Stock-Level Sentiment and the Security Market Line

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Signature:

Stock-Level Sentiment and the Security Market Line

Abstract

High market beta stocks experience overpricing in periods of high market sentiment, while traditional beta pricing prevails in periods of low market sentiment (Antoniou et al., 2016). I conjecture that the negative (positive) relationship between market beta and expected return in high (low) market sentiment periods is driven by the stocks that are more sensitive to market sentiment than the stocks that are less sensitive to market sentiment. Using non-financial common stocks listed on the NYSE and NASDAQ between 1980 to 2017, I weakly confirm this conjecture in my univariate results. However, the differential effects of the most and least sentiment sensitive stocks on the market beta-return relationship are not significant in a regression framework.

Chapter 1 Introduction

The Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) is an integral part of financial theory. However, beginning with the seminal paper of Black et al. (1972), the extensive documentation of the beta anomaly within the finance literature challenges whether the CAPM is applicable for pricing equities in the financial markets. The beta anomaly proposes that high market beta stocks receive too little compensation for their systematic risk exposure, and this causes a flatter than expected security market line (SML). The various explanations for beta's failure include leverage constraints (Black et al., 1972; Frazzini & Pedersen, 2014; Jylhä, 2018), the explanatory power of size and value (Fama & French, 1992), market proxy inefficiencies (Roll & Ross, 1994), risk misspecifications (Jagannathan & Wang, 1996), and the influence of institutional benchmarks (Baker et al., 2011; Christoffersen & Simutin, 2017). This paper uses sentiment trading to explain the beta anomaly further.

Investor sentiment represents the collective opinion of investors who hold overly optimistic or pessimistic views of the near-term future prosperity of the financial markets. When investors trade on market sentiment, a vast number of investors are trading in a similar direction, unrelated to changes in the fundamentals of a stock. To capitalize on sentiment, investors will predominately purchase risky stocks as they generally experience higher returns when markets rise. Sentiment traders are thus acting irrational, and because of the number of investors making similar trades, the trades of rational investors no longer entirely dominate them. In these instances, investors no longer adhere to the CAPM assumption of rationality, and sentiment trading influences stock returns. Due to the prevalence of sentiment trading, it is necessary to investigate further how sentiment influences the cross-section of stock returns.

Using Baker and Wurgler’s (2006) market-wide sentiment index (BW), Antoniou et al. (2016) find a downward sloping SML when the index is positive (high sentiment) while finding an upward sloping SML when the index is negative (low sentiment). Antoniou et al. (2016) hypothesize that high market sentiment causes irrational investors to enter the market and speculate on future market performance by purchasing high market beta stocks. Higher market beta stocks, therefore, experience overpricing and lower returns. However, the unwillingness of the same irrational investors to short sell causes them not to participate in the market when sentiment is low. Therefore, in periods of low market sentiment, equity prices represent only rational arbitragers' opinions, and higher market beta stocks receive returns expected under the CAPM. The asymmetric trading of sentiment traders causes the SML to be time-varying and means irrational investors are only willing to trade using sentiment when there is high market sentiment.

Using all periods of market sentiment, Glushkov (2006) finds that firms with high absolute sensitivity to market sentiment receive lower returns than those with low absolute sensitivity. Glushkov (2006) does not separately investigate stock-level sensitivity to investor sentiment in different periods of overall market sentiment, and therefore a gap within the literature exists. As Glushkov (2006) investigates absolute sentiment sensitivity, further separation of stocks with high sentiment sensitivity into the most positive and negative sentiment sensitive may offer valuable insight into the activity of different investors. As the BW sentiment index has explanatory power in determining stocks more susceptible to overpricing (Baker & Wurgler, 2006), I use stock-level sensitivity to the BW sentiment index to decide which stocks irrational investors purchase to speculate on market-wide performance. As investors tend to purchase overpriced high market beta stocks (Liu et al., 2018), sentiment sensitivity may better capture the trading of irrational investors rather than Antoniou et al. (2016) broad suggestion of irrational investors only purchasing high market beta stocks. Using non-financial common stocks listed on the NYSE and NASDAQ from 1980 to 2017, and as a proxy for a stock’s susceptibility to overpricing, I investigate both the most positive and negative return sensitivity to market sentiment changes and display this impact on the time-varying security market line.

I hypothesize that when the BW index is positive, representing periods of high market sentiment, the market risk premium is priced positively for stocks with the most negative sentiment sensitivity and priced negatively for stocks with the most positive sentiment sensitivity. I expect that sentiment traders will predominantly purchase the most positive sentiment sensitive stocks as they offer an efficient means of speculating on the continuation of market-wide performance, and this will lead to sentiment-driven overpricing. In contrast, the smaller number of investors who believe market sentiment is too high will purchase the most negative sentiment sensitive stocks as they are unwilling to short sell the most positive sentiment sensitive stocks. In periods of high market sentiment, I expect an upward sloping SML within the most negative sentiment sensitive stocks while expecting a downward sloping SML within the most positive sentiment sensitive stocks.

At the portfolio-level, and in periods of high market sentiment, the SML within the most negative sentiment sensitive stocks is downward sloping with a negatively priced market risk premium of -1.50% (test statistic -2.61) and a test statistic of a t-test between the two opposing pre-ranking market beta portfolios of -1.93. The SML within the most positive sentiment sensitive stocks has no prominent structure with a statistically insignificant market risk premium of -0.50% (test statistic -0.80). Stock-level Fama-Macbeth (1973) regressions which introduce control variables and use heteroskedasticity-consistent standard errors (HSCE), find a statistically insignificant market risk premium within the most positive and negative sentiment sensitive stocks. Therefore, I have no statistical evidence to reject my null hypotheses that the most positive (negative) sentiment sensitive stocks have a positively (negatively) priced market risk premium in periods of high market sentiment.

I also hypothesize that when the BW index is negative, representing periods of low market sentiment, the market risk premium is priced positively for both stocks with the most positive and negative sentiment sensitivity. I expect that investors who purchased the most positive sentiment sensitive stocks in periods of high market sentiment will sell these stocks as market sentiment decreases. The smaller number of investors who purchased the most negative sentiment sensitive stocks in periods of high market sentiment will sell less of these stocks as market sentiment decreases. The investors who brought the most negative sentiment sensitive stocks represent only a small proportion of the market and, therefore, the market risk premium is still positive. As investors trading on sentiment exit the market, most of the remaining investors price equities closer to their intrinsic values, and returns are now in line with those expected under the CAPM. In periods of low market sentiment, I expect an upward sloping SML for both the most positive and negative sentiment sensitive stocks.

At the portfolio-level, and in periods of low market sentiment, the SML for the most positive sentiment sensitive stocks is upward sloping with a positively priced market risk premium of 1.12% (test statistic 2.31) and a test statistic of a t-test between the two opposing pre-ranking market beta portfolios of 1.84. The SML within the most negative sentiment sensitive stocks has no prominent structure with a statistically insignificant market risk premium of 0.29% (test statistic 0.59). Stock-level Fama-Macbeth (1973) regressions which introduce control variables and use heteroskedasticity-consistent standard errors, find a statistically insignificant market risk premium within the most positive and negative sentiment sensitive stocks. Therefore, I have no statistical evidence to reject my null hypotheses that the most positive and negative sentiment sensitive stocks have a negatively priced market risk premium in periods of low market sentiment.

This research contributes to the relevant literature by separately investigating different stock-level sentiment sensitivity in varying periods of overall market sentiment to determine whether beta pricing prevails. The hypotheses are formulated on a few findings:

1. Individual (Antoniou et al., 2016; Yu & Yuan, 2011) and institutional investors (DeVault et al., 2019) trade asymmetrically in different market sentiment periods.
2. The most sentiment sensitive stocks underperform the least sentiment sensitive stock (Glushkov, 2006).
3. Not all high beta stocks experience underperformance in high market sentiment (Antoniou et al., 2016; Liu et al., 2018).

Using these findings, I pose four research questions (H1-H4) regarding the shape of the security market line using a combination of the most positive and negative sentiment sensitive stocks in periods of low and high market sentiment. This investigation further expands on Glushkov (2006) and Antoniou et al. (2016) by looking at a more efficient calculation of which stocks irrational investors tend to purchase in different periods of market sentiment. This research's marginal contribution is that I weakly confirm my hypotheses in the univariate results; however, the results are not significant in a regression framework. Thus, double sorting by sentiment sensitivity and different market sentiment periods provide limited information about the beta-return relationship.

This paper contributes to the growing body of literature regarding investor sentiment and the security market line's slope. In other related beta-driven explanations, Shen et al. (2017) and Yu and Yuan (2011) find the asymmetric trading of irrational investors in different market sentiment periods. Using the aggregate disagreement about the expected cash flow of high market beta stocks and short-sale constraints, Hong and Sraer (2016) investigate the time-varying security market line. Liu et al. (2018) use varying market sentiment periods and idiosyncratic volatility to explain the beta anomaly. Though the investor sentiment literature is extensive, I offer relevant statistical analysis by combining past findings to add to the body of knowledge.

I organize the rest of the paper as follows. Chapter 2 provides an overview of the relevant literature. Chapter 3 develops the testable hypotheses. Chapter 4 describes the data, the measurement of investor sentiment, and outlines the methods to test the paper's hypotheses. Chapter 5 presents the empirical results and interpretation. Chapter 6 ensures the findings are robust. Chapter 7 concludes the paper. Chapter 8 provides a list of references.

Chapter 2 Literature Review

2.1 Investor Sentiment

Friedman (1953) proposes that the market consists of both irrational investors and rational arbitrageurs. Irrational investors value stocks beyond the present value of their future cash flows (Baker & Wurgler, 2007), while rational arbitrageurs correct market inefficiencies by moving prices towards their intrinsic values (De Long et al., 1990). Friedman (1953) believes that in a competitive market, irrational investors cannot survive nor impact prices in the long run. As we have learned in more recent times, correcting market inefficiencies is neither riskless (De Long et al., 1990) nor capital-free (Shleifer & Vishny, 1997), and this allows mispricing to persist. Stocks with unique fundamentals have return correlation (Barberis et al., 2005; Lee et al., 1991), and this suggests that irrational investors continue to trade on non-fundamental information. These irrational investors increase market volatility (De Long et al., 1990) while impacting stock prices in both the short and long run with minimal or zero wealth (Kogan et al., 2006, 2017). Because of these findings, participants within the financial markets should now carefully consider the impact of irrational investors on equity prices.

One behavioral bias that causes investors to make irrational investment decisions is trading on the level of sentiment in the broader market. At least as early as Keynes (1936), academia has analyzed whether high levels of sentiment induce overly optimistic valuation and whether this leads prices to deviate from their intrinsic values. Sentiment traders will purchase equities based solely on the collective opinion of other investors, irrespective of any changes in the fundamentals of the underlying equities. Their collective views are either overly optimistic or pessimistic about future market performance, and this leads to errors in valuation. Depending on overall market sentiment, these irrational investors evaluate short-term returns and expect a continuation of performance (Fisher & Statman, 2000). Irrational investors can hold sentimental views for a substantial time (De long et al., 1990), with investor sentiment predicting stock returns for multiple years even after controlling for rational factors (Brown & Cliff, 2005). Increasing differences between the net asset value of a closed-end fund and its price (Lee et al., 1991), and the strengthening of return anomalies (Stambaugh et al., 2012) shows the impact of high levels of market sentiment. The influence of sentiment is prevalent in explaining why returns differ from the expectation of traditional asset pricing models.

Investor sentiment directly influences the decision making of individual investors. The investors who are more likely to trade on sentiment are unsophisticated individual investors. However, because individual investors represent a small proportion of the overall trading volume, there must be a substantial number of individual investors trading in the same direction to influence market movement. After rising equity prices, individual investors are more likely to enter the financial markets (Amromin & Sharpe, 2009; Grinblatt & Keloharju, 2009; Lamont & Thaler, 2003). Their tendency to herd (Barber et al., 2006, 2009) and purchase high market beta stocks (Barber & Odean, 2001) with lottery-like features (Kumar, 2009; Bali et al., 2016) increases trade correlation. Stocks with a high concentration of individual investor ownership have greater return comovement (Kumar & Lee, 2006) and are more sensitive to investor sentiment (Glushkov, 2006). When investor sentiment is high, individual investors are looking to purchase equities, but when investor sentiment is low, the same traders are not interested in entering the financial markets (Antoniou et al., 2016; Shen et al., 2017; Yu & Yuan, 2011). Therefore, the trading of individual investors is more likely to deviate from a mean-variance framework due to non-fundamental influences.

The investors that are more likely to act as rational arbitrageurs are institutional investors with extensive training and knowledge of the financial markets. These investors have access to large pools of capital, which can more easily influence equity prices. However, some institutions do deviate from the role of being a rational arbitrageur. These include institutional investors increasing exposure to high market beta stocks to beat benchmarks (Baker et al. 2011; Christoffersen & Simutin, 2017) and those with fear that clients will withdraw capital if short positions on overvalued stocks generate short-term losses (Shliefer & Vishny, 1997). Institutions with high-risk preferences such as mutual funds, independent advisors, and hedge funds account for 89% of institutional investor sentiment trading (DeVault et al., 2019). These institutional investors look to capitalize on the continuation of mispricing by taking advantage of the behavioral biases of individual investors and other institutional investors implementing similar strategies. For example, Brunnermeier and Nagel (2004) show that hedge funds rode the technology bubble because of predictable investor sentiment. High-risk institutions trade using sentiment to manage risk and reputation and to capitalize on institutional momentum and herding (DeVault et al., 2019). Glushkov (2006) finds that from the 1980s to the 1990s, institutional investors were purchasing more stocks with a higher sensitivity to investor sentiment. DeVault et al. (2018) also show that the ratio of speculative to safe stocks of institutional investors increases when market sentiment is high. Therefore, institutional investors may act irrationally when sufficient motivation is available.

