Three Essays on Asset Pricing

By

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Abstract

This dissertation consists of three essays. In the first essay, we present evidence that market sentiment is positively priced in the cross-section of stock returns in low-sentiment periods. We estimate individual stock exposure to market sentiment and find that, in periods of low market sentiment, stocks in the highest sentiment beta quintile generate a 0.74% higher ex-post monthly return than stocks in the lowest sentiment beta quintile. However, this return spread is not significant in medium- or high-sentiment periods. This finding is consistent with the argument that overpricing in high-sentiment periods is more prevalent than underpricing in low-sentiment periods due to short-sale constraints.

In the second essay, we use Yelp restaurant customer reviews to construct a novel consumption-based sentiment index. Our weekly index is based on the ratio of positive to negative user ratings to capture an embedded element of sentiment associated with consumption. To validate that our measure captures consumption sentiment, we show that it is correlated with aggregate market risk aversion. Furthermore, consistent with a flight to safety, our index predicts mutual fund flows from bond to equity funds. We find that consumption sentiment predicts stock return reversals, an effect that is particularly strong for difficult-to-arbitrage stocks. The evidence suggests that our consumption sentiment index captures sentiment-induced mispricing in the stock market. When we decompose our index into components of optimism and pessimism, we find that pessimism drives the predictive power of the index, a result that gives direct evidence for the negativity bias in our context.

The third essay examines the role of market disagreement in explaining the cross-section of hedge fund performance. In a market where disagreement fluctuates, skilled arbitrageurs may

employ different trading strategies to exploit the mispricing caused by disagreement and short-sale constraints. Skilled hedge funds with high sensitivity to disagreement can take advantage of mispricing in high-disagreement periods to improve their performance. We show that hedge funds with a high disagreement beta tend to have a disagreement exploitation skill and thus they can earn higher cross-sectional returns relative to other hedge funds that do not have this skill. Experienced hedge funds (using size and age as proxies) and hedge funds that charge a high incentive fee are likely to have high disagreement betas.

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1. General Introduction

This dissertation consists of five chapters, which include three essays, one general introduction, and one general conclusion. I focus on investors' belief and its impact on the financial market in all my essays. In chapter two, I present evidence that market sentiment is positively priced in the cross-section of stock returns particularly in low-sentiment periods. This is a study to test a theoretical prediction in Kozak, Nagel, and Santosh (2018). I estimate individual stock exposure to market sentiment and find that, in periods of low market sentiment, stocks in the highest sentiment beta quintile generate a 0.74% higher ex-post monthly return than stocks in the lowest sentiment beta quintile. However, this return spread is not significant in medium- or high-sentiment periods. The unique contribution of this essay is that it shows the sentiment beta effect is driven by results in low-sentiment months. The asymmetric pricing effect of sentiment beta is not documented in the previous literature. This finding is consistent with the argument that overpricing in high-sentiment periods is more prevalent than underpricing in low-sentiment periods due to short-sale constraints.

In the third chapter, I use Yelp restaurant customer reviews to construct a novel consumption-based sentiment index. Our weekly index is based on the ratio of positive to negative user ratings to capture an embedded element of sentiment associated with consumption. To validate that this measure captures consumption sentiment, I show that it is correlated with aggregate market risk aversion. Furthermore, consistent with a flight to safety, the index predicts mutual fund flows from bond to equity funds. I find that consumption sentiment predicts stock return reversals, an effect that is particularly strong for difficult-to-arbitrage stocks. The evidence suggests that the consumption sentiment index captures sentiment-induced mispricing in the stock market. The uniqueness of this sentiment index is that this sentiment measure is decomposable into optimism and pessimism components. When the consumption sentiment is decomposed into components of optimism and pessimism, this study finds that pessimism drives the predictive power of the index, a result that gives direct evidence for the negativity bias in our context.

The third chapter examines the role of market disagreement in explaining the cross-section of hedge fund performance. In a market where disagreement fluctuates, skilled arbitrageurs may employ different trading strategies to exploit the mispricing caused by disagreement and short-sale constraints. Skilled hedge funds with high sensitivity to disagreement can take advantage of mispricing in high-disagreement periods to improve their performance. This chapter shows that hedge funds with a high disagreement beta tend to have a disagreement exploitation skill and thus they can earn higher cross-sectional returns relative to other hedge funds that do not have this skill. Experienced hedge funds (using size and age as proxies) and hedge funds that charge a high incentive fee are likely to have high disagreement betas.

Chapter Two: Market Sentiment and the Cross-Section of Expected Stock Returns

2.1 Introduction

The question of how market sentiment affects asset prices has drawn a fair bit of attention for the past few decades. While a number of studies shed light on how aggregate market sentiment impacts time-series asset returns, less attention has been paid to how sentiment explains the cross-section of expected stock returns.[1] Theoretically, Kozak, Nagel, and Santosh (2018) show that sentiment can be priced in the cross-section. They suggest that sentiment-driven asset demand will not be eliminated by arbitrageurs if there are components of asset demand that are aligned with common factor covariances, making it risky for arbitrageurs to take the other side. In their model, time-varying sentiment can give rise to an ICAPM-like stochastic discount factor where sentiment is priced since it affects the investment opportunity set. Building on this work, we provide empirical evidence that market sentiment is priced in the cross section of asset returns following low-sentiment months.

We quantify market sentiment using the Financial and Economic Attitude Reveal by Search (FEARS) index developed by Da, Engelberg, and Gao (2015) based on Google search volume.[2] They propose that the daily FEARS index is an effective measure of market sentiment and find that the FEARS index predicts daily market return reversals and mutual fund flows. They argue the reason that the FEARS index can predict return reversals is because sentiment introduces demand for assets which can push prices away from fundamental values. To test whether sentiment

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[1] Brown and Cliff (2004) find that sentiment is strongly correlated with contemporaneous market returns. Da, Engelberg, and Gao (2015) show that the FEARS index predicts a negative market return and return reversal. Huang, Jiang, Tu, and Zhou (2015) find that aligned sentiment negatively predicts monthly returns in the long run.

[2] Kozak et al. (2018) define sentiment as a catch-all term for investors' distorted beliefs, which affects asset prices by introducing systematic excess demand for risky assets. In order to measure sentiment, we choose a sentiment index that is directly correlated with investor demand for assets.

can be priced in the cross section, we regress daily excess stock returns on market sentiment to estimate monthly individual stock loadings on market sentiment, which we refer to as sentiment betas. We sort stocks into quintiles based on their sentiment betas and find that stocks with high (low) loadings on market sentiment generate significantly higher (lower) returns following low-sentiment periods.

Prior studies show an asymmetric effect of sentiment on stock returns due to short-sale constraints because overpricing following high-sentiment periods is more prevalent than underpricing following low-sentiment periods (Stambaugh, Yu, and Yuan, 2012, 2015; Antoniou, Doukas, and Subrahmanyam, 2013, 2015; Shen, Yu, and Zhao, 2017; Liu, Stambaugh, and Yuan, 2018; Avramov, Cheng, and Hameed, 2020). Motivated by these studies, we explore potential differences in the relationship between sentiment beta and stock returns following high-sentiment versus low-sentiment periods by splitting the full sample into high-, medium-, and low-sentiment months. We find that the relationship between sentiment beta and cross-sectional stock returns is conditional on the monthly market sentiment level. Following periods of low sentiment, stocks in the highest sentiment beta quintile generate a 0.74% higher monthly return (8.88% annually) than stocks in the lowest sentiment beta quintile. The sentiment beta effect is insignificant following medium- or high-sentiment months.

This finding is consistent with investors preferring to hold low-sentiment beta stocks, which have a negative covariance with market sentiment and provide higher returns when market sentiment is low; investors therefore require additional compensation to hold riskier assets (i.e., high-sentiment beta stocks). However, this relation does not hold following medium- and high-sentiment periods. To examine whether short-sale constraints are driving this asymmetric effect, we estimate stock-level residual institutional ownership (RIO), a proxy for short-sale constraints

(Nagel, 2005), and form 25 portfolios double-sorted by RIO and sentiment beta. In the full sample, we find a positive relationship between sentiment beta and expected asset returns in the highest RIO quintile, but not in any of the lower RIO quintiles. Since stocks in lower RIO quintiles are more likely to be subject to short-sale constraints, this finding suggests that short-sale constraints obscure the relationship between sentiment beta and stock returns.

To ensure that our empirical findings are robust, we show that the return spreads of portfolios sorted by sentiment beta remain unchanged when controlling for various firm characteristics (i.e., market beta, size, book-to-market, momentum, liquidity, and disagreement). By using bivariate-sort portfolios, we show that when market sentiment is low, the risk-adjusted return difference between the highest and lowest sentiment beta-sorted quintile portfolios cannot be explained by well-known cross-sectional return predictors, such as market beta, size, book-to-market ratio (Fama and French, 1992), momentum (Jegadeesh and Titman, 1993; Carhart, 1997), illiquidity (Amihud, 2002; Pastor and Stambaugh, 2003), and disagreement (Diether, Malloy, and Scherbina, 2002). In the Appendix, we further show that our results are robust using alternative factor models in estimating stock-level sentiment beta.

Then, we verify that sentiment is priced when market sentiment is low using Fama-MacBeth (1973) regressions on 25 size- and sentiment-beta double-sorted portfolios. To address the concern that important information may be lost when aggregating stocks into portfolios, we use stock-level Fama-MacBeth (1973) cross-sectional regressions and confirm that stock-level sentiment betas are positively related to stock returns in periods of low market sentiment before and after controlling for various firm characteristics. Lastly, we show that our results are robust when using various test assets, as well as when using various measures of sentiment, including the FEARS index orthogonalized by market returns, the Baker and Wurgler (2006) monthly sentiment index, and sentiment loadings estimated using the sum-beta technique. Our results remain unchanged when excluding the bottom 20% of stocks by size, using randomly weighted portfolio returns, and using the mean (instead of median) level of sentiment within a given month to categorize low-, medium-, or high-sentiment months.

Our work is related to two strands of literature. First, we contribute to the literature that examines the role of sentiment in the stock market. Existing studies in the market sentiment literature, both theoretical and empirical, primarily focus on the short-term prediction of future market returns, anomalies, or macroeconomic characteristics using aggregate market sentiment.[3] In addition, researchers have focused on modeling market sentiment (Barberis, Shleifer, and Vishny, 1998), explaining cross-sectional stock market returns using sentiment (Baker and Wurgler, 2006), and using sentiment to explain stock market mispricing anomalies (Stambaugh et al., 2012). Though these studies document that investor sentiment can affect the cross-section of asset returns, they do not provide direct evidence that market sentiment is priced in the cross-section of asset returns.[4] Our study most closely relates to that of Glushkov (2006), who presents evidence that stocks with high sentiment sensitivity earn a lower return in the cross-section. Glushkov (2006) uses absolute sentiment loading to measure an asset's exposure to noise trader risk. However, we distinguish positive sentiment betas from negative sentiment betas because negative sentiment beta stocks provide a hedge against future states of the economy, whereas

[3] This literature includes, but is not limited to, Bodurtha, Kim, and Lee (1995); Baker and Stein (2004); Brown and Cliff (2004); Lemmon and Portniaguina (2006); Tetlock (2007); Da et al. (2015); Huang et al. (2015); and López-Salido, Stein, and Zakrajšek (2017).

[4] Gottesman, Jacoby, and Wang (2012) theoretically show that investors demand a higher risk premium when there is a higher covariance between the security's return and market-level sentiment with a sentiment pricing error-adjusted CAPM model; this implies that investors demand an additional premium for holding an asset that tends to pay a lower (higher) return when market sentiment is high (low). Ding, Mazouz, and Wang (2019) theoretically decompose sentiment into short-run and long-run components and empirically show that, using portfolios of stocks sorted by firm characteristics, the short-term component of change in sentiment positively explains contemporaneous returns, while the long-term moving average sentiment negatively explains future returns.

positive sentiment beta stocks do not. In addition, we find an asymmetric pricing effect of sentiment beta following high- versus low-sentiment months due to short-sale constraints. Moreover, our findings are also consistent with a study by Lee, Jiang, and Indro (2002) which conclude that sentiment is a systematic risk in the financial market.

More recently, Chen, Han, and Pan (2021) use the Baker and Wurgler index to show that exposure to market sentiment explains the cross-section of hedge fund returns; they find that a sentiment premium in hedge fund returns is driven by the sentiment-timing skill of hedge fund managers. In a related study, Massa and Yadav (2015) use mutual fund data and find that fund sentiment beta predicts fund returns even after controlling for standard risk factors and fund characteristics. Further, Liang (2018) proposes a consumption-based model augmented by sentiment and empirically finds that portfolio-level sentiment loadings positively predict expected returns, but does not provide evidence for individual stocks. Moreover, Hirshleifer, Jiang, and DiGiovanni (2020) describe investor mood as a special case of sentiment and show that assets' sensitivity to investor mood explains the seasonality of cross-sectional asset returns. Unlike these papers, we focus on the asymmetric pricing effect of the sentiment beta. Compared to the studies mentioned above, our research is the first to show that the results following low-sentiment months drive the relation between sentiment beta and expected stock returns.

Second, we contribute to the literature exploring the asymmetric pricing effects of sentiment on asset prices. Market sentiment affects asset prices asymmetrically following low-sentiment periods versus high-sentiment periods due to short-sale constraints (Yu and Yuan, 2011; Stambaugh et al., 2012, 2015; Antoniou et al., 2013, 2015; Shen et al., 2017; Avramov et al., 2020). Following high-sentiment months, sentiment-driven investors are optimistic and can act on their optimism by purchasing assets, resulting in overpricing. However, arbitrageurs cannot correct mispricings following periods of high sentiment due to short-sale impediments. As a result, mispricings are prominent following high-sentiment months. The above studies show that long-short strategies that exploit mispricing anomalies are more profitable following high-sentiment periods when assets are more likely to be overvalued due to short-sale constraints. We contribute to this literature by showing that the sentiment beta-return relationship does not hold following high-sentiment months when mispricing is likely prevalent.

This chapter is organized as follows. In Section 2.2, we provide the theoretical motivation for our empirical analyses. Section 2.3 describes the data and variables. We present the empirical results and robustness tests in Section 2.4. We examine whether short-sale constraints can explain our findings in Section 2.5. Section 2.6 concludes.

2.2 Theoretical Motivation

2.2.1 Why is sentiment priced?

To formalize the economic intuition for our study, we follow the literature and define investor sentiment as an aggregate error in investor beliefs about the future economy (Baker and Wurgler, 2006, 2007; Han, 2008; Kozak et al., 2018; DeVault, Sias, and Starks, 2019). This implies that investors are optimistic and expect excess returns in a market with high sentiment, while they are pessimistic in a market with low sentiment (Brown and Cliff, 2004; DeVault, Sias, and Starks, 2019). Kozak et al. (2018) construct a model where the stochastic discount factor is represented by a few dominant factors. In their economy, sentiment-driven demand for assets can affect asset prices in the cross-section when asset price variations are caused by distorted beliefs. This result is because some components of sentiment-driven asset demand are aligned with common factor covariances, while some are orthogonal. Though arbitrageurs can eliminate the pricing effects of the orthogonal components of sentiment-driven asset demand, it is risky for arbitrageurs to take the other side of sentiment-driven demand that is correlated with common factor exposures. In such an economy, arbitrageurs will not fully eliminate sentiment-driven investor demand for assets, and assets are systematically mispriced.

In Kozak et al.'s (2018) dynamic model, time-varying sentiment gives rise to time-varying hedging demand by arbitrageurs. As a result, time-varying sentiment can give rise to a state variable that proxies for shifts in the investment opportunity set and expected returns reflect this state-variable risk. Specifically, an expected asset return is determined by two covariance terms: (*i*) the covariance between an asset return and the market return and (*ii*) the covariance between an asset return and the investment opportunity proxied by sentiment. Therefore, Kozak et al. (2018) suggest that sentiment can serve as a state variable that is priced in the cross-section.

Kozak et al. (2018) argue that depending on the assumptions, the sign of the sentiment risk premium may be positive or negative. The key theoretical difficulty in specifying a sign for this state variable's risk premium is whether arbitrageurs have a better investment opportunity set in a positive or a negative sentiment market. Arbitrageurs can have good investment opportunities in markets with extreme sentiment states. Kozak et al.'s (2018) model indicates that the sign of priced sentiment risk can be positive if arbitrageurs face a better investment opportunity set in positive sentiment states. In this case, a decrease in sentiment results in an unfavorable shift in investment opportunities. Assets with negative (low) sentiment exposures provide a higher return when investors face poor investment opportunities relative to assets with positive sentiment exposures. This is because a decrease in sentiment generates higher returns for assets with a negative sentiment exposure. Hence, when sentiment decreases and investment opportunities decline, the higher return from these assets serve as a hedge for investors. Stated differently, assets that negatively covary with market sentiment can provide a hedge against future downturns and are safer relative to assets with positive (high) exposures to sentiment. Investors are willing to settle for a lower expected returns from these negative (low) sentiment exposure stocks. At the same time, assets that positively covary with sentiment have a positive risk premium because they do not allow for hedging against a time-varying investment opportunity set. In other words, sentiment is positively priced in the cross-section.

2.2.2 Sentiment and short-sale constraints

Recent studies have found asymmetric pricing effects following high- versus low-sentiment regimes as a result of binding short-sale constraints (Yu and Yuan, 2011; Stambaugh et al., 2012, 2015; Antoniou et al., 2015; Shen et al., 2017; Liu et al., 2018; Avramov et al., 2020). Stambaugh et al. (2012) examine the effect of short-sale constraints on the relationship between sentiment and stock market anomalies and find that overvaluation is prevalent following high-sentiment periods since pessimistic investors are unwilling or unable to short sell, while underpricing is rare following low-sentiment months since optimistic investors are not constrained to taking long positions. Similarly, Yu and Yuan (2011) find that the mean-variance relation is obscured following high-sentiment periods because sentiment traders are unable to sell short. Antoniou et al. (2015) argue that risky assets, measured by market beta, are overpriced following high-sentiment periods by sentiment-driven investors, but not following low-sentiment periods when these sentiment-driven investors stay on the sidelines. Moreover, Shen et al. (2017) and Avramov et al. (2020) document a similar asymmetric pricing effect for periods following high- and low-sentiment.

In this study, we consider that both rational and sentiment-driven investors exist in a market where aggregate investor sentiment fluctuates. Following high-sentiment periods, sentiment-driven traders are aggregately optimistic about the future state of the economy. They drive asset prices above fundamental values by purchasing risky assets when aggregate sentiment is high. Since short-sale constraints significantly limit the ability of rational investors to correct overpricing (Jones and Lamont, 2002; Nagel, 2005; Hong and Sraer, 2016), assets remain overpriced relative to fundamental values particularly following high-sentiment periods. However, following low-sentiment periods, sentiment-driven investors are aggregately pessimistic but limited by short-sale constraints, whereas rational investors are not limited in their ability to correct underpricing. Thus, following low-sentiment periods, underpricing is less likely, and prices more closely reflect fundamental values. In other words, the risk-return tradeoff is more prominent following low-sentiment periods. Therefore, consistent with prior literature (e.g., Stambaugh et al., 2012), we expect that the relationship between sentiment beta and expected cross-sectional stock returns will hold when sentiment is low and prices more likely reflect fundamental value, but will be obscured by mispricing following high-sentiment periods. In Section 2.4, we find that the positive relationship between sentiment beta and expected returns holds following low-sentiment months but not following high-sentiment months. Overall, our empirical findings show an asymmetry in the sentiment beta effect conditional on aggregate investor sentiment, consistent with the presence of short-sale constraints.

While short-sale constraints may not bind for all assets, some stocks may be easier to borrow and cost less to short. For these stocks that are easier to short and thus less likely to be overvalued, we expect the relationship between sentiment beta and returns to hold in all periods regardless of aggregate sentiment level. When market sentiment is high, stocks less subject to short-sale constraints are less likely to remain overpriced because arbitrageurs can correct overpricing by shorting. We provide evidence that the relationship between sentiment beta and returns is obscured for short-sale constrained stocks in Section 2.5.

2.3 Data

2.3.1 Sentiment beta

Given that market sentiment has a short-term effect on asset prices (Brown and Cliff, 2004), we use the FEARS index, which is available at a daily frequency, to measure sentiment.[5] The FEARS index is constructed using the internet search behavior of households (Da et al., 2015).[6] Since FEARS measures negative market sentiment, we measure market sentiment by multiplying the FEARS index by -1 (Chen et al., 2021).

Using daily market sentiment data, we classify each month as a high-, medium-, or low-sentiment month by using the median value of daily sentiment. Using the median instead of the mean level of sentiment avoids the impact of outliers, which may unduly influence the results.[7] Figure 2.1 plots the time series of monthly sentiment (i.e., the median of the daily FEARS index for each month, multiplied by -1). It is interesting to note that monthly sentiment is low during the 2008 global financial crisis. Moreover, market sentiment level was also low in November 2006,

[5] The FEARS index is more appropriate for our study rather than the Baker-Wurgler market sentiment index. This is because the latter index is available in monthly frequency that requires using rolling window data to estimate a monthly sentiment beta which leads to high persistence. On the other hand, the FEARS index is available in daily frequency that allows to estimate a sentiment beta for each month using daily data and avoiding issues related to autocorrelation. Since the FEARS index is available starting 2004, a shorter sample period relative to that of Baker-Wurgler (which starts in 1965), we address the shorter sample concern by including the latter index in our robustness tests.

[6] The daily FEARS index data for the period from July 2004 to December 2011 is obtained from Joseph Engelberg's website. The FEARS data from January 2012 to December 2016 was generously shared by Zhi Da. We extend the data to December 31, 2018 using the methodology outlined in Da et al. (2015). Please refer to Da et al. (2015) for further details on the construction of the FEARS index.

[7] Our results remain qualitatively the same when using the mean or the aggregate value of daily sentiment as the measure of monthly sentiment.

October 2012, and December 2016, which correspond to the U.S. housing bubble burst (2006) and the US presidential elections in late 2012 and 2016.

We calculate the correlation between monthly sentiment, changes in the monthly Baker and Wurgler (2006) sentiment index, and changes in the monthly University of Michigan Consumer Sentiment Index (UMCSI). Taking first-order differences for both the Baker and Wurgler (2006) sentiment index and the UMCSI mitigates concerns of non-stationarity for these sentiment measures. We find that monthly sentiment calculated using the FEARS index is significantly correlated with the change in monthly UMCSI at a 1% level (p=0.006) with the correlation of 0.2226, but is not correlated with the Baker and Wurgler (2006) measure.

[Insert Figure 2.1 Here]

We classify month *t* as a low (high) sentiment month when the median sentiment in month *t-1* is lower (higher) than the average of the median monthly sentiment across all months in our sample minus (plus) 0.5 of a full-sample standard deviation.[8] As reported in Panel A of Table 2.1, we have 486,100 firm-month observations over 173 months. The majority of these observations are within 0.5 standard deviation of the median level of sentiment and are thus classified as medium-sentiment months. Out of 173 months, 40 months are classified as low-sentiment months, 44 as high-sentiment months, and 89 as medium-sentiment months. Our portfolio analysis results are robust when classifying low-, medium-, and high-sentiment months using one standard deviation above and below the median; these results are provided in the Appendix.

Stock market data are extracted from CRSP, and accounting data are obtained from Compustat. We include stocks listed on the NYSE, NASDAQ, and AMEX in our sample and exclude stocks with a share price higher than $1,000 or lower than $5 at the end of each month

[8] We also ensure that using 30%/40%/30% breakpoints to define high-, medium-, or low-market sentiment months does not change results. See results in Table 2A.4 in the Internet Appendix.

(Pastor and Stambaugh, 2003). Stocks in the financial and utility sectors (CRSP SIC code ranges from 6000 to 6999 and from 4000 to 4999) are also excluded. We use daily and monthly common risk factors, such as market (MKT), size (SMB), value (HML), and momentum (MOM), from Professor Kenneth French's online data library.

[Insert Table 2.1 Here]

We report stock-level summary statistics for market beta, firm size, book-to-market ratio, momentum, and Amihud's (2002) illiquidity measure for the full sample period in Panel B of Table 2.1. These numbers are consistent with the literature. Panel C presents the mean, standard deviation, skewness, kurtosis, and a set of percentile breakpoints for market sentiment for the full sample, as well as for low-, medium-, and high-sentiment months. The averages of monthly median market sentiment are -0.002, -0.076, 0.001, and 0.062 for the full sample as well as low-, medium-, and high-sentiment months, respectively.

[Insert Table 2.2 Here]

Table 2.2 reports contemporaneous correlations between daily market sentiment, stock-market excess returns, and the common risk factors SMB, HML, and MOM for full sample (Panel A), low-sentiment months (Panel B), medium-sentiment months (Panel C), and high-sentiment months (Panel D). We find that daily market sentiment is positively correlated with excess market returns in all of these samples. The correlation coefficient is 0.106 (p-value=0.00) for full sample. This is consistent with sentiment-driven investors buying assets when market sentiment is high, generating positive contemporaneous market returns (Baker and Wurgler, 2007). For the full sample and low-sentiment months (Panels A and B), market sentiment is negatively correlated with the momentum factor, indicating that stocks with poor past performance have higher returns when market sentiment is high. As shown in Table 2.2, market sentiment is not significantly correlated with common risk factors, with the exception of the market and momentum factors.

To determine whether market sentiment can explain cross-sectional stock returns, we use a regression model, which includes the market factor and the aggregate sentiment index (Ang et al., 2006; Gao, Lu, Song, and Yan, 2019):

$$r_t^i = \alpha^i + \beta_{MKT}^i MKT_t + \beta_{Sent}^i Sent_t + \varepsilon_t^i, \tag{1}$$

where r_t^i is the excess return of stock i on day t and MKT_t is the contemporaneous daily market excess return. $Sent_t$ is the sentiment index on day t. β_{MKT}^i and β_{Sent}^i are the loadings on the market factor and sentiment index for stock i, respectively. Following Ang et al. (2006), stocks must have at least 17 daily return observations in a certain month to be included in the sample. For each month, we estimate the sentiment beta, β_{Sent}^i, using model (1) for each stock in our sample. The sentiment beta assigned to any particular month is estimated using data from the previous month. We then rank stocks into quintiles using the estimated sentiment beta such that stocks in the lowest quintile have the lowest sentiment loadings over the previous month, while stocks in the highest quintile have the highest sentiment loadings over the previous month. Our empirical findings are robust when controlling for additional risk factors (size, value, and momentum) when estimating sentiment beta. We discuss these results in Section 2.4.4.7.

2.3.2 Additional data

Throughout our empirical analysis, we control for a number of firm characteristics. At the end of each month, the size of firm i is computed as the product of the stock price and the number of outstanding shares. The book-to-market ratio of firm i is computed as the book value of the shareholder equity of firm i at the end of the most recent June, divided by current firm size. The momentum of each stock at month t is estimated using the cumulative return from month t-12 to t-2 to avoid short-term reversal effects. Following Amihud (2002), we compute illiquidity (ILLIQ) for stock i in month t as the ratio of the absolute raw stock return to the daily dollar amount trading volume averaged within a month, scaled by 10^6:

$$ILLIQ_{i,t} = Avg\left[\frac{|R_{i,d}|}{VOLD_{i,d}}\right] * 10^6, \tag{2}$$

where $|R_{i,d}|$ and $VOLD_{i,d}$ represent the absolute raw return and dollar amount of the trading volume of stock i on day d. Following Diether et al. (2002), we use data from I/B/E/S and measure stock-level disagreement as the standard deviation of analyst forecasts of one-year ahead earning-per-share (EPS) in the most recent month, scaled by the absolute value of the mean forecast in the previous month.

2.4. Empirical Results

First, we empirically show that when individual stocks are sorted by sentiment beta, stocks with higher sentiment betas have higher average expected returns in low-sentiment periods; however, we show that this relation does not hold following medium- or high-sentiment months, or in the full sample. We also use a bivariate portfolio sort to show that the return predictability of sentiment beta in low-sentiment periods is robust when controlling for well-known stock characteristics. Second, using portfolios that are double-sorted by size and sentiment beta, sentiment beta explains cross-sectional asset returns following low market sentiment periods. Third, we find that sentiment beta is priced using stock-level Fama-MacBeth regressions following low-sentiment periods. Fourth, we find that the portfolio-level Fama-MacBeth regression results hold after controlling for conventional risk factors (i.e., SMB, HML, and momentum). Lastly, we conduct additional robustness tests of our results.

2.4.1 Portfolio analysis

Panel A of Table 2.3 reports univariate sort results for equal-weighted quintile portfolios for the full sample period, as well as for low-, medium-, and high-sentiment months. Column (1) reports results for univariate sorts on sentiment beta for the full sample and shows no clear relation between beta-sorted portfolio returns and sentiment beta. Column (2) shows that higher sentiment beta stocks tend to have higher average excess returns following low-sentiment months. The highest sentiment beta portfolio generates an average monthly excess return of 1.49%, while the lowest sentiment beta quintile generates a 0.76% average monthly excess return. The return spread, calculated as the average time series difference between the return of the highest and lowest beta portfolios, is 0.74% (or 8.88% per annum) following low-sentiment months, and is economically large and statistically significant at the 5% level (t = 2.21). In columns (3) and (4) of Panel A, we report the univariate portfolio sorts following medium- and high-sentiment periods, respectively. The return spread between the highest and lowest sentiment beta portfolios is -0.16% following high-sentiment months but is not statistically significant. Similar to the results in the full sample period, there is no significant relation between portfolio return and sentiment beta following medium-sentiment periods.

