or drift?, *Journal of Finance* 50, 573-608.

Miller, Edward M., 1977, Risk, uncertainty, and divergence of opinion, *Journal of Finance* 32, 1151-1168.

Mishkin, Frederic S., 1978, The household balance sheet and the great depression, *Journal of Economic History* 38, 918-937.

Morck, Randall, Bernard Yeung, and Wayne Yu, 2000, The information content of stock markets: Why do eemerging markets have synchronous stock price movements?, *Journal of Financial Economics* 58, 215-260.

Moskowitz, Tobias J., Yao Hua Ooi, and Lasse Heje Pedersen, 2012, Time series momentum, *Journal of Financial Economics* 104, 228-250.

Nelson, Daniel B., 1991, Conditional heteroskedasticity in asset returns: A new approach, *Econometrica* 59, 347-370.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

Novy-Marx, Robert, 2012, Is momentum really momentum?, *Journal of Financial Economics* 103, 429-453.

Nyholm, Ken, 2002, Estimating the probability of informed trading, *Journal of Financial Research* 25, 485-505.

Olney, Martha L., 1999, Avoiding default: The role of credit in the consumption collapse of 1930, *Quarterly Journal of Economics* 114, 319-335.

Pástor, Ľuboš, Meenakshi Sinha, and Bhaskaran Swaminathan, 2008, Estimating the intertemporal risk–return tradeoff using the implied cost of capital, *Journal of Finance* 63, 2859-2897.

Pástor, Ľuboš, and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642-685.

Piazzesi, Monika, Martin Schneider, and Selale Tuzel, 2007, Housing, consumption and asset pricing, *Journal of Financial Economics* 83, 531-569.

Pindyck, Robert S., and Julio J. Rotemberg, 1993, The comovement of stock prices, *Quarterly Journal of Economics* 108, 1073-1104.

Piotroski, Joseph D, and Darren T. Roulstone, 2004, The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices, *Accounting Review* 79, 1119-1151.

Pontiff, Jeffrey, and Artemiza Woodgate, 2008, Share issuance and cross-sectional returns, *Journal of Finance* 63, 921-945.

Pritamani, Mahesh, and Vijay Singal, 2001, Return predictability following large price changes and information releases, *Journal of Banking and Finance* 25, 631-656.

Ren, Haohan, 2017, Investor sentiment and stock return comovement: The role of information and innovation, Working Paper (Chinese University of Hong Kong).

Richardson, Matthew, and Tom Smith, 1994, A direct test of the mixture of distributions hypothesis: Measuring the daily flow of information, *Journal of Financial and Quantitative Analysis* 29, 101-116.

Rzayev, Khaladdin, and Gbenga Ibikunle, 2019, A state-space modeling of the information content of trading volume, *Journal of Financial Markets* 46, 100507.

Säfvenblad, Patrik, 2000, Trading volume and autocorrelation: Empirical evidence from the stockholm stock exchange, *Journal of Banking and Finance* 24, 1275-1287.

Samuelson, Paul A., 1965, Proof that properly discounted present values of assets vibrate randomly, *Industrial Management Review* 6, 41-49.

Santos, Tano, and Pietro Veronesi, 2006, Labor income and predictable stock returns, *Review of Financial Studies* 19, 1-44.

Santos, Tano, and Pietro Veronesi, 2017, Habits and leverage, Working Paper (NBER).

Savor, Pavel G., 2012, Stock returns after major price shocks: The impact of information, *Journal of Financial Economics* 106, 635-659.

Savov, Alexi, 2011, Asset pricing with garbage, *Journal of Finance* 66, 177-201.

Schmeling, Maik, 2009, Investor sentiment and stock returns: Some international evidence, *Journal of Empirical Finance* 16, 394-408.

Schwarz, Norbert, Herbert Bless, and Gerd Bohner, 1991, Mood and persuasion: Affective states influence the processing of persuasive communications, in Mark P. Zanna, ed.: *Advances in experimental social psychology* (Academic Press).