The influence of sentiment trading persists due to the asymmetric trading of sentiment traders. When market sentiment is high, a sentiment trader will value a stock higher than that of a rational arbitrageur. These sentiment traders will value a stock above its intrinsic value, and its purchasing volume will increase (Baker & Stein, 2004). Antoniou et al. (2016), Shen et al. (2017), and Yu and Yuan (2011) find that mispricing predominantly occurs in periods of high market sentiment when sentiment-driven investors enter the market. Baker and Wurgler (2006, 2007) and DeVault et al. (2018) also states that increases in market sentiment induce sentiment traders to switch from safe to speculative stocks. However, because the same sentiment traders are unwilling to short sell, they do not participate in the financial market when sentiment is low. In these instances, sentiment traders value a stock below its intrinsic value and believe it is overpriced. As they are unwilling to short sell, they are unable to act on their opinions. For example, Barber and Odean (2008) find that short sales represent less than one percent of an individual investor's position. As only rational arbitrageurs are in the market when sentiment is low, prices should be closer to intrinsic values. Prices closer to their intrinsic values may be evident by return premiums from changes in market volatility (Labidi & Yaakoubi, 2016; Yu & Yuan, 2011) and exposure to macroeconomics shocks (Shen & Yu, 2012) only occurring in periods of low market sentiment. By investors becoming optimistic after increasing prices and becoming pessimistic after decreasing prices, investors make a vital decision-making error by buying high and selling low, and this results in a lower expected return.

The other reason that the influence of sentiment trading persists is that rational arbitrageurs have limits to their ability to correct sentiment-driven mispricing (noise trader risk). These limits include short-sale constraints in periods of high market sentiment (Stambaugh et al., 2011, 2015), the minimal number of institutions with the ability to short sell, i.e., hedge funds (Hong & Sraer, 2016), investment policy restrictions (Almazan et al., 2004), derivative restrictions on mutual funds (Koski & Pontiff, 1990), benchmark constraints (Baker et al., 2011; Christoffersen & Simutin, 2017), and the unpredictability and difficulty of forecasting investor sentiment (De Long et al., 1990; Shleifer & Thaler, 1996, 1997). A study by Kozak et al. (2018) finds that sentiment-driven noise traders only substantially influence returns when arbitrageurs have exposure to common risk factors. They state that rational arbitrageurs will only take the opposite side of sentiment-driven trades when they receive additional compensation to this exposure. As these constraints exist, stocks continue to be overpriced in periods of high market sentiment without mediation by rational arbitrageurs unless there is sufficient compensation for bearing this noise trader risk.

2.2 Sentiment Sensitivity

The sentiment sensitivity of a stock depends on its reaction to consumer sentiment announcements and firm-level characteristics. Only the announcement of a decrease in consumer sentiment levels impact stock prices, but this reverts quickly (Akhtar et al., 2011, 2013). The most sentiment sensitive stocks have firm-level characteristics that make it difficult to arbitrage and value (Baker & Wurgler, 2007; Glushkov, 2006). These stocks rely more heavily on opinions, have higher idiosyncratic volatility (Wurgler & Zhuravskaya, 2002), and cost more to buy and sell short (D'Avolio, 2002; Kumar & Lee, 2006). Baker and Wurgler (2007) and Glushkov (2006) find that most sentiment sensitive stocks are of smaller size, younger age, non-dividend paying, and are growth companies. In an international context, Baker et al. (2012) find that high global and country-level sentiment causes lower future returns in small, distressed, volatile, and growth companies. Glushkov (2006) suggests sentiment sensitivity is unrelated to the momentum effect. These fundamental characteristics influence the responsiveness of stocks to sentiment and are useful in explaining differences in the cross-section of stock returns.

According to Glushkov (2006), sentiment sensitivity determines whether investors agree on the fair value and earning potential of a stock. Positive (negative) sentiment sensitivity represents more (less) momentum sentiment traders purchasing a stock than contrarian sentiment traders selling the same stock when overall market sentiment increases (Glushkov, 2006).

Therefore, zero sentiment sensitivity suggests that price changes represent changes in a stock's underlying fundamentals, and the buying and selling between momentum and contrarian sentiment traders are in equilibrium or no sentiment traders are present in the market (Glushkov, 2006). Glushkov (2006) rejects a mean of zero at the 99% confidence interval between positive and negative sentiment sensitivity and states that the trades of momentum sentiment and contrarian sentiment traders do not cancel each other out. Therefore, he suggests that using absolute sentiment sensitivity values loses no information and uses absolute values in his investigation. As both positive and negative sentiment sensitivity values represent a non-fundamental change in decision making unrelated to systematic changes, I feel as if not using absolute values will better capture the trading of different investors and paint a better picture of the market. Therefore, I look to investigate the bi-directional impact of sentiment changes and do not employ absolute sentiment sensitivity in my primary analysis.

Recent literature also focuses on the result of high idiosyncratic volatility (IVOL) causing negative returns and how this relates to beta. Ang et al. (2006) were the first to find that expected returns correlate with idiosyncratic volatility, and this contradicts the one-factor CAPM's findings. IVOL risk is explained by Stambaugh et al. (2015) as representing the risk that deters rational arbitrageurs from correcting the mispricing of overpriced stocks. Even though buying low market beta stocks on margin offers higher idiosyncratic risk than buying high market beta stocks, it is a less efficient method of speculating (Bali et al., 2016; Hong & Sraer, 2016), and is susceptible to changes in leverage constraints (Jylhä, 2018). In the top 20% of overpriced stocks, Stambaugh et al. (2015) find an alpha difference of -150bps (-7.36) between portfolios sorted by IVOL versus a -60bps (-2.82) between portfolios sorted by market beta. When controlling for IVOL, there is little statistical significance of the beta anomaly (Liu et al., 2018). Though the evidence of IVOL seems conclusive, Asness et al. (2020) warn of the considerable microstructure noise in IVOL measures due to their high turnover. Therefore, stocks with high levels of sentiment sensitivity may identify stocks with high IVOL risk.

Idiosyncratic volatility research uses the implementation of market sentiment to strengthen the statistical significance of the negative IVOL-return relation. Stambaugh et al. (2015) use Baker and Wurgler's (2006) sentiment index (BW) to determine the direction of mispricing. They find a strong negative IVOL-return relationship for overpriced stocks in periods of high market sentiment due to the arbitrage risk of correcting overpriced stocks. Liu et al. (2018) use these findings to show that the beta anomaly only occurs in overpriced stocks, and this is relatively unrelated to market beta. Investors tend to purchase overpriced high market beta stocks even when underpriced high market beta stocks are available. The reasoning behind this is in line with the idea of investors using risky stocks to speculate on market performance as arbitrage risk deters rational arbitrageurs correcting mispricing. With a correlation of 0.33 between market beta and IVOL risk, the beta anomaly is only present when investor sentiment and the beta-IVOL correlation are above the median (Liu et al., 2018). In other words, the beta anomaly only occurs in high beta-IVOL stocks because IVOL and alpha are correlated. Therefore, this research shows the beta anomaly occurs because of IVOL risk within high market beta stocks. With the identification of the influence of overpriced risky stocks captured by the BW sentiment index, and periods of different market sentiment influencing returns, return sensitivity to the BW sentiment index may capture stocks experiencing lower subsequent returns than expected under the CAPM.

There exist numerous stock-level investor sentiment studies in the literature today. Kumar and Lee (2006) use retail investor transaction data and find investor sentiment can explain the returns of stocks with a high concentration of retail investors. Frazzini and Lamont (2008) and Lee (2013) use mutual fund flows and find stocks with higher investor sentiment levels have lower subsequent returns. Lee (2013) finds that some stocks can have high stock-level investor sentiment. In contrast, other stocks in the same period can have a low level of stock-level investor sentiment. Cen et al. (2013) and Yang and Zhou (2016) find the need for an additional firm-specific sentiment factor in pricing models. Glushkov (2006) looks at “sentiment beta”, which measures stock-level sensitivity to his sentiment index and finds stocks with high exposure to the sentiment index experience higher underperformance. Though Glushkov (2006) measures individual stock’s sensitivity to his sentiment index, he does not separate stocks based on this sensitivity in different market sentiment periods. These papers ignore the time-varying impact of stock-level sensitivity to sentiment on the market beta-return relationship, leaving a gap in the literature.

2.3 The Time-Varying Security Market Line

An investor can gain access to the financial markets by purchasing the common stock of a firm. Assuming an investor is a Markowitz (1952) mean-variance maximizer, they should treat returns as desirable while treating the variation in these returns as undesirable[1]. The expected return of a stock represents the reward for bearing financial risk while variance quantifies financial risk and measures the deviation of return around its mean (Markowitz, 1952). One measure of risk is the sensitivity of a stock to changes in the market's excess return (market beta). The market beta calculation uses the covariance of return between a stock and the market proxy divided by the stock's variance. Under the CAPM, an increase in market beta should result in a linear increase in expected return. However, many studies find that expected returns remain flat in the cross-section of stock returns even as market beta increases. One of the literature's focuses is explaining the beta anomaly and the shape of the security market line.

Beginning with Black et al. (1972), there are various explanations as to why the security market line is flatter than predicted under the CAPM. Fama and French (1992) find that firm size and the book-to-market ratio have explanatory power in the cross-section of stock returns. Cohen et al. (2005) use money illusion (see Modigliana & Cohn, 1979) to show that as inflation increases, the return of stocks with high market beta decreases. At extreme levels of inflation, the security market line becomes downward sloping. Frazzini and Pederson (2014) and Jylhä (2018) use periods of high leverage constraints to show investors' tendency to overprice high market beta stocks and flatten the security market line. Savor and Wilson (2014) show that high market beta assets have larger returns on macroeconomic announcement days than on non-announcement days. Huang et al. (2015) use the activity of beta arbitrageurs and find that when their activity is high, the security market line is downward sloping. Hong and Sraer (2016) use the higher aggregate disagreement about expected cash flows of high market beta stocks and short-sale constraints to explain the time-varying security market line. Bali et al. (2016) use irrational investors' demand for lottery-like stocks to explain why the security market line is flat.

Of importance to this research, Antoniou et al. (2016) use the asymmetric trading of

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[1] Some investors seek positive skewness (see Barberis & Huang, 2008)

individual investors in different periods of market sentiment, and their tendency to purchase high market beta stocks to explain the time-varying security market line. To capitalize on an optimistic market, individual investors try to gain as much equity market exposure without careful analysis of the fundamentals of a stock. To do this, these noise traders use the speculative nature of high market beta stocks to increase market exposure without the use of leverage (Frazzini & Pedersen, 2014). Hong and Sraer (2016) suggest that high market beta stocks are the most efficient way to speculate on the common factors of a firm's cash flow. Antoniou et al. (2016) find a downward sloping security market line in optimistic periods while finding an upward sloping security market line in pessimistic periods. In periods of high market sentiment, individual investors enter the market and purchase high market beta stocks, which causes them to become overpriced. In periods of low market sentiment, a smaller number of individual investors who use high market beta stocks as a pure speculation tool are in the market.

Antoniou et al. (2016) are implicitly suggesting that individual investors in periods of high market sentiment do not particularly care about the stock they purchase as long as it has a high market beta. However, at the same time, they find that only particular high market beta stocks with a low short ratio (see Shleifer & Summers, 1990) and low analyst coverage experience underperformance. As firm-level characteristics and idiosyncratic volatility influence sentiment sensitivity, particular high market beta stocks are more inclined to mispricing. Baker and Wurgler (2006) and Stambaugh et al. (2012) find that the BW sentiment index predicts returns on stocks with higher susceptibility to mispricing. Though Liu et al. (2018) find stocks within the highest 10% of pre-ranking market beta sorts are more likely to be overpriced than underpriced, not all stocks respond the same to sentiment. Periods of high market sentiment alone do not cause the beta anomaly as an above median beta-IVOL relationship is also required (Liu et al., 2018). As the BW sentiment index has explanatory power in the returns of stocks more susceptible to overpricing and the drivers of the beta anomaly (Baker & Wurgler, 2006), I look to further separate stocks based on both market beta and sentiment sensitivity and display this relationship on the time-varying security market line. This separation should simplify the identification of high market beta stocks receiving lower returns than expected under the CAPM and cause the beta anomaly.

The research separates stocks by overall market sentiment as done by Antoniou et al. (2016); however, it further separates stocks by their sensitivity to the BW sentiment index. This double sorting determines whether positive or negative sentiment sensitive stocks experience different beta-return relationships in varying periods of market sentiment. Glushkov (2006) provides empirical evidence of sentiment sensitivity impacting expected returns. Thus, combining these two findings from academically relevant research within the behavioural finance literature to more precisely investigate within double sorts of both stock and market-specific criteria will contribute to the body of knowledge within the literature.

Chapter 3 Hypotheses

I base my hypotheses on a few findings. Firstly, both individual investors (Antoniou et al., 2016; Yu & Yuan, 2011) and institutional investors (DeVault et al., 2019) trade asymmetrically in different market sentiment periods. Secondly, in all periods of market sentiment, the most sentiment sensitive stocks underperform the least sentiment sensitive stocks (Glushkov, 2006). Lastly, not all high market beta stocks experience underperformance in periods of high market sentiment (Antoniou et al., 2016; Liu et al., 2018).

I argue that since specific fundamental characteristics and IVOL risk drive the sentiment sensitivity of a stock, displaying the relationship between market beta and return relative to a stock's sensitivity to sentiment will offer a better proxy for sentiment-driven noise trading. If market returns correlate with investor sentiment, high IVOL risk stocks are more susceptible to sentiment induced mispricing (Baker & Wurgler, 2006). Therefore, stock-level sentiment sensitivity may identify overpriced high beta-IVOL stocks and better explain the beta anomaly. Studies such as Liu et al. (2018) require a large amount of data and multiple calculations while still requiring the use of a sentiment index to separate periods by market sentiment. Using the methodology of sentiment sensitivity to calculate sentiment-driven overpricing reduces the amount of data and calculations needed. At the same time, this research allows me to further separate stocks into the most positive and negative sentiment sensitive and investigate these stocks in different periods of market sentiment. I hypothesis the following:

In periods of high market sentiment, the increase in optimism about future market performance influences individual investors with minimal financial literacy to enter the market (Grinblatt & Keloharju, 2009; Lamont & Thaler, 2003). Due to leverage constraints and individual investor’s unwillingness to short sell, most individual investors will purchase the most positive sentiment sensitive stocks to speculate on market performance. Instead of institutional investors acting as rational arbitrageurs, some institutional investors look to capitalize on irrational investors sentiment-trading by changing their allocation of stocks to those with the most positive sentiment sensitivity. Positive sentiment sensitive stocks have high idiosyncratic volatility, which deters rational institutional investors from correcting stock mispricing.