[Insert Table 2.3 Here]

Though we observe that the return spread between the highest and lowest sentiment beta portfolios is statistically significant following low-sentiment months, it is possible that this effect can be explained by common risk factors. To mitigate this concern, we report risk-adjusted returns (alphas) for the long-short sentiment beta portfolio. Specifically, we construct a long-short portfolio by taking a long position in the high-sentiment-beta portfolio and a short position in the low-sentiment-beta portfolio. We then run time-series regressions of the long-short portfolio returns on common risk factors to estimate alphas. The rows labeled *CAPM Alpha, FF3 Alpha, and FF4 Alpha* in Panel A of Table 2.3 report alphas estimated using the CAPM, the Fama-French three-factor (FF3) model, and the Fama-French-Carhart four-factor (FF4) model, respectively. For example, in the column (2), we find that the CAPM alpha is 0.606% per month (7.272% per annum) following low-sentiment months and significant at the 5% level (t=2.25). This confirms that the positive relationship between sentiment beta and returns following low-sentiment months cannot be explained by market factor. Similarly in rows labeled *FF3 Alpha* and *FF4 Alpha* in the column (2), we show that neither the FF3 nor the FF4 models can explain the sentiment beta-returns relationship following low-sentiment months. Overall, our results suggest that sentiment beta is priced following low-sentiment periods but not following medium- or high-sentiment periods, and this effect is not captured by common risk factors.

In Section 2.2.2 above, we proposed a risk-based explanation whereby stocks with high sentiment betas are riskier because they exhibit larger exposures to sentiment than stocks with low sentiment betas. However, it is possible that the relationship between sentiment beta and long-short portfolio returns following low-sentiment months is due to known predictors of cross-sectional asset returns. We use bivariate portfolio sorts to determine whether commonly known return predictors, including market beta, size, book-to-market ratio, momentum, liquidity, and disagreement can explain the positive relation between returns and sentiment beta following low-sentiment periods. The results from bivariate portfolio sorts are reported in Panels B and C in Table 2.3 for the full sample, as well as for low-, medium-, and high-sentiment months, respectively. Using firm size as an example, we first sort stocks into quintiles based on their sizes at the end of each month, and subsequently sort stocks by sentiment beta into five portfolios within each size quintile. These portfolios are equally weighted and rebalanced at the end of every month. After forming 25 size and sentiment-beta portfolios, the five sentiment-beta quintile portfolios over each size quintile are aggregated to form five sentiment-beta portfolios. Thus, stocks in each bivariate sentiment beta quintile have relatively similar sizes, effectively removing the size effect from the relationship between sentiment beta and returns.

Results for the full sample as well as low-, medium- and high-sentiment months are shown in Panels B through E of Table 2.3, respectively. In each Panel, we report bivariate sentiment-beta results controlling for multiple firm characteristics in columns (1) through (6). For example, column (1) in Panel C shows that the lowest (highest) sentiment-beta portfolio has an excess return of 0.73% (1.27%) per month following low-sentiment months, controlling for market beta. The return spread between these two extreme quintiles is 0.54% and is significant at the 5% level (t = 2.21). We also report risk-adjusted returns (alpha) estimated using the CAPM, FF3, and FF4 models as well as their significance levels. For instance, in column (1) of Panel C, the row labeled *FF3 Alpha* reports a 0.52% per month (6.24% per annum) alpha using the FF3 model, which is significant at the 5% level. These results indicate that following low-sentiment months for firms with similar market betas, higher sentiment-beta stocks generate higher expected returns. In Panels B, D, and E, we find that the return spreads are insignificant in the full sample, as well as following periods of medium and high sentiment; this is consistent with our univariate portfolio results.

To control for firm size, columns (2) of Panels B through E report mean equally-weighted monthly portfolio excess returns double-sorted by size and sentiment beta in the full sample, as well as following low-, medium-, and high-sentiment months, respectively. After controlling for size, the highest sentiment-beta quintile portfolio continues to have higher excess returns (0.79%) relative to the lowest sentiment-beta portfolio (1.41%) following low-sentiment months (column

(2) of Panel C). The difference between these two extreme portfolios (high-low) is 0.62% per month and is significant at the 5% level (t = 2.23). Further, the return spread following low-sentiment months is not explained by the CAPM, FF3, and FF4 models since alphas estimated using these models remain significantly positive. Consistent with earlier results, column (2) in Panels B, D, and E show that return spreads remain insignificant in the full sample as well as following high- and medium-sentiment months when controlling for firm size.

In Table 2.3, we also report bivariate portfolio sort results controlling for book-to-market ratio, momentum, disagreement, and liquidity. We find that the results are generally similar; the return spreads are large and significant after controlling for each of these return predictors following low-sentiment months, while they are insignificant following high- and medium-sentiment months.

2.4.2 Fama-MacBeth regressions

We showed in Section 2.4.1 that market sentiment is priced in the cross-section of stock returns when market sentiment is low. In this section, we verify the pricing power of sentiment beta at the portfolio level. Each month, individual stocks are independently double-sorted by their market capitalization and sentiment beta into 25 equally weighted portfolios. The test portfolios are rebalanced at the end of each month. We implement Fama-MacBeth (1973) two-stage regression methodology and estimate a factor loading for each factor. We then run cross-sectional regressions of portfolio excess returns on factor loadings. More formally, first, for test asset i (i=1, 2, … 25), we run a time series model to estimate a monthly factor loading for each factor f:

$$r_{i,t}^{e} = \alpha_i + \beta_{i,f}' \boldsymbol{f}_t + \epsilon_{i,t}, \tag{3}$$

where $\boldsymbol{f}$ is a vector of risk factors, and $\hat{\beta}'_{i,f}$ is a transposed vector of factor loadings. To estimate the cross-sectional price of factors, we then estimate the following cross-sectional regression each month, regressing the excess return of test assets on factor loadings:

$$r^e_{i,t} = a_t + \hat{\beta}'_{i,f}\lambda_{f,t} + \varepsilon_t, \tag{4}$$

where the mean value of λ_f can be interpreted as the risk premium for each factor in the vector $\boldsymbol{f}$.

[Insert Table 2.4 Here]

Table 2.4 reports average risk premiums estimated using the two-stage regression described above where we treat sentiment as a risk factor along with other conventional risk factors, including market, size, value, and momentum factors. Panel A shows that the average portfolio sentiment-beta risk premium is economically large and statistically significant at the 5% level following low-sentiment periods using different factor models. The first column of Panel A reports that market sentiment is priced using 25 test portfolios following low-sentiment months. The average time-series sentiment-beta coefficient is 0.781 (t = 2.86), which is significant at the 1% level. As shown in columns (2) to (4), sentiment beta remains positively priced when adjusting for risk using the CAPM model, the Fama-French three-factor model (FF3), and the Fama-French-Carhart four-factor model (FF4). Consistent with our intuition, we find that the sentiment beta effect is insignificant following medium- or high-sentiment months in Panels B and C.

For example, we first estimate the exposures (betas) of 25 test assets to the Fama-French three factors and market sentiment in the time series, and then run a cross-sectional regression of monthly portfolio excess returns on factor and sentiment loadings. We report the time-series average coefficients on factor and sentiment exposures in column (3) of each panel. Column (3) of Panel A shows that following low-sentiment periods, the average sentiment beta coefficient is 0.955 (t = 2.39). The results of the same test for medium- and high-sentiment months can be found in Panels B and C, respectively. In general, we show that consistent with our previous results, sentiment is priced following low-sentiment month (Panel A) but is not priced following medium- and high-sentiment months (Panels B and C). We further show that the result in this section is robust to using additional test assets, including size and B/M sorted portfolios. We report results in Table 2A.1 in the Appendix.

2.4.3 Stock-level cross-sectional regressions

We have shown that sentiment beta is a strong and robust determinant of cross-sectional returns following low-sentiment months using sentiment beta-sorted portfolios. However, it is possible that portfolio sorts result in a loss of information through aggregation. Thus, in this section, we examine the cross-sectional relation between monthly sentiment beta and future individual stock returns using Fama and MacBeth (1973) regressions.

First, we regress the excess returns of individual stocks on their corresponding sentiment betas and lagged firm characteristics in each month. Next, we determine whether the time-series average of the slope coefficients of sentiment beta and other variables is significant. Monthly regressions are estimated using the following model:

$$r_t^i = \delta_t + \lambda_{Sent,t}\beta_{Sent}^i + \lambda_t \boldsymbol{X}_t^i + \varepsilon_{t+1}^i, \tag{5}$$

where r_t^i is the realized excess return of stock *i* in month *t*, β_{Sent}^i is the sentiment beta of stock *i* in month *t*, and $\boldsymbol{X}_t^i$ is a matrix of lagged firm characteristics of stock *i* in month *t-1*, including market beta, the log of firm size, book-to-market ratio, momentum, disagreement, and illiquidity.

[Insert Table 2.5 Here]

Panels A-D of Table 2.5 report the time-series average of $\lambda_{Sent,t}$ for the full sample, as well as for low-, medium-, and high-sentiment months, respectively. Column (1) in Panel B shows that when market sentiment is low, the average slope from the monthly regressions of realized stock return on sentiment beta is 0.109 (t = 2.61); this suggests a significantly positive relationship between individual stock returns and sentiment beta, consistent with a higher sentiment beta being associated with higher risk. Columns (2) through (7) of Panel B show that the coefficient estimate on sentiment beta remains positive and significant after successively controlling for market beta (β_{MKT}), the log of firm size, book-to-market ratio, momentum, disagreement, and illiquidity, respectively. In column (8), when controlling for all these firm characteristics, the coefficient estimate on sentiment beta becomes weakly significant, displaying a robust predictability of sentiment beta on the excess returns of individual stocks following low-sentiment months. We also report the results for the full sample as well as for medium- and high-sentiment months in Panels A, C, and D, respectively. We find that sentiment beta is not priced in the full sample, nor is it priced following medium- or high-sentiment periods.

2.4.4 Robustness tests

2.4.4.1 Additional test assets

In this section, we verify the robustness of our results using additional test assets including 10 size-sorted portfolios, 10 book-to-market sorted portfolios, 25 size and book-to-market double-sorted portfolios, and 25 size and momentum double-sorted portfolios. In addition, since Lewellen, Nagel, and Shanken (2011) argue that size and book-to-market double-sorted portfolios cannot be used to test the SMB and HML factors, we also use 25 univariate sentiment beta-sorted portfolios plus 30 industry portfolios.[9] All test portfolios are equally weighted. The results are reported in Table 2A.1 of the Appendix.

[9] We obtain daily portfolio return data from Kenneth French's online data library for portfolios sorted by firm characteristics used in this section and calculate the daily return for the 25 sentiment-beta sorted portfolios.

Panel A of Table 2A.1 shows that following low-sentiment months, consistent with our results in Table 2.4, sentiment is priced in the cross-section of asset returns and generates an economically large and statistically significant premium for assets with higher exposures to sentiment. For example, column (1) of Panel A shows that following months of low sentiment, the average coefficients of sentiment beta of 10 size-sorted portfolios of sentiment beta are 1.879 (t = 2.10). Further, columns (2) through (5) of Panel A show that the positive sentiment beta-return relation following low-sentiment months remains significant and robust when using various test assets. However, Panels B and C show that sentiment is not priced following high- and medium-sentiment months for all test assets. In an unreported table, we observe that the positive relationship between sentiment beta and cross-sectional stock returns is stronger in equal-weighted portfolios than in value-weighted portfolios, suggesting that larger firms are less affected by market sentiment.

2.4.4.2 Orthogonalized sentiment index

Da et al. (2015) construct FEARS using the 30 words with search volumes most negatively correlated with the market return. Thus, the FEARS index may be mechanically correlated with the market index. This raises the concern that the explanatory power of sentiment beta on cross-sectional asset returns stems from the correlation between FEARS and market returns. To examine whether this is the case, we create an alternative sentiment index by orthogonalizing FEARS index to market returns and short-term interest rates. Specifically, we run a time-series regression of daily market sentiment on market returns and short-term interest rates, then use the residual term of this regression as an orthogonalized sentiment index. We then use model (1) to estimate individual stock loadings on orthogonalized sentiment index. Table 2A.2 of the Appendix reports quintile portfolio returns sorted by stock-level loadings on orthogonalized sentiment index. Column (2) shows that following low-sentiment months, the monthly return spread between the lowest and highest orthogonalized sentiment beta portfolios is 0.84% and is significant at the 5% level (t=2.04). However, the return spread is insignificant for the full sample, as well as for medium-, and high-sentiment periods.

2.4.4.3 Baker and Wurgler sentiment index

To ensure that our results are not unique to using the FEARS index to measure sentiment, we confirm that our results remain unchanged when using the Baker and Wurgler (2006) monthly index to measure sentiment. We estimate stock-level sentiment beta using the monthly Baker and Wurgler (2007) sentiment change index, as done in Chen et al. (2021). The index is the first principal component of the first-order differences in sentiment indicators. Specifically, we estimate each stock's Baker-Wurgler (BW) sentiment change index beta using 36-month rolling-window regressions controlling for contemporaneous market return. We classify month *t* as a low (high) sentiment month when the sentiment in month *t-1* is lower (higher) than the mean value of the monthly sentiment in the full sample minus (plus) 0.5 of a full-sample standard deviation. The sample from July 1965 to December 2018 includes 606 months in total. Overall, 153 months, 289 months, and 164 months are classified as low-, medium-, and high-sentiment months, respectively. In Table 2A.3 of the Internet Appendix, we report quintile portfolio returns sorted by each stock's BW sentiment beta. Consistent with our earlier results, we find that following low-sentiment months, the lowest BW sentiment-beta quintile portfolio has an equal-weighted return of 1.243%, while the highest BW sentiment beta quintile portfolio has a return of 1.892%; a return spread of 0.649% (t = 2.72). The return spread is weakly significant in the full sample (t=1.89) as shown in column (1). Also consistent with our earlier results, the relationship between BW sentiment betas and returns does not hold following medium- or high-sentiment months.

2.4.4.4 Alternative classifications of low-, medium-, and high-sentiment months

We use the mean (instead of the median) level of daily sentiment each month and conduct the univariate portfolio analysis following the same method as in Section 2.4.1. We demonstrate that our results are robust to classifying low- (high-) sentiment months using the sample average minus (plus) one sample standard deviation (instead of 0.5 standard deviation). We also use 30%/40%/30% breakpoints to define high-, medium-, and low-market sentiment months. Table 2A.4 of the Internet Appendix shows that the results are qualitatively the same as those shown in Table 2.3.

2.4.4.5 Sum betas

Since Google search volume index data are updated at midnight each day, FEARS is effectively measured over a calendar day. However, the returns in our sample are measured from close to close, giving rise to a non-synchronicity issue whereby FEARS may reflect after-trading-hours sentiment and daily stock returns may be affected by lagged daily sentiment. To address this concern, we follow the sum-beta methodology in Fama and French (1992) and run a monthly stock-level time series regression as follows:

$$r_t^i = \alpha^i + \beta_{MKT,t}^i MKT_t + \beta_{Sent,t}^i Sent_t + \beta_{Sent,t-1}^i Sent_{t-1} + \varepsilon_t^i, \tag{6}$$

where r_t^i is the excess stock return, and the sum beta is estimated as the sum of the sentiment beta and lagged sentiment beta, $\beta_{Sent,t}^i$ and $\beta_{Sent,t-1}^i$. Table 2A.5 of the Appendix reports the results from sorting stocks into portfolios using their sum beta instead of $\beta_{Sent,t}^i$. We find that when market sentiment is low, the long-short return spread is 0.765% (t = 2.47), indicating that our results are robust when using a sum-beta methodology.

2.4.4.6 Small stocks

Firms with smaller market caps may be more prone to sentiment, relative to large-cap stocks with high institutional ownership (Baker and Wurgler, 2006). To ensure our results are not driven by the smallest stocks, we verify that our results using univariate portfolio sorts are unchanged when eliminating from our sample the 20% of stocks with the smallest market value at the end of the previous month. We continue to find a significantly positive relationship between sentiment beta and returns following low-sentiment months for the 80% of stocks in our sample with the largest market caps.

To further ensure that our results are not driven by firm size, we rank stocks into quintiles by sentiment beta; we then randomly assign each stock the market value of another stock in the same quintile and use these randomly assigned weights to calculate portfolio returns. We find that our results using sentiment-beta univariate portfolio sorts remain unchanged when using randomly assigned portfolio weights that neutralize the effect of firm size. The results are reported in Table 2A.6 of the Appendix.

2.4.4.7 Additional factors in sentiment beta estimation

Currently, stock-level sentiment beta is estimated using regression (1) which only controls for the market factor. In this section, we show that our results are robust to controlling for additional factors in the sentiment beta estimation, including size (SMB), value (HML), and momentum (UMD) factors. The two alternative models are specified as follows:

$$r_t^i = \alpha^i + \beta_{Sent}^i Sent_t + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \varepsilon_t^i, \quad (7)$$

$$r_t^i = \alpha^i + \beta_{Sent}^i Sent_t + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \beta_{UMD}^i UMD_t + \varepsilon_t^i, \quad (8)$$

where β_{SMB}^i, β_{HML}^i, and β_{UMD}^i are monthly exposures of stocks to the SMB, HML, and UMD factors. In unreported results, we find that sentiment betas in the main analysis and the sentiment betas estimated when controlling for additional factors are highly correlated. Specifically, we find that average correlations are 82.6% and significant (t=20.03). In Table 2A.7 of the Appendix, we report results that rank stocks into quintiles using sentiment betas estimated from regressions (7) and (8). These finding suggests that controlling for more factors in beta estimation does not alter our results.

2.4.4.8 Additional firm characteristics in bivariate portfolio analysis

Using the bivariate portfolio analysis described in section 2.4.1, we have demonstrated that the sentiment beta effect is robust after controlling for a number of firm variables. In this test, however, more firm-level variables can be controlled. Since both investor sentiment and disagreement reflect investor beliefs about the financial market, it is possible that our investor sentiment beta effect is driven by the disagreement beta effect (e.g., Gao et al., 2018). In addition, as established in the literature (e.g., Hou, Xue, and Zhang, 2015), profitability is a well-known anomaly that may drive the sentiment beta effect. In Table 2A.8, we further apply bivariate portfolio analysis on sentiment beta after controlling for stock level-disagreement beta, profitability (ROE), and industry. Overall, these results indicate that our findings are not driven by these cross-sectional effects.

2.4.4.9 Look Ahead Bias

Since we classify monthly sentiment levels using the average and standard deviation of monthly sentiment in the full sample, there is a possibility that our results are subject to a "look ahead" bias. In this subsection, we apply a 36-month rolling window to classify a month as a low-, medium-, or high-sentiment month using previous observations. Specifically, month *t* is defined as a low (high) sentiment month when the median sentiment in month *t*-1 is lower (higher) than the average of the median monthly sentiment of the last 36 months minus (plus) a 0.5 standard deviation of the median monthly sentiment of the last 36 months. We present the findings of a univariate portfolio analysis in Table 2A.9 of the Appendix. The results in column (2) indicate that our findings are not skewed by the "look ahead" bias and are robust with respect to the method for categorizing months with low-, medium-, and high-sentiment.

2.5 Short-Sale Constraints and Asymmetric Pricing of Sentiment Beta

Finally, we provide evidence that short-sale constraints may indeed play a role in obscuring the relationship between sentiment beta and returns following medium- and high-sentiment months. To address this issue, we test whether sentiment is priced differently in high versus low short-sale constrained stocks using institutional ownership as a proxy for short-sale constraints (Nagel, 2005). Short-sale constraints are more likely to be prominent for stocks with low institutional holdings since the loan supply of these stocks tends to be sparse, making them expensive to borrow and short sell (D'Avolio, 2002; Nagel, 2005; Hirshleifer, Teoh, and Yu, 2011; Stambaugh et al., 2015). Thus, we expect a significant relationship between sentiment betas and expected returns among stocks with high institutional ownership that are more easily shorted, but no pricing effect of sentiment beta for low institutional ownership stocks that are more short-sale constrained.

Using stock-level institutional ownership data from Thompson Reuters, we construct stock-level institutional ownership as the sum of the holdings of all available institutions. Since this data is self-reported by financial institutions, we follow Nagel (2005) and exclude small-cap stocks below the 20^{th} NYSE size percentile. We further winsorize stock-level institutional ownership by replacing values higher (lower) than 99^{th} (1^{st}) percentile with the value of institutional ownership at the 99^{th} (1^{st}) percentile. Since institutional ownership is bounded by 0 and 1 while other variables in our analyses are not, we perform a logit transformation of stock-level institutional ownership as follows:

$$Logit(Institutional\ Ownership) = log\left(\frac{Institutional\ Ownership}{1 - Institutional\ Ownership}\right). \tag{9}$$

Next, we orthogonalize the logit-transformed institutional ownership to the natural log of firm size and the natural log of book-to-market ratio since both are correlated with institutional ownership. We use the residual from this regression, which we call the stock-level residual institutional ownership (RIO), to measure institutional ownership (Nagel, 2005).[10]

[Insert Table 2.6 Here]

Following the methodology in Nagel (2005) and Stambaugh et al. (2015), at the end of each month, we use NYSE breakpoints to independently double-sort stocks by RIO and sentiment beta into 25 portfolios using the full sample. Panel A of Table 2.6 reports equal-weighted portfolio returns for these 25 portfolios, as well as the return spread between extreme sentiment-beta portfolios for each RIO quintile. Sentiment beta is significantly related to expected returns only in the highest RIO quintile with a return spread of 0.434% per month (t = 2.02); this return spread remains significant after adjusting for risk using the CAPM, FF3, and FF4 models. However, we

[10] This methodology is also used in Stambaugh, Yu, and Yuan (2015) and similar to that used in Hong, Lim, and Stein (2000) and Diether et al. (2002) to estimate residual analyst coverage.

do not observe a significant relationship between sentiment beta and returns in the four quintile portfolios with lower RIO, which are thus more likely subject to short-sale constraints.

Further, we analyze the effect of short-sale constraints on the relationship between sentiment beta and expected stock returns following low-, medium-, and high-sentiment months. We conjecture that the relation between sentiment beta and return is significant in the highest RIO quintile when market sentiment is low, while it is obscured following medium- and high-sentiment months. Further, we expect this pattern to be weak in low-RIO quintiles where short-sale constraints are more likely to be binding. We report returns for 25 portfolios double-sorted by RIO and sentiment beta in the full sample, as well as following low-, medium-, and high-sentiment months in Panels A through D of Table 2.7. In Panel B, we find that sentiment beta return spreads in high RIO quintile portfolios are significantly positive following low-sentiment months. For example, the return spread between the two extreme sentiment beta portfolios in the highest RIO quintile following low-sentiment months is 0.982 (t=2.45), and decreases to 0.725 (t=1.30) in the lowest RIO quintile. The results remain unchanged when we estimate risk-adjusted returns using the CAPM, FF3, and FF4. Consistent with our findings in Section 2.4, the return spreads are weakly significant in the full sample and insignificant following medium- and high-sentiment months suggesting that short-sale constraints obscure a positive relation between sentiment beta and expected stock return.

[Insert Table 2.7 Here]

Next, we verify these findings using stock-level Fama-MacBeth cross-sectional regressions. Again, we sort stocks into quintile portfolios using stock-level RIO and estimate monthly regressions for each quintile portfolio by regressing expected stock returns on sentiment beta and control variables including market beta, lagged log of firm size, lagged book-to-market ratio, momentum, disagreement, and illiquidity. The time-series averages of regression coefficients for the full sample are reported in Panel A of Table 2.7. We find that the coefficient estimate for sentiment beta is 0.165 (t = 2.36) and significantly positive in the highest RIO quintile, suggesting that the relationship between sentiment beta and returns holds for stocks that are less short-sale constrained. The coefficient is weakly significant in the fourth-highest RIO quintile (t = 1.79) but insignificant in all other RIO quintiles. These results suggest that short-sale constraints do appear to obscure the relationship between sentiment beta and cross-sectional returns.

Furthermore, we report Fama-MacBeth regression results following low-, medium-, and high-sentiment months in Panels B, C, and D of Table 2.7, respectively. Our empirical findings in this table are consistent with the portfolio analysis results reported in the Table 7. For example, in the highest RIO quintile, the sentiment beta coefficient is significant following low-sentiment months (t=2.14), weakly significant following medium-sentiment months (t=1.89), and insignificant following high-sentiment months (t=-0.60). However, in low-RIO quintiles, the sentiment beta coefficient is significant only following low-sentiment months. For instance, the sentiment beta coefficient in the second-lowest RIO quintile is 0.224 (t=1.98) following low-sentiment months (Panel B), but is insignificant following medium- and high-sentiment months (Panels C and D). Overall, our results suggest an investment strategy for rational investors (with a taste for sentiment risk) to take long positions in high-sentiment beta stocks and short positions in low-sentiment beta stocks following low-sentiment months.

2.6 Conclusion

In this chapter, we test whether the sentiment beta of individual stocks is priced in the cross-section of returns. Consistent with this view, we find that high-sentiment beta stocks generate a 0.74% higher monthly return, on average, relative to low-sentiment beta stocks following low-sentiment months. We show that this relationship cannot be explained by existing factor models and provide evidence for a risk-based explanation. We do not find evidence of this relationship following medium- or high-sentiment months, likely due to short-sale constraints that lead to overpricing following high-sentiment periods and a lack of underpricing in low-sentiment periods when prices more closely reflect the fundamental value. This suggests a tradable and profitable investment strategy for investors following low-sentiment months.

Chapter Three: Yelp Consumption Sentiment and Asset Pricing

3.1 Introduction

Canonical theories in financial economics assume that all investors are fully rational, but recent theoretical and empirical works show that the subjective beliefs of households are biased. Sentiment often serves as a catch-all term to capture distorted beliefs (Kozak, Nagel, and Santosh, 2018; DeVault, Sias, and Starks, 2019). Households with distorted beliefs may be optimistic or pessimistic about future economic states, and this affects their stock selection and aggregate consumption (Bram and Ludvigson, 1998; Ludvigson, 2004). When these subjective beliefs covary across households, sentiment-driven noise trading can cause mispricings when limits to arbitrage exist (e.g., DeLong, Shleifer, Summers, and Waldmann, 1990). In this chapter, we use Yelp restaurant customer reviews to construct a novel sentiment index that captures sentiment associated with consumption. Founded in 2004, Yelp is a leading online platform where consumers can post ratings for businesses that range from one (low) to five (high) stars and in-depth reviews about their experiences. According to the company's financial statements, Yelp has had more than 138.4 million unique visitors, 4.9 million claimed businesses, and 177.4 million reviews, as of June 2019. Our Yelp customer ratings-based sentiment index directly extracts individuals' moods based on their consumption experiences at restaurants of a broad cross-section of consumers over time.

We collect more than eleven million Yelp reviews for restaurants in the twenty most populated U.S. metropolitan areas. We use the number of positive ratings (four or five stars) scaled by the number of negative ratings (one or two stars) to measure consumption sentiment. Since consumers are more likely to give more positive (negative) ratings when sentiment is high (low) (Westbrook, 1981; Szymansky and Henard, 2001; Phillips and Baumgartner, 2002), our measure contains an embedded element of sentiment associated with consumption. Our index is high (low) when customers post more positive (negative) reviews.

The focus of the empirical analyses in this chapter is on examining the relation between consumption sentiment and stock market returns. We find that the consumption sentiment index positively correlates with same-week stock market returns and negatively correlates with next-week stock market returns. We show that a one standard deviation increase in consumption sentiment is associated with a contemporaneous increase in returns of 16.8 basis points (9.15% annualized), which is statistically significant at the 5% level. A one standard deviation increase in consumption sentiment also predicts a 23.2 basis point decrease in stock market returns in the following month, and is significant at the 1% level. These results are consistent with the finding that a change in sentiment induces temporary mispricings, which arbitrageurs will subsequently correct (e.g., Delong et al., 1990; Baker and Wurgler, 2006; Da, Engelberg, and Gao, 2015). Further, the consumption sentiment index predicts a return reversal that is economically larger in high-beta, small, and high-volatility stocks. Since these assets tend to be more difficult to arbitrage, this is also evidence that mispricings correspond to changes in consumption sentiment.

There is a long history of using rating systems to measure customer satisfaction with products and services, and to provide businesses with feedback from their consumers (Westbrook, 1980; Peterson and Wilson, 1992). Churchill and Surprenant (1982) document that customer satisfaction is key to customer ratings and reviews. Reviewers tend to provide more positive (negative) feedback for consumption experiences when their mood is high (low) (Westbrook, 1981; Szymansky and Henard, 2001; Phillips and Baumgartner, 2002). For instance, Westbrook (1981) finds that mood can explain approximately one-third of the variation in customer satisfaction. Assuming that food and service quality is not affected due to changes in the mood of restaurant employees, this quality should not significantly change over a short time period. This is reasonable given that restaurant employees—both cooks and wait staff—do not change at a rate rapid enough to affect the quality of a restaurant.[11] Hence, under this assumption and following the literature, fluctuations in ratings over time represent sentiment changes. It is likely that mood will affect a restaurant's rating through the employee channel, and the quality of both food and service will also fluctuate due to changes in the moods of restaurant employees. However, the customer and employee mood channels will move ratings in the same direction; When sentiment is high (low) customers will be more (less) generous with their rating of a restaurant, independent of the actual quality of food and service, but their rating will be higher (lower) due to the positive (negative) impact of employee moods on quality. Thus, our sentiment index captures changes in both customer and employee moods.