Sharpe, William F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425-442.

Sharpe, William F., and Lawrence G. Tint, 1990, Liabilities— a new approach, *Journal of Portfolio Management* 16, 5-10.

Shen, Junyan, Jianfeng Yu, and Shen Zhao, 2017, Investor sentiment and economic forces, *Journal of Monetary Economics* 86, 1-21.

Shiller, Robert J., 1981, Do stock prices move too much to be justified by subsequent changes in dividends?, *The American Economic Review* 71, 421-436.

Shiller, Robert J., 1989, Comovements in stock prices and comovements in dividends, *Journal of Finance* 44, 719-729.

Shleifer, Andrei, and Robert W. Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35-55.

Shu, Hui-Chu, and Jung-Hsien Chang, 2015, Investor sentiment and financial market volatility, *Journal of Behavioral Finance* 16, 206-219.

Sias, Richard W., and Laura T. Starks, 1997, Return autocorrelation and institutional investors, *Journal of Financial Economics* 46, 103-131.

Sinclair, Robert C., and Melvin M. Mark, 1995, The effects of mood state on judgemental accuracy: Processing strategy as a mechanism, *Cognition and Emotion* 9, 417-438.

Sloan, Richard G., 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings?, *Accounting Review* 71, 289-315.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2012, The short of it: Investor entiment and anomalies, *Journal of Financial Economics* 104, 288-302.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2014, The long of it: Odds that investor sentiment spuriously predicts anomaly returns, *Journal of Financial Economics* 114, 613-619.

Stambaugh, Robert F., and Yu Yuan, 2017, Mispricing factors, *Review of Financial Studies* 30, 1270-1315.

Stulz, René M., 1986, Asset pricing and expected inflation, *Journal of Finance* 41, 209-223.

Sweeney, Richard J., and Arthur D. Warga, 1986, The pricing of interest-rate risk: Evidence from the stock market, *Journal of Finance* 41, 393-410.

Tauchen, George E., and Mark Pitts, 1983, The price variability-volume relationship on speculative markets, *Econometrica* 51, 485-505.

Tetlock, Paul C., 2007, Giving content to investor sentiment: The role of media in the stock market, *Journal of Finance* 62, 1139-1168.

Tetlock, Paul C., 2011, All the news that's fit to reprint: Do investors react to stale information?, *Review of Financial Studies* 24, 1481-1512.

Thaler, Richard, 1985, Mental accounting and consumer choice, *Marketing science* 4, 199-214.

Turner, Christopher M., Richard Startz, and Charles R. Nelson, 1989, A markov model of heteroskedasticity, risk, and learning in the stock market, *Journal of Financial Economics* 25, 3-22.

Tversky, Amos, and Daniel Kahneman, 1974, Judgment under uncertainty: Heuristics and biases, *Science* 185, 1124-1131.

Vijh, Anand M., 1994, S&p 500 trading strategies and stock betas, *Review of Financial Studies* 7, 215-251.

Waring, M. Barton, and D.uane Whitney, 2009, An asset–liability version of the capital asset pricing model with a multi-period two-fund theorem, *Journal of Portfolio Management* 35, 111-130.

Weinstein, Neil D., 1980, Unrealistic optimism about future life events, *Journal of Personality and Social Psychology* 39, 806.

Whitelaw, Robert F., 1994, Time variations and covariations in the expectation and volatility of stock market returns, *Journal of Finance* 49, 515-541.

Yogo, Motohiro, 2004, Estimating the elasticity of intertemporal substitution when instruments are weak, *Review of Economics and Statistics* 86, 797-810.

Yogo, Motohiro, 2006, A consumption-based explanation of expected stock returns, *Journal of Finance* 61, 539-580.

Yu, Jianfeng, and Yu Yuan, 2011, Investor sentiment and the mean–variance relation, *Journal of Financial Economics* 100, 367-381.