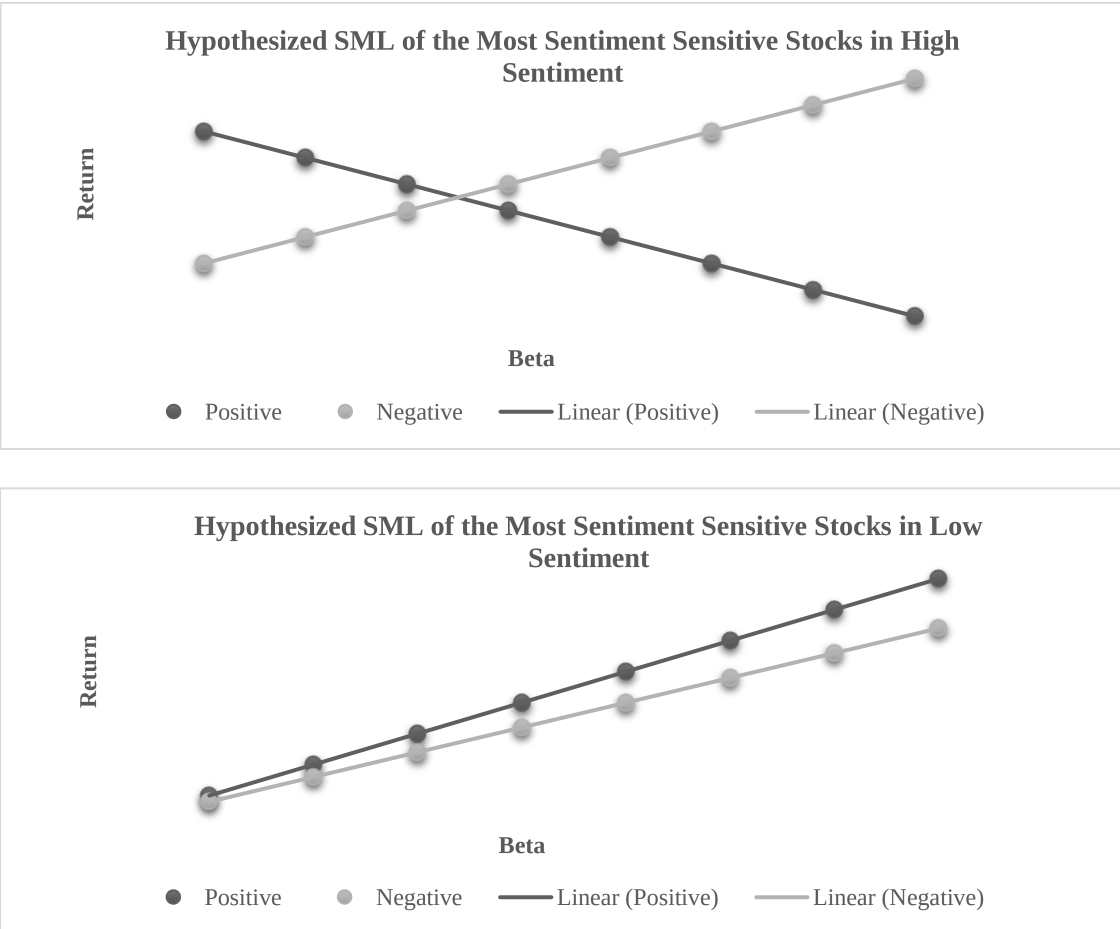
Institutional investors thus purchase positive sentiment sensitive stocks to capture irrational investor sentiment-trading. However, if some individual investors believe that market sentiment is too high, their unwillingness to short sell means they cannot short sell the most positive sentiment sensitive stocks. Therefore, instead, they purchase the most negative sentiment sensitive stocks. Similarly, if some institutional investors believe market sentiment is too high, even with the ability to short sell, they may not due to substantial noise trader risk in betting against a rising market by short selling the most positive sentiment sensitive stocks. Instead, they also purchase the most negative sentiment sensitive stocks.

In periods of low market sentiment, there is pessimism about future market performance. Individual investors believe there is no capital appreciation potential of stocks and exit the financial markets. Individual investors using the most positive sentiment sensitive stocks to speculate on future market performance in high sentiment periods will now sell these stocks and leave the financial markets. Institutional investors who usually capitalize on irrational investor's sentiment trading will no longer trade on their sentiment and act rationally. Institutional investors using the most positive sentiment sensitive stocks to speculate on irrational investor's sentiment trading in high sentiment periods will switch their allocation away from the most positive sentiment sensitive stocks. However, the smaller number of individual and institutional investors who were purchasing the most negative sentiment sensitive stocks in high sentiment periods will sell less of these stocks relative to those investors holding the most positive sentiment sensitive stocks. Departing from the market in low sentiment periods means there is a larger proportion of rational arbitrageurs in the market than irrational investors, and prices are closer to their intrinsic values. In these instances, the market risk premium is priced positively and correctly.

I propose that stocks in different periods of market sentiment and with different sensitivity to sentiment will behave differently even at similar market betas. When market sentiment is high, there will be more buying of the most positive sentiment sensitive stocks than the least sentiment sensitive stocks. Different stocks will, therefore, experience different levels of sentiment-driven overpricing. I expect to find a/an downward (upward) sloping security market line and, therefore, a negatively (positively) priced market risk premium for the most positive (negative) sentiment sensitive stocks in high sentiment periods. When market sentiment is low, investors who purchased the most positive sentiment sensitive stocks in high sentiment periods will sell these stocks more than those who brought the most negative sentiment sensitive stocks. I expect to find an upward sloping security market line and, therefore, a positively priced market risk premium in both the most positive and negative sentiment sensitive stocks in low sentiment periods. However, I expect the slope of the security market line and size of the positive market risk premium of the most positive sentiment sensitive stocks to be larger than that of the most negative sentiment sensitive stocks. I expect this as the ratio of irrational investors to rational investors will be higher in the most negative sentiment sensitive stocks than the most positive sentiment sensitive stocks. I provide a visual representation of the hypothesized security market lines within different sentiment sensitive stocks and in varying sentiment periods using Figure 1 below:

Figure 1

Hypothesized SML of the Most Sentiment Sensitive Stocks in Varying Sentiment



Hypothesis H1: When the BW sentiment index is positive, representing periods of high market sentiment, the most negative sentiment sensitive stocks will have a positively priced market risk premium.

Hypothesis H2: When the BW sentiment index is positive, representing periods of high market sentiment, the most positive sentiment sensitive stocks will have a negatively priced market risk premium.

Hypothesis H3: When the BW sentiment index is negative, representing periods of low market sentiment, the most negative sentiment sensitive stocks will have a positively priced market risk premium.

Hypothesis H4: When the BW sentiment index is negative, representing periods of low market sentiment, the most positive sentiment sensitive stocks will have a positively priced market risk premium.

Chapter 4 Data and Methodology

4.1 Data

In the following tests, I use the common stock of non-financial firms listed on the New York Stock Exchange (NYSE) and the National Association of Securities Dealers Automated Quotations System (NASDAQ). I gather data for price, total return index, book value of equity, and shares outstanding from Thomson Reuters Datastream from 1980 to 2017. The proxy for US equity market returns is the Center for Research in Security Prices (CRSP) value-weighted return, and the proxy for the risk-free rate of return is the one-month US treasury bill rate. Subtracting the one-month US Treasury bill rate from the CRSP value-weighted return results in the excess market return (RMRF). As developed by Fama and French (1993) in their factor-based model, I use the value premium (SMB): the average return difference between three large and three small portfolios, and the book-to-market premium (HML): the average return difference between two value portfolios and two growth portfolios. Kenneth French's website provides the data for RMRF, SMB, and HML premiums. [2] Data for the updated BW sentiment index, which I explain in Chapter 4.2, is from Jeffery Wurgler's website. [3] The Pastor and Stambaugh (2003) liquidity factor (LIQ); the value-weighted return difference between portfolio ten and one based on sorts of historical liquidity betas, is from Robert Stambaugh's website. [4]

4.2 Measuring Investor Sentiment

The most popular proxies for investor sentiment are market-wide proxies (Aboody et al., 2018). One of these proxies is market co-movement. These include closed-end fund discounts (Lee et al., 1991), turnover rates (Baker & Stein, 2004), mutual fund flows (Frazzini & Lamont, 2008), consumer confidence/survey-based indexes (Brown & Cliff, 2005; Lemmon & Portniaguina, 2006), and internet search volumes (Da et al., 2014). However, Baker and Wurgler (2006) state that market co-movement measures contain an idiosyncratic component, and to resolve this issue, they offer a solution via their BW sentiment index. Therefore, the proxy I use for investor sentiment is an update to the original BW investor sentiment index.

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[2] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/
[3] http://people.stern.nyu.edu/jwurgler/
[4] http://finance.wharton.upenn.edu/~stambaug/

The updated BW sentiment index removes NYSE turnover as one of the sentiment proxies within the index. According to the notes of this sentiment index, increases in high-frequency institutional trading and the different available trading venues reduce the value of NYSE turnover as a proxy for whether individuals will invest in stocks.[5] The updated BW index uses the first principle components of the five measures of investor sentiment. These include the value-weighted dividend premium (Baker & Wurgler, 2004), first-day IPO returns and IPO volume (Ibbotson et al., 1994), closed-end fund discount (Neal & Wheatley, 1998), and equity share in new issues (Baker & Wurgler, 2000). Baker and Wurgler (2006) then regress all five proxies against six macroeconomic indicators to reduce systematic risk correlation and use the residuals to build the sentiment index (Yu & Yuan, 2011). These macroeconomic indicators reflect business cycle fluctuations. They include the industrial growth production index, growth in the real value of nominal durables consumption, nominal nondurables consumption, nominal services consumption, the NBER recession indicator, and the consumer price index (CPI).

Though the BW index is orthogonalized to indices representing systematic changes, Sibley et al. (2013) find that the orthogonalized index still contains a substantial amount of fundamental economic information. Similarly, Glushkov (2006) finds that sentiment proxies within his sentiment index have statistically significant correlations to macroeconomic variables. Investor sentiment indexes are supposed to represent investor's feelings towards the market that are unrelated to systematic changes. If the index captures systematic changes, then the information from the index becomes less valuable. Both Sibley et al. (2013) and Antoniou et al. (2016), however, state that they cannot determine whether the index captures both sentiment and economic fundamentals. Therefore, I assume the index provides information regarding investor sentiment and systematic influences in the ensuing tests.

As I will be using the updated BW sentiment index, it is worth noting the findings of DeVault et al. (2018). Past literature that uses sentiment metrics suggests that individual investors are predominately the investors who trade using sentiment. However, DeVault et al. (2018), using an array of sentiment metrics which include the BW sentiment index, find that these metrics

[5] Jeffrey Wurgler's website provides these comments on the information page of the BW sentiment index data.

capture institutional investors' demand shocks rather than individual investors. Contrary to prior literature, they hypothesize that an increase in sentiment increases demand for risky stocks by institutional investors rather than individual investors. Due to a trade requiring both a buyer and a seller, as institutional investors demand increases, they suggest there must also be a decrease in demand by individual investors (DeVault et al., 2018). Though debate exists on the particular investors trading using sentiment, I suggest that the BW sentiment index captures individual and institutional investors induced to trade when sentiment increases.

Both Antoniou et al. (2016) and Yu and Yuan (2011) use the original annual BW index within their primary studies to measure investor sentiment. They classify a period as being optimistic (pessimistic) when the sentiment index in year *t-1* is positive (negative). However, as my sample (1980-2017) includes more recent periods where stock-level information is more readily available via the internet, monthly fluctuations in sentiment may better capture changes in investor's opinions. Therefore, I use the monthly updated BW index. Figure 2 presents the sentiment index between July 1982 and June 2016, while measuring a period of high (low) market sentiment when month *t-1* is positive (zero or negative). When measuring sentiment this way, 278 periods have high market sentiment, while only 127 periods have low market sentiment. As most of the sample period has sentiment above zero, I follow Liu et al. (2018) and allocate a month as having high (low) market sentiment when the monthly updated BW index in month *t-1* is above (below or equal) the sample median. The median for the lagged sentiment index within this sample period is 0.18, and this means that when month *t-1* is above 0.18, then in month *t*, the market has high market sentiment. When the sentiment index value is equal to or below 0.18 in month *t - 1*, the market in month *t* has low market sentiment. Classification of sentiment using this methodology results in 205 periods classified as having high market sentiment and 200 periods classified as having low market sentiment.[6] Using the median value method of Liu et al. (2018), I achieve a more even split of high and low market sentiment periods in my sample, and this is closer to what Antoniou et al. (2016) use (276 and 264).[7]

Recent literature is also using direct measures of stock-level investor sentiment through

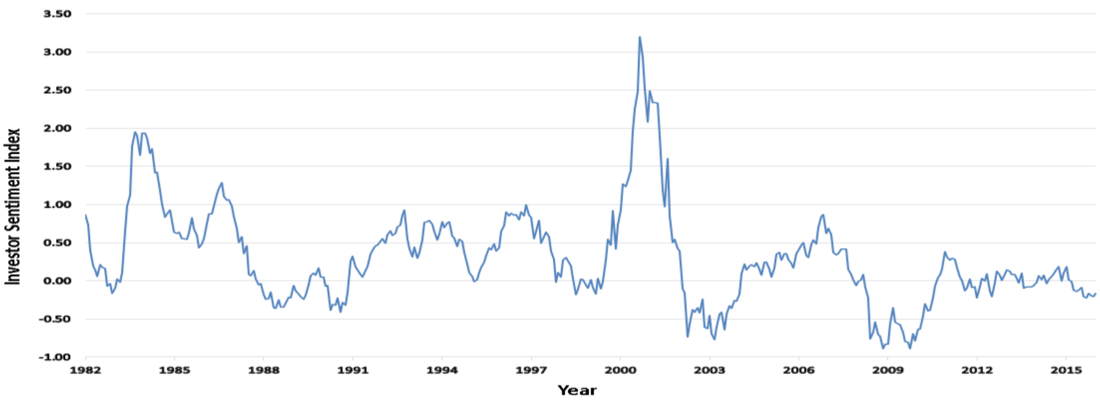
[6] I remove 2008 October, November, December from the sample as they represent the beginning of the GFC.
[7] I have fewer observations than Antoniou et al. (2016) because I focus on a more recent sample period where internet access has a more significant impact.

components within each stock's daily returns (Aboody et al., 2018; Seok et al., 2018; Yang & Zhou, 2015, 2016). Academia uses return proxies for investigating emerging markets when market-wide sentiment indexes are not available. As I will be using the NYSE and NASDAQ, which are stock exchanges within the United States, I can ignore daily return measures that are more susceptible to microstructure noise (Seok et al., 2018).