The finance literature suggests that mood is a special case of sentiment (Hirshleifer, Jiang, and DiGiovanni, 2020) and can also serve as its proxy (Baker and Wurgler, 2007). Since the customer behavior literature suggests that customers' ratings can reflect mood, we thus posit that a period of high (low) aggregate ratings on Yelp reflects positive (negative) household sentiment.

We perform several additional tests to ensure that our index captures sentiment. First, the impact of sentiment should be more substantial for retail investors since institutional investors are usually assumed to be sentiment-free (e.g., Da et al., 2015). Since retail investors hold 90% of mutual funds (Brown, Goetzmann, Hiraki, Shiraishi, and Watanabe 2003; Da, et al., 2015), we examine the predictability of consumption sentiment for mutual fund flows. We find that the consumption sentiment index positively correlates with same-week equity fund inflows and bond

[11] According to a report by the U.S. Bureau of Labor Statistics, the job turnover rate in the American restaurant industry was about 72.5% in 2017, which means that a restaurant will entirely replace all its employees every 1.38 years on average. Thus, our assumption that the food quality will not change in the short-run is solid, given that the job turnover rate is not very high from week to week.

fund outflows in the three weeks following. Consistent with a flight to safety, our results suggest that retail investors shift demand from equity to bond funds in low-sentiment months.

Next, we test whether consumption sentiment correlates with market-level risk aversion. Several studies suggest that sentiment should be negatively associated with contemporaneous market-level risk aversion since households are more willing to purchase risky assets when sentiment is high (Tetlock, 2007; Barberis and Huang, 2008; Yu and Yuan, 2011). Consistent with the literature, our consumption sentiment index is negatively associated with contemporaneous market-level risk aversion. This relation supports evidence that investors will buy and hold risky assets in high-sentiment periods.

Third, the literature suggests the effect of negative sentiment (i.e., pessimism) is stronger than positive sentiment (i.e., optimism) since households tend to have a stronger reaction to bad news than to good news due to a negativity bias (e.g., Tetlock, 2007; Da, Engelberg, and Gao, 2015; Hirshleifer et al., 2021). Using the numbers of positive and negative reviews, we decompose consumption sentiment into a positive (optimistic) and a negative (pessimistic) component. We find that negative consumption sentiment is strongly predictive of market returns and reversals, whereas positive sentiment alone cannot predict future returns. Overall, the results of these additional tests suggest that our index measures sentiment.

Our Yelp consumption sentiment index is the first sentiment metric in the literature to separate optimism and pessimism into independent parts. The decomposition enables us to study the impact of each component on the financial market independently, and to corroborate the negativity bias documented in the literature. Theoretically, one can decompose the University of Michigan Consumer Confidence (UMCC) index and the music sentiment index developed by Edmans, Fernandez-Perez, Garel, and Indriawan (2021) into optimism and pessimism components.

To obtain these sentiment index components, one would need access to raw data at a respondent level. However, to the best of our knowledge raw survey data are not readily available and no attempts were made to examine the pricing impact of the separate optimism and pessimism components inherited in these indices. Thus, using our novel sentiment measure, we are the first in the literature to confirm directly that investors react more strongly to negative sentiment than positive sentiment.

Our study contributes to three strands of literature. First, we enrich our current understanding of sentiment by creating a measure that contains an embedded element of sentiment associated with consumption. Recent studies in economics, banking, and marketing have used Yelp reviews to examine household behavior (e.g., Parikh, Behnke, Vorvoreanu, Almanza, and Nelson, 2014; Zukin, Lindeman, and Hurson, 2015; Luca and Zervas, 2016; Nakayama and Wan, 2019; and Lantzy, Hamilton, Chen, and Stewart, 2021). For instance, Huang (2020) shows that businesses with higher Yelp ratings have a greater chance of receiving better loan terms and have better loan performance. To the best of our knowledge, our study is the first in the literature to use Yelp ratings to capture households' consumption sentiment and examine its impact on the financial market.

Second, we contribute to the investor sentiment literature. For over three decades scholars have documented that investors' sentiment can affect assets. For example, De Long et al. (1990) theoretically posit that noise traders' beliefs are unpredictable, and rational investors bear risk when trading against them. Baker and Wurgler (2006) build a novel sentiment index as the first principal component of six market sentiment indicators, including average closed-end fund discount, number of IPOs, average IPO first-day returns, the share of equity issues, and dividend premium. In addition to Baker and Wurgler's index, Da et al. (2015) and Edmans et al. (2021)

construct sentiment measures using the Google search volume index and music content, respectively. We add to this literature by proposing a new measure associated with consumption decisions and show it is associated with stock market returns. In addition, our sentiment measure can be decomposed into optimistic and pessimistic components. In line with the negativity bias (see, Nguyen and Claus, 2013), we show that pessimistic sentiment has a stronger impact on the stock market than optimistic sentiment. To the best of our knowledge, we are the first to provide direct evidence of the negativity bias in the context of comparing the impacts of optimism and pessimism on asset prices.

Third, we advance the stock market prediction literature by showing our index can predict future market returns. Da et al. (2015) propose a measure of investor sentiment based on Google searches and show that it can predict daily stock return reversals. While they find that sentiment-induced mispricing lasts for three days, we find longer term effects. For example, our consumption sentiment index can predict mutual fund flows for up to three weeks after a sentiment change. Huang et al. (2015) create a sentiment index aligned with macroeconomic variables after eliminating noise from the Baker and Wurgler (2006) measure. Overall, we add to the literature by proposing a new consumption sentiment index that is able to predict future stock market returns for up to two weeks.

The rest of this chapter is organized as follows. First, we provide our theoretical motivation and describe the detailed construction of the consumption sentiment index. Second, we discuss financial market data sources. Third, we provide empirical analysis results. Fourth, we show multiple robustness checks. Lastly, we conclude the chapter.

3.2 Data and Consumption Sentiment Index Construction

3.2.1 Consumption Sentiment

Our goal is to construct an index that captures consumption-based sentiment in the U.S. We collect Yelp ratings data for restaurants in the twenty most populated metropolitan statistical areas (MSAs) in the U.S from October 12, 2004, the date of the earliest review, to September 18, 2019. According to demographic data from the U.S. Census Bureau, these twenty MSAs have a combined population of 125,005,928 or approximately 41% of the total U.S. population in 2018. In Panel B of Table 3.1, we report the names of these metropolitan areas. We attempt to collect all ratings for the 1,000 most reviewed restaurants in each of the twenty MSAs from September to November 2019. Our unique dataset includes 19,640 restaurants since some businesses are unavailable to scrape. The most reviewed restaurant nationwide is *Bottega Louie* in Los Angeles, California, with 16,591 reviews as of the data collection date. Though New York City is the most populated MSA, Los Angeles, San Francisco, and San Diego have more Yelp reviews than New York City. Overall, our sample contains 11,232,951 Yelp ratings from January 2007 to September 2019. We do not have unrecommended reviews in our sample since they are not displayed on the Yelp website.[12]

[Insert Table 3.1 Here]

According to its financial reports, the number of reviews on Yelp grows steadily every year.[13] We focus on a period starting in 2007 to ensure that there are sufficient rating data in the analysis.[14] Considering the possibility that households may post a review several days after they

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[12] Yelp uses software to filter out fake reviews (https://www.yelp-support.com/Recommended_Reviews). According to its website, Yelp hides the review if the software detects it is fake or an advertisement. If Yelpers want to see them, they can change their personal settings to render these unrecommended reviews visible. About one-quarter of all reviews are unrecommended.

[13] Yelp's annual financial statements are available on the Security Exchange Committee (SEC) website, at https://sec.report/Document/Search/?search_text=YELP&formType=10-K#results.

[14] This is because we do not have sufficient rating data for the first three years. There are 141, 11,596, and 48,196 ratings observed in 2004, 2005, and 2006, respectively. We find that the weekly sentiment measure is highly volatile in these years due to insufficient data. Hence, our consumption sentiment index starts in 2007.

visited a restaurant, we believe that a sentiment index constructed at a daily frequency does not represent daily household sentiment. Thus, our sentiment measure is at a weekly frequency, which is unique among aggregate measures available in the literature.[15] In order to avoid the day-of-the-week effect, we construct a weekly measure from Wednesday to the following Tuesday, which is consistent with studies analyzing weekly returns in the finance literature (e.g., Chordia and Swaminathan, 2000; Antweiler and Frank, 2004; Hou and Moskowitz, 2005; Gutierrez and Kelley, 2008; Aboody, Even-Tov, Lehavy, and Trueman, 2018; Birru, 2018; Hou, Xue, and Zhang, 2020). Figure 3.1 plots average weekly ratings from January 2007 to September 2019 and shows that average ratings tend to be lower during recessions. To address the non-stationarity of average weekly ratings shown in Figure 3.1, we define weekly consumption sentiment measure at time *t* as follows:

$$ConsumptionSentiment_t = \log\left(\frac{N(Positive)_t}{N(Negative)_t} + 1\right) \tag{10}$$

where $N(Positive)_t$ and $N(Negative)_t$ are the number of positive (i.e., 5-star or 4-star ratings) and number of negative (i.e., 1-star or 2-star) ratings, respectively, in week t.[16] Higher (lower) levels of $Sentiment_t$ correspond to relatively more positive (negative) ratings.

[Insert Figure 3.1 Here]

To construct our final measure of consumption sentiment, we keep the residual of $ConsumptionSentiment_t$ after applying an AR (2) process, a methodology used in Acharya and Pedersen (2005). We then orthogonalize it to monthly and weekly dummy variables to account for

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[15] Sentiment measures in the literature are either at a monthly frequency, such as the Baker and Wurgler index (2006) and University of Michigan consumer confidence index (UMCC) or at a daily frequency, such as the FEARS index (Da et al., 2015) and the music sentiment (Edmans, 2021).

[16] This measure is similar to the construction of the news-sentiment measure in Calomiris and Mamaysky (2019), who define the sentiment in article i as $\frac{N(Positive)_i - N(Negative)_i}{N(All)_i}$, where $N(Positive)_i$ and $N(Negative)_i$ are the numbers of positive and negative words in the article i, and $N(All)_i$ is the total number of words.

seasonality and retain the residual. Panel A of Table 3.1 reports descriptive statistics for weekly consumption sentiment from January 2007 to September 2019.

In Section 3.4, we show that our baseline results are robust to alternative construction methods for consumption sentiment, including taking the log change of consumption instead of using the AR (2) model in equation (10). We also verify that our results are robust to using the subsample of ratings provided on weekdays, the subsample of ratings for cheap restaurants (i.e., one or two dollar-sign ratings out of five), and the subsample of ratings of expensive restaurants (i.e., four or five dollar-sign ratings out of four).[17]

3.2.2 Validation of Consumption Sentiment

Before examining the predictive power of consumption sentiment for stock returns, we validate our consumption sentiment measures using two sets of tests. First, we verify that consumption sentiment correlates with existing sentiment measures, including the UMCC index, the Baker and Wurgler (2006) sentiment index, and two measures based on the FEARS index (Da et al., 2015). The UMCC index is based on over 500 telephone interview surveys conducted monthly by the University of Michigan in the U.S. and is commonly used to measure consumer sentiment (Lemmon and Portnaiguina, 2006; Qiu and Welch, 2006). The Baker and Wurgler (2006) sentiment index is the first principal component of five stock market variables. To avoid non-stationarity, we calculate the growth rates of both the UMCC and the Baker and Wurgler (2006) index. Further, we create two additional monthly measures of the sentiment using the median and mean values of the daily FEARS index in each month, multiplied by -1.

[17] While we do not winsorize or standardize consumption sentiment to avoid look-ahead bias, our main results are unchanged when the index is winsorized and standardized.

Table 3.2 reports the correlations between our consumption sentiment measure (labeled Consumption Sentiment), the growth rate of average monthly ratings on Yelp, and four alternative sentiment measures. Though our main empirical analysis uses a weekly consumption sentiment index, in Table 3.2, we use a monthly consumption sentiment index following equation (10) to examine its correlations to other monthly indices. Overall, we find that the consumption sentiment index is highly correlated with monthly measures based both on the FEARS index and the UMCC index. These correlations suggest that our consumption sentiment index does indeed capture sentiment.

[Insert Table 3.2 Here]

Second, we verify that our consumption sentiment measure is correlated with future consumption growth. We use four measures of consumption from Federal Reserve Economic Data, including monthly personal consumption expenditure, nondurable goods personal consumption expenditure, durable goods personal consumption expenditure, and real personal consumption expenditure.[18] We compute the monthly growth rate for each consumption series to eliminate non-stationarity and deseasonalize by orthogonalizing to monthly dummy variables (e.g., Attanasio and Weber, 1995). Panel B of Table 3.2 shows that our consumption sentiment is significantly correlated with three-month-ahead growth rates for all three consumption measures. Overall, the correlation analyses indicate that our consumption-based index contains information regarding sentiment and consumption.

3.2.3 Financial Market Data

[18] The data are available at https://fred.stlouisfed.org/series/PCE.

We convert daily stock market return data from CRSP to weekly market returns using the value-weighted CRSP market return, the equal-weight CRSP market return, and the S&P 500 index return. We obtain weekly mutual fund flows data from Datastream and weekly ETF data, including SPDR S&P 500 (SPY), PowerShares QQQ Trust (QQQQ), Russell 1000 Index ETF (IWB), and Russell 2000 Index ETF (IWM) from Thompson Reuters Datastream.

Daily aggregate risk aversion data is obtained from Professor Nancy Xu's website (Bekaert et al., 2021).[19] We use the monthly economic policy uncertainty (EPU) index constructed by Baker, Bloom, and Davis (2016) as a control variable.[20] The Aruoba-Diebold-Scotti (ADS) business conditions index, a daily measure of latent business conditions, serves as an additional control variable (Aruoba, Diebold, and Scotti, 2009).[21] The last control variable is the Financial and Economic Attitude Reveal by Search (FEARS) index constructed by Da et al. (2015). FEARS data are available (from Engelberg's website) between July 2004 and December 2016, and we follow Da et al. (2015) to construct the index and extend the sample period to December 2018.

3.1.Empirical Analyses

3.3.1 Consumption Sentiment and Equity Returns

In our main analysis, we examine the relation between consumption sentiment and equity returns. When sentiment is high, sentiment-driven investors may trade based on their distorted beliefs resulting in an increased demand for risky assets that will push prices above fundamental

[19] The data are available at https://www.nancyxu.net/risk-aversion-index.
[20] The data are available at https://www.policyuncertainty.com/us_monthly.html.
[21] This index is estimated using various fundamentals such as real GDP growth, jobless claims, payroll employment, industrial production, personal income, manufacturing sales, and trade sales. The data are available at https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/ads.

values; any mispricings should be followed by a correction. To test this hypothesis, we estimate the following regression:

$$Ret_{t+k} = \alpha + \beta\ ConsumptionSentiment_t + \sum_n \gamma_n Control_t^n + \varepsilon_t \qquad (11)$$

where Ret_{t+k} is the stock market return in week $t+k$, and $ConsumptionSentiment_t$ is consumption sentiment index in week t. Control variables ($Control_t^n$) include weekly market returns at one, two, three, four, and five lags, as well as the weekly VIX index, changes in the weekly EPU index, and changes in the weekly ADS index.[22] These control variables have been shown to predict future stock market returns, and we include them to account for return predictabilities from other indices (e.g., Da et al., 2015 and Da, Hua, Hung, and Peng, 2020). We adjust for Newey-West (1987) time-series autocorrelation in all estimations.

Column (1) in panel A of Table 3.3 shows a positive contemporaneous relation between consumption sentiment and same-week returns for the CRSP value-weighted index. A one standard deviation increase in consumption sentiment is associated with a 17.5 basis points increase in weekly returns (9.52% annualized) and is significant at the 5% level. In column (2), we find a negative relation between consumption sentiment and returns in the following week, indicating a return reversal as a result of temporary, sentiment-induced mispricing. A one standard deviation increase in consumption sentiment predicts a 25.66 basis points return decrease in the following week and is significant at the 1% level (t=-2.80). The magnitude of the negative coefficient in column (2) (-5.941) is greater than the magnitude of the coefficient in the column (1) (4.057), suggesting that the temporary contemporaneous increase in weekly equity prices is entirely reversed in the following week. Consistent with the literature that argues sentiment is a short-term effect (e.g., Brown and Cliff, 2005), we find that consumption sentiment does not

[22] These weekly measures are the weekly averages of the daily VIX, ADS, and EPU indices.

predict equity returns at longer horizons. This result indicates that the impact of consumption sentiment occurs mainly in the first two weeks.

[Insert Table 3.3 Here]

Sentiment should have a more substantial impact on smaller stocks since these assets are difficult to arbitrage (e.g., Baker and Wurgler, 2006). Thus, we expect the relation between the consumption sentiment index and returns for the CRSP equal-weighted index to be stronger than that between sentiment and value-weighted returns. This is because small stocks are overrepresented in the CRSP equal-weighted index. We verify in panel B of Table 3.3 the relation between consumption sentiment and contemporaneous weekly returns is statistically significant with a coefficient of 4.737 (shown in column (1)), which is larger in magnitude than the coefficient reported in panel A (4.057). Column (2) shows that there is also a negative and significant relation between consumption sentiment and next-week returns for the equal-weighted market, but no significant relation in the following weeks. This short-term effect is universal to other asset classes we consider, so we only report results for same-week and next-week returns in other tables. Overall, we have shown that the consumption sentiment index, constructed from online consumer restaurant ratings, is correlated with and predicts equity returns.

Next, we confirm in Table 3.4 that our results are unchanged when using the S&P 500 index and four ETFs that passively track the equity market, including SPDR S&P 500 (NYSE: SPY), PowerShares QQQ Trust (NASDAQ: QQQQ), Russell 1000 Index ETF (NYSE: IWB), and Russell 2000 Index ETF (NYSE: IWM), as additional test assets. Using highly liquid ETFs as test assets ensures highly illiquid assets do not drive our results. Consistent with our baseline results, Table 3.4 shows that the consumption sentiment index has a significantly positive contemporaneous relation with the weekly returns of all five test assets. Furthermore, consumption sentiment negatively predicts next-week returns for each of the test assets. Across the five test assets, the magnitude of the consumption sentiment coefficient on Russell 2000 Index ETF returns appears to be the largest. This is not surprising since it tracks comparatively small stocks relative to other ETFs, and small stocks are more likely affected by sentiment (Baker and Wurgler, 2006).

[Insert Table 3.4 Here]

3.3.2 Consumption Sentiment and Limits to Arbitrage

Limits to arbitrage can exacerbate the effect of sentiment on asset prices and returns (Baker and Wurgler, 2006, 2007). In this section, we verify that the predictability of the sentiment index is stronger for assets that are more difficult to arbitrage, including high-beta, small (Jones and Lamont, 2002), and high return volatility (Wurgler and Zhuravskaya, 2002) stocks.[23] Daily univariate-sorted beta portfolio returns are obtained from CRSP, which we convert to weekly returns, and then construct return spreads between high-beta and low-beta stocks. We obtain size-sorted portfolio returns from Professor French's data. Similarly, volatility-sorted portfolio returns are also obtained from CRSP.

For beta-, size-, and volatility-sorted quintile portfolios, regression (11) is separately conducted to examine the impact of consumption sentiment. Panels A, B, and C of Table 3.5 report beta-, size-, and volatility-sorted quintile portfolio results, respectively. In odd-numbered columns of panel A, we report contemporaneous beta-sorted portfolio returns that are regressed on the sentiment index. From columns (1), (3), (5), (7), and (9), the magnitude of consumption sentiment

[23] Beta is commonly used to proxy for limits to arbitrage in the literature. Brennan (1993) argues that high-beta assets are more difficult to arbitrage due to the agency issues. In the same line as agency issue, Baker, Bradley, and Wurgler (2011) claim that institutional investors are mandated to maximize the Sharpe ratio. As a result, high-beta assets are relatively unattractive to institutional investors and thus difficult to arbitrage. Similarly, Hong and Sraer (2016) build a model that shows high-beta assets are more prone to market disagreement and subject to equilibrium overpricing due to short-sale constraints.

coefficients on portfolio returns monotonically increases from the lowest- to the highest-beta quintile. Comparing regression coefficients across beta quintiles, we find that sentiment has a stronger positive relation with contemporaneous returns in high-beta stocks than in low-beta stocks. The results are similar when using sentiment to predict a return reversal.

[Insert Table 3.5 Here]

Similarly, we find that our conjecture is confirmed in size- and volatility-sorted quintile portfolio results in panels B and C of Table 3.5. In both panels, odd-numbered and even-numbered columns report regression results of quintile portfolio returns on contemporaneous and lagged sentiment, respectively. Overall, these results confirm our conjecture that the sentiment effect is strong in difficult-to-arbitrage (high-beta, small size, and high volatility) assets.

In panel D of Table 3.5, we show that our consumption sentiment index is associated with beta return spreads. We form long-short portfolios by taking a long position in the highest beta quintile and a short position in the lowest beta quintile and calculate the return spread between the two extreme beta portfolios. Next, we regress return spreads on the consumption sentiment index using regression (11). In columns (1) and (2), we report that the consumption sentiment index is positively associated with contemporaneous beta-sorted portfolio return spreads and can significantly predict a reversal. The results are similar for size and volatility spreads, as shown in columns (3) to (6). Overall, our results are consistent with consumption sentiment having a stronger effect on difficult-to-arbitrage stocks.

3.3.3 Consumption Sentiment and Other Financial Market Variables

3.3.3.1 Consumption Sentiment and Aggregate Market Risk Aversion

Sentiment as a distorted belief can reflect a time-varying risk appetite and is orthogonal to macroeconomic news; such a relation has been proposed in Tetlock (2007), Baberis and Huang (2008), and Yu and Yuan (2011). We investigate whether our consumption sentiment is associated with market-aggregate risk aversion by examining whether sentiment can directly affect an aggregate risk appetite. Bekaert et al. (2021) propose a daily market-level risk aversion index constructed using fundamental macroeconomic variables. We take the weekly average of this daily index. Risk aversion is high if the risk-return tradeoff is prominent in the financial market. Bekaert et al. (2021) show that the aggregate risk aversion index negatively correlates with various sentiment measures. Thus, we expect a negative association between consumption sentiment and the aggregate risk aversion index.

We directly examine whether our consumption sentiment index is associated with aggregate risk aversion. The literature suggests that investors' aggregate risk aversion can be persistent. For example, Brandt and Wang (2003) provide two models to generate a time variation of risk aversion. They show that the first-order autocorrelations are about 0.94 to 0.99, so risk aversion can be highly persistent in the time series. Thus, we implement an ARFIMA (1,d,1) framework to investigate the relation between the consumption sentiment index and risk aversion and eliminate concerns related to time-series autocorrelation. Panel A of Table 3.6 reports the results. The rows labeled p and q confirm that the risk aversion index is highly persistent since the AR and MA components are significant at a 1% level. We find that the consumption sentiment index is significantly and negatively associated with risk aversion contemporaneously. It is not surprising that the coefficient estimates on consumption sentiment are not significant starting from the second week because consumers update their beliefs on asset prices. Overall, these results provide evidence that sentiment-driven investors have a higher risk appetite and are willing to bear more risk in periods of high market sentiment.

[Insert Table 3.6 Here]

3.3.3.2 Consumption Sentiment and Mutual Fund Flows

This subsection examines whether our consumption sentiment index can predict mutual fund flows. Da et al. (2015) suggest that retail investors are less risk averse when sentiment is high. Using their FEARS index they show that retail investors switch from bond funds to equity funds when sentiment increases. In this subsection, we provide evidence that our consumption sentiment index is associated with contemporaneous equity mutual fund inflows and is predictive of future outflows from bond mutual funds. Since retail investors hold more than 90% of total mutual fund assets (Brown et al., 2003), these findings are consistent with our consumption sentiment index capturing investor beliefs.

For both equity and bond mutual fund flows, we use a time-series regression. We regress net fund flows on contemporaneous (*k*=0) and consumption sentiment for up to four lags (*k*=1, 2, 3, or 4) using the following model:

$$NetFlow_t = \alpha + \beta\ ConsumptionSent_{t-k} + \sum_n \gamma_n Control_{t-k}^n + \varepsilon_t. \qquad (12)$$

Control variables ($Control_t^n$) include the VIX index return, changes in the EPU, and changes in the ADS. Regression results on equity fund net flows are reported in columns (1) to (4) in panel B of Table 3.6. Our consumption sentiment index is significantly associated with a contemporaneous inflow into equity mutual funds. This finding suggests that U.S. households increase their positions in risky assets when market sentiment is high, consistent with the results in Tetlock (2007) and Da et al. (2015). In columns (5) to (8), we report results of regression (12) on bond mutual fund net flows on lagged consumption sentiment. Interestingly, we find that our sentiment index predicts outflows from bond funds in the following three weeks (k=1, 2, and 3) since the coefficients of consumption sentiment are significant in columns (7), (8), and (9). Combined with the equity fund results, this suggests that investors withdraw from bond funds and invest in equity funds when households have high consumption sentiment; this is consistent with flight-to-safety when sentiment is low.

3.3.4 Disentangling the Optimism and Pessimism Components of Sentiment

The literature finds that pessimism affects asset prices more strongly than optimism (Richey, Koenigs, Richey, and Fortin, 1975; Taylor, 1991). In a wide range of contexts, negative information has a stronger impact than positive information, and this is referred to as a negativity bias in behavioral science (Nguyen and Claus, 2013). In the finance literature, Tetlock (2007) and Da et al. (2015) focus only on pessimism in in the construction of their sentiment measures. However, as far as we know, there is no direct evidence in the literature to confirm that pessimistic sentiment affects the stock market more strongly than optimistic sentiment.[24] Unlike several news-based or search-based sentiment measures that only focus on pessimistic sentiment (e.g., Tetlock, 2007; Da et al., 2015), our consumption sentiment is constructed using a comprehensive index containing information on both optimism and pessimism, which allows us to determine whether optimism, pessimism, or both drive the relation between consumption sentiment and the stock market return.

[24] Tetlock (2007) and Da et al. (2015) show that negative sentiment can predict market returns, but their findings may not indicate whether positive sentiment can predict stock returns. For example, Da et al. creates their sentiment index based on search volume from Google Trends of words signifying negative market sentiment. We perform analyses with both components and find pessimism is the key. Our analysis in this subsection advances the understanding of the rule of sentiment based on the prior literature.

We decompose consumption sentiment into its optimistic and pessimistic sentiment components in week t as follows:

$$Optimism_t = \log\left(\frac{N(Positive)_t}{N(All)_t} + 1\right)$$

$$Pessimism_t = \log\left(\frac{N(Negative)_t}{N(All)_t} + 1\right) \tag{13}$$

where $N(Positive)_t$ and $N(Negative)_t$ represent the numbers of positive and negative reviews at week t, and $N(All)_t$ is the total number of reviews in a certain week. Both optimism and pessimism indices are detrended and deseasonalized weekly like the consumption sentiment index. Notably, the consumption sentiment index in our main results is not standardized due to a concern of look-ahead bias. In this subsection, we use the full-sample standard deviation to standardize both optimism and pessimism sentiment components so that the magnitude of the two components are directly comparable.[25] In regressions (14) and (15), we replace the consumption sentiment index with its optimistic and pessimistic components individually:

$$Ret_{t+k} = \alpha + \beta\ Optimism_t + \sum_n \gamma_n Control_t^n + \varepsilon_t \tag{14}$$

$$Ret_{t+k} = \alpha + \beta\ Pessimism_t + \sum_n \gamma_n Control_t^n + \varepsilon_t \tag{15}$$

We report empirical results estimated from equations (14) and (15) in panels A and B of Table 3.7. In columns (1) to (4) of panel A, we show that optimism is not associated with the contemporaneous market return or future market returns for up to three weeks (k=0, 1, 2, and 3). We should expect optimism to be positively associated with contemporaneous market returns and negatively associated with future market returns. However, we find that the coefficient on

[25] We do not winsorize indices due to a concern of look-ahead bias. Winsorization does not change our findings. Further, our results are similar without standardization.

optimism is negative and insignificant for contemporaneous returns (k=0) and is positive and insignificant for returns in the following week (k=1). Overall, these results suggest that optimism does not drive the predictive power of consumption sentiment on market returns.

[Insert Table 3.7 Here]

We expect pessimism to negatively correlate with the contemporaneous market return and positively predict future market returns. As reported in column (1) of panel B in Table 3.7, the coefficient estimate on pessimism is -0.212 and is significant at a 5% level after a Newey-West adjustment (t=-2.00). A one standard deviation increase in the pessimistic sentiment corresponds to a 0.212% lower contemporaneous weekly stock market return. The magnitude of this coefficient is also larger in absolute terms than that of optimism (-0.122). In column (2), we regress stock market returns on lagged pessimism and find a positive coefficient. Specifically, a one standard deviation increase in pessimism can predict a 0.188% market return next week (t=1.91). Combining results from panels A and B, pessimistic sentiment appears to drive the consumption sentiment's predictive power, confirming the negativity bias in this context. The findings in this subsection are robust to using CRSP equal-weighted and S&P 500 index returns.[26]

3.3.5 Out-of-Sample Tests

It is possible that in-sample results may not provide precise estimates of coefficients in predictive regressions. An influential study by Welch and Goyal (2008) examines various empirical asset pricing models and finds that most models perform poorly out-of-sample. Welch and Goyal (2008) further argue that out-of-sample tests allow investors to assess a real-time

[26] The results are available upon request.

prediction of asset pricing models. This subsection provides evidence that our results can hold in out-of-sample tests.

