On the Time Variation of Aggregate Stock Returns and Cross-Sectional Anomalies *

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December, 2024

Abstract

This paper introduces a novel framework for constructing portfolios, placing stocks that are relatively safer(defined as less risky or less-mispriced) on the long side, while leaving the unsafe ones to be placed on the short side. This approach, grounded in theoretical insights from models addressing limits to arbitrage, provides a robust rationale for well-known cross-sectional puzzles, including the low-volatility puzzle and the distress risk puzzle. In addition, our theoretical framework predicts: i) a negative *contemporaneous* association between aggregate stock market returns and cross-sectional signals, ii) a short-term (conditional) influence of sentiment on expected returns, contrasted with a long-term (unconditional) effect driven by fundamental risk, and iii) a reduction in both short- and long-term returns as sentiment increases, with the latter representing an unexplored aspect in existing research. Applying our methodology across 100 anomalies in the United States, we find robust support for our model's predictions. Overall, our findings highlight the critical role of market sentiment in linking the cross-sectional and time-series dynamics of stock market returns.

Keywords: Market Sentiment, Noise Traders, Stock Market, Risk Anomalies

JEL Classification: G12, G14

*We thank Malcolm Baker, Naresh Bansal (discussant), Pedro Bordalo, Lauren Cohen, Andrei Shleifer, and seminar participants at Inter-Finance PhD Seminar, Behavioural Finance Working Group 17th Annual Conference, FMA 2024 and SFA 2024 for their valuable comments.

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1 Introduction

In this paper, we develop a framework for constructing portfolios where relatively safer stocks (defined as less risky or less mispriced) are placed on the long side, while less safe stocks are allocated to the short side.[1] This approach, which is novel to the finance literature, is able to explain three insights into both the cross-section of stock returns and the time-series variation of aggregate stock market returns.

First, our model explains why anomalies driven by mispricing (rather than risk) emerge, offering an *economic interpretation* of stock market signals.[2] Our model builds upon the theoretical foundation of noise trader risk and limits to arbitrage, as proposed by De Long et al. (1990) and Shleifer and Vishny (1997). We show that cross-sectional anomalies arise when noise traders, who exhibit biased perceptions, dominate trading in certain stocks. This leads to systematic pricing errors, particularly in riskier assets typically found in the short-leg of portfolio strategies. The mispricing is amplified during high sentiment periods as unsophisticated investors flood the market, pushing prices further away from their fundamental values. Our empirical findings confirm this, showing that stocks more susceptible to sentiment changes exhibit greater deviations from expected returns. By aligning the long and short sides of portfolios with safer and riskier characteristics, respectively, we offer an economically grounded explanation for the emergence and persistence of well-known cross-sectional puzzles where firm characteristics associated with lower levels of risk yield higher returns, such as the low-volatility puzzle (Ang et al. 2006), the distress risk puzzle (Campbell et al. 2008), and the quality anomaly (Asness et al. 2019).

This economic interpretation is important and is best illustrated by comparing two prominent factors: the size factor (SMB, Fama and French 1992) and the quality factor (QMJ, Asness et al. 2019). Both factors are priced in the stock market, yet SMB places riskier firms (small-cap stocks) in the long leg, whereas QMJ assigns similarly risky firms (low-quality or junk" stocks) to the short leg.[3] How should we reconcile this inconsistency?

[1]The classification of whether maximum or minimum exposure to a given firm characteristic is considered "safe" is open to interpretation. In the Online Appendix, we include a full list of the anomalies analyzed, along with our interpretations of the associated firm characteristics, grounded as closely as possible in the original literature.

[2]In asset pricing, the conventional approach in the factor zoo literature has primarily focused on a *"statistical interpretation"* — either by testing out-of-sample performance (McLean and Pontiff 2016) or applying dimension-reduction techniques to identify the most influential factors (Feng et al. 2020; Bryzgalova et al. 2023). The *"economic interpretation"* of factor anomalies, on the other hand, focus on how investors should form portfolio strategy, rather than focusing on the performance of factor returns over time.