It is important to note that the updated BW sentiment index's calculation involves extracting the principal component from multiple sentiment proxy times-series. Therefore, full sample information is required (Antoniou et al., 2016). Though the index calculates an overall market sentiment value in month *t* using one-month lags, it is still predicting market sentiment using past values after the fact. If investors are to use overall market sentiment to create a trading strategy, they would have to forecast sentiment, which increases uncertainty and noise. In contrast, I am using past information where I have values of the sentiment index in the period in which I calculate stock returns, and this may present a look-ahead bias.

Figure 2

Updated BW Sentiment Index



Note. This figure depicts the monthly updated BW investor sentiment index from 06/1982 to 06/2016. The index uses the first principle components of value-weighted dividend premium, first-day IPO returns, IPO volume, closed-end fund discount, and equity share in new issues. These proxies are regressed against the industrial growth production index, growth in the real value of nominal durables consumption, nominal nondurables consumption, nominal services consumption, the NBER recession indicator, and the consumer price index (CPI). The residuals from the first principal components form the sentiment index.

4.3 Methodology

To offer a visual representation of the market beta-return relationship between stocks with different sentiment sensitivity, I double sort portfolios based on pre-ranking sentiment sensitivity and market beta. Double sorting by the sensitivity to changes in the sentiment index and the market return will help evaluate whether substantial market beta differences between stocks account for return differences between different sentiment sensitive stocks. If no market beta differences exist, then the sentiment index may be capturing systematic changes.

I begin by calculating a one-factor sentiment sensitivity value by regressing a stock's monthly excess return in month *t* against the updated BW sentiment index also in month *t*. As the NASDAQ has a large proportion of firms with a smaller market value of equity and, therefore, higher risk, I only use NYSE firms to create the subsequent breakpoints as this ensures no overestimation of sentiment sensitivity and market beta values. I calculate excess stock returns using the continuously compounded return of the total return index minus the proxy for the risk-free rate of return. The sentiment sensitivity calculation uses 24 to 60 months' worth of excess return data. More specifically, if there is less than 60 months' worth of excess return data available, I use the maximum value above 24 months. If there is less than 24 months' worth of excess return data, I calculate no sentiment sensitivity value. The last value in the sentiment sensitivity calculation for June of year *t* uses the period ending one month prior (May of year *t*). I present the formula for calculating pre-ranking sentiment sensitivity values below:

$$R_{i,t} = \alpha_i + \beta_{BW,i} BW_t + \varepsilon_{i,t} \tag{1}$$

In the same way that I calculate the sentiment sensitivity value, I calculate the pre-ranking market beta for all NYSE firms, using Fama and French's RMRF variable instead of the BW sentiment index. As I will be using value-weighted returns, to include a firm in the subsequent tests, it must have a size value in June of year *t*. Size represents a shares outstanding value multiplied by its corresponding cleaned price. [8] Using only NYSE non-financial stocks, with a pre-ranking sentiment sensitivity, market beta, and size value in June of year *t*, I calculate sentiment sensitivity quintile breakpoints using sentiment sensitivity values (β_{BW}) and assign stocks to one of five sentiment sensitivity portfolios in June of year *t*. Using only NYSE non-financial stocks in quintile 5 (most positive sentiment sensitive) and quintile 1 (most negative sentiment sensitive), I further subdivide these sentiment sensitivity quintiles into ten portfolios based on pre-ranking market beta for individual stocks in June of year *t*. Sorting portfolios by

[8] Cleaned price means that illiquid price values are removed, i.e., if a stock's last price value is the same as the months before, it is removed.

market beta after sentiment sensitivity accounts for variation in market beta unrelated to sentiment sensitivity. Next, I add NASDAQ stocks to portfolios using the NYSE quintile and decile breakpoints of sentiment sensitivity and pre-ranking market beta. The result is 20 sentiment-beta portfolios in June of year *t*. I present the formula for calculating pre-ranking market beta below:

$$R_{i,t} = \alpha_i + \beta_{RMRF,i} RMRF_t + \varepsilon_{i,t} \tag{2}$$

I hold the 20 sentiment-beta portfolios from July of year *t* to June of year *t+1* and determine post-formation value-weighted portfolio returns and market betas. I estimate these post-formation market betas regressing excess portfolio returns against the CRSP value-weighted excess return (RMRF) in varying market sentiment periods. All calculations of portfolio returns are transformed from cumulative returns to simple returns as cumulative returns are not additive across stocks. Antoniou et al. (2016) suggest full sample market betas are less affected by noise traders. Therefore, I calculate full sample rather than rolling window post-formation market betas to ensure I do not calculate market betas using only periods of high (low) market sentiment, where noise trading has a larger (weaker) influence. I create three graphs (Figure 3) displaying the security market lines in different periods of market-wide sentiment. I allocate month *t* as having high (low) market sentiment when the updated BW sentiment index in month *t-1* is above (equal or below) 0.18. One graph represents all periods (N=405) in which market betas and portfolio returns use full sample return data. The second graph represents low sentiment periods (n=200) in which market betas and portfolio returns only use periods when the updated BW sentiment index has a value equal or less than 0.18 in month *t-1*. The final graph represents high sentiment periods (n=205) in which market betas and portfolio returns only use periods when the updated BW sentiment index has a value above 0.18 in month *t-1*. Each graph will consist of two security market lines with one representing stocks with the most positive sentiment sensitivity values (quintile 5 of sentiment sensitivity sorts) and the other representing stocks with the most negative sentiment sensitivity values (quintile 1 of sentiment sensitivity sorts).

I then conduct the CAPM procedure at the portfolio-level using the methodology developed by Fama and Macbeth (1973). Using post-formation excess returns of the ten portfolios sorted by pre-ranking market beta within the most positive and negative sentiment sensitive stocks, I run first stage time-series regressions of each portfolio's excess returns against the excess market return proxy (RMRF). The time-series portfolio regressions occur using periods of different market sentiment, and the market beta estimates represent a factor loading measuring the sensitivity of portfolio returns to the market. Using market beta estimates, I employ the second stage of the Fama Macbeth (1973) methodology and run separate monthly cross-sectional regressions by regressing excess portfolio returns against the time-series market beta estimates. The time-series average of these values represents the premium for exposure to the market beta. It can determine whether, on average, market betas are priced in the cross-section of stock returns. I present the equations for the portfolio-level regressions below:

Stage One: $R_{i,t} = \alpha_{i,t} + \beta_{RMRF,i}RMRF_t + \varepsilon_{i,t}$ (3)

Stage Two: $R_{i,t} = \alpha_{i,t} + \lambda_{RMRF,}\beta_{RMRF,i} + \varepsilon_{i,t}$ (4)

Next, I investigate whether the market risk premium is priced at the stock-level using the Fama and Macbeth (1973) methodology. In June of year *t*, I assign portfolio post-ranking market betas to individual stocks using the sentiment-beta portfolios calculated previously. Each month within the sample, using only stocks with the most positive sentiment sensitive stocks (quintile 5 of sentiment sensitivity sorts) and the most negative sentiment sensitive stocks (quintile 1 of sentiment sensitivity sorts), I run cross-sectional regressions of stocks excess returns against post-ranking market betas and controls. These include controls for size (natural logarithm of the market value of equity), value (natural logarithm of (book value of equity/market value of equity)), and momentum (excess return in month $t - 1$). I average the time-series coefficient estimates on post-ranking market betas using all, high and low periods of market sentiment as determined by the median value of the updated BW sentiment index. Next, I calculate the test statistics of these time-series averages using heteroskedasticity-consistent standard errors to determine whether market beta is statistically different from zero. I present the equation for the stock-level regression below:

$$R_{i,t} = \alpha_{i,t} + \lambda_{RMRF}\,\beta_{RMRF,i} + \lambda_{ln(ME)}\,ln(ME)_i + \lambda_{ln(B/M)}ln(B/M)_i + \lambda_{Ret1}Ret1_i + \varepsilon_{i,t} \quad (5)$$

4.4 Summary Statistics

Table 1 reports the average characteristics of individual stocks within the 20 portfolios doubled sorted by pre-ranking sentiment sensitivity and market beta. I find that both the most positive and negative sentiment sensitive stocks have pre-ranking sentiment sensitivity values that stay relatively consistent within pre-ranking market beta sorts. At the same time, there are substantial market beta differences within portfolios of similar sentiment sensitivity. For example, between the most positive sentiment sensitive stocks in portfolio 4 to 5, sentiment sensitivity drops 0.0005, while pre-ranking market beta increases from 0.74 to 0.88. Also, the smallest pre-ranking market beta portfolios of the most positive and negative sentiment sensitive stocks have very small market betas, which suggests that sentiment sensitivity has additional explanatory power to market beta. The above results indicate additional information unrelated to market movement is due to changes in the sentiment index.

Table 1 also reports the average natural logarithmic of the market value of equity of individual stocks within each of the portfolios. The most positive sentiment sensitive stocks show a linear decrease in ln (ME) as market beta increases, which is consistent with the fact that smaller stocks have more significant risk. However, the most negative sentiment sensitive stocks show no such relationship. For example, the difference between the highest and lowest pre-ranking market beta portfolio within the most positive sentiment sensitive stocks is -1.32, while only being -0.21 for the most negative sentiment sensitive stocks. Even though the most negative sentiment sensitive stocks have higher market betas, the difference between the average ln (ME) of high positive and negative sentiment sensitive stocks is 0.01. As expected, and presented within Table 1, as pre-ranking market beta increases between portfolios, the total volatility of each portfolio increases consistent with the fact that higher market beta firms have greater risk.

Table 1

Characteristics of Sentiment-Beta Sorted Portfolios

	Low β	2	3	4	5	6	7	8	9	High β	H-L
Positive- Sentiment Value	0.0461	0.0383	0.0350	0.0360	0.0355	0.0378	0.0387	0.0398	0.0411	0.0603	0.0142
Negative- Sentiment Value	-0.0554	-0.0499	-0.0488	-0.0499	-0.0517	-0.0511	-0.0543	-0.0606	-0.0653	-0.0832	-0.0278
Positive- Market Beta	0.08	0.43	0.60	0.74	0.88	1.01	1.15	1.33	1.55	2.12	2.04
Negative- Market Beta	0.34	0.70	0.88	1.05	1.20	1.35	1.52	1.71	1.98	2.65	2.31
Positive- Ln (ME)	15.75	15.54	15.35	15.29	14.95	14.88	14.79	14.80	14.50	14.43	-1.32
Negative- Ln (ME)	14.93	15.21	15.39	15.42	15.23	15.00	14.75	14.85	14.68	14.72	-0.21
Positive- Volatility	4.54%	4.66%	5.01%	5.07%	5.59%	6.31%	6.68%	6.71%	7.08%	9.61%	5.07%
Negative- Volatility	6.06%	5.19%	6.06%	6.00%	6.74%	6.82%	7.03%	7.79%	9.19%	9.36%	3.30%

Note. This table reports the average characteristics of individual stocks with the most positive sentiment sensitive values (Positive), and the most negative sentiment sensitive values (Negative) within pre-ranking market beta sorts in June of year *t*. The most positive (negative) sentiment sensitive stocks are stocks within quintile 5 (1) of NYSE sorts by pre-ranking sentiment sensitivity. Portfolios are held from July of year *t* to June of year *t+1*. Sentiment Value represent the average pre-ranking sentiment sensitivity value of individual stocks within the portfolios. Market Beta represents the average pre-ranking market beta of individual stocks within the portfolios. Ln (ME) represents the average natural logarithm of the market value of equity of individual stocks within portfolios. Volatility represents the total volatility of the average portfolio returns over the entire sample period.

Chapter 5 Results

5.1 Sentiment Sensitivity Portfolio Results

Looking at portfolios doubled sorted by pre-ranking sentiment sensitivity and market beta, I find that the post-formation market betas of the most negative sentiment sensitive stocks are higher than that of the most positive sentiment sensitive stocks. I expected larger post-formation market betas of the most negative sentiment sensitive stocks as pre-ranking market betas are also larger. In periods of high (low) market sentiment, all portfolios' post-formation market beta is lower (higher) than the same portfolios using all periods of market sentiment. The implication of a smaller (higher) market beta in periods of high (low) market sentiment is that stocks covary less (more) with market returns when there is a larger (smaller) influence of sentiment traders. Also, as the most positive and negative sentiment sensitive stocks have portfolios with similar post-formation market betas, it suggests that differences between market beta and return are not solely from market beta differences between portfolios.

Using all stocks, Antoniou et al. (2016) find a flat security market line in the cross-section of stock returns. However, using only 20% of the most positive and 20% of the most negative sentiment sensitive stocks, I see both an upward and downward sloping security market line between the two groups. The most positive sentiment sensitive stocks show a linear increasing security market line with a difference of 0.57% between the highest and lowest pre-ranking market beta portfolios. The most negative sentiment sensitive stocks show a linear decreasing security market line with a difference of -0.45% between the highest and lowest pre-ranking market beta portfolios. However, these security market lines have relatively small R^2's, and there is no statistical significance of a t-test between the highest and lowest pre-ranking market beta portfolios assuming unequal variance within both sentiment sensitive groups. Figure 3 offers a visual representation of these security market lines using all periods of market sentiment.

As reported in Table 2, using only periods when market sentiment is below or equal to the median (n=200), I find that the average portfolio return difference of the highest and lowest pre-ranking market beta portfolios within the most positive and negative sentiment sensitive stocks is 1.57% and 0.51%, respectively. The stocks with the most positive sentiment sensitivity have an upward sloping security market line, while the stocks with the most negative sentiment sensitivity have a security market line with a low R^2 and no prominent structure. Using the most positive sentiment sensitive stocks, I can reject the null hypothesis at the 95% confidence interval that the highest pre-ranking market beta portfolio has a lower average return than the lowest pre-ranking market beta portfolio using a t-test between two samples assuming unequal variance (test statistic 1.84). There is no statistical significance of a t-test between the highest and lowest pre-ranking market beta portfolios of the most negative sentiment sensitive stocks.