Following Welch and Goyal (2008), Huang et al. (2015), and Da et al. (2020), we first split the full sample into a training sample and a validation sample. Then, we estimate a predictive coefficient for lagged consumption sentiment on value-weighted market returns using the regression (11) in the training sample and use the coefficient to forecast market returns in the validation sample. The training sample is comprised of the first two sample years, and the rest of the sample is used to validate the prediction. We then compare the training sample data to two benchmark forecast returns, the first of which is a forecasted value-weighted market return using all control variables excluding the consumption sentiment index, and the second a random walk return with the same mean and variance of the actual market return in the validation sample. For each benchmark, we calculate an out-of-sample R-squared as follows:

$$R_{OOS}^2 = 1 - \frac{\left(Ret - \widehat{Ret_s}\right)^2}{\left(Ret - \overline{Ret_0}\right)^2} \tag{16}$$

where $\widehat{Ret_s}$ is the predicted market return using in-sample estimated sentiment coefficient as well as all control variables, and $\overline{Ret_0}$ is the predicted market return using estimated coefficients of control variables only. Thus, we expect R_{OOS}^2 to be positive if the consumption sentiment index improves predictability, as long as the model with the consumption sentiment index generates a smaller forecast error. R_{OOS}^2 is equal to or below zero if our sentiment index does not improve the out-of-sample return prediction.

Using a value-weighted market index and under the first benchmark, in Table 3.8, we find the $R_{OOS}^2$is 0.0638. Reported in rows below the out-of-sample R-squared, a predictive model with the consumption sentiment generates a lower MSE (5.544) than a model with control variables only (MSE=5.921) in the validation sample. To assess whether the difference between the two models is significant, we report corresponding Diebold-Mariano t-statistics to each benchmark. Under the first benchmark, the prediction of the sentiment index is significantly better than the first benchmark since the Diebold-Mariano test provides a t-value equal to 2.446 (p-value=0.0144). Switching to the second benchmark, we find that sentiment prediction outperforms the random walk model. A model under the second benchmark generates a larger MSE. According to the Diebold-Mariano test, the out-of-sample R-squared is 0.3722 and is strongly significant (t-stat=5.881). In summary, the results in this section show that our sentiment index can predict market return in both in- and out-of-sample tests. These findings are robust to using CRSP equal-weighted and S&P 500 index returns.[27]

[Insert Table 3.8 Here]

3.4 Robustness

We provide robustness checks in this section by offering several alternative construction methods for our consumption sentiment index and applying additional data processing techniques on the Yelp ratings.

3.4.1 Alternative Consumption Sentiment Index Construction Methods

We consider three alternative construction methods of the consumption sentiment index. First, we detrend the index in equation (10) by taking the log difference instead of applying an AR (2) process. This is common in index construction, such as FEARS (Da et al., 2015) and EPU (Baker et al., 2016). We then examine whether this consumption sentiment measure can predict the return-reversal pattern by regressing market returns on the contemporaneous and lagged consumption sentiment. As reported in columns (1) and (2) in panel A of Table 3.9, both

[27] Results of these robustness tests are available upon request.

coefficients on these alternative sentiment measures in the row labeled consumption sentiment remain significant.

[Insert Table 3.9 Here]

Next, we propose two alternative constructions using weekly Yelp rating data without taking the natural logarithm. Two indices are shown in equations (17) and (18). Following the definition of sentiment in the literature, both indices should capture a similar sentiment as our baseline index in equation (10).

$$Alternative\ Index\ One_t = \frac{N(Positive)_t}{N(Negative)_t} \tag{17}$$

$$Alternative\ Index\ Two_t = \frac{N(Positive)_t - N(Negative)_t}{N(All)_t} \tag{18}$$

where $Alternative\ Index\ One_t$ and $Alternative\ Index\ Two_t$ are the values of two indices at week t, and $N(All)_t$ is the number of all reviews in week t. We again perform regression (11) on these indices to examine whether they are associated with the contemporaneous market return and predictive to future market returns. Columns (3) and (5) in panel A of Table 3.9 show that both alternative indices are significantly associated with contemporaneous market returns, and they can also predict a return reversal, as shown in columns (4) and (6). Overall, our empirical findings are robust to multiple alternative construction methods.

3.4.2 Subsample Analysis

Next, we show our results are robust to subsample analyses. First, we examine whether Yelp ratings on weekends and holidays can affect our results. We construct an index that exclusively includes reviews posted on trading days to mitigate this concern. After using these additional data filters and constructing the consumption sentiment index described in Section 3.2, we estimate regression (11). The first two columns in panel B of Table 3.9 show that the weekly consumption sentiment index constructed using only weekday ratings remains significantly associated with contemporaneous market returns and continues to predict a return reversal in the following week.

On Yelp, reviewers can rate the price range for restaurants. Specifically, a restaurant with a one-dollar sign ($) means an average transaction per person is $10 or lower; a two-dollar sign ($$) represents an average price per person is between $11 and $30; a three-dollar sign ($$$) indicates that an average cost per person is between $31 and $60, and a four-dollar sign ($$$$) translates to a cost that is above $61. Next, we examine whether the consumption sentiment embedded in reviews for cheap versus expensive restaurants could be driving our results by constructing two additional consumption sentiment measures. The first one is computed using ratings on expensive restaurants only, defined as businesses with three- or four-dollar signs ($$$ or $$$$). The second measure is computed using ratings on cheap restaurants only, identified as those with one-dollar or two-dollar signs ($ or $$). As reported in columns (3) to (6) in panel B of Table 3.9, we show that both indices are significantly correlated with contemporaneous weekly returns and can predict future return reversals, thus suggesting that removing reviews for expensive or cheap restaurants does not affect our results.

3.5 Conclusions and Connection to Chapter Four

In this chapter, we collect over 11 million user ratings from Yelp for approximately twenty thousand restaurants and construct a sentiment measure associated with consumption decisions. We contribute to the literature by proposing this novel measure of aggregate consumption sentiment and showing that it can predict patterns in stock market return. We find that consumption sentiment is positively correlated with same-week stock market returns and negatively correlated with next-week returns. This pattern is consistent with a temporary, sentiment-induced mispricing followed by a market correction. We also show that our consumption-based sentiment index is associated with the aggregate consumption level, predicts mutual fund flows, and correlates with market-aggregate risk aversion. We then decompose the sentiment index into optimistic and pessimistic components and find that the pessimism component has a stronger impact on stock market returns than the optimism component.

In future research, one may apply textual analysis techniques to examine whether the content of reviews provide additional data relative to the ratings data in predicting financial market activity. Furthermore, our consumption sentiment measure can be estimated at the state or city levels to examine the relationship between regional sentiment and municipal bond prices or real estate prices.

Chapter Four: Disagreement Exploitation and the Cross-Section of Hedge Funds Performance

4.1 Introduction

Historically, finance theories have typically assumed that investors have *homogeneous* beliefs about asset returns, but over the past two decades studies have examined the possibility that asset pricing is influenced by *heterogeneous* beliefs among investors.[28] The asset pricing literature focuses on a mispricing effect that is induced by investors' disagreement on assets' values, and it posits that assets with high disagreement are likely being overpriced due to short-sale constraints (e.g., Diether, Malloy, and Scherbina, 2002). Meanwhile, recent studies on hedge funds focus on investigating hedge fund performance. Studies in this area indicate that some hedge funds can exploit mispricing opportunities by acting as arbitrageurs (e.g., Cao, Goldie, Liang, and Petrasek, 2016; Chen, Han, and Pan, 2021). Following both strands of the literature, we focus on the impact of disagreement on the performance of hedge funds. Specifically, we consider a group of hedge funds that can recognize fluctuations in aggregate disagreement and take advantage of mispricing that is induced by changes in disagreement. Hedge funds that can exploit market disagreement essentially possess a "disagreement exploitation skill," and we relate this skill to the cross-section of hedge fund performance.

Miller (1977) is the first to assert that an asset may be overpriced in the presence of short-sale constraints when investors disagree on the asset price. Studies in this area often use the dispersion in analysts' forecasts on earnings as a proxy for stock-level disagreement; they find a

[28] Influential studies in the heterogeneous belief literature include, but not are limited to Diether, Malloy, and Scherbina (2002), Chen, Hong, and Stein (2002), Basak (2005), Hong and Stein (2007), Yu (2011), Xiong (2013), Hong and Sarer (2016), Gao, Lu, Song, and Yan (2018), Atmaz and Basak (2018), Cujean and Hasler (2017), and Cookson and Niessner (2019).

negative relation between disagreement and expected asset returns (e.g., Diether et al., 2002; Hong and Sraer, 2016). Similar to other studies, we consider an economy with two retail investors who disagree on the asset value and an arbitrageur. Both retail investors have distorted beliefs with biased opinions on the asset value, but one investor is optimistic while the other is pessimistic. The optimistic (pessimistic) investor who believes the asset is underpriced (overpriced) tends to take a long (short) position on this asset. In a frictionless market, their trading will not affect asset prices. However, due to short-sale constraints, disagreement can lead to a market where only the optimistic investor can express an opinion (Miller, 1977). This occurs because the pessimistic investor who believes the asset is overpriced cannot sell short due to short-sale constraints. On the other hand, the optimistic investor who considers the asset to be underpriced can always take a long position on this asset. Thus, assets with high disagreement tend to be overpriced and generate lower expected returns than assets with low disagreement. As a result, mispricing should be more prominent in high-disagreement periods than in low-disagreement periods.

The asset pricing literature assumes that arbitrageurs can identify mispriced assets and correct mispricing (e.g., Nagel, 2005). Empirical studies usually assume that institutional investors are arbitrageurs. For instance, Brunnermeier and Nagel (2004) posit that hedge funds are "closer to arbitrageurs than other sophisticated investors." Nagel (2005) argues that sophisticated investors will short sell if an asset is overpriced, and hedge funds are a sample of sophisticated investors. Nagel (2005) further shows that assets will remain overpriced if institutional investors face a constraint to sell short; this suggests that hedge funds are important in correcting mispricing. Cao, Chen, Goetzmann, and Liang (2016) document that hedge funds exploit mispricing opportunities by massively holding stocks with extreme ex-post alphas. They argue that hedge funds trade assets according to alpha, and that is evidence that they function as arbitrageurs. Akbas, Armstrong, Sorescu, and Subrahmanyam (2015) and Chen, Da, and Huang (2019) suggest that hedge funds are the only type of institutional investors that trade as arbitrageurs while other institutional investors do not. Following the literature, the study presented here uses a large sample of hedge funds to examine the ability of arbitrageurs to exploit disagreement mispricing. The data show that some hedge funds that are skilled in exploiting market disagreement outperform unskilled hedge funds.

We hypothesize that some hedge funds can exploit aggregate disagreement while others cannot, and hedge funds under skilled management should outperform other hedge funds that do not exploit disagreement. To test this hypothesis directly, we propose a measure at the individual hedge fund level of a hedge fund's disagreement exploitation skill: the hedge fund-level disagreement beta. This measure is the sensitivity of hedge fund returns to the change of market disagreement. Specifically, we regress monthly hedge fund returns on monthly changes of market disagreement to estimate funds' exposures to disagreement at the individual hedge fund level. It is intuitive to use hedge funds' exposures to measure their disagreement exploitation skill. A hedge fund with a high (low) disagreement exposure represents a high (low) correlation between the hedge fund return and market disagreement, and this hedge fund is able to generate a high (low) payoff when market disagreement is high. Therefore, hedge funds that can take advantage of market disagreement should show a positive correlation between cross-sectional hedge fund returns and market disagreement; these hedge funds will have high exposures to disagreement. Overall, we consider that hedge fund-level disagreement beta can measure disagreement exploitation skill at the individual hedge fund level.

We then relate disagreement beta to the cross-section of hedge fund performance. We first consider whether disagreement beta can explain cross-sectional hedge fund returns. Following the literature (e.g., Bali, Brown, and Caglayan, 2014; Chen, Han, and Pan, 2021), we sort hedge funds into decile portfolios according to their disagreement beta and find a clear pattern that hedge funds with high (low) disagreement beta can generate high (low) returns. In such a portfolio analysis, we show that hedge fund portfolio returns increase from 0.438% per month in the lowest-disagreement beta decile to 0.835% per month in the highest-disagreement beta decile. The highest disagreement beta decile outperforms the lowest disagreement beta decile by 0.397% per month (4.87% per annum). The return spread between two extreme portfolios is statistically significant at the 5% level after adjusting for the Newey-West (1987) time-series autocorrelation (t = 2.12).

Next, we investigate whether commonly known hedge fund risk factors can explain the positive relation between disagreement beta and hedge fund performance. There could be a concern that the disagreement beta effect at the cross-section of hedge funds may be captured by risk factors. Following the literature (e.g., Bali, Brown, and Caglayan, 2014; Chen, Han, and Pan, 2021), we first form a long-short portfolio that takes a long position on the highest-disagreement beta decile, and a short position on the lowest-disagreement beta decile. We then test whether common hedge fund factors can explain the alpha spread between two extreme disagreement beta deciles by examining whether the long-short portfolio's risk-adjusted return (alpha) remains significant after controlling for these factors. We show that these risk factors do not capture the return spread between the two extreme beta deciles. Specifically, the long-short portfolio alpha under the CAPM augmented by Fung and Hsieh (2004) five factors is 0.496% per month (6.12% per annum) and is statistically significant at the 5% level (t = 2.42). The alpha remains significant after additional risk factors are controlled.

Our data sample enables us to analyze hedge funds according to their primary categories, and hedge funds belonging to different categories have distinct primary investment styles. We then investigate which investment style hedge funds are likely to possess the disagreement exploitation skill. We find that individual hedge funds in various categories have heterogeneous disagreement beta in the cross-section. Specifically, hedge funds in the dedicated short bias category have a higher disagreement beta than hedge funds in all other categories. This observation is intuitive because hedge funds in this category primarily take short positions in equities and derivatives (Getmansky, Lee, and Lo, 2018). Taking short positions allows hedge funds in this category to better exploit disagreement. Our further analyses suggest that disagreement beta is high in large, mature, and high-incentive fee funds. This finding indicates that hedge funds that are more experienced (in terms of fund size and age) and charge higher incentive fees tend to have a better skill in exploiting market-level disagreement than other funds. Overall, these findings are likely to support our skill-based intuition.

We make some genuine contributions to several strands of the finance literature. First, we contribute to the hedge fund skill literature by discovering a new source of fund performance. Studies on hedge fund performance find multiple fund characteristics that can predict hedge fund performance, but some provide risk-based explanations for their findings while others provide skill-based explanations.[29] The literature has documented multiple hedge fund skills and shows that these skills are able to deliver high returns in the cross-section. For example, Avramov, Kosowski, Naik, and Teo (2011) document that hedge funds' managerial skills consist of two skills: a predictability of macroeconomic variables skill and a stock selection skill. They further find that the predictability skill on macroeconomic variables is the primary source of hedge fund performance. Recently, Chen et al. (2021) find that hedge fund managers have a sentiment

[29] Multiple influential studies propose risk-based explanations for fund characteristics that are predictive to cross-sectional hedge fund returns. Hedge fund risks that are documented include, but are not limited to, systematic liquidity risk (Sadka, 2010), tail risk (Jiang and Kelly, 2012), macroeconomic risk (Bali et al., 2014), and correlation risk (Buraschi, Kosowski, and Trojani, 2014).

exploitation skill, predicting the cross-sectional hedge fund return.[30] In line with the studies mentioned above, we first document a novel skill of hedge fund managers, the disagreement exploitation skill, and show strong evidence that this skill contributes to hedge fund performance.

Second, we contribute to the literature on the impact of disagreement on the financial market. Gao, Lu, Song, and Yan (2018) show that stock-level exposure to macroeconomic disagreement is able to explain cross-sectional stock returns. Similarly, David and Farhat (2018) estimate stock-level exposures to aggregate dispersion of analysts' opinions and show that the price of disagreement is positive (negative) in high- (low-) disagreement periods. The above studies rationalize their findings under an Intertemporal Capital Asset Pricing Model (ICAPM) framework where disagreement is a priced state variable. To the best of our knowledge, our study is the first to show a positive relation between hedge funds' exploitation of disagreement and the cross-sectional hedge fund returns. Our findings are consistent with the conventional wisdom that skilled hedge funds trade mispriced assets, as well as exploiting and correcting mispricing (e.g., Kokkonen and Suominen, 2015; Cao et al., 2016).

The remainder of this chapter is organized as follows. We describe our data and methodology in Section 4.2, and our main empirical results in Section 4.3. In Section, 4.4 we present the results of several tests to determine whether other variables can affect the positive relation between disagreement beta and cross-sectional hedge fund return. We provide concluding thoughts in Section 4.5.

4.1.Data and Methodology

[30] Other studies that posit hedge fund skills include, but are not limited to, Griffin and Xu (2009), Kacperczyk and Seru (2007), Jagannathan, Malakhov, and Novikov (2010), Nohel, Wang, Zheng (2010), Titman and Tiu (2010), Sun, Wang, and Zheng (2011), Aragon and Martin (2012), Agarwal, Jiang, Tang, and Yang (2013), Cao, Chen, Liang, and Lo (2013), Cao, Goldie, Liang, and Patrasek (2014), Gao and Huang (2016), and Gao, Gao, and Song (2018).

4.1.1. Hedge Fund Data

We use monthly hedge fund data to analyze arbitrageurs' skills in exploiting market disagreement. We obtain hedge fund data from the Thompson Reuters Lipper Hedge Fund Database (Trading Advisor Selection System, TASS). Hedge fund returns and characteristics in this database are available from January 1994 to December 2020. The database is free of survivorship bias since TASS covers both live and defunct funds during the sample period. According to their primary investing styles, all hedge funds are categorized into fourteen categories: convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed income arbitrage, fund of funds, global macro, long/short equity hedge, managed futures, multi-strategy, options strategy, others, and undefined.[31] Fund of funds is the largest category in terms of fund-month observations; with 28.46% of hedge funds belonging to this category.

We apply the following screenings to the dataset. First, we exclude hedge funds in the fixed income arbitrage and managed future categories since our research mainly focuses on equity-oriented hedge funds.[32] Following the literature (Bali et al., 2014), we then omit all hedge funds reporting returns in non-U.S. dollar currencies to avoid any duplicated funds.[33] Next, we follow the literature and omit the first 12-month observations for all hedge fund observations to prevent a backfilling bias (e.g., Fung and Hsieh, 2004; Bali et al., 2014). Finally, we require all hedge funds in our sample to have at least a $15 million net asset value (NAV). After these screenings,

[31] Detailed descriptions of hedge fund categories and their investing styles are discussed in Getmansky, Lee, and Lo (2018).
[32] This is also a standard data processing procedure in the literature, such as Bali et al. (2014) and Chen et al. (2021).
[33] Bali et al. (2014) and Chen et al. (2021) suggest that the TASS database assigns different reference numbers to one hedge fund if it is reported in different currencies. This could happen if an institution has both on-shore and off-shore funds and reports them separately.

our sample contains 9,848 unique hedge funds from 01/1994 to 12/2020. Most of the funds (8,338, 84.67%) are graveyard hedge funds, while 1,510 (13.33%) are alive.

Table 4.1 shows summary statistics for all hedge fund returns and characteristics in the full sample. From the first row to the last, we report statistics including the number of observations, mean values, standard deviations, skewness, and the 1%, 25%, 50%, 75%, and 99% breakpoints of all variables. Statistics of net-of-fee returns are shown in column (1) and are winsorized at 1% on both tails every month (Chen et al., 2021). We have 689,570 return-month observations in total. The average hedge fund return is 0.341% per month in the entire sample. The mean (median) value of fund size is \$179.59 (\$72.90) million, and the average fund age is 78.97 months. The average management and incentive fees are 1.39% of total assets under management and 14.71% of total profit, respectively. A minimum initial investment amount is required by some hedge funds, and their mean (median) value is \$1.272 (\$0.5) million dollars. The leverage dummy variable indicates whether a particular hedge fund uses leverage (one if the fund uses leverage, and zero otherwise).

[Insert Table 4.1 Here]

Panel B of Table 4.2 provides a correlation matrix among these fund characteristics. Specifically, we first take natural logarithms of hedge fund size, age, management fee, incentive fee, and minimum investment, and then standardize them on a monthly basis. We then calculate correlations between fund characteristics every month and report time-series averages of all correlation coefficients. As shown in panel B, all fund characteristics are significantly correlated. For example, we find that fund size is positively correlated with age, incentive fee, and minimum investment, and is negatively correlated with management fee. These results suggest that large hedge funds tend to be experienced funds in terms of age, charge higher incentive fees and lower management fees, and require high minimum initial investment from investors.

[Insert Table 4.2 Here]

4.1.2. Disagreement Measure

This study uses analysts' forecasts of the long-term growth rate of earnings per share (EPS) as a proxy for investors' beliefs on individual asset values. The data are available from the history summary statistics sample in the I/B/E/S database. Using this database has several advantages. First, it is widely used to extract investors' beliefs on asset prices in the literature since it is less likely to be affected by firms' short-term earnings guidance (Yu, 2011).[34] Second, I/B/E/S contains a large sample of analysts' opinions that covers analysts' forecasts on multiple stock-level financial ratios, including the EPS.

Following Yu (2011), we consider that the aggregate disagreement represents investors' diverged opinions on all assets in the market. We construct a bottom-up aggregate disagreement measure as the average firm-level standard deviation (disagreement) of analysts' forecasts of the long-term growth rate of EPS on individual stocks. In order to estimate the firm-level disagreement, we require stocks to have at least two forecasted long-term EPS growth rates every month. We only include analysts' forecasts in stocks that are common shares (Share code is 10 or 11) and listed on the NYSE/NASDAQ/Amex. The disagreement sample period in this study runs from January 1994 to December 2020. We report summary statistics for the disagreement index in the full sample in column (7) of Table 4.1. The index contains 324 monthly observations, and the mean value is 4.983. We plot the time-series of the disagreement measure in Figure 4.1, where NBER recession periods are shaded blue. As is shown, the disagreement index peaks in May 2001

[34] Studies that use the I/B/E/S database to obtain information regarding investors' beliefs about assets include, but are not limited to Diether et al. (2002), Moeller, Schlingemann, and Stulz (2007), Antoniou, Doukas, and Subrahmanyam (2015), Hong and Sraer (2016), Engelberg, McLean, and Pontiff (2018), and Kozak, Nagel, and Santosh (2018).

during the dot-com period, in May 2012 during the European debt crisis, and in March 2020 at the onset of the covid-19 pandemic, suggesting that investors are likely to disagree with each other during periods with extreme market conditions.

[Insert Figure 4.1 Here]

In order to validate that our measure does indeed reflect aggregate disagreement, we relate it to standard deviations of professional forecasts on a number of U.S. macroeconomic variables, which are proxies for aggregate disagreement, as used in Gao et al. (2018). The data are extracted from the BCEI survey, which contains macroeconomic disagreement of expectations on real GDP, consumption, investment, industrial production, and unemployment. Panel A of Table 4.2 shows the correlations between our disagreement index and macroeconomic disagreement indices. Our disagreement index highly correlates with all disagreement proxies, except for the disagreement of the unemployment rate. For example, the correlation coefficient between our disagreement and the real GDP disagreement is 0.1309, and is statistically significant at the 5% level (t = 0.02). Overall, this correlation matrix shows that our bottom-up aggregate disagreement measure can capture the information of aggregate disagreement.

4.2.Risk Factors

We utilize the standard risk factors that are used in hedge fund research. Our factors include market (MKT), size (SMB), value (HML), and momentum (UMD); the data are obtained from Kenneth French's data library. These equity market risk factors are controlled for in estimating hedge fund-level disagreement betas. Multiple studies in the literature have posited several standard factors that may capture the risk of well-diversified hedge fund portfolios and explain the cross-section of hedge fund performance. They are Fung and Hsieh (2004) five factors, including three trend-following risk factors and two bond-oriented factors. Trend-following factors include a bond trend-following factor (PTFSBD), a currency trend-following factor (PTFSFX), and a commodity trend-following factor (PTFSCOM).[35] Bond-oriented factors include a credit risk factor and a bond market factor. The credit risk factor is defined as the monthly change in the difference between BAA-rated corporate bond yield and the 10-year T-bond yield. The bond market factor is defined as the monthly change in the 10-year T-bond yield. Data on these two factors are obtained from the Federal Reserve Economic Data (FRED).[36] Panel C of Table 4.2 shows a correlation matrix between the change of the disagreement index and hedge fund risk factors. One can observe that the change of disagreement is positively correlated with the bond trend-following factor and the currency trend-following factor, and is negatively correlated with the value (HML) factor.

4.3.Empirical Findings

In this section, we first introduce hedge fund-level disagreement beta estimation and univariate portfolio analysis. Next, we provide evidence that disagreement beta can predict cross-section hedge fund returns using Fama-MacBeth (1973) regressions. Finally, we relate hedge fund-level disagreement beta to their investment styles and characteristics.

4.3.1. Portfolio Analysis

To estimate disagreement betas at the individual hedge fund level, we use a regression model, including the change of the aggregate disagreement index and all risk factors (Bali et al., 2014; Chen et al., 2021):

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[35] The data are obtained from Dr. David A. Hsieh's Data Library at: https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm.

[36] Bond-oriented risk factors are available at https://fred.stlouisfed.org/.

$$r_t^i = \alpha^i + \beta^i \boldsymbol{F}_t + \beta_{Disag}^i * \Delta Disag_t. + \varepsilon_t^i, \quad (19)$$

where r_t^i is the excess return of hedge fund i on month t and $\boldsymbol{F}_t$ is a vector of contemporaneous monthly risk factors. $\Delta Disag_t$ is the change of disagreement on month *t*. β_{Disag}^i is the loading on the disagreement index for hedge fund *i*. For each fund, we use rollover regressions. We run a time series regression of hedge fund excess returns over the past 36 months, and we require at least 24 monthly return observations to be included. We then sort hedge funds into equal-weighted decile portfolios using the estimated disagreement beta from the previous month. Hedge funds in the lowest quintile have the lowest disagreement loadings, while hedge funds in the highest decile have the highest disagreement loadings. Referring to Column (6) of Table 4.1, which reports summary statistics of hedge fund-level disagreement beta, there are 611,720 hedge fund disagreement betas in our sample; the mean (median) value is -0.312 (-0.030).

Table 4.3 reports univariate sort results for equal-weighted decile portfolios. In the column labeled β_{Disag}, we report the average disagreement betas in each decile. The average disagreement beta in the lowest (highest) decile is -7.418 (7.799). The column labeled *Ret* shows that higher disagreement beta hedge funds tend to have higher average excess returns than low disagreement beta hedge funds. One can observe a pattern that hedge fund returns increase from the lowest-disagreement to the highest-disagreement beta decile. The highest- (lowest-) disagreement beta portfolio generates an average monthly excess return of 0.835% (0.438%). The return spread, calculated as the average difference between the returns of the highest and lowest disagreement beta portfolios, is 0.397% per month (4.87% per annum) and is statistically significant at the 5% level (t = 2.12). The cumulative return spread between two extreme disagreement beta deciles from January 1997 to December 2020 is 174.97%.

[Insert Table 4.3 Here]

Figure 4.2 plots a time-series of the return spread in the full sample. The figure shows that the return spread between two extreme disagreement beta portfolios is high during the 2008-2010 period and the 2020 onset of the covid-19 pandemic, suggesting that high disagreement beta hedge funds are more likely to outperform low disagreement beta hedge funds in periods characterized by turbulent markets. Section 4.4.2 will further investigate whether the relation between hedge fund disagreement beta and cross-sectional hedge fund performance is conditional on market states.

[Insert Figure 4.2 Here]

Though we provide evidence that the return spread between the highest and lowest disagreement beta decile portfolios is statistically significant, it is possible that existing hedge fund risk factors can explain this return difference. This concern arises because there are significant correlations between the change in the disagreement measure and several hedge fund risk factors, including PTFSBD, PTFSFX, and HML, as shown in panel C of Table 4.2. To mitigate this concern, we first estimate risk-adjusted returns (alphas) in each decile portfolio and examine whether a positive relation exists between disagreement beta and portfolio alpha. Second, we examine whether alphas for the long-short disagreement beta portfolio remain statistically significant in multiple factor models. Specifically, we construct a long-short portfolio by taking a long position in the highest disagreement beta portfolio and a short position in the lowest disagreement beta portfolio. We then run time-series regressions, regressing the long-short hedge fund portfolio returns on common risk factors to estimate full-sample alphas under various factor models.