As depicted in Figure 3 in low sentiment periods, there exist interesting implications of portfolio returns at different post-ranking market betas. For example, the return difference between the lowest pre-ranking market beta portfolios within the most positive and negative sentiment sensitive stocks are 0.98%. This return difference may well be due to the post-formation market beta difference of 0.21 between portfolios. However, comparing portfolio 3 of the most positive sentiment sensitive stocks and portfolio 1 of the most negative sentiment sensitive stocks, there is a 1.01% return difference at a smaller market beta. For these stocks to receive returns higher than expected under the CAPM, other factors must be influencing stock returns. Though return variations exist at similar market betas, due to a low R^2 of the security market line in the most negative sentiment sensitive stocks, I can say very little about the influence of sentiment on them. Figure 3 offers a visual representation of the security market line in periods of low market sentiment.

As reported in Table 2, using only periods when market sentiment is above the median (n=205), I find that the average portfolio return difference of the highest and lowest pre-ranking market beta portfolios within the most positive and negative sentiment sensitive stocks is -0.40% and -1.39%, respectively. The stocks with the most positive sentiment sensitivity have a low R^2 with no prominent structure. However, using the most negative sentiment sensitive stocks, the security market line is downward sloping with the highest pre-ranking market beta portfolio receiving a negative return. Though portfolios with similar post-ranking market betas have return differences, portfolios 8, 9, and 10 of the most negative sentiment sensitive stocks have higher post-ranking market beta than those of the most positive sentiment sensitive stocks.

The post-formation market beta difference may be a leading explanation for the significant downward slope of the most negative sentiment sensitive stocks as higher market beta stocks are more susceptible to market sentiment. Using the most negative sentiment sensitive stocks, I can reject the null hypothesis at the 95% confidence interval that the highest pre-ranking market beta portfolio has a higher average return than the lowest pre-ranking market beta portfolio using a t-test between two samples assuming unequal variance (test statistic -1.93). There is no statistical significance of a t-test between the highest and lowest pre-ranking market beta portfolios of the most positive sentiment sensitive stocks. Figure 3 offers a visual representation of the security market in periods of high market sentiment.

As reported in Table 3, I conduct the Fama Macbeth (1973) regression at the portfolio-level and find that the market risk premium is priced positively at the portfolio-level using the most positive sentiment sensitive stocks in periods of low market sentiment. I find a market risk premium of 1.12%, which is statistically significant at the 95% confidence interval, with a test statistic of 2.31. The market risk premium of the most negative sentiment sensitive stocks is statistically insignificant at 0.29%, with a test statistic of 0.59. In periods of high market sentiment, the most negative sentiment sensitive stocks have a negatively priced market risk premium of -1.50%, which is statistically significant at the 99% confidence interval, with a test statistic of -2.61. The market risk premium of the most positive sentiment sensitive stocks is statistically insignificant at -0.50%, with a test statistic of -0.80. These portfolio-level Fama-Macbeth regressions in Table 3 confirm the findings of the security market lines in Figure 3 with the upward slope of the security market line of the most positive sentiment sensitive stocks in low sentiment and the downward slope of the security market line of the most negative sentiment sensitive stocks in high sentiment. Though the positively priced market risk premium of the most positive sentiment sensitive stocks in periods of low market sentiment confirm one of the four alternative hypotheses, I offer further empirical support and evaluate the market risk premium at the stock-level.

5.2 Sentiment Sensitivity Regression Analysis

Portfolio-level results in Chapter 5.1 show the market beta-return relationships in different periods of market sentiment. In Chapter 5.2, I use the Fama and Macbeth (1973) methodology at the stock-level and provide more straightforward evidence of whether the market risk premium is priced positively or negatively. The Fama-Macbeth regressions I present below in Table 4 report the average time-series market risk premiums in different periods of market sentiment. Panel A and B use all periods within the sample, panel B and C use periods of low market sentiment, while panel D and E use periods of high market sentiment. Within Chapter 5.2, I also control for other stock-level characteristics that have explanatory power in the cross-section of stock returns. Controlling for other stock-level characteristics ensures that the previous market beta-return relationships did not occur from known characteristics that influence stock returns and not sentiment sensitivity.

Within the most positive and negative sentiment sensitive stocks and in all periods of market sentiment (panel A and B of Table 4), I find market risk premiums of 0.0083 and 0.0023, respectively. However, after accounting for heteroskedasticity-consistent standard errors, the test statistic of the most positive sentiment sensitive stocks is 0.30, while the test statistic of the most negative sentiment sensitive stocks is 0.08. The market risk premiums are statistically insignificant and, therefore, not priced either positively or negatively in the cross-section of stock returns. I also find that my control variable for value (ln(B/M) has no statistical significance in all periods, while Antoniou et al. (2016) do find value is priced.

Within the most positive and negative sentiment sensitive stocks and in periods of low market sentiment (panel C and D of Table 4), I find market risk premiums of 0.0186 and 0.0097, respectively. However, after accounting for heteroskedasticity-consistent standard errors, the test statistics of the most positive sentiment sensitive stocks is 0.65, while the test statistic of the most negative sentiment sensitive stocks is 0.34. The market risk premiums are statistically insignificant, and therefore, not priced positively or negatively in the cross-section of stock returns. Interestingly, the test statistic of the most positive sentiment sensitive stocks after controlling for size, value, and momentum without using heteroskedasticity-consistent standard errors was 4.28. Therefore, the upward-sloping security market line of the most positive sentiment sensitive stocks in Figure 3 is statistically significant after controlling for stock characteristics. Firm-level characteristics, thus, do not explain the positive market risk premium. However, due to the variance of the regression errors being inconstant, I have no statistical grounds to conclude a positive market risk premium in periods of low market sentiment. The security market line in

Figure 3 is inconclusive of any relationship between market beta and return within the most positive sentiment sensitive stocks in periods of low market sentiment. I also find no statistical significance of my control variable for size (ln(ME)) in periods of low market sentiment, while Baker and Wurgler (2006) do find sized is priced. In this sample, I cannot reject the two null hypotheses that the market risk premium is priced negatively for both the most positive and negative sentiment sensitive stocks in periods of low market sentiment.

Within the most positive and negative sentiment sensitive stocks and in periods of high market sentiment (panel E and F of Table 4), I find market risk premiums of -0.0017 and -0.005, respectively. However, after accounting for heteroskedasticity-consistent standard errors, the test statistic of the most positive sentiment sensitive stocks is -0.06, while the test statistic of the most negative sentiment sensitive stocks is -0.18. The market risk premiums are statistically insignificant, and therefore, not priced positively or negatively in the cross-section of stock returns. Looking at the test statistic of the most negative sentiment sensitive stocks after controlling for size, value, and momentum without using heteroskedasticity-consistent standard errors was only -1.40. Even without heteroskedasticity-consistent standard errors, the most negative sentiment sensitive stocks do not show a strong negative market beta-return relationship as firm-level characteristics reduce the significance of the market risk premium. The security market line in Figure 3 is inconclusive of any relationship between market beta and return within the most negative sentiment sensitive stocks in periods of high market sentiment. I also find no statistical significance of my control variable for momentum (Ret1) in periods of high market sentiment, while Antoniou et al. (2016) do find momentum is priced. In this sample, I cannot reject the null hypothesis that the market risk premium for the most negative sentiment sensitive stocks are priced negatively in periods of high market sentiment. Similarly, I cannot reject the null hypothesis that the most positive sentiment sensitive stocks are priced positively in periods of high market sentiment.

I have no statistical significance to reject any of the four null hypotheses in this sample. Though the portfolio-level results in Chapter 5.1 seem to show security market lines with consistent market beta-return relationships and Fama-Macbeth regressions with statistical significance, these values do not account for firm-level characteristics and heteroskedasticity-consistent standard errors. Once considering these factors using stock-level Fama-Macbeth regressions, it eliminates all statistical significance. One reason for finding no statistical significance may be due to my methodology substantially reducing the stocks I use within the stock universe and the periods within the sample. By selecting only stocks with either the most positive or negative sentiment sensitivity, I am effectively reducing the stock universe to 20% per sentiment sensitivity group (quintile 5 and quintile 1). Also, separating periods by either high or low market sentiment further reduces the sample period by nearly half (200/405 low sentiment, 205/405 high sentiment). The methodology reduces the sample and increases noise, and this may contribute to the statistically insignificant market risk premiums that may falter the statistical inference from this investigation.

Addressing the sample size issue, I believe that increasing the number of periods within this investigation may introduce suggested shifts in sentiment unknown to the investor population. I chose the original sample period from 1980 to 2017 as investors in this period have easy access to stock-level information through medians like the internet. Access to this information helps shift market-wide sentiment faster than what was possible in the 1960s, and therefore using a monthly sentiment index may better measure market sentiment changes. Using a sample period before the introduction of the internet may require using the original yearly BW sentiment index instead. Surprisingly, Liu et al. (2018) use the monthly BW index and use a sample period from 1965 to 2010. Though they do not explain their reasoning, further empirical research using a larger period may require future investigation.

Table 2

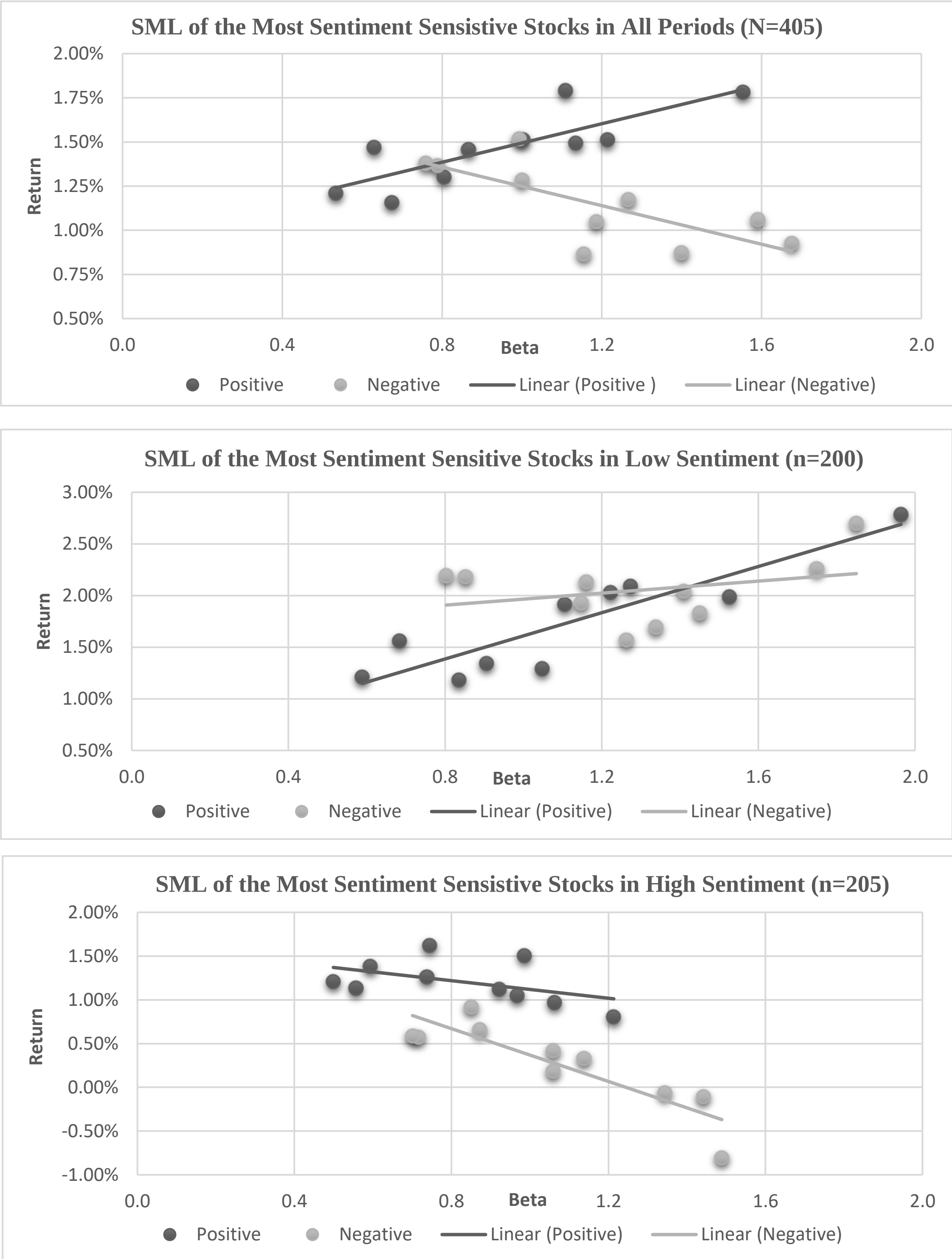
Returns of Sentiment-Beta Sorted Portfolios

	Low β	2	3	4	5	6	7	8	9	High β	H-L
Positive-All Periods	1.21%	1.47%	1.16%	1.30%	1.46%	1.51%	1.49%	1.79%	1.51%	1.78%	0.57%
Negative-All Periods	1.38%	1.36%	1.52%	1.28%	1.05%	0.87%	1.17%	0.87%	1.06%	0.93%	-0.45%
Positive-Low Sentiment	1.21%	1.56%	1.18%	1.34%	1.29%	1.91%	2.03%	2.09%	1.99%	2.78%	1.57%**
Negative-Low Sentiment	2.19%	2.18%	2.13%	1.93%	1.69%	1.57%	2.04%	1.83%	2.26%	2.70%	0.51%
Positive-High Sentiment	1.21%	1.38%	1.13%	1.26%	1.62%	1.12%	0.97%	1.50%	1.05%	0.81%	-0.40%
Negative-High Sentiment	0.59%	0.57%	0.91%	0.66%	0.42%	0.18%	0.33%	-0.06%	-0.11%	-0.81%	-1.39%**

Note. This table reports the average value-weighted portfolio returns of the most positive sentiment sensitive stocks (Positive) and the most negative sentiment sensitive stocks (negative) in different periods of market sentiment. The most positive (negative) sentiment sensitive stocks are stocks within quintile 5 (1) of NYSE sorts by pre-ranking sentiment sensitivity. Portfolios are sorted by pre-ranking stock level sentiment sensitivity and market beta in June of year *t*. These portfolios are held from July of year *t* to June of year *t+1*. I classify the market as having High (Low) Sentiment when month *t-1* of the updated Sentiment index is above (equal/below) the sample median of 0.18. The sample covers a period from 1982 to 2016. ** denotes statistical significance at the 95% confidence level.

Figure 3

SML of the Most Sentiment Sensitive Stocks in Varying Sentiment



Note. This figure depicts the security market line of the most positive sentiment sensitive stocks (Positive/Black) and the most negative sentiment sensitive stocks (Negative/Grey) within periods of different market sentiment. The most positive (negative) sentiment sensitive stocks are stocks within quintile 5 (1) of NYSE sorts by pre-ranking sentiment sensitivity. I classify the market as having low (high) sentiment when month *t-1* of the updated BW sentiment index is equal/below (above) the sample median of 0.18. Portfolios are sorted by pre-ranking sentiment sensitivity and market beta in June of year *t*. These portfolios are held from July of year *t to* June of year *t+1*. Portfolio returns are value-weighted. The sample is from 1982 to 2016.

Table 3

Portfolio-Level Fama-Macbeth Regressions of Sentiment Sensitive Stocks in Varying Sentiment

	Positive	Negative
All (N=405)	0.54%	-0.54%
	(1.39)	(-1.43)
Low Sentiment (n=200)	1.12%	0.29%
	(2.31)**	(0.59)
High Sentiment (n=205)	-0.50%	-1.50%
	(-0.80)	(-2.61)***

Note. This Table reports the market risk premiums (Fama-Macbeth methodology) of the most positive sentiment sensitive stocks (Positive) and the most negative sentiment sensitive stocks (Negative) within different periods of market sentiment. Post-ranking times-series market betas are calculated and used to determine market risk premiums in the cross-section of stock returns. I classify the market as having high (low) sentiment when month *t-1* of the updated BW sentiment index is above (equal/below) the sample median of 0.18. Portfolios are sorted by pre-ranking sentiment sensitivity and market beta in June of year *t.* These portfolios are held from July of year *t to* June of year *t+1*. The sample is from 1982 to 2016. ** denotes statistical significance at the 95% confidence level.*** denotes statistical significance at the 99% confidence interval

Table 4

Stock-Level Fama-Macbeth Regressions of Sentiment Sensitive Stocks in Varying Sentiment

Panel A: Positive All Periods (N=405)				Panel C: Positive Low Sentiment(n=200)				Panel E: Positive High Sentiment(n=205)			
β	Ln (ME)	Ln (B/M)	Ret1	β	Ln (ME)	Ln (B/M)	Ret1	β	Ln (ME)	Ln (B/M)	Ret1
0.0083				0.0181				-0.0013			
(0.30)				(0.63)				(-0.05)			
0.0071	-0.0014			0.0156	-0.0009			-0.0012	-0.002		
(0.26)	(-0.27)			(0.54)	(-0.15)			(-0.04)	(-0.39)		
0.0086	-0.0007	-0.0106		0.0187	-0.0018	-0.0113		-0.0012	-0.0003	-0.0099	
(0.31)	(-0.13)	(-0.93)		(0.64)	(-0.30)	(-0.96)		(-0.04)	(-0.43)	(-0.90)	
0.0083	-0.0006	-0.0111	-0.0498	0.0186	-0.0017	-0.0122	-0.0646	-0.0017	-0.0005	-0.0101	-0.0354
(0.30)	(-0.10)	(-0.95)	(-0.47)	(0.65)	(-0.28)	(-0.99)	(-0.57)	(-0.06)	(-0.09)	(-0.90)	(-0.36)

Panel B: Negative All Periods (N=405)				Panel D: Negative Low Sentiment(n=200)				Panel F: Negative High Sentiment(n=205)			
β	Ln (ME)	Ln (B/M)	Ret1	β	Ln (ME)	Ln (B/M)	Ret1	β	Ln (ME)	Ln (B/M)	Ret1
0.003				0.0097				-0.0036			
(0.11)				(0.35)				(-0.13)			
0.0036	-0.0021			0.0099	-0.0022			-0.0025	-0.0019		
(0.13)	(-0.36)			(0.35)	(-0.37)			(-0.09)	(-0.34)		
0.0024	-0.0001	-0.0117		0.0105	-0.0002	-0.0111		-0.0054	0	-0.0122	
(0.09)	(-0.01)	(-1.00)		(0.37)	(-0.03)	(-0.93)		(-0.20)	(-0.08)	(-1.08)	
0.0023	-0.0003	-0.0117	-0.0447	0.0097	-0.0004	-0.0111	-0.0439	-0.005	-0.0002	-0.0122	-0.0454
(0.08)	(-0.05)	(-1.02)	(-0.48)	(0.34)	(-0.06)	(-0.95)	(-0.44)	(-0.18)	(-0.04)	(-1.09)	(-0.52)

Note. This table reports the average time-series market risk premiums (Fama-Macbeth regressions) of the most positive sentiment sensitive stocks (Positive) and the most negative sentiment sensitive stocks (Negative). The most positive (negative) sentiment sensitive stocks are stocks within quintile 5 (1) of NYSE sorts by pre-ranking sentiment sensitivity. Test statistics are calculated using HSCE. Panel A and B use all 405 periods. Panel C and D (E and F) use periods when the updated BW sentiment index is equal/below (above) the sample median of 0.18. In June of year *t*, stocks are assigned into sentiment-beta portfolios and held for 12 months. These stocks are assigned post-formation betas, which are full sample portfolio betas. Ln (ME) is the natural logarithm of the shares outstanding multiplied by price. Ln (B/M) is the natural logarithm of the book value of equity divided by the market value of equity. Ret1 is the cumulative return of a stock in month *t-1*. The sample is from 1982 to 2016.

Chapter 6 Robustness Checks

6.1 The Time-Varying SML Based on Pre-ranking Market Beta

As a robustness test, I investigate the time-varying security market line to confirm Antoniou et al. (2016) findings using more recent observations (2010-2016) and the monthly BW sentiment index instead of an annual BW sentiment index. Following the methodology of Antoniou et al. (2016), I use all stocks with a market value of equity (shares outstanding multiplied by price) and a pre-ranking market beta in June of year *t*. As previously, I calculate pre-ranking market beta decile breakpoints in June of each year using only NYSE stocks with the available information. I then assign both NYSE and NASDAQ stocks into one of ten portfolios in June of year *t* based on the pre-ranking market beta decile breakpoints. Next, I hold these portfolios for one year from July of year *t* to June of year *t +1* and calculate portfolio value-weighted portfolio excess and standard returns. I now calculate post-formation market betas (using excess returns) and portfolio returns (normal returns) over a variety of times-series to display the market beta-return relationship.

Stock-level characteristics within the portfolios show similar trends to Antoniou et al. (2016). Sorting stocks by pre-ranking market beta finds a large discrepancy between average firm sizes and total volatility within each portfolio. The difference between the natural logarithm of the market value of equity between the highest and lowest pre-ranking market beta portfolios is -0.95. The difference between the total volatility of the highest and lowest pre-ranking market beta portfolio is 4.76%. These characteristics are consistent with the fact that the higher pre-ranking market beta portfolios have smaller and more volatile stocks.

Using the full sample period (N=405), I evaluate the average portfolio value-weighted monthly returns of the ten market beta sorted portfolios. Per Fama and French (1992), as pre-ranking market beta increases, there is no subsequent increase in portfolio return. The results show that the relationship between post-ranking market beta and return is flat, and investors receive no compensation for the additional riskiness of higher market beta stocks. Antoniou et al. (2016) find the difference between the average value-weighted return of the highest and lowest pre-ranking market beta portfolios of -0.01%, whereas I similarly find a small difference of

0.13%. Using Figure 4, I then further sort stocks the same way but into 20 portfolios and offer a visual representation of the flat market beta-return relationship over the full times-series.

Using periods when the market has low sentiment (n=200), I evaluate the average portfolio value-weighted monthly returns of the ten market beta sorted portfolios. Antoniou et al. (2016) and I both find a relatively linear increase in returns as market beta between portfolios increases. The difference between the highest and lowest portfolio return was 1.33%, while Antoniou et al. (2016) find a value of 1.09%. With a test statistic of 2.16, I can reject the null hypothesis of the t-test that the highest pre-ranking market beta portfolio has a lower value-weighted return than the lowest pre-ranking beta portfolio at the 95% confidence interval. Portfolio-level Fama-Macbeth regressions find a positive market risk premium of 1.06% with a test statistic of 2.04. Figure 4 depicts a visual representation of the upward sloping market beta-return relationship in periods of low market sentiment using 20 portfolios based on the pre-ranking market beta.

Using periods when the market has high sentiment (n=205), I evaluate the average portfolio value-weighted monthly returns of the ten market beta sorted portfolios. I find the difference between the average value-weighted return of the highest pre-ranking market beta portfolio and the lowest pre-ranking market beta portfolio of -1.05%. With a test statistic of -1.65, I can reject the null hypothesis of the t-test that the highest pre-ranking market beta portfolio has a higher value-weighted return than the lowest pre-ranking market beta portfolio at the 90% confidence interval. Antoniou et al. (2016) use the original annual BW index and a different sample period and find a more substantial -1.16% difference, with a test statistic that is significant at 95% confidence interval. Portfolio-level Fama-Macbeth regressions find a negative market risk premium of -0.93%, with a test statistic of -1.82. Figure 4 depicts a visual representation of the downward sloping market beta-return relationship in periods of high market sentiment using 20 portfolios based on the pre-ranking market beta. Note, I also investigate market sentiment as being high or low depending on the value of sentiment index instead of the median value and the relationships hold.

6.2 Absolute Sentiment Sensitivity Portfolios

Next, I recalculate double sorted portfolios based on pre-ranking sentiment sensitivity and market beta but use absolute sentiment sensitivity values, like those done by Glushkov (2006). Absolute sentiment sensitivity represents all trades by investors that are unrelated to changes in the underlying fundamentals of a stock. I classify stocks in quintile 5 of NYSE absolute sentiment sensitivity sorts as representing the most sentiment sensitive, while stocks in quintile 1 of NYSE absolute sentiment sensitivity sorts represent the least sentiment sensitive.

The pre-ranking market beta of the most sentiment sensitive stocks within pre-ranking market beta portfolios is 54% higher than in similar portfolios within the least sentiment sensitive stocks. Post-ranking portfolio market beta differences between the most and least sentiment sensitive stocks are 55%. Variations between returns come from the fact that the most sentiment sensitive stocks have higher pre-ranking market betas than the least sentiment sensitive stocks. As these stocks have higher market betas, the influence of sentiment is greater. Therefore, there may be little information from the market beta-return differences in these tests.

Using one-factor absolute sentiment sensitivity, all the risky stocks prone to movement in sentiment are in the most sentiment sensitivity stocks, so we cannot see each type of trader's individual effects.

In all periods (N=405), the security market line of stocks with the most sentiment sensitivity has a flat security market line, while the least sentiment sensitive stocks have a slightly upward sloping security market line. However, t-tests between the highest and lowest pre-ranking market beta portfolios have no statistical significance in either of the groups. Using non-absolute sentiment sensitivity, as depicted in Figure 3, there is both an upward and downward sloping security market line. The reason that the most sentiment sensitive stocks have a flat security market line is due to combining both the upward slope of the most positive sentiment sensitive stocks and the downward slope of the negative sentiment stocks. Compared to the least sentiment sensitive stocks, the most sentiment sensitive stocks have higher market betas that have a considerable influence from market sentiment, which results in the flatter security market line as market beta increases. Figure 5 depicts the security market line using ten portfolios based on the pre-ranking market beta of the most and least sentiment sensitive stocks in all periods of market sentiment.

In periods of low market sentiment (n=200), both the most and least sentiment sensitive stocks show an upward sloping security market line. When comparing this to the most positive sentiment sensitive stocks in Figure 3, introducing the most positive and negative sentiment sensitive stocks together by using absolute values means the loss of information about the two different types of stocks, and there is a linear relationship. As both the most and least sentiment sensitive stocks show the same relationship, there is no explanatory power of sentiment sensitivity, and merely the fact that all stocks generate increasing returns as post-ranking market beta increases due to higher sentiment sensitive stocks having higher market betas. The most and least sentiment sensitivity groups have t-tests assuming unequal variances between the highest and lowest pre-ranking market beta portfolios with test statistics of 2.46 and 2.00, respectively. For the most and least sentiment sensitive stocks, I can reject the null hypothesis that the lowest pre-ranking market beta portfolio earns a lower return than the highest pre-ranking market beta portfolio in periods of low market sentiment. The portfolio-level Fama-Macbeth regressions for the most and least sentiment sensitive stocks are 1.24% and 1.28% (test statistics 2.34, 1.93), respectively. Figure 5 depicts the security market line using ten portfolios based on the pre-ranking market beta of the most and least sentiment sensitive stocks in periods of low market sentiment.

In periods of high market sentiment (n=205), both the most and least sentiment sensitive stocks show a downward sloping security market line. When comparing this to the most negative sentiment sensitive stocks in Figure 3, absolute sentiment sensitivity reduces the slope of the overall security market line due to the most positive sentiment sensitive stocks having a smaller downward sloping security market line. A t-test assuming unequal variance between the highest and lowest pre-ranking market beta portfolios within both the most and least sentiment sensitive stocks show no statistical significance. I cannot reject the null hypothesis that the lowest market beta portfolio earns a higher return than the highest market beta portfolio in periods of high market sentiment. Portfolio-level Fama-Macbeth regressions find that the most and least sentiment sensitive stocks have a market risk premium of -1.11% and -0.37% (test statistic -2.00, -0.65), respectively. Figure 5 depicts the security market line using ten portfolios based on the pre-ranking market beta of the most and least sentiment sensitive stocks in periods of high market sentiment. Though Fama-Macbeth regressions at the portfolio-level show statistical significance, the tests do not have controls for firm-level characteristics and heteroskedastic-consistent standard errors, which I will cover in Chapter 6.3.