The columns labeled *CAPM, CAPM+FH5, FF3, FF3+FH5, FF4, FF+FH5, FF5, FF5+FH5* in Table 4.3 report portfolio alphas estimated using the CAPM, the CAPM augmented by Fung and Hsieh (FH5, 2004) five factors, the Fama-French three-factor (FF3) model, the FF3 augmented by Fung and Hsieh (2004) five factors, the Fama-French-Carhart four-factor (FF4), the FF4 augmented by Fung and Hsieh (2004) five factors, the Fama-French five-factor (FF5) model, and the FF5 augmented by Fung and Hsieh (2004) five factors, respectively. For example, in the column labeled *FF3+FH5*, we show that the lowest (highest) disagreement beta portfolio has the lowest (highest) alpha. Specifically, the portfolio alpha increases from -0.331% from the lowest-disagreement beta decile to 0.163% in the highest disagreement beta decile. When long-short portfolio returns are regressed on Fama-French three factors and Fung and Hsieh five factors, we find that the alpha is 0.494% per month (6.09 % per annum) and is significant at the 5% level (t = 2.44). We further report alphas under other factor models and find alphas remain statistically significant in other factor models. The empirical findings in this subsection suggest that none of the risk factors can explain the positive relation between disagreement beta and cross-sectional hedge fund returns. Our results show that high-disagreement beta hedge funds outperform low-disagreement hedge funds in the cross-section, and that disagreement exploitation skill delivers hedge funds high risk-adjusted returns.

4.3.2. Fama-MacBeth Regressions

We have provided evidence that hedge fund disagreement beta is a robust predictor of cross-sectional hedge fund returns using univariate portfolio analysis. However, it is possible that portfolio sorts can result in a loss of information through the aggregation of individual hedge funds. Following Chen et al. (2021), we examine the cross-sectional relation between individual hedge fund returns and disagreement beta using individual hedge fund-level Fama and MacBeth (1973) regressions. First, we regress the excess returns of individual hedge funds on their disagreement betas each month, controlling for lagged hedge fund characteristics. The regression is specified as follows:

$$r_t^i = \delta_t + \lambda_{Disag,t}\beta_{Disag}^i + \lambda_t \boldsymbol{X}_{t-1}^i + \varepsilon_t^i, \tag{20}$$

where r_t^i is the excess return of individual hedge fund *i* in month *t*, β_{Disag}^i is the disagreement beta of hedge fund *i* estimated from the previous month, and $\boldsymbol{X}_{t-1}^i$ is a matrix of lagged hedge fund characteristics of hedge fund *i* in month *t*-1, including fund size, age, management fee, and incentive fee. In these regressions, we use natural logarithms of all hedge fund characteristics. Hedge fund style dummy variables are also included in regressions (Chen et al., 2021). A positively significant $\lambda_{Disag,t}$ indicates a positive relation between hedge fund disagreement betas and cross-sectional hedge fund returns. Next, we estimate the time-series average of the slope coefficients of disagreement beta ($\lambda_{Disag,t}$) and determine whether it is statistically significant. The cross-sectional regressions are performed every month from January 1997 to December 2020.

We report hedge fund-level Fama-MacBeth (1973) regression results in Table 4.4. Column (1) shows that the time-series average slope from the monthly regressions of hedge fund excess return on disagreement beta is 0.013. It is significant at the 5% level after adjusting for Newey-West (1987) autocorrelation (t = 2.47). This coefficient confirms a positive relation between the individual hedge fund return and disagreement beta, suggesting hedge funds that exploit market disagreement earn higher returns. Columns (2) to (5) of Table 4.4 show that the coefficient estimate on disagreement beta remains positive and significant after controlling for hedge fund size, age, management fee, and incentive fee, respectively. For instance, in column (5), when controlling for all these fund characteristics, the coefficient estimate on disagreement beta is 0.022 and becomes highly significant at the 1% level (t = 2.75). It shows a robust predictive power of the disagreement beta on the cross-section of hedge fund returns. In summary, the empirical findings confirm that hedge funds with a disagreement exploitation skill outperform other hedge funds.

[Insert Table 4.4 Here]

4.3.3. Hedge Fund Styles and Disagreement Exploitation

In this subsection, we relate hedge funds' disagreement betas to fund styles. Since we argue that hedge fund disagreement beta measures a fund-level disagreement exploitation skill, then a natural question is this: which investment style hedge funds tend to possess this skill? To answer this question, we calculate mean hedge fund disagreement beta in every category in every month and report time-series average disagreement betas in all categories. As reported in panel A of Table 4.5, the category with the highest-disagreement beta on average is the dedicated short bias category. The average beta of all hedge funds in this category is 0.995 (t = 9.516). This result suggests that hedge funds in this category tend to have a highly positive correlation between hedge fund returns and market disagreement. Given that hedge funds in this category style take short positions primarily in equities and derivatives (Getmansky et al., 2018), this result is expected since hedge funds with a disagreement exploitation skill are likely to use short sales to exploit market disagreement. Besides, hedge funds in the emerging markets category tend to have low disagreement betas (-1.230, t =-14.701), indicating that they are likely to have negative correlations between their returns and market disagreement. Domestic institutional investors in emerging markets may have superior skills in exploiting disagreement to that of hedge funds that focus on emerging markets. Thus, domestic institutional investors in emerging markets can exploit the domestic disagreement and generate positive returns while causing negative returns for U.S. based emerging markets hedge funds. Therefore, hedge funds in the emerging market category are characterized by negative disagreement betas.

Next, we examine the contributions of different hedge fund styles in each hedge fund decile portfolio sorted by disagreement beta. Panel B of Table 4.5 reports average ratios of hedge fund investment styles in each of the disagreement beta deciles. Specifically, we compute the ratios of the twelve investment styles in every disagreement beta decile every month, and then calculate their time-series average ratios. As shown in panel B, the dedicated short bias hedge fund ratio increases from 0.42% in the lowest-disagreement beta decile to 0.76% in the highest-disagreement beta decile. This result is consistent with our findings in panel A that hedge funds in this category tend to have high disagreement betas.

[Insert Table 4.5 Here]

4.3.4. Hedge Fund Characteristics and Disagreement Exploitation

In this subsection, we further relate hedge funds' disagreement betas to common fund characteristics in order to advance our understanding of the disagreement exploitation skill. We conjecture that hedge funds possessing such a skill will be more experienced in terms of fund size and age, and will charge a higher incentive fee than hedge funds without such a skill. Thus, we expect to observe a relation between hedge fund-level disagreement beta and multiple hedge fund characteristics. We test this conjecture using Fama-MacBeth (1973) regressions. Due to significant correlations among fund characteristics as discussed in section 4.2.1, we orthogonalized each fund characteristic on all other variables to mitigate a multi-collinearity concern. We run monthly cross-sectional regressions, regressing hedge fund disagreement beta on multiple hedge fund characteristics, including size, age, management fee, incentive fee, and minimum initial investment. We then compute time-series average slope coefficients of disagreement beta on fund characteristics and determine whether they are statistically significant.

We report average slope coefficients from Fama-MacBeth regressions, and corresponding Newey-West (1987) adjusted t-statistics in Table 4.6. Column (1) shows that the coefficients of fund size and age are positive and significant, implying that hedge funds with high disagreement beta tend to be older in age (since inception) and large in size. This finding confirms our conjecture that experienced hedge funds are likely to have a disagreement exploitation skill. Also, we find that the average coefficient of the incentive fee is significantly positive, suggesting that a hedge fund that exploits market disagreement is likely to charge a higher incentive fee. Further, we include a style dummy variable in cross-sectional regressions and find our results remain unchanged, as shown in column (2). Results reported in columns (3) and (4) show robust results when a leverage dummy variable is included. In summary, the empirical findings support the skill-based explanation for a positive relation between disagreement beta and hedge fund performance.

[Insert Table 4.6 Here]

4.5 Additional Tests

4.5.1 The Role of Market Disagreement Level

In this section, we check whether the level of market disagreement can affect the positive relation between disagreement beta and cross-sectional hedge fund return. Existing studies have documented that cross-sectional equity returns can differ, conditional on the aggregate disagreement level. For example, Hong and Sraer (2016) develop a theory in which high-beta stocks are likely to be overpriced since investors tend to have a large disagreement on these assets. This prediction can explain a flat relation between stock betas and expected returns. They further show that the overpricing of high-beta stocks is more prominent in high-disagreement months than in low-disagreement months. In this study, we conjecture that the positive relation between disagreement beta and hedge fund return can be more pronounced in high-disagreement periods than in low-disagreement periods. This is because mispricing can be pronounced in high-disagreement months (Hong and Sraer, 2016), and hedge funds that possess a stronger disagreement exploitation skill can gain greater benefit in high-disagreement months than in low-disagreement months.

We classify month *t* as a high- (low-) disagreement month when the disagreement in month *t*-1 is higher (lower) than the average monthly disagreement through all months in the full sample. We report univariate portfolio sort results in high- and low-disagreement months in Table 4.7. Our results show that, in high-disagreement months, higher disagreement beta hedge funds tend to have higher average excess returns than low disagreement beta hedge funds. The return spread between the two extreme disagreement beta deciles is 0.525 per month (6.48% per annum) and is statistically significant at the 5% level ($t = 1.96$). However, when market disagreement is low, the relation between disagreement beta and hedge fund returns is flat, and the return spread between the lowest- and the highest-disagreement beta decile is not significant.

[Insert Table 4.7 Here]

4.5.2 The Role of Market Uncertainty

Finally, we examine whether the relation between disagreement beta and the cross-sectional hedge fund performance is conditional on market states. Suppose our conjecture is true that high disagreement beta hedge funds possess a disagreement exploitation skill. In this case, skilled hedge funds are more likely to take advantage of market-level disagreement in high- and low-uncertainty months. Thus, we conjecture that hedge funds are more likely to exploit aggregate disagreement when market uncertainty is high. The positive relation between disagreement beta and cross-sectional hedge fund returns can be stronger in periods of high uncertainty. We measure market-level uncertainty using the CBOE implied volatility index (VIX) and the economic policy uncertainty (EPU) index. The monthly EPU index is constructed by Baker, Bloom, and Davis (2016).[37] Figure 4.3 plots both indices in the time-series. As the blue curve shows, VIX peaked in October 2008 during the financial crisis and is high in March 2020 during the onset of the Covid-19 pandemic. As the red curve shows, the EPU index was high in August 2011 during the European debt crisis.

[Insert Figure 4.3 Here]

Using both VIX and EPU to proxy for market-level uncertainty, we classify month t as a high- (low-) uncertainty month when the uncertainty index in month t-1 is higher (lower) than the full sample average uncertainty (see Stambaugh, Yu, and Yuan, 2015). Moreover, market-level uncertainty can be high during recession periods. We use a monthly dummy as another indicator, which equals one in a month that falls in NBER recession periods and zero otherwise. We then perform univariate portfolio analyses in high- and low-uncertainty periods separately and report the results in Table 4.8. We find that the relation between disagreement betas and cross-sectional hedge fund returns is statistically significant in high-uncertainty months. Specifically, when VIX is used to indicate aggregate uncertainty, the return spread between two extreme disagreement beta deciles is 0.847% per month (t = 2.83) in high uncertainty months.

[Insert Table 4.8 Here]

[37] The EPU index data is available at https://www.policyuncertainty.com/.

The return spread becomes statistically insignificant in low-uncertainty months. A similar pattern can be found when other indicators are used to measure market uncertainty. The relation between disagreement beta and hedge fund performance is significant at the cross section in high-EPU months and NBER recession periods. Overall, the analyses in this subsection support our skill-based explanation of the positive relation between disagreement beta and the cross-section of hedge fund performance.

4.6 Conclusion

In this chapter, we test whether the disagreement beta of individual stocks is predictive of the cross-section of hedge fund returns. We hypothesize that hedge funds with high disagreement betas are skilled to exploit market disagreement, and these hedge funds can outperform hedge funds without the disagreement exploitation skill. Consistent with this view, we find that high-disagreement beta hedge funds generate a 0.397% higher monthly return on average than low-disagreement beta hedge funds in the cross section. We show that existing equity risk factors or hedge fund risk factors cannot explain the relation between disagreement beta and hedge fund performance. Moreover, hedge funds that are experienced and charge high incentive fees tend to have a disagreement exploitation skill.

Future research following this chapter can be conducted in several areas. First, more extensive evidence is needed to support a strong linkage between market disagreement and market mispricing. Second, researchers can investigate whether hedge funds have a disagreement timing skill that enables them to predict future changes in disagreement. Third, there is a need to examine whether hedge funds are able to increase (decrease) their disagreement betas if they anticipate a high- (low-) market disagreement in the future. Fourth, one can extend this research to study disagreement exploitation skills for mutual funds.

5 General Conclusion

This dissertation consists of three essays on asset pricing. The impact of investor beliefs on the financial market is the topic of all three essays. The first essay examines how sentiment is priced at the cross-section using the FEARS index as a measure of sentiment. The second essay introduces a novel measure of sentiment and demonstrates how it affects asset prices at the time-series. The concluding chapter investigates the impact of investor disagreement on the cross-sectional performance of hedge funds. Overall, I believe that my thesis can contribute to the literature in a number of ways, but additional research is needed to enhance our understanding of the financial market.

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Figure List

Figure 2.1: Time-Series Plot of Monthly Sentiment in the Full Sample (07/2004 to 12/2018)
This figure plots monthly sentiment in the full sample. We obtain daily FEARS data from Professor Engelberg's website and from Professor Da, and then extend it to the end of 2018. The monthly sentiment value is the median of the daily FEARS index for each month, multiplied by -1.

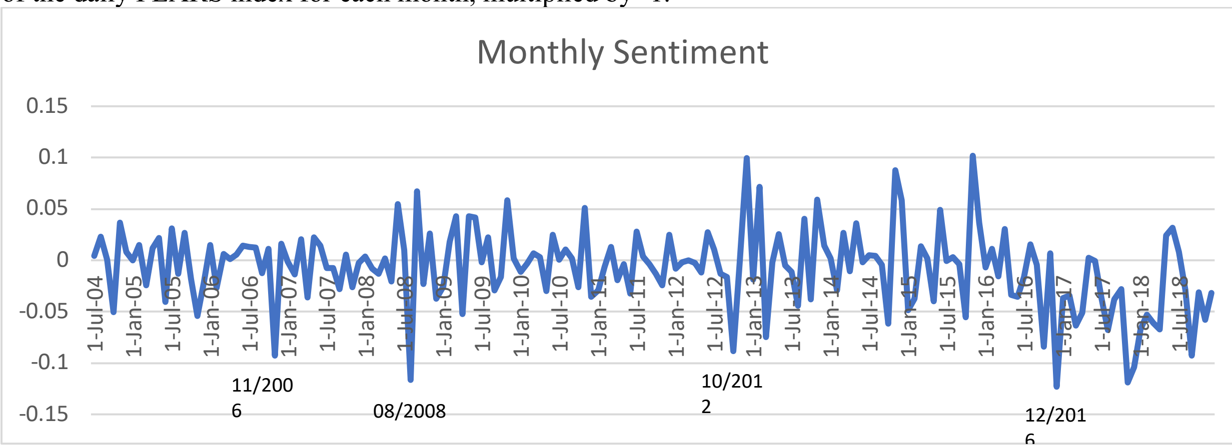

Figure 3.1: Time-Series of Average Yelp Ratings (January 2007 to October 2019)

This figure plots the time series of weekly average review ratings of restaurants on the Yelp platform spanning the period from January 2007 to October 2019. The shaded area represents the financial crisis period according to the NBER recession dates, and the average review rating hits its lowest record the week of September 4th to September 10th, 2008.

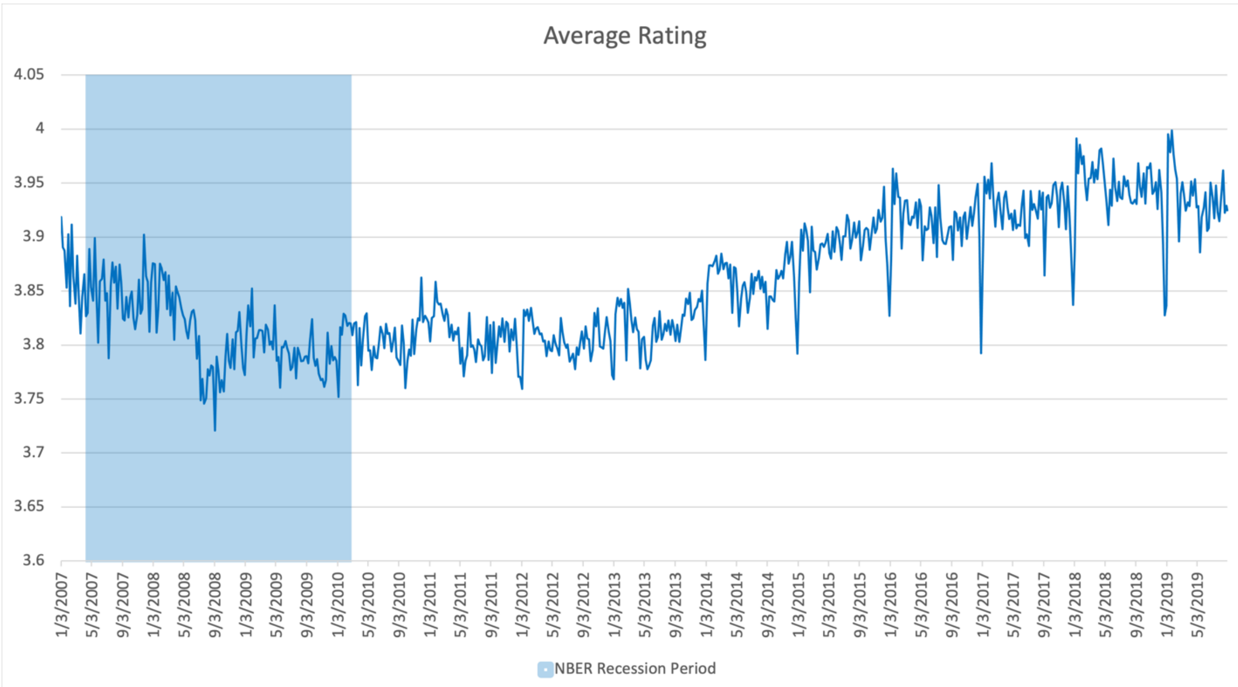

Figure 4.1: Time-Series Plot of Monthly Disagreement (01/1994 to 12/2020)

This figure plots monthly disagreement in the full sample. Market disagreement level is determined every month as the average of analysts' forecast standard deviations of the long-term EPS growth rate. The sample period is from January 1994 to December 2020. NBER recession periods are represented in shaded areas. The market disagreement reached an all-time high in March 2020, during the Covid-19 crisis.

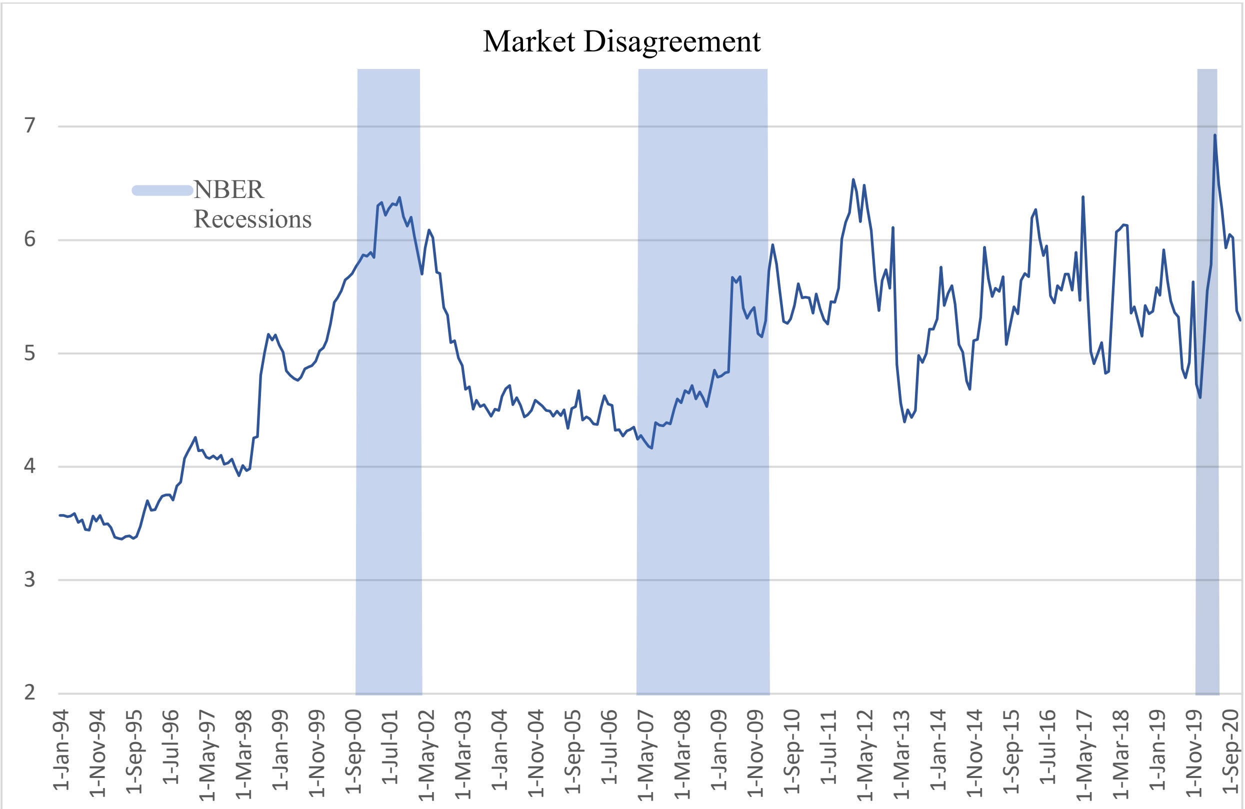

Figure 4.2: Cumulative Return Spread in the Full Sample (January 1997 to December 2020)

Every month from January 1997 to December 2020, we estimate hedge fund-level disagreement beta using the regression (16). We then form decile portfolios by sorting hedge funds by their disagreement betas and calculate a return spread as the return difference between two extreme disagreement beta portfolios. This figure plots a cumulative return spread between the full sample's two extreme disagreement beta deciles.

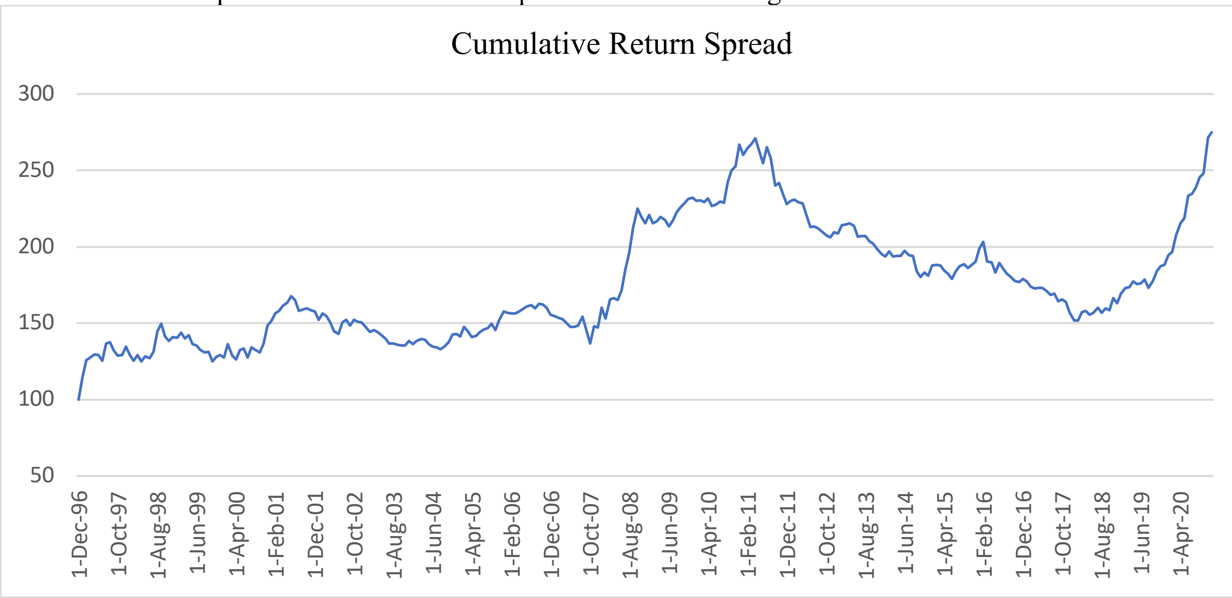

Figure 4.3: Time-Series Plot of Monthly Disagreement (01/1994 to 12/2020)

This figure plots the monthly implied volatility index (VIX) and the Economic Policy Uncertainty (EPU) index in the whole sample. The blue curve plots monthly VIX, calculated as the average daily VIX in a month. The red curve plots the monthly EPU index constructed by Baker, Bloom, and Davis (2016). We show the mean values of both indices by straight lines. The sample period is from January 1994 to December 2020.

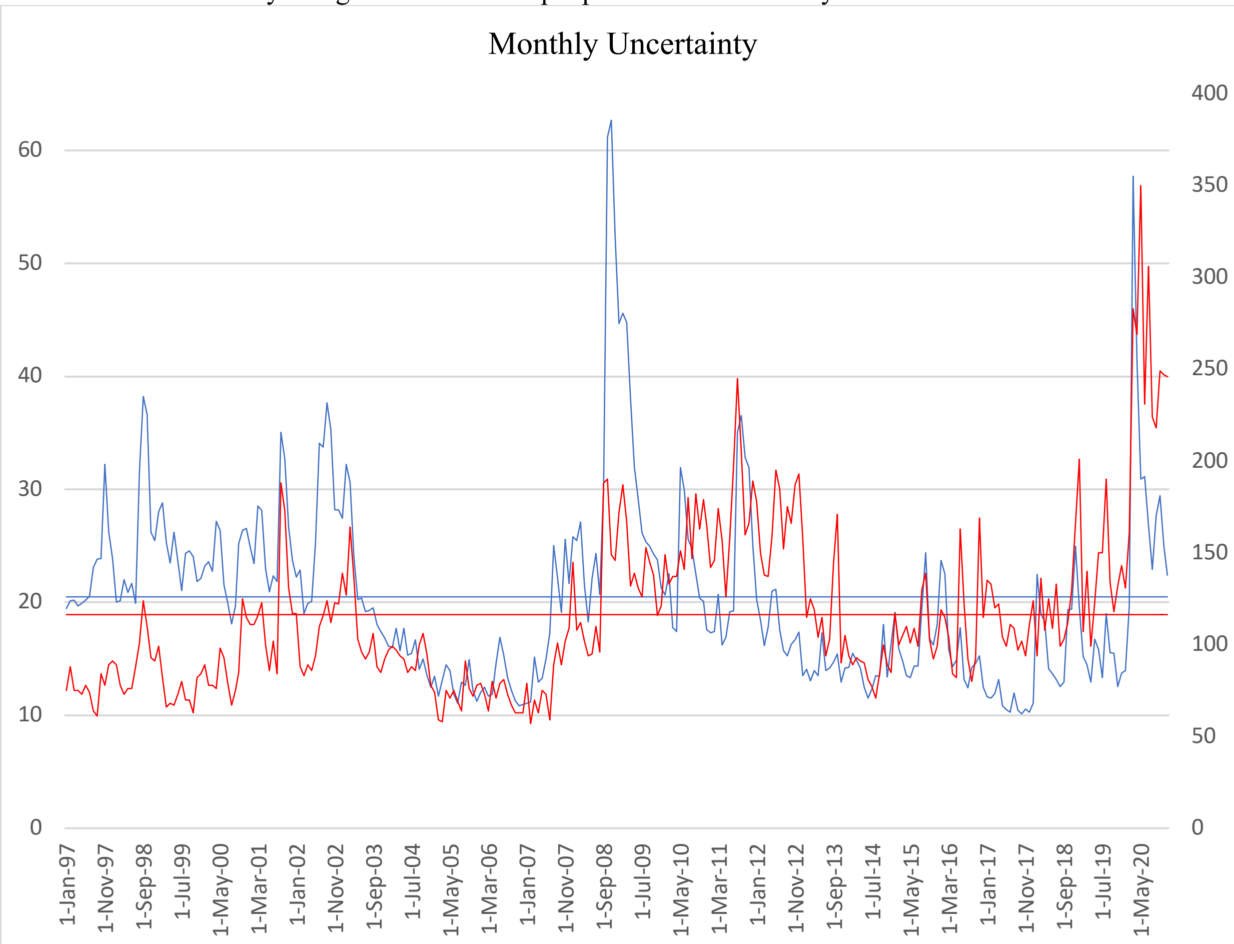

Table List

Table 2.1: Summary Statistics

Panel A shows summary statistics for market sentiment in each year from August 2004 to December 2018, for the full sample, as well as for low-, medium-, and high-sentiment months. Columns labeled *N* report the number of months in a certain year. Columns labeled *Obs.* report the number of firm-month observations in a certain year. We classify month *t* as a low (high) sentiment month when the median sentiment in month *t-1* is lower (higher) than the average of the median monthly sentiment across all months in our sample minus (plus) 0.5 standard deviation. Panel B presents summary statistics of firm characteristics used in our empirical analyses, including market beta, firm size (reported as the natural logarithm of market capitalization in millions), book-to-market ratio, momentum (stock cumulative returns in percentage from the month *t*-12 to month *t*-2), and illiquidity. The rows labeled *N, Mean*, *Stdev*, and *Skewness* report the number of observations, mean value, standard deviation, and skewness for each variable. In Panel C, we report summary statistics of monthly market sentiment in the full sample, as well as in low-, medium-, and high-sentiment months, respectively.