6.3 Multi-Factor Sentiment Sensitivity

In Chapter 6.3, I run Fama-Macbeth (1973) regressions at the stock-level in a similar fashion to Chapter 5.2, while introducing a few key differences. Firstly, I allocate the post-formation market beta using the methodology of Fama and French (1992). In June of year *t*, all non-financial common stocks within the NYSE are sorted by size (ln(ME)) into ten portfolios between 1982 to 2017. Sorting first by size accounts for the effect of firm size in the cross-section of stock returns. Along with many others, Banz (1981) and Chan and Chen (1988) find that small (large) stocks receive a higher (lower) average expected return relative to the size of their market betas. Within the ten size portfolios, I further sort NYSE non-financial common stocks into ten portfolios by their pre-ranking market betas in June of year *t* (equation (2)), as this accounts for variations in beta that is unrelated to size (Fama & French, 1992). I then assign NYSE and NASDAQ non-financial common stocks to their designated portfolios.

With these 100 size-beta portfolios, I calculate one-year equally weighted excess portfolio returns from July of year *t* to June of year *t + 1* while transforming stock-level cumulative returns to arithmetic returns. I then calculate full sample post-ranking market betas of each portfolio using 405 months' worth of portfolio excess return data regressed against the proxy for the excess market return over the same period. Table 5 reports the post-formation betas of the size-beta portfolios. I find that higher pre-ranking market beta portfolios within the same size deciles have higher post-ranking market betas. Post-ranking market beta changes are unrelated to size, and Fama and French (1992) state pre-ranking market beta captures true post-ranking market beta. Fama and French (1992) find a post-formation difference in market beta between the highest and lowest pre-ranking market beta portfolios of 0.85, whereas the difference in my sample is 0.99. Also, portfolios with higher size values typically have lower post-ranking market betas. Fama and French (1992) find a post-formation difference in market beta between the highest and lowest size portfolios of 0.52, whereas the difference in my sample is 0.17. Therefore, both size and pre-ranking market beta are prevalent in explaining differences in the cross-section of stock returns.

Next, I determine the stock-level sensitivity to market-wide investor sentiment by following the equation of Glushkov (2006). I run a regression of monthly excess stock returns against a five-factor model of the monthly sentiment index and control variables. Glushkov (2006) finds that multicollinearity is not a significant issue in this model. Using the entire sample period, I rank stocks into five quintiles based on β_{BW} (equation (6)) and the absolute value of β_{BW} (equation (7)). Calculating sentiment sensitivity this way further ensures stock-level sentiment sensitivity is not identifying other stock-level characteristics. I present the equation for calculating the sentiment sensitivity value below:

$$R_{i,t} = \alpha_{i,t} + \beta_{BW,i}BW_t + \beta_{RMRF,i}RMRF_t + \beta_{SMB,i}SMB_t + \beta_{HML,i}HML_t + \beta_{LIQ,i}LIQ_t + \varepsilon_{i,t} \quad (6)$$

$$R_{i,t} = \alpha_{i,t} + \beta_{BW,i}BW_t + |\beta_{RMRF,\,i}|\, RMRF_t + \beta_{SMB,i}SMB_t + \beta_{HML,i}HML_t + \beta_{LIQ,i}LIQ_t + \varepsilon_{i,t} \quad (7)$$

I assign portfolio post-ranking market betas to individual stocks using the size-beta portfolios previously determined. In each month, using only stocks with the most positive sentiment sensitivity value (quintile 5 of sentiment sensitivity sorts) and stocks with the most negative sentiment sensitivity value (quintile 1 of sentiment sensitivity sorts), I run the monthly regression presented in equation (5). I average the coefficient on the RMRF variable (market risk premium) across time, depending on whether updated BW investor sentiment value is above or below the sample median. Next, I calculate the test statistics of these time-series averages using heteroskedastic-consistent standard errors.

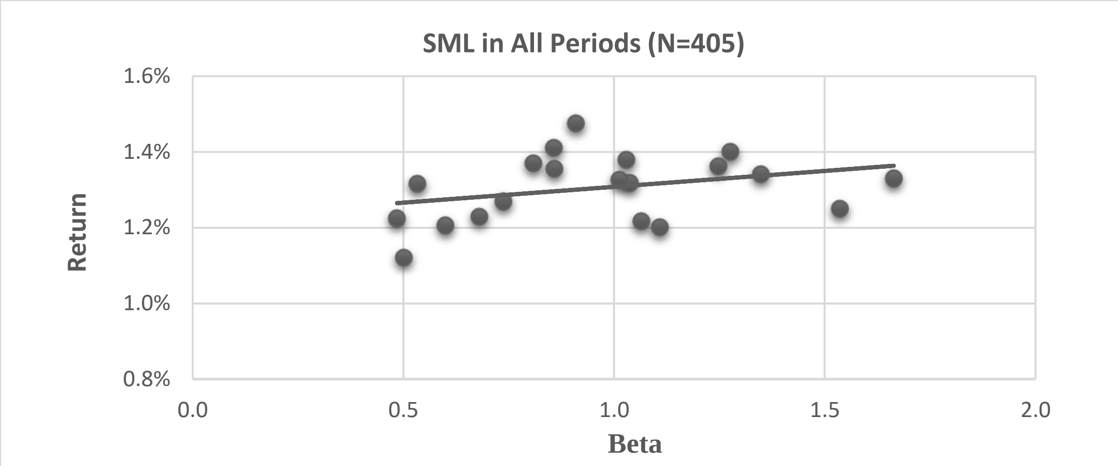
Similar to the results in Chapter 5.2, and reported in Table 6, all market risk premium estimates have no statistical significance using all, low, and high periods of market sentiment. Allocating post-ranking betas utilizing the methodology of Fama and French (1992) and using the equation of Glushkov (2006) that uses control variables when determining sentiment sensitivity values still does not produce market risk premiums that have any grounds for making statistical inferences.

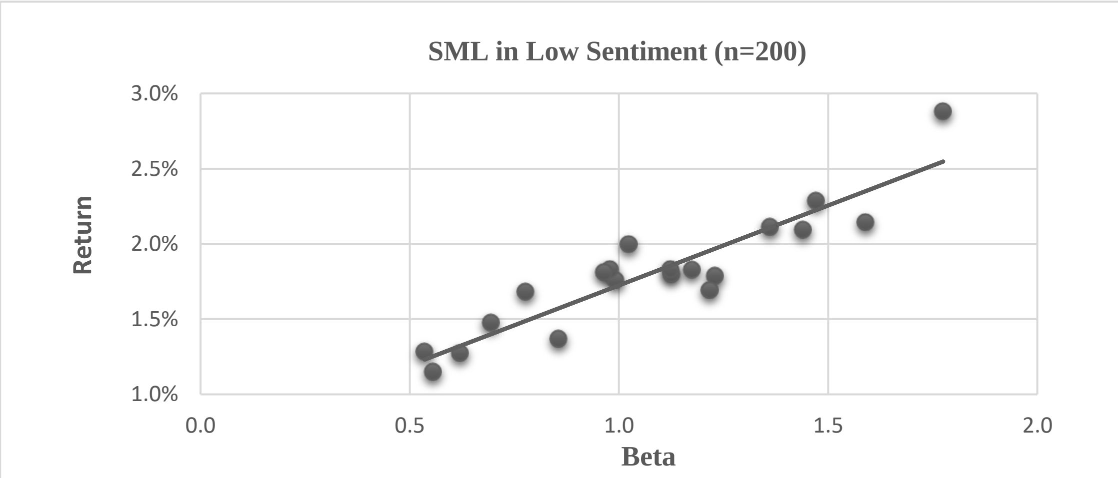
In Table 7, I report the regression results of using absolute sentiment sensitivity. Absolute sentiment sensitivity uses equation (7) instead of equation (6), which uses the absolute value of the $\beta_{RMRF,}$ where quintile 5 represents the most sentiment sensitive stocks, while quintile 1 represents the least sentiment sensitive stocks. I then run regressions using equation (5) in each month of the sample as previously. I find the same result that all values of the market risk premium have no statistical significance. The market risk premium of the most positive and negative sentiment sensitive stocks in all periods is -0.017 and -0.002, respectively. The market risk premium has a large difference between the most and least sentiment sensitive, and in line with Glushkov's (2006) findings. However, these values have statistically insignificant test statistics. Glushkov (2006) finds that portfolios with high exposure to sentiment underperform portfolios with low exposure to sentiment by 25 basis points per month when using all periods within his sample.

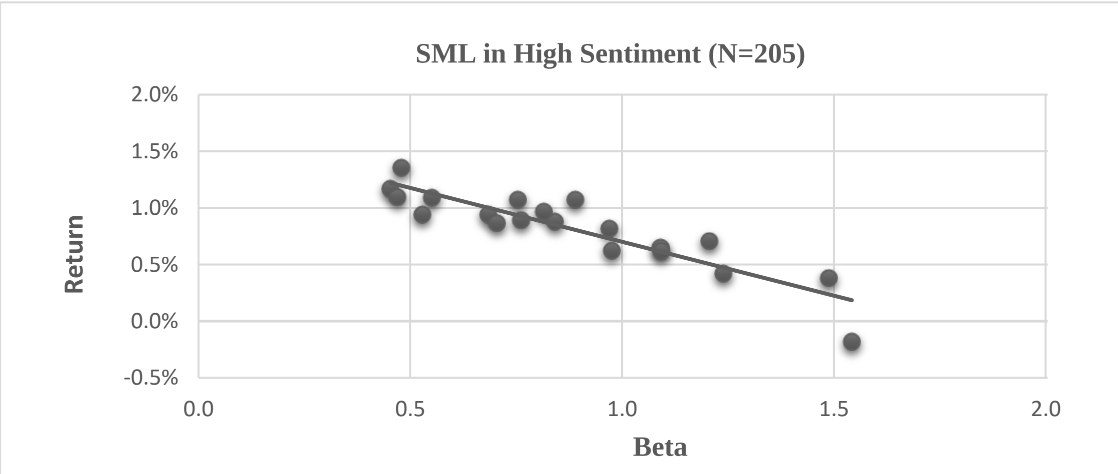
Within the portfolio with the most sentiment sensitive stocks, I find the average post-ranking market beta value of these stocks is 1.20. In contrast, the stocks that are the least sensitive to sentiment have an average post-ranking market beta value of 1.07. Running a t-test of the two samples assuming unequal variances finds a test statistic of 12.8, which suggests the difference between these two samples is statistically significant from zero. Similarly, the natural logarithmic of the market value of equity between portfolios look very similar at 12.29 for the most sentiment sensitive stocks and 13.06 for the least sentiment sensitive stocks. The t-test between the two samples assuming unequal variances finds a test statistic of -11.8 and finds the two series have a statistically significant mean difference between size. Though stock-level Fama-Macbeth regressions find no control variables as statistically significant, substantial market beta and size differences between stock are present, which may cause return differences.