Panel A: Median Sentiment Value by Year

	Full Sample		Low-Sentiment Months		Medium-Sentiment Months		High-Sentiment Months	
	N	Obs.	N	Obs.	N	Obs.	N	Obs.
2004	5	14,629	2	5,913	2	5,743	1	2,973
2005	12	35,521	3	8,962	5	14,686	4	11,873
2006	12	36,177	2	5,944	8	24,184	2	6,049
2007	12	35,678	1	2,809	9	26,913	2	5,956
2008	12	29,686	3	6,691	5	13,166	4	9,829
2009	12	25,522	6	12,777	4	8,735	2	4,010
2010	12	29,226	2	5,006	7	16,928	3	7,292
2011	12	30,056	2	5,084	6	14,875	4	10,097
2012	12	28,849	3	7,155	7	16,918	2	4,776
2013	12	29,934	3	7,594	6	14,743	3	7,597
2014	12	32,399	3	8,096	7	18,931	2	5,372
2015	12	32,197	2	5,294	8	21,561	2	5,342
2016	12	30,749	3	7,677	3	7,688	6	15,384
2017	12	48,245	2	7,786	7	27,200	3	13,259
2018	12	47,232	3	11,794	5	19,738	4	15,700
Total	173	486,100	40	108,582	89	252,009	44	125,509

Panel B: Summary Statistics of Firm Characteristics

	β_{MKT}	Size	B/M	MOM	Illiquidity
N	486,100	486,100	414,472	444,332	473,298
Mean	0.742	8.326	0.354	0.186	105.800
Stdev	1.288	14.431	16.337	0.625	46.182
P1	-1.572	-4.017	-0.367	-0.646	0.002
P25	0.110	4.338	0.256	-0.115	0.052
P50	0.558	6.187	0.466	0.101	0.291
P75	1.307	7.580	0.788	0.354	2.026
P99	3.992	11.120	25.730	2.204	775.111

Panel C: Summary Statistics of Monthly Market Sentiment

	Full Sample	Low-Sentiment Months	Medium-Sentiment Months	High-Sentiment Months
N	173	40	89	44
Mean	-0.002	-0.076	0.001	0.062
Stdev	0.058	0.042	0.015	0.026
P1	-0.173	-0.197	-0.028	0.029
P25	-0.030	-0.109	-0.012	0.040
P50	0.006	-0.068	0.003	0.056
P75	0.034	-0.043	0.014	0.079
P99	0.111	-0.028	0.028	0.121

Table 2.2: Correlation Matrix

The table presents Pearson's correlation coefficients between daily market sentiment and other common risk factors. Panels A-D report correlations for the full sample and for low-, medium-, and high-sentiment months, respectively. The sample period is from August 2004 to December 2018. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. *p*-values are reported in parentheses.

Panel A: Daily Sentiment and Common Risk Factors in Full Sample

	Sentiment	MKT	SMB	HML
MKT	0.1062***			
	(0.00)			
SMB	0.0172	0.1821***		
	(0.30)	(0.00)		
HML	0.0322	0.3196***	-0.1028***	
	(0.05)	(0.00)	(0.00)	
MOM	-0.0409***	-0.3178***	0.0391**	-0.5410***
	(0.01)	(0.00)	(0.02)	(0.00)

Panel B: Daily Sentiment and Common Risk Factors in Low-Sentiment Months

	Sentiment	MKT	SMB	HML
MKT	0.1528***			
	(0.00)			
SMB	-0.0054	0.1149***		
	(0.88)	(0.00)		
HML	0.0838**	0.3299***	-0.0908**	
	(0.02)	(0.00)	(0.01)	
MOM	-0.0824**	-0.3952**	0.0836**	-0.6445*
	(0.02)	(0.00)	(0.02)	(0.00)

Panel C: Daily Sentiment and Common Risk Factors in Medium-Sentiment Months

	Sentiment	MKT	SMB	HML
MKT	0.0522**			
	(0.02)			
SMB	0.0095	0.2940***		
	(0.68)	(0.00)		
HML	-0.0165	0.1767***	-0.1075***	
	(0.47)	(0.00)	(0.00)	
MOM	-0.0232	-0.1350***	0.0001	-0.3863***
	(0.31)	(0.00)	(1.00)	(0.00)

Panel D: Daily Sentiment and Common Risk Factors in High-Sentiment Months

	Sentiment	MKT	SMB	HML
MKT	0.1341***			
	(0.00)			
SMB	0.0481	0.1000***		
	(0.15)	(0.00)		
HML	0.0388	0.4878***	-0.1022***	
	(0.24)	(0.00)	(0.00)	
MOM	-0.0267	-0.4302***	0.0297	-0.5611***
	(0.42)	(0.00)	(0.37)	(0.00)

Table 2.3: Univariate Sorts by Sentiment Beta and Bivariate Sorts by Firm Characteristics and Sentiment Beta

This table reports equal-weighted portfolio returns sorted by sentiment beta as well as bivariate portfolio sorts. Panel A reports returns from univariate sorts by sentiment beta for the full sample, as well as for low-, medium-, and high-sentiment months. Panels B, C, D, and E report bivariate-sort returns for the full sample, as well as for low-, medium-, and high-sentiment months, respectively. Columns (1) through (6) in each of these panels show returns from bivariate sorts on sentiment beta and market beta, size, book-to-market ratio, momentum, liquidity, and stock-level analyst disagreement, respectively. In each panel, we also report the return spread between the high and low quintile portfolios, as well as the number of observations (months). *t*-statistics are reported in parentheses. We also report risk-adjusted return spreads for the high-sentiment beta minus the low-sentiment beta portfolios as well as their alphas estimated using different factor models including the CAPM, FF3, and FF4. *t*-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Univariate Sort

	Full Sample (1)	Low (2)	Medium (3)	High (4)
1 (Low)	1.148	0.755	1.076	1.621
2	1.028	0.606	1.107	1.241
3	1.053	0.820	1.029	1.305
4	1.057	0.928	1.021	1.204
5 (High)	1.301	1.492	1.088	1.457
Obs.	173	40	89	44
High-low	0.154	0.74**	0.01	-0.16
	(0.96)	(2.21)	(0.06)	(-0.39)
CAPM Alpha	0.138	0.606**	0.138	-0.003
	(0.90)	(2.25)	(0.85)	(-0.01)
FF3 Alpha	0.144	0.595**	0.144	0.002
	(0.97)	(2.16)	(0.88)	(0.01)
FF4 Alpha	0.167	0.577**	0.167	0.046
	(1.10)	(2.00)	(1.03)	(0.25)

Panel B: Bivariate Sort in the Full Sample

	β_{MKT} (1)	Size (2)	BM (3)	MOM (4)	Liquidity (5)	Disagreement (6)
1 (Low)	0.89	0.96	0.88	0.90	0.91	1.06
2	0.93	0.90	0.90	0.96	0.94	1.03
3	0.98	0.89	0.94	0.90	0.95	1.06
4	0.99	0.91	0.89	0.89	0.94	1.04
5 (High)	1.04	1.14	0.99	1.02	1.09	1.23
High-low	0.15	0.18	0.11	0.12	0.18	0.17
	(1.07)	(1.13)	(0.75)	(0.88)	(1.11)	(1.11)
CAPM Alpha	0.15	0.19	0.12	0.12	0.11	0.06
	(0.11)	(0.20)	(0.77)	(0.81)	(0.71)	(0.40)
FF3 Alpha	0.16	-0.01	0.13	0.12	0.12	0.07
	(1.19)	(-0.05)	(0.85)	(0.85)	(0.81)	(0.45)
FF4 Alpha	0.18	0.01	0.17	0.14	0.16	0.09
	(1.37)	(0.06)	(0.11)	(0.98)	(1.08)	(0.58)
Obs.	173	173	173	173	173	173

Panel C: Bivariate Sort in Low-sentiment Months

	β_{MKT} (1)	Size (2)	BM (3)	MOM (4)	Liquidity (5)	Disagreement (6)
1 (Low)	0.73	0.79	0.75	0.68	0.64	0.63
2	0.72	0.70	0.70	0.83	0.71	0.61
3	0.73	0.62	0.59	0.72	0.65	0.59
4	0.80	0.70	0.64	0.80	0.73	0.68
5 (High)	1.27	1.41	1.18	1.19	1.13	1.25
High-low	0.54**	0.62**	0.44*	0.52**	0.49**	0.62**
	(2.21)	(2.23)	(1.92)	(2.08)	(1.99)	(2.30)
CAPM Alpha	0.51***	0.64**	0.46*	0.53**	0.58**	0.57*
	(3.05)	(2.28)	(1.92)	(2.23)	(2.42)	(1.96)
FF3 Alpha	0.52***	0.63**	0.44*	0.52**	0.57**	0.55*
	(3.08)	(2.20)	(1.94)	(2.24)	(2.34)	(1.84)
FF4 Alpha	0.52***	0.63**	0.44*	0.52**	0.58**	0.55*
	(3.06)	(2.17)	(1.87)	(2.21)	(2.34)	(1.87)
Obs.	40	40	40	40	40	40

Panel D: Bivariate Sort in Medium-sentiment Months

	β_{MKT} (1)	Size (2)	BM (3)	MOM (4)	Liquidity (5)	Disagreement (6)
1 (Low)	0.55	0.80	0.48	0.54	0.49	0.42
2	0.56	0.59	0.48	0.48	0.49	0.43
3	0.54	0.50	0.36	0.42	0.39	0.48
4	0.54	0.68	0.55	0.52	0.54	0.41
5 (High)	0.50	0.89	0.51	0.50	0.45	0.39
Obs.	89	89	89	89	89	89
High-low	-0.05	0.09	0.02	-0.04	-0.04	-0.04
	(-0.26)	(0.42)	(0.12)	(0.20)	(-0.21)	(-0.18)
CAPM Alpha	-0.03	0.07	0.05	-0.06	-0.06	-0.11
	(-0.13)	(0.32)	(0.25)	(-0.31)	(-0.27)	(-0.57)
FF3 Alpha	-0.05	0.03	0.04	-0.09	-0.06	-0.10
	(-0.22)	(0.16)	(0.20)	(-0.48)	(-0.60)	(-0.51)
FF4 Alpha	-0.05	0.07	0.01	-0.09	-0.01	-0.13
	(-0.20)	(0.29)	(0.04)	(-0.45)	(-0.06)	(-0.59)
Obs.	89	89	89	89	89	89

Panel E: Bivariate Sort in High-sentiment Months

	β_{MKT} (1)	Size (2)	BM (3)	MOM (4)	Liquidity (5)	Disagreement (6)
1 (Low)	1.87	1.99	2.03	1.63	1.88	1.98
2	1.92	1.86	1.76	1.75	1.82	1.92
3	1.95	1.70	1.78	1.74	1.87	1.86
4	1.91	1.67	1.81	1.48	1.87	1.85
5 (High)	1.91	2.00	1.90	1.63	1.85	1.92
Obs.	44	44	44	44	44	44
High-low	0.04	0.01	-0.13	-0.01	-0.03	-0.05
	(0.12)	(0.02)	(-0.36)	(-0.02)	(-0.09)	(-0.15)
CAPM Alpha	-0.38	-0.12	-0.10	-0.03	-0.12	-0.17
	(-0.84)	(-0.31)	(-0.25)	(-0.08)	(-0.29)	(-0.44)
FF3 Alpha	-0.22	0.06	0.13	0.15	0.09	-0.03
	(-0.45)	(0.13)	(0.30)	(0.42)	(0.22)	(-0.01)
FF4 Alpha	-0.30	0.04	0.11	0.14	0.07	-0.02
	(-0.65)	(0.09)	(0.27)	(0.40)	(0.18)	(-0.04)
Obs.	40	40	40	40	40	40

Table 2.4: Second-Stage Fama-MacBeth Regressions on 25 Size-Beta Portfolios

This table reports second-stage Fama-MacBeth regression results using 25 five-by-five size and sentiment beta double-sorted portfolios as our test assets. We report full sample results, as well as the results in low-, medium-, and high-sentiment months in Panels A, B, C, and D, respectively. *t*-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Full Sample

	(1)	(2)	(3)	(4)
Sentiment	0.618**	0.890**	0.599**	0.731**
	(2.45)	(2.44)	(2.23)	(2.22)
MKT		0.479***	1.055***	0.958**
		(3.03)	(3.04)	(2.33)
SMB			0.588**	0.424
			(2.24)	(1.30)
HML			-0.372	-0.294
			(-1.13)	(-0.72)
MOM				-0.636
				(-1.18)
Adj. R^2	7.18%	18.30%	15.57%	14.76%

Panel B: Low-Sentiment Months

	(1)	(2)	(3)	(4)
Sentiment	0.781***	0.832**	0.955**	0.812**
	(2.86)	(2.40)	(2.39)	(2.10)
MKT		1.311**	0.704	1.723***
		(2.45)	(1.05)	(2.73)
SMB			0.745	-0.165
			(1.35)	(-0.42)
HML			-0.095	0.021
			(-0.13)	(0.04)
MOM				1.032*
				(1.89)
Adj. R^2	10.28%	11.79%	11.99%	26.37%

Panel C: Medium-Sentiment Months

	(1)	(2)	(3)	(4)
Sentiment	0.545	0.229	0.533	0.076
	(1.40)	(0.59)	(1.18)	(0.31)
MKT		0.698	0.475	0.769*
		(1.50)	(0.94)	(1.73)
SMB			0.600*	-0.012
			(1.82)	(-0.04)
HML			-0.410	-0.516*
			(-0.99)	(-1.88)
MOM				0.272
				(0.81)
Adj. R^2	4.94%	13.22%	18.37%	25.55%

Panel D: High-Sentiment Months

	(1)	(2)	(3)	(4)
Sentiment	0.130	0.407	0.121	0.102
	(0.23)	(1.34)	(0.21)	(0.47)
MKT		2.065***	2.232***	1.650***
		(3.73)	(3.43)	(3.13)
SMB			0.426	0.276
			(1.07)	(0.61)
HML			-0.573	-0.173
			(-0.85)	(-0.27)
MOM				-0.128
				(-0.32)
Adj. R^2	3.92%	14.91%	14.76%	29.35%

Table 2.5: Stock-Level Cross-Sectional Regressions

This table reports the time-series average of monthly cross-sectional regression coefficients, regressing excess returns of individual stocks on sentiment beta, estimated from daily stock returns from the previous month, as well as control variables including market beta, size, book-to-market ratio, momentum, disagreement, and illiquidity. Results for the full sample, as well as for low-, medium-, and high-sentiment months are shown in panels A, B, C, and D, respectively. *t*-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Full Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sent. Beta	0.002	0.006	0.011	0.006	-0.010	0.024	0.033
	(0.08)	(0.24)	(0.40)	(0.20)	(-0.29)	(0.48)	(0.96)
β_{MKT}		0.054	0.065	0.040	0.060	0.313	0.027
		(0.38)	(0.45)	(0.27)	(0.38)	(0.77)	(0.16)
log(ME)			-0.111***	-0.120***	-0.096**	-0.109***	-0.245***
			(-2.73)	(-2.93)	(-2.45)	(-3.25)	(-4.78)
B/M				-0.011***	-0.009***	-0.044*	-0.026
				(-3.28)	(-2.89)	(-1.75)	(-1.63)
MOM					1.510***	1.514***	0.691**
					(5.89)	(5.33)	(2.47)
Disagreement						-0.003	-0.008
						(-0.02)	(-0.17)
Illiquidity							0.005
							(0.96)
Avg. Adj. R^2	0.26%	1.44%	1.84%	1.99%	4.12%	6.84%	4.76%

Panel B: Low-Sentiment Months

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sent. Beta	0.109**	0.088**	0.088**	0.089**	0.089**	0.083**	0.098*
	(2.61)	(2.41)	(2.46)	(2.32)	(2.22)	(2.18)	(1.98)
β_{MKT}		-0.162	-0.177	-0.293	-0.264	-0.27	-0.008
		(-0.75)	(-0.81)	(-1.27)	(-1.14)	(-1.20)	(-0.40)
log(ME)			-0.093	-0.095	-0.102	-0.101	-0.170*
			(-0.13)	(-1.41)	(-1.54)	(-1.54)	(-1.75)
B/M				-0.011	-0.085***	-0.085***	-0.204***
				(-1.47)	(-2.77)	(-2.83)	(-6.75)
MOM					1.408***	1.419***	1.282*
					(5.67)	(5.68)	(1.98)
Disagreement						0.04	-0.054
						(0.26)	(-0.59)
Illiquidity							-0.013
							(-0.22)
Avg. Adj. R^2	1.56%	0.76%	1.13%	1.25%	3.21%	3.38%	3.65%

Panel C: Medium-Sentiment Months

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sent. Beta	-0.018	-0.001	0.004	-0.008	-0.013	-0.017	-0.022
	(-0.37)	(-0.02)	(0.07)	(-0.13)	(-0.23)	(-0.31)	(0.36)
β_{MKT}		0.010	0.042	0.001	-0.015	-0.013	-0.066
		(0.04)	(0.18)	(0.00)	(-0.06)	(-0.05)	(0.25)
log(ME)			-0.122	-0.127***	-0.109**	-0.110**	-0.132*
			(-0.28)	(-2.79)	(-2.41)	(-2.46)	(1.82)
B/M				-0.007***	-0.078***	-0.079***	-0.723***
				(-2.77)	(-3.53)	(-3.60)	(-2.72)
MOM					1.466***	1.467***	0.028
					(5.36)	(7.42)	(0.10)
Disagreement						-0.021	0.038
						(0.29)	(0.49)
Illiquidity							0.020**
							(2.01)
Avg. Adj. R^2	0.20%	1.52%	1.91%	2.02%	4.34%	4.49%	4.66%

Panel D: High-Sentiment Months

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sent. Beta	-0.017	-0.015	-0.010	-0.012	-0.025	-0.009	0.041
	(-0.31)	(-0.28)	(-0.18)	(-0.23)	(-0.45)	(-0.17)	(0.83)
β_{MKT}		0.299	0.305	0.380	0.452*	0.430	0.336
		(0.73)	(0.07)	(0.90)	(1.75)	(1.01)	(0.93)
log(ME)			-0.106	-0.125	-0.119	-0.114**	-0.358***
			(-1.52)	(-1.71)	(-1.61)	(-2.56)	(-3.52)
B/M				-0.017***	-0.123***	-0.123***	-0.136***
				(-2.76)	(-4.57)	(-4.66)	(-4.36)
MOM					1.654***	1.669***	1.377**
					(6.36)	(6.40)	(2.11)
Disagreement						0.154	-0.035
						(0.93)	(0.44)
Illiquidity							-0.011
							(1.41)
Avg. Adj. R^2	0.17%	1.89%	2.32%	2.46%	4.98%	5.22%	4.90%

Table 2.6: Sentiment Beta and Average Firm Characteristics

This table reports average firm characteristics across decile portfolios sorted by sentiment beta. Every month, stocks are ranked by their sentiment betas into ten portfolios and mean firm characteristics in decile portfolios are calculated. Then, we report average firm characteristics over the full sample in order to examine their relationships with sentiment beta. Firm characteristics include market beta, size, B/M ratio, firm age, total volatility, ROE, dividend-per-share (DPS), and illiquidity.

Deciles	(1) Sentiment Beta	(2) MKT Beta	(3) Size ($M)	(4) B/M	(5) Age	(6) Total Volatility	(7) ROE	(8) DPS	(9) Illiquidity
1 (L)	-3.53	1.284	3326.60	1.774	211.09	0.155	-0.014	0.0206	53.313
2	-1.63	1.173	5765.22	1.808	238.39	0.141	0.073	0.0206	24.195
3	-0.98	1.117	7532.45	1.873	256.16	0.133	0.092	0.0209	20.925
4	-0.52	1.075	8763.79	1.933	268.98	0.130	0.144	0.0210	18.282
5	-0.15	1.056	9350.84	1.952	273.56	0.128	0.101	0.0230	15.048
6	0.21	1.046	8755.95	1.527	272.40	0.127	0.207	0.0206	14.737
7	0.58	1.073	8443.99	1.823	266.52	0.129	0.113	0.0206	16.005
8	1.04	1.119	7033.68	1.705	256.17	0.133	0.100	0.0209	19.973
9	1.71	1.156	5080.19	1.843	235.68	0.142	0.068	0.0210	33.555
10 (H)	3.60	1.237	2801.16	1.701	208.47	0.157	-0.015	0.0230	60.966

Table 2.7: Monthly Returns of Sentiment-Beta Sorted Portfolios Conditional on Institutional Ownership

This table reports equal-weighted returns of 25 portfolios independently double-sorted by residual institutional ownership (RIO) and sentiment beta. Columns (1) to (5) report portfolio returns for quintiles sorted on RIO. Rows labeled *1 (low)* to *5 (high)* show portfolio returns of stocks sorted by sentiment beta. The row labeled *High-Low* shows return spreads between the two extreme sentiment-beta quintiles for each RIO quintile. Rows labeled *CAPM, FF3,* and *FF4* report risk-adjusted returns of the sentiment-beta return spread for each RIO quintile using the CAPM, FF3, and FF3 plus the momentum factor. Panels A, B, C, and D report portfolio returns for the full sample, as well as low-, medium-, and high-sentiment months, respectively. Newey-West time-series autocorrelation adjusted *t*-statistics are reported in parentheses. The row labeled *Obs.* reports the number of total observations (months) in the full sample. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Full Sample

	RIO Quintiles				
Sent. Beta	1 (Low)	2	3	4	5 (High)
1 (Low)	1.841	1.532	0.812	1.443	0.367
2	1.67	1.238	1.240	1.322	0.492
3	1.628	1.364	0.586	1.405	0.456
4	1.504	1.386	1.134	1.257	0.634
5 (High)	2.194	1.411	1.375	1.605	0.801
High-Low	0.353	-0.121	0.563	0.162	0.434**
	(1.36)	(-0.60)	(1.30)	(0.79)	(2.02)
CAPM	0.31	-0.132	0.236	0.115	0.395**
	(0.91)	(-0.68)	(0.51)	(0.50)	(2.03)
FF3	0.335	-0.14	0.258	0.134	0.416**
	(1.51)	(-0.72)	(0.56)	(0.62)	(2.09)
FF4	0.353	-0.125	0.222	0.165	0.466**
	(1.57)	(-0.63)	(0.50)	(0.74)	(2.41)
Obs.	173	173	173	173	173

Panel B: Low-sentiment Months

	RIO Quintiles				
Sent. Beta	1 (Low)	2	3	4	5 (High)
1 (Low)	1.137	0.084	1.373	-1.341	-0.708
2	0.160	-0.263	0.444	-1.253	-0.570
3	0.240	-0.011	0.786	-1.396	-0.941
4	0.416	-0.10	0.363	-1.396	-0.794
5 (High)	1.863	0.103	2.218	-0.446	0.274
High-Low	0.725	0.018	0.845**	0.895**	0.982**
	(1.30)	(0.04)	(2.03)	(2.60)	(2.45)
CAPM	0.556	0.093	0.768*	0.895**	0.895*
	(0.98)	(0.28)	(1.90)	(2.35)	(1.93)
FF3	0.544	0.142	0.729*	0.775**	0.916**
	(1.00)	(0.44)	(1.86)	(2.22)	(2.09)
FF4	0.551	0.134	0.731*	0.785**	0.966**
	(1.01)	(0.41)	(1.77)	(2.23)	(2.41)
Obs.	40	40	40	40	40

Panel C: Medium-sentiment Months

	RIO Quintiles				
Sent. Beta	1 (Low)	2	3	4	5 (High)
1 (Low)	2.582	2.209	1.236	0.009	0.276
2	2.181	1.668	0.104	0.220	0.400
3	2.221	1.563	0.260	0.239	0.089
4	1.671	1.659	0.296	0.546	0.369
5 (High)	2.786	1.854	1.911	0.238	0.667
High-Low	0.203	-0.355	0.675	0.228	0.391
	(0.43)	(-1.05)	(1.27)	(0.85)	(1.27)
CAPM	0.250	-0.066	0.430	0.161	0.351
	(0.51)	(-0.19)	(1.21)	(0.91)	(1.12)
FF3	-0.001	-0.049	0.426	0.188	0.370
	(-0.00)	(-0.14)	(1.14)	(1.18)	(1.18)
FF4	-0.169	-0.006	0.485	0.193	0.523
	(-0.32)	(-0.12)	(1.26)	(1.17)	(1.61)
Obs.	89	89	89	89	89

Panel D: High-sentiment Months

	RIO Quintiles				
Sent. Beta	1 (Low)	2	3	4	5 (High)
1 (Low)	1.359	1.761	2.733	1.738	1.924
2	0.476	1.085	2.283	1.757	2.114
3	0.724	1.021	2.174	1.500	2.057
4	0.445	1.670	1.696	1.692	2.010
5 (High)	1.191	2.014	2.795	2.114	2.445
High-Low	-0.167	0.254	0.062	0.375	0.521
	(-0.53)	(0.48)	(0.13)	(0.69)	(0.80)
CAPM	0.106	0.079	0.280	0.322	0.180
	(0.38)	(0.14)	(0.50)	(0.57)	(0.31)
FF3	0.240	0.024	0.322	0.177	0.098
	(0.67)	(0.17)	(0.57)	(0.28)	(0.17)
FF4	0.269	0.040	0.189	0.204	0.230
	(0.72)	(0.33)	(0.36)	(0.35)	(0.43)
Obs.	44	44	44	44	44

Table 2.8: Stock-Level Fama-MacBeth Regressions Conditional on Institutional Ownership

This table reports the time-series average of monthly cross-sectional regression coefficients for quintiles sorted by residual institutional ownership (RIO) for the full sample. In each quintile portfolio, we regress excess returns of individual stocks on sentiment beta and control variables including stock-level market beta, lagged log of firm size, lagged book-to-market ratio, momentum, disagreement, and illiquidity. Panels A, B, C, and D report time-series average coefficients for the full sample, as well as low-, medium-, and high-sentiment months, respectively. Newey-West (1987) standard error *t*-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Full Sample

	RIO Quintiles				
	1 (Low)	2	3	4	5 (High)
Sent. Beta	0.051	0.015	0.052	0.116*	0.165**
	(1.03)	(0.22)	(0.90)	(1.79)	(2.36)
β_{MKT}	0.200	0.205	0.352*	0.306*	0.109
	(1.09)	(0.92)	(1.85)	(1.82)	(0.51)
Log(ME)	-0.029	-0.348***	-0.697***	-1.846***	-0.162
	(-0.55)	(-2.83)	(-2.85)	(-3.50)	(-0.31)
B/M	3.418***	3.476***	3.112***	1.389***	3.637***
	(3.52)	(3.43)	(3.15)	(2.70)	(4.28)
MOM	1.412***	0.302	1.443**	2.164***	-0.161
	(2.87)	(0.73)	(2.09)	(4.97)	(-0.33)
Disagreement	0.172	0.081	0.296	-0.120	-0.702**
	(0.58)	(0.17)	(0.67)	(-0.94)	(-2.23)
Illiquidity	-0.010	5.632***	6.705***	0.704***	-0.021**
	(-1.12)	(5.70)	(3.63)	(4.83)	(-2.04)
Adj. R^2	5.89%	7.79%	7.47%	5.95%	7.30%

Panel B: Low-sentiment Months

	RIO Quintiles				
	1 (Low)	2	3	4	5 (High)
Sent. Beta	0.100	0.224**	0.284**	0.315**	0.467**
	(0.70)	(1.98)	(2.12)	(2.26)	(2.14)
β_{MKT}	-0.013	0.198	0.270	0.294	-0.054
	(-0.48)	(0.64)	(0.81)	(1.12)	(-0.14)
Log(ME)	-0.010	-0.302*	-0.657***	-1.290***	-0.252**
	(-0.10)	(-1.72)	(-2.71)	(-3.77)	(-2.63)
B/M	3.329***	2.819**	2.565**	1.556***	4.244***
	(3.25)	(2.46)	(2.41)	(2.95)	(3.72)
MOM	1.708**	1.504*	2.223***	3.081***	0.234
	(2.23)	(1.94)	(2.44)	(4.85)	(0.25)
Disagreement	0.454	-1.401**	-0.415	-0.274	-0.469
	(0.82)	(-2.37)	(-0.55)	(-1.13)	(-0.62)
Illiquidity	0.014	5.387***	7.357***	0.496**	-0.033*
	(0.75)	(4.88)	(4.99)	(2.32)	(-1.74)
Adj. R^2	4.41%	4.72%	6.15%	4.92%	6.82%

Panel C: Medium-sentiment Months

	RIO Quintiles				
	1 (Low)	2	3	4	5 (High)
Sent. Beta	-0.049	-0.097	0.036	0.232**	0.326*
	(-0.65)	(-0.79)	(0.40)	(2.01)	(1.89)
β_{MKT}	0.029	-0.043	0.228	0.172	0.049
	(0.11)	(-0.13)	(0.72)	(0.65)	(0.16)
Log(ME)	0.035	-0.519***	-0.804***	-1.462***	-0.087
	(0.39)	(-3.56)	(-4.78)	(-3.51)	(-1.14)
B/M	2.962***	3.557***	2.911***	1.856***	2.912***
	(3.53)	(4.62)	(4.12)	(4.96)	(3.06)
MOM	0.246	-0.691	0.262	1.192*	0.943
	(0.44)	(-0.92)	(0.36)	(1.96)	(1.57)
Disagreement	0.477	1.441	1.250*	-0.135	-1.146**
	(1.27)	(1.47)	(1.79)	(-0.67)	(-2.57)
Illiquidity	-0.003	5.027***	6.784***	0.970***	0.011
	(-0.22)	(4.56)	(5.47)	(5.28)	(0.60)
Adj. R^2	5.88%	8.63%	7.77%	6.56%	6.86%

Panel D: High-sentiment Months

	RIO Quintiles				
	1 (Low)	2	3	4	5 (High)
Sent. Beta	0.028	-0.009	-0.162	-0.060	-0.057
	(0.24)	(-0.07)	(-1.49)	(-0.93)	(-0.60)
β_{MKT}	0.730	0.660	0.662	0.559	0.387
	(1.50)	(1.26)	(1.25)	(1.02)	(0.68)
Log(ME)	-0.166	0.087	-0.548**	-1.460***	0.204**
	(-1.38)	(0.39)	(-2.48)	(-3.68)	(2.18)
B/M	4.330***	4.015***	4.046***	2.349***	4.307***
	(3.34)	(3.12)	(3.22)	(3.85)	(2.89)
MOM	3.202***	0.833	3.698***	2.356***	2.070*
	(3.14)	(0.75)	(2.97)	(2.55)	(1.97)
Disagreement	-0.673**	-0.819	-0.680	-0.020	-0.146
	(-2.17)	(-0.55)	(-0.88)	(-0.10)	(-0.23)
Illiquidity	-0.048*	6.976***	5.881***	0.585***	-0.065***
	(-1.93)	(4.35)	(2.98)	(3.98)	(-2.32)
Adj. R^2	7.47%	9.50%	8.30%	5.94%	8.61%

Appendix to the Chapter Two

"Market Sentiment and the Cross-Section of Expected Stock Returns"

Table 2A.1: Robustness to Additional Test Assets

This table reports results from second-stage Fama-MacBeth regressions using multiple portfolios as test assets. We report the results for low-, medium-, and high-sentiment months in Panels A, B, and C, respectively. Columns (1) through (5) show results using 10 size-sorted portfolios, 10 B/M-sorted portfolios, 25 size- and B/M-double-sorted portfolios, 25 size- and momentum-double-sorted portfolios, and 25 univariate sentiment-beta-sorted plus 30 industry portfolios, respectively. *t*-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Low-Sentiment Months

	(1) Size	(2) B/M	(3) Size/BM	(4) Size/MOM	(5) Beta+Ind.
Sent. Beta	1.879**	2.312**	1.083*	1.510**	0.965*
	(2.10)	(2.43)	(1.91)	(2.13)	(1.80)
β_{MKT}	-1.257	-3.217**	-1.874	-0.519	0.247
	(-1.04)	(-2.11)	(-1.36)	(-0.68)	(0.27)
# Portfolios	10	10	25	25	55

Panel B: Medium-Sentiment Months

	(1) Size	(2) B/M	(3) Size/BM	(4) Size/MOM	(5) Beta+Ind.
Sent. Beta	-0.439	0.341	0.924	0.035	0.041
	(-1.10)	(1.02)	(1.08)	(0.14)	(0.19)
β_{MKT}	-0.348	-0.724	1.038	0.206	-0.463
	(-0.79)	(-1.34)	(1.17)	(0.56)	(-0.91)
# Portfolios	10	10	25	25	55

Panel C: High-Sentiment Months

	(1) Size	(2) B/M	(3) Size/BM	(4) Size/MOM	(5) Beta+Ind.
Sent. Beta	-0.526	-1.219	0.048	0.526	-0.852
	(-0.35)	(-1.10)	(0.25)	(0.41)	(-1.07)
β_{MKT}	1.623	-1.489	-0.008	0.560	0.700
	(1.43)	(-1.10)	(-0.03)	(0.77)	(0.59)
# Portfolios	10	10	25	25	55

Table 2A.2: Robustness to Orthogonalized Sentiment Beta

This table reports the equal-weighted portfolio returns sorted by orthogonalized sentiment beta. We orthogonalize market sentiment index using market return and short-term interest rates; the orthogonalized sentiment beta from each stock is then estimated using regression (1). Columns (1), (2), (3), and (4) report returns for the full sample, as well as for low-, medium-, and high-sentiment months, respectively. In each column, we show portfolio returns from univariate sorts on orthogonalized sentiment beta, as well as the return spread between the two extreme portfolios. The row labeled *Obs.* reports the number of total observations (months) in the full sample and each subsample. *t*-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Full Sample (1)	Low (2)	Medium (3)	High (4)
1 (Low)	1.028	0.054	0.868	1.120
2	1.024	0.192	0.842	1.069
3	1.020	0.300	0.914	0.938
4	1.034	0.391	0.942	0.813
5 (High)	1.148	0.897	1.030	0.965
Obs.	173	40	89	44
High-Low	0.120	0.840**	0.162	-0.156
t-stat	(0.79)	(2.04)	(0.84)	(0.37)

Table 2A.3: Robustness to using Baker-Wurgler Sentiment Change Index

This table reports equal-weighted portfolio returns sorted by sentiment beta, where individual stock level sentiment betas are estimated by regressing stock returns on the monthly Baker and Wurgler (2007) sentiment change index controlling for the market return. The sample is from July 1965 to December 2018. Similar to our baseline results, we classify a month as a high- (low-) sentiment month if the sentiment index in the previous month is higher (lower) than the full sample average sentiment plus (minus) 0.5 of a full-sample standard deviation. Columns (1), (2), (3), and (4) report returns for the full sample, as well as for low-, medium-, and high-sentiment months, respectively. In each column, we show univariate sort quintile portfolio returns, as well as the return spread between the two extreme portfolios. The row labeled *Obs.* reports the number of total observations (months) in the full sample and in subsamples. *t*-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Full Sample (1)	Low (2)	Medium (3)	High (4)
1 (Low)	0.958	1.243	0.883	0.737
2	0.775	1.086	0.707	0.604
3	0.904	1.314	0.652	0.512
4	1.085	1.493	0.943	0.733
5 (High)	1.346	1.892	1.253	0.905
Obs.	606	153	289	164
High-Low	0.388*	0.649***	0.369	0.168
t-stat	(1.89)	(2.72)	(1.03)	(0.47)

Table 2A.4: Robustness to Classifying Monthly Sentiment Levels

This table reports equal-weighted portfolio returns sorted by sentiment beta, where we apply alternative ways to classify high-, medium-, or low-sentiment months. In panel A, we classify month t as a low (high) sentiment month when the median sentiment in month t-1 is lower (higher) than the average of the median monthly sentiment across all months in our sample minus (plus) one full-sample standard deviation. In panel B, we classify monthly sentiment levels using 30%/40%/30% breakpoints**.** In panel C, we calculate monthly sentiment level using the mean value of daily sentiment while we used the median value in baseline results. Columns (1), (2), (3), and (4) report returns for the full sample, as well as for low-, medium-, and high-sentiment months, respectively. In each column, we show the univariate sort quintile portfolio returns, as well as the return spread between the two extreme portfolios. The row labeled *Obs.* reports the number of total observations (months) in the full sample and each subsample. *t*-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Defining High-, Medium-, or Low-sentiment Months using One Standard Deviation

	Full Sample (1)	Low (2)	Medium (3)	High (4)
1 (Low)	1.148	-0.16	0.92	2.19
2	1.028	-0.08	0.74	2.07
3	1.053	0.06	0.79	1.98
4	1.057	0.16	0.80	1.93
5 (High)	1.301	0.51	1.03	2.14
Obs.	173	28	116	29
High-low	0.154	0.66**	0.12	-0.04
t-stat	(0.96)	(2.14)	(0.55)	(-0.21)

Panel B: Defining High-, Medium-, or Low-sentiment Months using 30%/40%/30% Breakpoints

	Full Sample (1)	Low (2)	Medium (3)	High (4)
1 (Low)	1.148	0.59	1.03	1.85
2	1.028	0.45	1.11	1.50
3	1.053	0.54	1.07	1.55
4	1.057	0.67	1.09	1.41
5 (High)	1.301	1.13	1.20	1.61
Obs.	173	53	67	53
High-low	0.154	0.53*	0.17	-0.24
t-stat	(0.96)	(1.78)	(0.84)	(-0.72)

Panel C: Defining Monthly Sentiment using Mean level of daily sentiment

	Full Sample (1)	Low (2)	Medium (3)	High (4)
1 (Low)	1.148	0.755	1.076	1.621
2	1.028	0.606	1.107	1.241
3	1.053	0.820	1.029	1.305
4	1.057	0.927	1.021	1.203
5 (High)	1.301	1.492	1.088	1.457
Obs.	173	40	89	44
High-low	0.198	0.74**	0.012	-0.165
t-stat	(1.08)	(2.21)	(0.06)	(-0.39)

Table 2A.5: Robustness to Sum Beta Methodology

This table reports equal-weighted portfolio returns sorted by sum sentiment beta, where individual stock level sentiment betas are estimated using the sum of sentiment beta and lagged sentiment beta, controlling for the market return. Columns (1), (2), (3), and (4) report returns for the full sample, as well as for low-, medium-, and high-sentiment months, respectively. In each column, we show the univariate sort quintile portfolio returns, as well as the return spread between the two extreme portfolios. The row labeled *Obs.* reports the number of total observations (months) in the full sample and each subsample. *t*-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Full Sample (1)	Low (2)	Medium (3)	High (4)
1 (Low)	1.831	0.978	2.034	1.713
2	1.287	1.118	1.486	0.875
3	1.312	1.235	1.479	0.806
4	1.316	1.657	1.435	1.280
5 (High)	1.831	1.744	1.957	1.844
Obs.	173	40	89	44
High-Low	0.000	0.765**	-0.077	0.130
t-stat	(-0.01)	(2.47)	(-0.31)	(0.24)

Table 2A.6: Robustness to Excluding 20% Small Stocks

This table reports equal-weighted portfolio returns sorted by sentiment beta, where we exclude from our sample the 20% of stocks with the smallest market value at the end of the previous month. Columns (1), (2), (3), and (4) report returns for the full sample, as well as for low-, medium-, and high-sentiment months, respectively. In each column, we show the univariate sort quintile portfolio returns, as well as the return spread between the two extreme portfolios. The row labeled *Obs.* reports the number of total observations (months) in the full sample and each subsample. *t*-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Full Sample (1)	Low (2)	Medium (3)	High (4)
1 (Low)	1.048	0.978	0.879	1.360
2	0.857	0.895	0.676	1.087
3	0.824	0.780	0.654	1.114
4	0.824	0.907	0.680	0.959
5 (High)	1.246	1.595	0.897	1.437
Obs.	173	40	89	41
High-low	0.198	0.617**	0.019	0.077
t-stat	(1.08)	(1.99)	(0.08)	(0.18)

Table 2A.7: Robustness: Alternative Factor Models in Sentiment Beta Estimation

This table reports equal-weighted portfolio returns sorted by sentiment beta estimated from the previous month, using the Fama-French three-factor (FF3) model (1993) and the Fama-French-Carhart four-factor (FF4) model (1997). Panel A shows portfolio results using stock-level sentiment betas, which are estimated using FF3. Panel B reports results that sentiment betas are estimated using FF4. In both panels, columns (1), (2), (3), and (4) report returns for the full sample, as well as following low-, medium-, and high-sentiment months, respectively. In each column, we show the univariate sort quintile portfolio returns, as well as the return spread between the two extreme portfolios. The row labeled *Obs.* reports the number of total observations (months) in the full sample and each subsample. *t-statistic*s are reported in parentheses. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Sentiment beta Estimation Controlling for FF3

	Full Sample (1)	Low (2)	Medium (3)	High (4)
1 (Low)	0.641	0.598	0.375	1.927
2	0.956	0.905	0.624	1.867
3	0.862	0.654	0.537	1.913
4	0.755	0.649	0.623	1.978
5 (High)	1.091	0.973	0.805	2.085
Obs.	173	40	89	44
High-Low	0.450	0.374**	0.431*	0.158
t-stat	(1.64)	(2.17)	(1.91)	(0.46)

Panel B: Sentiment beta Estimated Controlling for FF4

	Full Sample (1)	Low (2)	Medium (3)	High (4)
1 (Low)	1.021	0.165	0.547	2.025
2	1.038	0.642	0.567	1.890
3	0.949	0.444	0.596	1.687
4	0.982	0.372	0.559	1.950
5 (High)	1.201	0.673	0.696	2.217
Obs.	173	40	89	44
High-Low	0.181	0.507**	0.149	0.192
t-stat	(1.59)	(2.00)	(0.93)	(0.87)

Table 2A.8: Additional Control Variables in Bivariate Portfolio Analysis

This table reports equal-weighted portfolio returns sorted by sentiment beta using bivariate portfolio analysis. The methodology is the same as in Table 2.4, however, we control for two additional firm characteristics as well as industry. Panels A, B, C, and D report bivariate-sort returns for the full sample, as well as low-, medium-, and high-sentiment months, respectively. Columns (1) through (3) in each of these panels show returns from bivariate sorts on sentiment beta and stock-level loadings on market disagreement (disagreement beta), profitability (ROE), and industry, respectively. In each panel, we also report the return spread between the high and low quintile portfolios, as well as the number of observations (months). *t*-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Full Sample

	(1) Disagreement Beta	(2) ROE	(3) Industry
1 (Low)	0.96	0.96	1.19
2	0.97	1.02	1.02
3	0.98	0.94	0.98
4	0.93	0.97	1.00
5 (High)	1.06	1.08	1.22
Obs.	173	173	173
High-low	0.10	0.12	0.03
t-stat	(-0.60)	(-0.76)	(-0.22)

Panel B: Low-sentiment Months

	Disagreement Beta	ROE	Industry
1 (Low)	0.66	0.72	0.63
2	0.69	0.48	0.8
3	0.56	0.78	0.86
4	0.67	0.58	0.94
5 (High)	1.26	1.28	1.34
Obs.	47	47	47
High-low	0.60**	0.56**	0.48*
t-stat	(2.45)	(2.20)	(1.82)

Panel C: Medium-sentiment Months

	Disagreement Beta	ROE	Industry
1 (Low)	0.53	0.49	0.42
2	0.45	0.52	0.43
3	0.49	0.41	0.48
4	0.5	0.48	0.41
5 (High)	0.35	0.42	0.39
Obs.	75	75	75
High-low	-0.19	-0.07	-0.04
t-stat	(-1.13)	(-0.40)	(-0.18)

Panel D: High-sentiment Months

	Disagreement Beta	ROE	Industry
1 (Low)	2.01	1.81	1.98
2	1.77	1.86	1.92
3	1.77	1.93	1.86
4	1.72	1.82	1.85
5 (High)	1.86	1.81	1.92
Obs.	51	51	51
High-low	-0.15	-0.01	-0.05
t-stat	(-0.47)	(-0.02)	(-0.15)

Table 2A.9: Rolling Window Method to Classify Low-, Medium-, and High-sentiment Months

This table reports equal-weighted portfolio returns sorted by sentiment beta. The methodology is the same as in Table 2.4, however, we classify low-, medium-, and high-sentiment months using a 36-month rolling window to mitigate a concern about a "look ahead" bias. A month *t* is categorized as a low-, medium-, or high-sentiment month based on monthly sentiment from the previous 36 months. Specifically, we classify a month *t* as a low (high) sentiment month when the median sentiment in month *t-1* is lower (higher) than the average of the median monthly sentiment of the last 36 months minus (plus) 0.5 standard deviation of the median monthly sentiment of the last 36 months. Columns (1), (2), (3), and (4) report univariate-sort portfolio returns for the full sample, as well as low-, medium-, and high-sentiment months, respectively. In each column, we also show the return spread between the high and low quintile portfolios, as well as the number of observations (months). *t*-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Full Sample (1)	Low (2)	Medium (3)	High (4)
1 (Low)	1.179	1.118	0.531	2.252
2	0.977	0.950	0.408	2.001
3	1.012	1.109	0.468	1.832
4	1.007	1.227	0.431	1.724
5 (High)	1.256	1.693	0.589	1.848
Obs.	137	44	59	34
High-Low	0.078	0.575*	0.059	-0.404
t-stat	(0.40)	(1.86)	(0.23)	(-0.83)

Table 3.1: Summary Statistics

Panel A shows the twenty most populated U.S. metropolitan areas where online reviews are collected, and the largest metropolitan areas are based on 2018 demographic data from the U.S. Census Bureau. For each metropolitan area, the panel reports the total population in 2018 and the number of Yelp reviews we obtained. Panel B provides descriptive statistics for the consumption sentiment (*Consumption Sentiment*) index, average weekly ratings, and stock market variables including the weekly CRSP value-weighted market return (*Ret*), the implied volatility index (*VIX*), the economic policy uncertainty (*EPU*) index, the Aruoba-Diebold-Scotti business conditions index (*ADS*), the risk aversion index, the optimistic sentiment component (*Optimism*), the pessimistic sentiment component (*Pessimism*), and all review ratings that are collected in the data sample. We show the full-sample mean, the standard deviation, the minimum observation, the maximum observation, and a set of percentile breakpoints for all the variables. The row labeled *Obs.* reports the total number of observations.

Panel A: Populations and Yelp Reviews of Top Twenty U.S. Metropolitan Areas

Metropolitan Areas ©	Population in 2018 (in millions)	Total Number of Reviews
New York, Newark, Jersey City	19,979	957,691
Los Angeles-Long Beach-Anaheim	13,291	1,369,503
Chicago-Naperville-Elgin	9,498	877,768
Dallas-Fort Worth-Arlington	7,539	389,589
Houston-The Woodlands-Sugar Land	6,997	433,768
Washington-Arlington-Alexandria	6,249	590,873
Miami-Fort Lauderdale-Pompano Beach	6,198	436,971
Philadelphia-Camden-Wilmington	6,096	410,968
Atlanta-Sandy Springs-Alpharetta	5,949	397,727
Boston-Cambridge-Newton	4,875	503,131
Phoenix-Mesa-Chandler	4,857	471,520
San Francisco-Oakland-Berkeley	4,729	1,200,908
Riverside-San Bernardino-Ontario	4,622	388,043
Detroit-Warren-Dearborn	4,326	161,495
Seattle-Tacoma-Bellevue	3,939	586,493
Minneapolis-St. Paul-Bloomington	3,629	203,771
San Diego-Chula Vista-Carlsbad	3,343	1,059,268
Tampa-St. Petersburg-Clearwater	3,143	220,218
Denver-Aurora-Lakewood	2,932	388,358
St. Louis	2,805	184,888
Total	125,005,928	11,232,951

Panel B: Consumption Sentiment, Ratings, and Stock Market Variables

	Consumption Sentiment	Average Weekly Rating	Ret	VIX	EPU	ADS	Risk Aversion	Optimism	Pessimism	All Ratings
Mean	-0.0019	3.8593	0.1250	19.391	104.6611	-0.3625	2.8511	-0.0942	0.1443	3.8798
Std. Dev.	0.2324	0.0775	2.3431	9.0834	65.5382	0.8350	1.1813	0.8566	0.8416	1.2640
Min.	-0.1424	3.6429	-16.1732	9.480	7.40	-4.2713	2.3024	-2.7538	-2.2660	1
P1	-0.1131	3.6954	-6.2387	9.836	20.08	-3.9736	2.3161	-1.9551	-1.9522	1
P5	-0.0693	3.7303	-3.8768	11.096	37.16	-2.4331	2.3499	-1.4352	-1.4012	1
P25	-0.0283	3.8052	-0.8450	13.445	59.36	-0.4196	2.4390	-0.7484	-0.4800	3
P50	-0.0024	3.8547	0.2854	16.728	87.53	-0.1730	2.5582	-0.1409	0.2820	4
P75	0.0232	3.9132	1.3687	22.466	132.30	0.0482	2.8248	0.6476	0.7981	5
P95	0.0683	3.9958	3.4380	37.264	226.71	0.4170	3.9462	1.2054	1.3123	5
P99	0.1447	4.0196	5.7174	61.532	356.20	0.6937	7.9591	1.5329	1.6926	5
Max.	0.1622	4.0513	10.2058	72.782	548.95	0.9150	18.1088	1.8646	1.9443	5
Obs.	661	661	661	661	661	661	661	661	661	11,232,951

Table 3.2: Correlations Between Sentiment Measures and Consumption Growth

This table shows the correlations of consumption sentiment with other sentiment indices and aggregate consumption growth rates. Panel A provides a correlation matrix among our consumption sentiment index, the monthly average rating on Yelp, and various monthly sentiment measures in the literature. All indices are detrended to eliminate non-stationarity. The first index, *Consumption Sentiment,* is our consumption sentiment measure, constructed by equation (10) using monthly data. *Mean Rating* represents a monthly average Yelp rating. *Median FEARS* and *Mean FEARS* are the median and mean values of the daily negative sentiment measure, FEARS, multiplied by -1 (Da et al., 2015). *UMCC* is the growth rate of University of Michigan Consumer Confidence Index, which is based on surveys conducted at a monthly frequency. Lastly, *BW* represents the Baker and Wurgler sentiment measure orthogonalized by macroeconomic variables as in the study by Baker and Wurgler (2006). Panel B reports a correlation matrix among our consumption sentiment index (*Consumption Sentiment*), mean Yelp rating (*Mean Rating*), and the growth rates of several consumption measures. Nondurable goods PCE (*PCEND*), durable consumption goods PCE (*PCEDG*), *Real PCE*, and Personal consumption expenditure (*All PCE*) are selected to proxy U.S. monthly consumer spending. All consumption indices are detrended and deseasonalized. Consumption data is extracted from the FRED website. Corresponding p-values are reported below all correlation coefficients. Significance at the 1%, 5%, and 10% statistical levels is denoted by ***, **, and *, respectively.

Panel A: Correlations with Other Sentiment Measures

	Consumption Sentiment	Mean Rating	Median FEARS	Mean FEARS	UMCC	BW
Consumption Sentiment	1.000					
Mean Rating	0.9112***	1.000				
	(0.0000)					
Median FEARS	0.3015***	0.2261***	1.000			
	(0.0002)	(0.0052)				
Mean FEARS	0.2530***	0.2047**	0.6123***	1.000		
	(0.0017)	(0.0117)	(0.0000)			
UMCC	0.2449**	0.1874**	0.0929	0.1098	1.000	
	(0.0260)	(0.0217)	(0.2520)	(0.1753)		
BW	0.0723	0.0378	-0.0244	0.0845	-0.0922	1.000
	(0.3943)	(0.6567)	(0.7737)	(0.3192)	(0.2768)	

Panel B: Correlations with Consumption Growth

	Consumption Sentiment	Mean Rating	PCEDG	PCEND	Real PCE	All PCE
Consumption Sentiment	1					
Mean Rating	0.9112***	1				
	(0.0000)					
PCEDG	0.1678**	0.1571*	1			
	(0.0388)	(0.0540)				
PCEND	0.1919**	0.1675**	0.5727***	1		
	(0.0178)	(0.0398)	(0.0000)			
Real PCE	0.3236***	0.3046***	0.8288***	0.7217***	1	
	(0.0000)	(0.0001)	(0.0000)	(0.0000)		
All PCE	0.3163***	0.3022***	0.8208***	0.7665***	0.9905***	1
	(0.0001)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	

Table 3.3: Consumption Sentiment and Stock Market Returns

This table relates time-series returns of market equity indices to consumption sentiment using regression (11). Dependent variables in panel A are contemporaneous CRSP value-weighted market returns (column (1)) and returns in the next three weeks (columns (2), (3), and (4), respectively), and panel B report results where CRSP equal-weighted market returns are dependent variables. The key independent variable is the consumption sentiment, and coefficients of the sentiment index are reported in the row labeled Consumption Sentiment. Control variables include weekly average implied volatility (VIX), changes in economic policy uncertainty (EPU), changes in the Aruoba-Diebold-Scotti business conditions index (ADS), and five lags of index returns. The numbers of observations and adjusted R-squared of all regressions are reported in rows labeled Obs. and Adj. R-Sq. Newey-West (1987) standard error-adjusted t-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% statistical levels is denoted by ***, **, and *, respectively.

Panel A: CRSP Value-Weighted Market Returns

	(1) Ret (t)	(2) Ret (t+1)	(3) Ret (t+2)	(4) Ret (t+3)
Consumption Sentiment	4.057**	-5.941***	1.475	2.332
	(2.12)	(-2.80)	(0.68)	(1.05)
VIX	-0.0554**	0.0109	-0.00151	0.00551
	(-2.56)	(0.74)	(-0.10)	(0.38)
EPU	-0.00118	-0.00108	-0.00278	0.000518
	(-0.64)	(-0.58)	(-1.29)	(0.28)
ADS	-1.357	-1.262	-0.163	1.281
	(-0.58)	(-0.57)	(-0.11)	(0.98)
FEARS	-0.867	-0.518	0.229	0.33
	(-1.13)	(-1.02)	(0.39)	(0.56)
Ret (t-1)	-0.111*	-0.0221	0.0044	0.0107
	(-1.76)	(-0.41)	(0.08)	(0.21)
Ret (t-2)	-0.0858	0.0212	0.00855	0.0622
	(-1.45)	(0.40)	(0.16)	(0.95)
Ret (t-3)	-0.0337	0.0145	0.0599	0.0423
	(-0.55)	(0.28)	(0.93)	(0.93)
Ret (t-4)	-0.0282	0.0724	0.0405	-0.0888
	(-0.53)	(1.04)	(0.88)	(-1.34)
Ret (t-5)	0.0283	0.0543	-0.0935	0.0821*
	(0.43)	(1.14)	(-1.47)	(1.93)
Cons.	1.234***	-0.118	0.141	-0.00762
	(3.27)	(-0.45)	(0.53)	(-0.03)
Obs.	626	626	626	626
Adj. R-sq.	0.041	0.009	0.006	0.011

Panel B: CRSP Equal-Weighted Market Returns

	(1) Ret (t)	(2) Ret (t+1)	(3) Ret (t+2)	(4) Ret (t+3)
Consumption Sentiment	4.737**	-6.635***	1.014	1.388
	(2.28)	(-2.74)	(0.41)	(0.59)
VIX	-0.0352	0.0312*	0.0193	0.0254
	(-1.38)	(1.77)	(1.05)	(1.37)
EPU	-0.00144	-0.000824	-0.003	-0.0000133
	(-0.73)	(-0.46)	(-1.16)	(-0.01)
ADS	-0.978	-0.884	-0.00309	1.33
	(-0.41)	(-0.39)	(-0.00)	(0.87)
FEARS	0.629	0.514	0.973	-0.618
	(0.63)	(0.71)	(1.21)	(-0.97)
Ret (t-1)	-0.0186	0.0133	0.0441	0.0175
	(-0.30)	(0.24)	(0.71)	(0.34)
Ret (t-2)	-0.0465	0.0541	0.0125	0.0908
	(-0.69)	(0.96)	(0.23)	(1.29)
Ret (t-3)	0.00762	0.0213	0.0846	0.0963
	(0.11)	(0.38)	(1.19)	(1.54)
Ret (t-4)	-0.024	0.093	0.0921	-0.0825
	(-0.39)	(1.23)	(1.48)	(-1.19)
Ret (t-5)	0.0473	0.105	-0.0886	0.0723
	(0.66)	(1.62)	(-1.34)	(1.54)
Cons.	0.848*	-0.496	-0.236	-0.354
	(1.89)	(-1.61)	(-0.72)	(-1.09)
Obs.	626	626	626	626
Adj. R-sq.	0.041	0.009	0.006	0.011

Table 3.4: Consumption Sentiment and Alternative Test Assets

This table examines the association between the consumption sentiment index and other classes of test assets. We test whether our consumption sentiment index can predict a return reversal of the S&P 500 index and several highly liquid exchange traded funds (ETFs). Dependent variables in panel A are contemporaneous S&P 500 returns (column (1)) and returns in the next three subsequent weeks (columns (2), (3), and (4), respectively). Panel B reports regression results in which dependent variables are contemporaneous returns and future returns in the next week of four different ETFs, including *SPY* (columns (1) and (2)), *QQQQ* (columns (3) and (4)), *IWM* (columns (5) and (6)), and *IWB* (columns (7) and (8)). The key independent variable is consumption sentiment, and coefficients of the sentiment index are reported in the row labeled *Consumption Sentiment*. The set of control variables is the same as in Table 3.3. Numbers of observations and adjusted R-squared of all regressions are reported in rows labeled *Obs.* and *Adj. R-Sq*. Newey-West (1987) standard error-adjusted t-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% statistical levels is denoted by ***, **, and *, respectively.