Figure 4

SML in Varying Sentiment



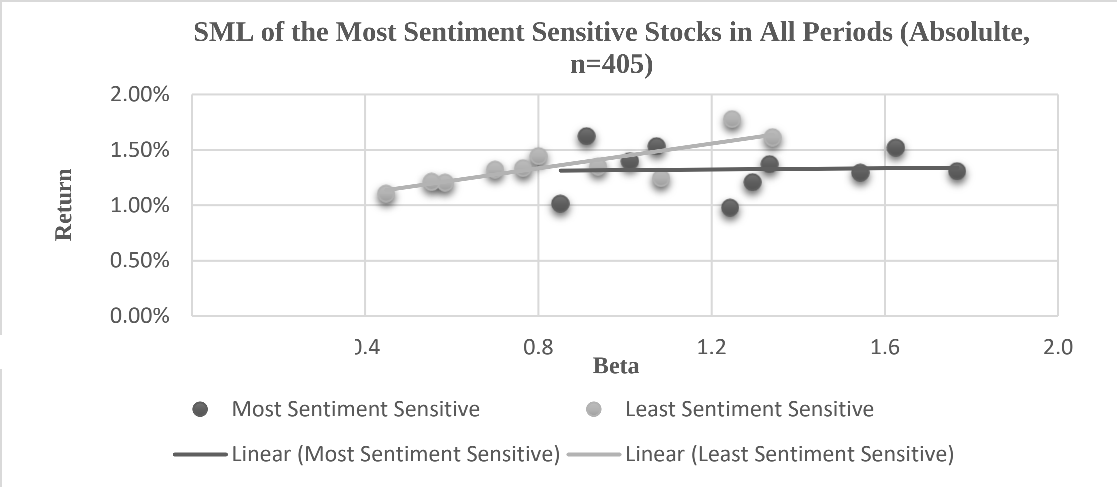


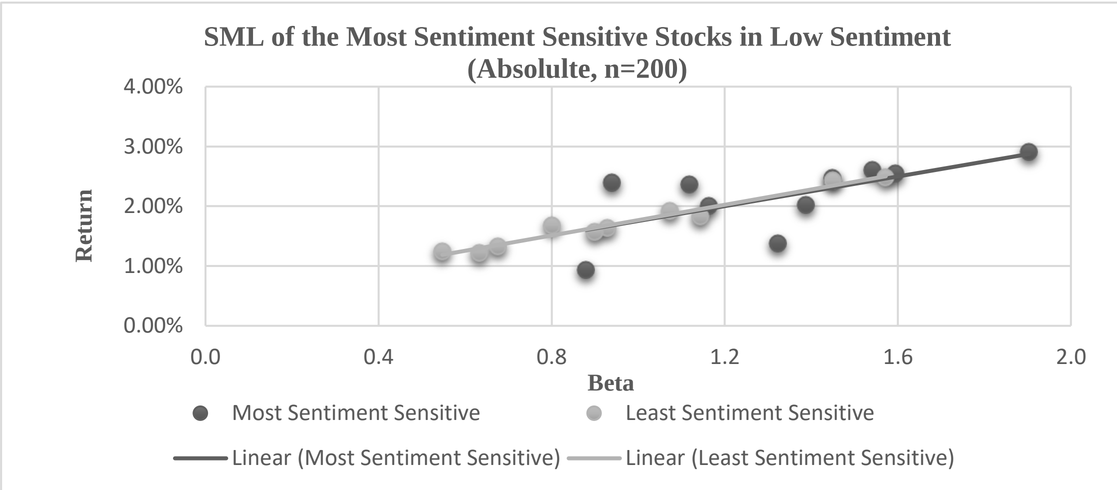


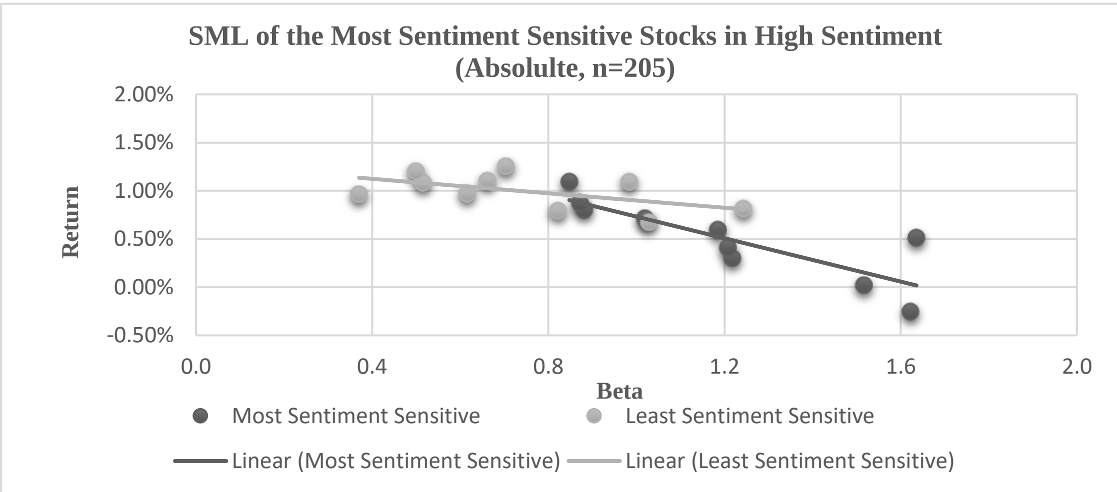
Note. This figure depicts the security market line of all stocks within periods of different market sentiment. I classify the market as having low (high) sentiment when month *t-1* of the updated BW sentiment index is equal/below (above) the sample median of 0.18. Portfolios are sorted by pre-ranking market beta in June of year *t*, and these portfolios are held from July of year *t to* June of year *t+1*. Portfolio returns are value-weighted. The sample is from 1982 to 2016.

Figure 5

SML of the Most Sentiment Sensitive Stocks in Varying Sentiment (Absolute)







Note. This figure depicts the security market line of the most sentiment sensitive and the least sentiment sensitive stocks. Stocks in the most (least) sentiment sensitive stocks are in quintile 5 (1) of NYSE absolute sentiment sensitivity sorts. Each portfolio is held from June of year *t* to July year *t+1*. Returns are calculated as value-weighted returns. I classify the market as having low (high) sentiment when month *t-1* of the updated BW sentiment index is equal/below (above) the sample median of 0.18. The sample is from 1982 to 2016.

Table 5

Post-Formation Beta of 100 Size-Beta Portfolios

	All	Low β	2	3	4	5	6	7	8	9	High β
All		0.63	0.69	0.8	0.92	1	1.07	1.14	1.22	1.31	1.63
Small ME	1.09	0.83	0.82	0.89	0.94	1.03	1.1	1.14	1.27	1.3	1.57
2	1.11	0.76	0.79	0.82	0.94	1.05	1.18	1.24	1.31	1.34	1.67
3	1.09	0.75	0.7	0.88	0.98	1.13	1.04	1.15	1.3	1.41	1.6
4	1.06	0.64	0.69	0.88	0.89	1.02	1.08	1.11	1.22	1.4	1.71
5	1.07	0.68	0.71	0.78	0.93	0.99	1.16	1.18	1.23	1.38	1.69
6	1.04	0.6	0.63	0.81	0.93	0.98	1.08	1.18	1.21	1.35	1.63
7	1.03	0.64	0.74	0.76	0.94	0.99	1.05	1.07	1.19	1.25	1.66
8	1.03	0.55	0.67	0.82	0.94	0.99	1.09	1.1	1.22	1.31	1.58
9	0.97	0.44	0.6	0.69	0.95	0.93	0.98	1.13	1.09	1.2	1.66
Large ME	0.91	0.45	0.57	0.65	0.81	0.82	0.94	1.09	1.13	1.18	1.49

Note. This table reports full sample post-ranking market beta of portfolios first sorted into ten portfolios by their market value of equity in June of year *t*, and then within size deciles into 100 portfolios by their pre-ranking market beta in June of year t. These portfolios are held from June of year *t* to July of year *t + 1*. Pre-ranking market beta values use 24-60 months' work of excess return data. Post-ranking market beta uses the full 405 sample period of average portfolio returns regressed against the RMRF variable. The sample is from 1982 to 2016.

Table 6

Stock-Level Fama-Macbeth Regressions of Sentiment Sensitive Stocks in Varying Sentiment (Multi-Factor Sentiment Sensitivity)

Panel G: Positive All Periods (Multi-Factor, N=405)				Panel I: Positive Low Sentiment (Multi-Factor, n=200)				Panel K: Positive High Sentiment (Multi-Factor, n=205)			
β	Ln (ME)	Ln (B/M)	Ret1	β	Ln (ME)	Ln (B/M)	Ret1	β	Ln (ME)	Ln (B/M)	Ret1
-0.008				0.002				-0.018			
(-0.26)				(0.05)				(-0.57)			
-0.007	-0.007			0.005	-0.008			-0.019	-0.006		
(-0.22)	(-1.09)			(0.14)	(-1.28)			(-0.59)	(-0.89)		
-0.01	-0.004	0.011		0.002	-0.005	0.011		-0.021	-0.003	0.012	
(-0.30)	(-0.58)	(0.88)		(0.06)	(-0.74)	(0.88)		(-0.67)	(-0.42)	(0.88)	
-0.01	-0.004	0.012	-0.043	0.002	-0.005	0.012	-0.047	-0.022	-0.003	0.012	-0.04
(-0.30)	(-0.62)	(0.91)	(-0.47)	(0.07)	(-0.79)	(0.93)	(-0.51)	(-0.67)	(-0.46)	(0.89)	(-0.43)
Panel H: Negative All Periods (Multi-Factor, N=405)				Panel J: Negative Low Sentiment (Multi-Factor, n=200)				Panel L: Negative High Sentiment (Multi-Factor, n=205)			
β	Ln (ME)	Ln (B/M)	Ret1	β	Ln (ME)	Ln (B/M)	Ret1	β	Ln (ME)	Ln (B/M)	Ret1
-0.007				0.007				-0.02			
(-0.18)				(0.2)				(-0.51)			
-0.01	-0.008			0.002	-0.008			-0.022	-0.007		
(-0.27)	(-1.01)			(0.05)	(-1.15)			(-0.55)	(-0.89)		
-0.014	-0.005	0.014		-0.003	-0.005	0.016		-0.025	-0.005	0.011	
(-0.37)	(-0.66)	(0.94)		(-0.08)	(-0.69)	(1.19)		(-0.61)	(-0.64)	(0.72)	
-0.014	-0.006	0.014	-0.05	-0.003	-0.005	0.018	-0.062	-0.025	-0.006	0.011	-0.038
(-0.36)	(-0.72)	(0.97)	(-0.49)	(-0.09)	(-0.72)	(1.27)	(-0.65)	(-0.60)	(-0.72)	(0.71)	(-0.36)

Note. This table reports the average time-series market risk premiums of the most positive sentiment sensitive stocks (Positive) and the most negative sentiment sensitive stocks (Negative). Test statistics are calculated using HSCE. Sentiment sensitivity is determined using a five-factor model in all periods, and each stock is assigned into quintiles. The most positive (negative) sentiment sensitive stocks are in quintile 5 (1). Panel G and H uses all 405 periods within the sample. Panel I and J (K and L) only use periods when the updated BW sentiment index is equal/below (above) the sample median of 0.18. These stocks are assigned full sample post-formation market betas from the size-beta portfolios. Ln (ME) is calculated as the natural logarithm of the shares outstanding multiplied by price. Ln (B/M) is calculated as the natural logarithm of the book value of equity divided by (shares outstanding multiplied by price). Ret1 is the cumulative return of a stock in month *t-1*. The sample is from 1982 to 2016.

Table 7

Stock-Level Fama-Macbeth Regressions of Sentiment Sensitive Stocks in Varying Sentiment (Multi-Factor Absolute Sentiment Sensitivity)

Panel M: Most All Periods (N=405)				Panel O: Most Low Sentiment (n=200)				Panel Q: Most High Sentiment (n=205)			
β	Ln (ME)	Ln (B/M)	Ret1	β	Ln (ME)	Ln (B/M)	Ret1	β	Ln (ME)	Ln (B/M)	Ret1
-0.009				0.004				-0.023			
(-0.17)				(0.08)				(-0.42)			
-0.018	-0.01			-0.006	-0.011			-0.029	-0.01		
(-0.32)	(-0.91)			(-0.11)	(-1.00)			(-0.51)	(-0.01)		
-0.019	-0.006	0.012		-0.007	-0.006	0.013		-0.032	-0.006	0.012	
(-0.34)	(-0.52)	(0.61)		(-0.12)	(-0.54)	(0.67)		(-0.54)	(-0.51)	(0.56)	
-0.017	-0.007	0.013	-0.038	-0.006	-0.007	0.014	-0.05	-0.029	-0.007	0.011	-0.027
(-0.31)	(-0.56)	(0.6)	(-0.29)	(-0.10)	(-0.59)	(0.69)	(-0.37)	(-0.49)	(-0.54)	(0.52)	(-0.21)
Panel N: Least All Periods (N=405)				Panel P: Least Low Sentiment (n=200)				Panel R: Least High Sentiment (n=205)			
β	Ln (ME)	Ln (B/M)	Ret1	β	Ln (ME)	Ln (B/M)	Ret1	β	Ln (ME)	Ln (B/M)	Ret1
-0.005				0.004				-0.013			
(-0.33)				(0.26)				(-0.93)			
-0.001	-0.003			0.008	-0.003			-0.01	-0.002		
(-0.10)	(-1.02)			(0.52)	(-1.09)			(-0.73)	(-0.95)		
-0.002	-0.001	0.009		0.007	-0.001	0.009		-0.012	-0.001	0.008	
(-0.17)	(-0.46)	(1.4)		(0.51)	(-0.51)	(1.53)		(-0.84)	(-0.42)	(1.27)	
-0.002	-0.001	0.009	-0.057	0.007	-0.001	0.01	-0.061	-0.012	-0.001	0.008	-0.054
(-0.16)	(-0.49)	(1.45)	(-0.94)	(0.49)	(-0.55)	(1.61)	(-0.96)	(-0.80)	(-0.44)	(1.31)	(-0.92)

Note. This table reports the average time-series market risk premiums of the most sentiment sensitive stocks and the least sentiment sensitive stocks. Test statistics are calculated using HSCE. Sentiment sensitivity is determined using a five-factor model in all periods, and each stock is assigned into quintiles. The most (least) sentiment sensitive stocks are in quintile 5 (1) of NYSE absolute sentiment sensitivity sorts. Panel M and N use all 405 periods within the sample. Panel O and P (Q and R) only use periods when the updated BW sentiment index is equal/below (above) the sample median of 0.18. These stocks are assigned full sample post-formation market betas from size-beta portfolios. Ln (ME) is calculated as the natural logarithm of the shares outstanding multiplied by price. Ln (B/M) is calculated as the natural logarithm of the book value of equity divided by (shares outstanding multiplied by price). Ret1 is the cumulative return of a stock in month *t-1*. The sample is from 1982 to 2016.

Chapter 7 Conclusion

In this paper, I investigate stock-level sensitivity to investor sentiment in different periods of market sentiment. Expanding on Antoniou et al. (2016) work, I further investigate how market sentiment levels cause stocks to receive lower returns than expected under the CAPM. While separating periods by market sentiment, I also evaluate stock-level return sensitivity to changes in these sentiment levels as a measure of overpricing. Using non-financial common stocks listed on the NYSE and NASDAQ between 1980 to 2017, I sort stocks based on return sensitivity to the updated Baker and Wurgler (2006) sentiment index (BW) and run both portfolio and stock-level Fama-Macbeth regressions. These regressions determine whether stock-level sensitivity to investor sentiment has any explanatory power in the cross-section of stock returns.

I expect that different irrational investors consider overall market sentiment levels and a stock's sensitivity to that sentiment. Due to the unwillingness of sentiment traders to short sell in periods of high market sentiment, I propose sentiment traders purchase the most negative sentiment sensitive stocks when they believe market sentiment is too high. I hypothesis that in periods of high market sentiment, the most positive (negative) sentiment sensitive stocks will have a negatively (positively) priced market risk premium. Secondly, I hypothesis that in periods of low market sentiment, both the most positive and negative sentiment sensitive stocks will have a positively priced market risk premium.

I find that at the portfolio-level, Fama-Macbeth regressions of portfolios doubled sorted by pre-ranking sentiment sensitivity and market beta show statistically significant market risk premiums. Confirming my expectations, the most positive sentiment sensitive stocks have an upward sloping security market line with a positively priced market risk premium of 1.12% that is statistically significant at the 95% confidence interval in periods of low market sentiment. Contrary to my expectations, the most negative sentiment sensitive stocks have a downward sloping security market line with a negatively priced market risk premium of -1.50% that is statistically significant at the 99% confidence interval in periods of high market sentiment. Portfolio-level findings do not account for firm-level characteristics that influence stock returns or use heteroskedastic-consistent standard errors in calculating test statistics. Addressing these factors in stock-level Fama-Macbeth regressions, I find that the market risk premiums of stocks with both the most positive and negative sentiment sensitivity have statistically insignificant market risk premiums in both high and low market sentiment periods. Therefore, I have no statistical evidence to reject any of my null hypotheses.

To evaluate sentiment sensitivity in different periods of market sentiment, I focus on a small proportion of stocks within stock exchanges while also reducing the periods I use to run cross-sectional regressions. Reducing sample sizes by stocks and periods increases noise. This paper contributes to the literature by establishing that sorting stocks by sentiment sensitivity and periods based on market sentiment, does not explain the time-varying nature of the security market line. The result of my methodology may mean that sentiment sensitivity has very little explanatory power as a stock-by-stock measure of the movement of returns relative to a sentiment proxy.

Chapter 8 References

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