Panel A: Consumption Sentiment and S&P 500 Index Returns

	(1) S&P 500 Ret (t)	(2) S&P 500 Ret (t+1)	(3) S&P 500 Ret (t+2)	(4) S&P 500 Ret (t+3)
Consumption Sentiment	3.417*	-5.050**	1.419	2.254
	(1.90)	(-2.53)	(0.71)	(1.10)
Controls	Yes	Yes	Yes	Yes
Obs.	661	660	659	658
Adj. R-sq.	0.055	0.017	0.017	0.019

Panel B: Consumption Sentiment and ETF Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SPY	QQQQ	IWM	IWB				
	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)
Consumption Sentiment	3.763**	-5.005**	2.984**	-4.028**	5.302**	-8.558***	3.785**	-5.161**
	(2.07)	(-2.42)	(2.26)	(-2.02)	(2.03)	(-3.03)	(2.02)	(-2.45)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	657	656	657	656	657	656	657	656
Adj. R-sq.	0.056	0.017	0.01	0.01	0.049	0.022	0.055	0.017

Table 3.5: Consumption Sentiment and Limits to Arbitrage

This table shows that the effect of the consumption sentiment index is stronger in assets that are difficult to arbitrage relative to assets that are less subject to limits to arbitrage. We select several firm characteristics to proxy stock-level limits to arbitrage following the literature, including stock beta, size, and volatility. In panel A, we regress beta quintile portfolio returns on contemporaneous (columns (1), (3), (5), (7), and (9)) and lagged consumption sentiment (columns (2), (4), (6), (8), and (10)). We focus on the coefficients of consumption sentiment in different beta quintiles. The sentiment coefficient monotonically increases from low-beta to high-beta assets, consistent with the literature. Results of size- and volatility-sorted portfolios are reported in panels B and C, respectively, and we find that the sentiment effect is strong on small and volatile stocks. Panel D shows the consumption sentiment index can also predict return reversals on beta, size, and volatility spread portfolios. The set of control variables is the same as in Tables 3.3 and 3.4. Numbers of observations and adjusted R-squared of all regressions are reported in rows labeled *Obs.* and *Adj. R-Sq*. Newey-West (1987) standard error-adjusted t-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% statistical levels is denoted by ***, **, and *, respectively.

Panel A: Market Beta-Sorted Quintile Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Beta Quintile 1		Beta Quintile 2		Beta Quintile 3		Beta Quintile 4		Beta Quintile 5	
	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)
Consumption Sentiment	3.697***	-3.284**	3.981**	-5.068**	5.261**	-6.722***	5.597**	-7.881***	7.317**	-9.210**
	(2.65)	(-2.15)	(2.11)	(-2.52)	(2.32)	(-2.81)	(2.08)	(-2.82)	(2.07)	(-2.53)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	661	660	661	660	661	660	661	660	661	660
Adj. R-sq.	0.075	0.040	0.030	0.027	0.026	0.025	0.023	0.028	0.025	0.025

Panel B: Size-Sorted Quintile Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Size Quintile 1		Size Quintile 2		Size Quintile 3		Size Quintile 4		Size Quintile 5	
	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)
Consumption Sentiment	4.976**	-8.261***	4.848*	-7.973***	4.660**	-6.491***	4.196*	-5.946**	3.360*	-4.888**
	(2.00)	(-3.12)	(2.34)	(-2.88)	(2.08)	(-2.67)	(2.28)	(-2.58)	(2.18)	(-2.52)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	661	660	661	660	661	660	661	660	661	660
Adj. R-sq.	0.043	0.019	0.046	0.020	0.047	0.016	0.051	0.019	0.056	0.015

Panel C: Volatility-Sorted Quintile Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Volatility Quintile 1		Volatility Quintile 2		Volatility Quintile 3		Volatility Quintile 4		Volatility Quintile 5	
	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)
Consumption Sentiment	3.567**	-5.117***	4.039**	-6.362***	5.212**	-6.469***	5.401**	-7.287**	8.341**	-7.211**
	(2.31)	(-3.02)	(1.99)	(-2.82)	(2.14)	(-2.60)	(2.00)	(-2.56)	(2.47)	(-2.19)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	661	660	661	660	661	660	661	660	661	660
Adj. R-sq.	0.044	0.022	0.035	0.024	0.034	0.036	0.025	0.024	0.039	0.035

Panel D: Univariate-Sorted Portfolio Return Spreads

	(1)	(2)	(3)	(4)	(5)	(6)
	Beta Spread		Size Spread		Volatility Spread	
	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)
Consumption Sentiment	4.022*	-6.189**	1.513**	-2.501***	6.512**	-5.861*
	(1.91)	(-2.40)	(2.18)	(-2.65)	(1.97)	(-1.65)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	661	660	661	660	661	660
Adj. R-sq.	0.033	0.023	0.015	0.020	0.038	0.047

Table 3.6: Consumption Sentiment and Stock Market Variables

This table relates the consumption sentiment index to market risk aversion and mutual fund flows. Panel A examines the relation between consumption sentiment and aggregate risk aversion under the Autoregressive Fractional Integrated Moving Average (ARFIMA) framework. Control variables include VIX, changes in the EPU, and changes in the ADS. Panel B reports regression results that equity and bond mutual fund flows are regressed on a contemporaneous and lagged consumption sentiment index, following the regression (11). The coefficients of the consumption sentiment index to fund flows are shown in the row labeled *Consumption Sentiment.* The dependent variable in column (1) is contemporaneous equity fund flow, and dependent variables in columns (2), (3), (4), and (5) are equity fund flows that lag, equal to 1, 2, 3, and 4, respectively. Results of bond mutual fund flows are reported in columns (6) to (10). Control variables are the same as in panel A. Numbers of observations are reported in the row labeled *Obs*. Significance at the 1%, 5%, and 10% statistical levels is denoted by ***, **, and *, respectively.

Panel A: Sentiment and Aggregate Risk Aversion

	(1) Risk Aversion	(2) Risk Aversion	(3) Risk Aversion
p	0.884***	0.887***	0.889***
	(11.89)	(11.37)	(11.20)
q	-0.467***	-0.464**	-0.462**
	(-2.74)	(-2.53)	(-2.46)
d	0.122	0.113	0.108
	(0.50)	(0.44)	(0.41)
Consumption Sentiment	-1.398**		
	(-2.24)		
L. Consumption Sentiment		0.451	
		(0.89)	
L2. Consumption Sentiment			0.295
			(0.58)
Controls	Yes	Yes	Yes
Obs.	661	660	659

Panel B: Sentiment and Mutual Fund Flows

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Aggregate Equity Fund Flows					Aggregate Bond Fund Flows				
	Flow (t)	Flow (t+1)	Flow (t+2)	Flow (t+3)	Flow (t+4)	Flow (t)	Flow (t+1)	Flow (t+2)	Flow (t+3)	Flow (t+4)
Consumption Sentiment	17.69**	4.992	8.601	-1.325	-1.237	0.163	-1.496*	-1.528*	-1.951**	-0.48
	(2.19)	(0.69)	(1.36)	(-0.18)	(-0.18)	(0.18)	(-1.85)	(-1.74)	(-2.40)	(-0.58)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	661	660	659	658	657	661	660	659	658	657
Adj. R-sq.	0.02	0.02	0.02	0.02	0.02	0.00	0.00	0.01	0.01	0.01

Table 3.7: Optimistic and Pessimistic Components of Consumption Sentiment

This table relates times-series returns of market equity indices to the optimistic and pessimistic components of consumption sentiment. Dependent variables in both panels are contemporaneous CRSP value-weighted market returns (column (1)) and returns in the following three weeks (columns (2), (3), and (4), respectively). The key independent variable in panel A (B) is optimism (pessimism), and coefficients of the optimism (pessimism) index are reported in the row labeled *Optimism* (*Pessimism*). Control variables include weekly average implied volatility (VIX), changes in economic policy uncertainty (EPU), changes in the Aruoba-Diebold-Scotti business conditions index (ADS), and five lags of the value-weighted market index returns. The number of observations and adjusted R-squared of all regressions are reported in rows labeled *Obs.* and *Adj. R-Sq*. Newey-West (1987) standard error-adjusted t-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% statistical levels is denoted by ***, **, and *, respectively.

Panel A: The Optimistic Component

	(1)	(2)	(3)	(4)
	Ret (t)	Ret (t+1)	Ret (t+2)	Ret (t+3)
Optimism	-0.122	0.0571	0.162	0.0744
	(-1.07)	(0.49)	(1.15)	(0.66)
Controls	Yes	Yes	Yes	Yes
Obs.	661	660	659	658
Adj. R-sq.	0.05	0.01	0.023	0.022

Panel B: The Pessimistic Component

	(1)	(2)	(3)	(4)
	Ret (t)	Ret (t+1)	Ret (t+2)	Ret (t+3)
Pessimism	-0.212**	0.188*	0.084	0.063
	(-2.00)	(1.91)	(0.96)	(0.72)
Controls	Yes	Yes	Yes	Yes
Obs.	661	660	659	658
Adj. R-sq.	0.053	0.013	0.02	0.022

Table 3.8: Out-of-Sample Tests

This table provides out-of-sample tests of the consumption sentiment index in predicting the CRSP value-weighted market index return. In order to show the out-of-sample (OOS) R-squared of our sentiment measure, two benchmarks of market returns are selected in order to examine the precision of predictability of sentiment on equity returns. The first benchmark is predicted market index using control variables only, and the second is a random walk market return. Under each benchmark, equation (16) is used to compute OOS R-squared. The MSEs of the model with or without the consumption sentiment index are reported in rows below the OOS R-squared. Diebold-Mariano t-statistics and corresponding p-values are shown in the last two rows in order to check the significance of the OOS R-squared. Significance at the 1%, 5%, and 10% statistical levels is denoted by ***, **, and *, respectively.

Benchmark 1		Benchmark 2	
R-squared	0.0638	R-squared	0.3722
Sentiment model MSE	5.544	Sentiment model MSE	5.544
Benchmark model MSE	5.921	Benchmark model MSE	8.831
Diebold-Mariano t-stat	2.446**	Diebold-Mariano t-stat	5.881***
Diebold-Mariano P-value	0.0144	Diebold-Mariano P-value	0.0000

Table 3.9: Robustness—Alternative Construction Methodologies for Consumption Sentiment

This table provides results using alternative methodologies in constructing the consumption sentiment index. In panel A, the first two columns show that our baseline results are robust when taking a log difference on the weekly data instead of an AR (2) process. Column (1) of panel A reports regression results when the contemporaneous CRSP value-weighted return is the dependent variable. The returns in the next week are the dependent variable in column (2). Columns (3) and (4) report empirical results when the consumption sentiment index is constructed using equation (17), and columns (5) and (6) show the results when the index is constructed following equation (18). Panel B shows empirical results of the consumption index using additional data filtrations. Three different filtrations are applied. Columns (1) and (2) report results of the index using workday reviews only. Columns (3) and (4) show results when only expensive restaurants are used, and columns (5) and (6) report results when only reviews from cheap restaurants are included. Control variables include weekly average implied volatility (VIX), changes in economic policy uncertainty (EPU), changes in the Aruoba-Diebold-Scotti business conditions index (ADS), and five lags of the value-weighted market index returns. Numbers of observations and adjusted R-squared of all regressions are reported in rows labeled *Obs.* and *Adj. R-Sq*. Newey-West (1987) standard error adjusted t-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% statistical levels is denoted by ***, **, and *, respectively.

Panel A: Index Construction

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Difference		Alternative Index One		Alternative Index Two	
	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)
Consumption Sentiment	3.874**	-4.033**	0.535*	-0.865***	11.23*	-16.42**
	(2.37)	(-2.19)	(1.89)	(-2.72)	(1.65)	(-2.47)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	661	660	661	660	661	660
Adj. R-sq.	0.042	0.003	0.039	0.006	0.039	0.003

Panel B: Robustness to Workday and Expensiveness of Restaurants

	(1)	(2)	(3)	(4)	(5)	(6)
	Reviews Excluding Holidays		Expensive Restaurants		Cheap Restaurants	
	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)	Ret (t)	Ret (t+1)
Consumption Sentiment	3.105*	-4.568**	2.235**	-1.77*	3.107*	-5.784***
	(1.86)	(-2.36)	(2.03)	(-1.80)	(1.85)	(-2.76)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	661	660	661	660	661	660
Adj. R-sq.	0.052	0.018	0.115	0.02	0.11	0.022

Table 4.1: Summary Statistics

This table presents summary statistics for the hedge fund characteristics used in our empirical analyses, including fund net-of-fee return, fund size (reported in millions of dollars), fund age (reported as the number of months in existence since inception), management fee (reported as a percentage of total assets), incentive fee (reported as a percentage of total profit), disagreement beta, minimum initial investment (reported in millions of dollars), and a dummy variable indicating whether the hedge fund uses leverage. The last column reports summary statistics of the disagreement index we constructed. The rows labeled *N, Mean*, *Stdev*, and *Skewness* report the number of observations, mean value, standard deviation, and skewness for each variable, respectively. We also show a set of percentile breakpoints for each variable.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Return	Size	Age	Management Fee	Incentive Fee	Disag. Beta	Minimum Investment	Leverage	Disagreement
N	689,570	665,207	611,720	642,594	610,649	611,720	601,486	611,720	324
Mean	0.416	179.585	78.966	1.390	14.712	-0.312	1.272	0.520	4.983
Stdev	3.989	245.650	52.661	0.554	7.792	5.143	9.013	0.500	0.792
Skewness	-0.201	29.943	1.486	3.359	-0.749	-0.684	45.053	-0.081	-0.160
P1	-11.669	15.56	17	0	0	-17.50	0	0	3.38
P25	-0.890	33.23	40	1.00	10	-1.77	0.1	0	4.45
P50	0.420	72.90	65	1.50	20	-0.03	0.5	1	5.01
P75	1.762	199.70	105	1.75	20	1.34	1	1	5.58
P99	12.340	1090.00	258	2.75	25	14.65	10	1	6.48

Table 4.2: Correlation Metrics

Panel A provides a correlation matrix among our disagreement index and multiple macroeconomic disagreement indices. Following Gao et al. (2016), we obtained the data from the BCEI survey, which contains macroeconomic disagreement of expectations on real GDP, consumption, investment, industrial production, and unemployment. Panel B is a correlation matrix showing correlations among multiple hedge fund characteristics. We first take natural logarithms of hedge fund size, age, management fee, incentive fee, and minimum investments. We then standardize them at the monthly basis. Correlation coefficients between fund characteristics are calculated every month, and time-series averages of all correlation coefficients are reported, as well as their significance levels. Panel C is a correlation matrix between the change of our market disagreement index and other hedge fund risk factors. These factors include Fung and Hsieh (2004) five factors, including three trend-following risk factors and two bond-oriented factors. Trend-following factors include a bond trend-following factor (PTFSBD), a currency trend-following factor (PTFSFX), and a commodity trend-following factor (PTFSCOM). Two bond-oriented factors are a credit risk factor and a bond market factor. We also include three Fama-French factors (MKT, SMB, and HML) and the momentum factor (UMD). Corresponding p-values are reported below all correlation coefficients. Significance at the 1%, 5%, and 10% statistical levels is denoted by ***, **, and *, respectively.

Panel A: Correlations between Our Disagreement Measure and Macro Disagreement

	Disag.	GDP Disag.	Consumption Disag.	Investment Disag.	Production Disag.
GDP Disag.	0.1309**				
	(0.03)				
Consumption Disag.	0.1566**	0.8848***			
	(0.01)	(0.00)			
Investment Disag.	0.1489**	0.8691***	0.7933***		
	(0.01)	(0.00)	(0.00)		
Production Disag.	0.1934***	0.6311***	0.5823***	0.5657***	
	(0.00)	(0.00)	(0.00)	(0.00)	
Unemployment Disag.	0.0799	0.8562***	0.8367***	0.7998***	0.6105***
	(0.18)	(0.00)	(0.00)	(0.00)	(0.00)

Panel B: Correlations among Fund Characteristics

	Ln (Fund Size)	Ln (Fund Age)	Ln (Management Fee)	Ln (Incentive Fee)
Ln (Fund Age)	0.0910***			
	(0.00)			
Ln (Management Fee)	-0.0046**	-0.0253***		
	(0.01)	(0.00)		
Ln (Incentive Fee)	0.0301***	0.0025*	0.1829***	
	(0.00)	(0.09)	(0.00)	
Ln (Minimum Investment)	0.3076***	0.1988***	0.0092***	-0.0837***
	(0.00)	(0.00)	(0.00)	(0.00)

Panel C: Correlations between Disagreement and Other Factors

	ΔDisag.	PTFSBD	PTFSFX	PTFSCOM	DGS10	Credit Spread	MKT	SMB	HML
PTFSBD	0.1191**								
	(0.03)								
PTFSFX	0.1176**	0.3936***							
	(0.03)	(0.00)							
PTFSCOM	-0.0091	0.2794***	0.3856***						
	(0.87)	(0.00)	(0.00)						
DGS10	-0.01	-0.2914***	-0.1537**	-0.1311**					
	(0.86)	(0.00)	(0.01)	(0.02)					
Credit Spread	0.0232	0.0127	0.0472	0.0192	-0.1637***				
	(0.68)	(0.82)	(0.40)	(0.73)	(0.00)				
MKT	-0.0038	-0.3139***	-0.2390***	-0.2118***	0.2252***	-0.0901			
	(0.95)	(0.00)	(0.00)	(0.00)	(0.00)	(0.11)			
SMB	-0.0744	-0.0897	-0.0288	-0.0731	0.2109***	-0.0533	0.2473***		
	(0.18)	(0.11)	(0.61)	(0.19)	(0.00)	(0.34)	(0.00)		
HML	-0.1085*	-0.1865***	-0.067	-0.1276***	0.0592	-0.03	-0.0793	-0.2315***	
	(0.05)	(0.00)	(0.23)	(0.02)	(0.29)	(0.59)	(0.15)	(0.00)	
UMD	0.0325	0.104*	0.1690***	0.1945***	-0.2157***	0.1288**	-0.3054***	0.0217	-0.2470***
	(0.56)	(0.06)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.70)	(0.00)

Table 4.3: Univariate Portfolio Analysis

At the end of each month, we sort hedge funds into decile portfolios based on disagreement beta. Hedge fund-level disagreement beta (β_{Disag}) is estimated from a 36-month rollover regression by regressing month excess hedge fund return on the change of disagreement index, controlling for Fung and Hsieh (2004) five factors and Fama-French-Carhart four factors. Decile 1 (10) contains hedge funds with the lowest (highest) disagreement beta from the past 36 months. All portfolios are equally-weighted. The column labeled *Ret* shows the mean excess return of hedge funds in each decile, and the row "*High-Low*" reports the long-short return of the first and last decile portfolio with the significance level reported below. We then report portfolio risk-adjusted return, measured by alphas from factor models for each portfolio. Alphas are estimated by time-series regression of portfolio excess return on factors, and we test if the return spread between two extreme portfolios can be explained by common hedge fund risk factors. Starting with the fourth column, we report portfolio alphas in the CAPM model, CAPM augmented by Fung and Hsieh (2004) five hedge fund factors, Fama-French 3-factor model (FF3), FF3 augmented by Fung and Hsieh (2004) five hedge fund factors, FF-Carhart-4 (FF4), FF4 augmented by Fung and Hsieh (2004) five hedge fund factors, Fama-French 5-factor model (FF5), and FF5 model augmented by Fung and Hsieh (2004) five hedge fund factors, respectively. Newey-West (1987) adjusted t-test values are given in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. All returns (including alphas) are expressed in percentages. The sample period includes 288 months, from January 1997 to December 2020.

Deciles	β_{Disag}	Ret	CAPM	CAPM+ FH5	FF3	FF3+ FH5	FF4	FF4+ FH5	FF5	FF5+ FH5
1 (Low)	-7.418	0.438	-0.211	-0.329	-0.228	-0.331	-0.277	-0.356	-0.107	-0.192
2	-3.289	0.554	0.105	0.061	0.096	0.061	0.072	0.048	0.201	0.175
3	-1.975	0.458	0.055	-0.015	0.047	-0.015	-0.010	-0.050	0.116	0.066
4	-1.159	0.460	0.112	0.060	0.103	0.059	0.050	0.027	0.188	0.152
5	-0.529	0.390	0.055	-0.010	0.047	-0.011	-0.003	-0.041	0.093	0.047
6	0.064	0.460	0.134	0.074	0.124	0.072	0.082	0.048	0.143	0.106
7	0.737	0.481	0.130	0.091	0.121	0.090	0.068	0.057	0.136	0.118
8	1.623	0.470	0.091	0.036	0.081	0.034	0.031	0.004	0.105	0.071
9	3.156	0.529	0.054	-0.010	0.040	-0.013	-0.023	-0.050	0.087	0.049
10 (High)	7.799	0.835	0.193	0.167	0.172	0.163	0.125	0.137	0.272	0.272
High-Low		0.397**	0.405**	0.496**	0.401**	0.494**	0.401*	0.492**	0.379*	0.464**
t		(2.12)	(2.02)	(2.42)	(1.97)	(2.44)	(1.94)	(2.41)	(1.87)	(2.35)

Table 4.4: Fama-MacBeth Regressions of Hedge Fund Performance on $\boldsymbol{\beta_{Disag}}$

This table reports the time-series average of coefficients on monthly cross-sectional regressions, regressing excess return of individual hedge funds on disagreement beta (β_{Disag}) and other fund characteristics. Column (1) reports the average slope of a univariate monthly regression of excess hedge fund return on disagreement beta only. From columns (2) to column (5), we add fund age, management fee, and incentive fee into regressions. A hedge fund style dummy variable is included in all regression. Newey-West adjusted t-statistics are given in parentheses. The row labeled *Avg. Obs.* reports average observations each month in various regressions. The row labeled *Avg. Adj. R^2* reports time-series average adjusted R-squared in different regressions. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. All returns (including alphas) are expressed in percentages. The sample period includes 288 months, from January 1997 to December 2020.

	(1)	(2)	(3)	(4)	(5)
β_{Disag}	0.013**	0.011**	0.013***	0.019***	0.022***
	(2.47)	(2.41)	(2.48)	(2.66)	(2.75)
Ln (Fund Size)		0.451***	0.462***	0.467***	0.492***
		(7.66)	(7.17)	(6.82)	(5.74)
Ln (Fund Age)			-0.454***	-0.449***	-0.473***
			(-6.94)	(-6.70)	(-6.52)
Ln (Management Fee)				0.029	-0.010
				(0.33)	(-0.10)
Ln (Incentive Fee)					-0.048
					(-0.51)
Style Dummies	Yes	Yes	Yes	Yes	Yes
Avg. Obs.	2124	1344	1344	1286	1092
Avg. Adj. R^2	0.57%	1.34%	1.50%	1.67%	1.90%

Table 4.5: Fund Primary Styles and Disagreement beta

In panel A, we calculate average hedge fund disagreement beta across each category every month and report time-series average betas, as well as their significance levels. Panel B reports average ratios of hedge fund investment styles in each disagreement beta decile. Specifically, we compute the investment styles' ratios in every disagreement beta decile every month and then calculate their time-series average ratios. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A: Average $\boldsymbol{\beta_{Disag}}$ in each Hedge Fund Style

Primary Style	Average β_{Disag}	T-statistics
Convertible Arbitrage	-0.670***	-12.199
Dedicated Short Bias	0.995***	9.516
Emerging Markets	-1.230***	-14.701
Equity Market Neutral	0.139***	2.926
Event Driven	-0.564***	-5.620
Fund of Funds	-0.440***	-4.756
Global Macro	0.655***	5.442
Long/Short Equity Hedge	-0.180**	-2.604
Multi-Strategy	-0.054	-1.086
Options Strategy	-0.318***	-3.168
Other	0.059	1.160
Undefined	-0.113	-1.549

Panel B: Ratios of Hedge Fund Investment Styles within each β_{Disag} Decile Portfolios

Deciles	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fund of Funds	Global Macro	Long/ Short Equity Hedge	Multi Strategy	Options Strategy	Other	Undefi ned
1 (Low)	2.37%	0.42%	17.09%	2.86%	6.47%	11.47%	5.56%	42.26%	6.50%	0.76%	3.60%	0.63%
2	2.55%	0.50%	8.75%	3.81%	8.89%	22.75%	4.57%	34.77%	7.15%	0.43%	5.31%	0.54%
3	2.59%	0.40%	5.90%	3.81%	9.07%	33.94%	3.26%	26.17%	8.60%	0.36%	5.56%	0.35%
4	2.45%	0.31%	4.59%	3.41%	8.69%	40.68%	2.47%	21.24%	9.51%	0.60%	5.77%	0.28%
5	2.40%	0.30%	4.27%	3.03%	8.08%	44.91%	2.27%	19.15%	9.24%	0.74%	5.31%	0.30%
6	2.88%	0.37%	4.31%	3.18%	7.93%	43.25%	2.59%	19.67%	9.65%	0.55%	5.34%	0.28%
7	3.39%	0.41%	4.87%	4.07%	7.83%	37.60%	3.10%	22.41%	9.42%	0.60%	6.00%	0.30%
8	3.28%	0.64%	6.47%	4.31%	8.21%	29.30%	4.62%	27.65%	8.92%	0.50%	5.69%	0.40%
9	1.66%	0.83%	8.18%	4.40%	7.07%	19.31%	6.63%	37.51%	8.30%	0.55%	5.04%	0.51%
10 (High)	0.67%	0.76%	12.84%	3.44%	5.48%	11.71%	8.35%	44.21%	7.47%	0.64%	3.86%	0.56%

Table 4.6: Disagreement beta and Fund Characteristics

This table reports the time-series averages of the slope coefficients from the regressions of the hedge fund disagreement beta on the hedge fund-level characteristics, including fund size, age, management fee, incentive fee, and minimum investment. In column (2), we include a leverage dummy equal to 1 if leverage is used by the hedge fund, and 0 otherwise. Column (3) shows regression results that style dummy variables are included. Monthly cross-sectional regressions are run every month from January 1997 to December 2020. The row labeled *Avg. Obs.* reports average observations each month in all regressions. The row labeled *Avg. Adj.* R^2 reports time-series average adjusted R-squared in different regressions. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)
Ln (Fund Size)	0.026***	0.037*	0.026***	0.036***
	(2.69)	(1.70)	(2.71)	(4.40)
Ln (Fund Age)	0.115**	0.116**	0.116**	0.116***
	(2.31)	(2.59)	(2.35)	(2.62)
Ln (Management Fee)	0.036	0.012	0.032	0.116
	(0.95)	(0.05)	(0.83)	(0.43)
Ln (Incentive Fee)	0.054***	0.110***	0.042**	0.104***
	(3.05)	(7.71)	(2.46)	(7.39)
Ln (Minimum Investment)	-0.079	-0.082	-0.081	-0.080
	(-1.52)	(-1.43)	(-1.55)	(-1.30)
Leverage Dummy	No	No	Yes	Yes
Style Dummies	No	Yes	No	Yes
Avg. Obs.	1081	1081	1081	1081
Avg. Adj. R^2	1.15%	5.66%	1.20%	5.68%

Table 4.7: Univariate-sort Portfolio Analysis Conditional on Aggregate Disagreement Levels

This table reports separately univariate portfolio sort results in high- and low-disagreement months. In this table, month *t* is classified as a high- (low-) disagreement month if the disagreement level in month *t-1* is higher (lower) than the average monthly disagreement across all months in the full sample. T-test values are given in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. All returns are expressed in percentages. The sample period includes 288 months, from January 1997 to December 2020.

	High-disagreement		Low-disagreement	
Deciles	β_{Disag}	Return	β_{Disag}	Return
1 (Low)	-5.981	0.302	-8.855	0.574
2	-2.540	0.503	-4.039	0.605
3	-1.490	0.424	-2.460	0.493
4	-0.821	0.406	-1.496	0.514
5	-0.304	0.422	-0.754	0.359
6	0.154	0.478	-0.026	0.441
7	0.654	0.437	0.820	0.525
8	1.331	0.462	1.916	0.479
9	2.571	0.448	3.741	0.610
10 (High)	6.447	0.827	9.151	0.843
High-Low		0.525**		0.268
t		(1.96)		(1.13)

Table 4.8: Portfolio Analysis in Various Market States

This table reports hedge fund returns in decile portfolios based on disagreement beta, estimated using the regression (19). The aim is to examine whether the relation between disagreement beta and hedge fund performance in the cross-section is conditional on market states. The table reports univariate decile portfolio returns and spreads between two extreme disagreement beta portfolios, conditional on the market-level VIX and EPU. Univariate portfolio returns sorted by hedge funds' disagreement beta are also reported for NBER recession and expansion periods. We show that the predictability of disagreement beta on the cross-sectional hedge fund performance is prominent in high-volatility, high-uncertainty, and NBER recession periods. The row labeled *Obs.* reports the numbers of months in different market states. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. All returns (including alphas) are expressed in percentages. The sample period includes 288 months, from January 1997 to December 2020.

	Volatility		Uncertainty		Economic States	
	High	Low	High	Low	NBER Recessions	Expansion
1 (Low)	0.535	0.329	-0.073	0.798	-1.312	0.721
2	0.593	0.509	0.118	0.861	-1.047	0.812
3	0.475	0.440	-0.038	0.808	-1.039	0.700
4	0.489	0.427	0.005	0.781	-0.839	0.670
5	0.398	0.382	-0.035	0.690	-0.905	0.599
6	0.514	0.399	0.122	0.697	-0.500	0.615
7	0.618	0.325	0.136	0.723	-0.283	0.604
8	0.638	0.279	0.113	0.721	-0.252	0.587
9	0.695	0.340	0.126	0.812	-0.345	0.670
10 (High)	1.381	0.216	0.673	0.949	0.661	0.863
Obs.	153	135	119	169	40	248
High-Low	0.847***	-0.113	0.747***	0.150	1.973***	0.142
t	(2.83)	(-0.69)	(2.87)	(0.63)	(3.50)	(0.78)