[3]Figure 4 in Asness (2018) shows that many small firms are ranked as low-quality ("junk").

Should it simply be accepted, given that cross-sectional signals are designed to generate statistically significant positive returns? While the risk-based explanation that forward-looking investors demand compensation for bearing higher levels of risk associated with certain firm characteristics are well-established, the mispricing argument lacks a comparable framework to justify its role in explaining cross-sectional anomalies. Our first contribution lies in addressing this gap.

Our second contribution is to use the model to unify the explanation of both time-series variations in aggregate stock returns and cross-sectional anomalies.[4] In particular, periods of strong market performance often coincide with weaker cross-sectional anomaly returns, and vice versa, raising a key question "Is there a common force driving these patterns simultaneously?" Our framework identifies a common driving force: market sentiment.

The key insight in our framework stems from the simple intuition that both time-series and cross-sectional patterns emerge from the same set of equity prices: the long and short legs of equity portfolios. Unlike the single risky asset assumed in De Long et al. (1990), we incorporate two risky assets. We interpret one as the long side of portfolio returns and the other as the short side. In this setup, aggregate stock market returns are the average of the two risky assets, while cross-sectional anomaly returns are the return difference between the long and short sides of the portfolio. When sentiment is low, diminished demand for risky assets elevates aggregate returns but weakens long-short strategies. Conversely, high sentiment inflates prices, reducing aggregate returns while amplifying the profitability of anomalies, particularly for sentiment-sensitive short-leg stocks. These dynamics create a *negative contemporaneous relationship* between aggregate market returns and the average performance of long-short portfolios based on firm characteristics. This unified explanation of time-series and cross-sectional patterns constitutes a key contribution of our paper.

Finally, our theoretical framework predicts a short-term (conditional) influence of sentiment on expected returns, contrasted with a long-term (unconditional) effect driven by fundamental risk.

Our empirical analysis provides two additional contributions regarding the performance of portfolio strategies conditioned on sentiment. First, contrary to the existing literature,

[4]Traditional asset pricing theories treat time-series and cross-sectional phenomena separately. In the time-series domain, Mehra and Prescott (1985) documented that aggregate stock returns in the U.S. average approximately 5% per annum. Additionally, Jagannathan and Wang (1996) and Lettau and Ludvigson (2002) observed time-varying risk premia. In the cross-section, Fama and French (1992) showed that small-cap and value stocks tend to outperform large-cap and growth stocks. Since then, researchers have identified numerous additional factors, often referred to as the "Factor Zoo" (Cochrane 2011; McLean and Pontiff 2016; Hou et al. 2020).

we find that during high-sentiment periods, even a broad range of long-leg strategies become unprofitable.[5] Additionally, the negative relationship between market sentiment and short-leg returns is pervasive across many well-established risk anomalies. Taken together, our findings reveal that both long- and short-leg returns, on average, decline as sentiment rises, offering significant insights into the empirical asset pricing literature.

Literature review: our paper relates to a large literature on theoretical and empirical asset pricing. Sentiment is a powerful empirical predictor of difficult-to-arbitrage stocks, as demonstrated by Baker and Wurgler (2006), and also of the aggregate stock market, as shown by the time-series result of Huang et al. (2015). In the cross section, numerous works have attempted to link the role of sentiment to individual or a small number of anomalies.[6] Instead, we document the role of sentiment across the 100 number of anomalies. Other related papers in the cross section include Hong et al. (2000) and Avramov et al. (2013). Dong et al. (2022) investigate links between long-short anomaly portfolio returns from the cross-sectional literature and the U.S. market excess returns (See, however, Engelberg et al. (2023) and Cakici et al. (2024) for some conflicting pieces of evidence). Specifically, they show that a group of 100 long-short anomaly portfolio returns is indeed useful for forecasting the future monthly market excess return on an out-of-sample basis. We differentiate in two ways. First, Dong et al. (2022) focus on forecasting relationship between time-series of stock market and cross-sectional signals. Our work focuses on documenting *contemporaneous* relationship of the two. Second, through our model, we provide a sentiment-based explanation which drives the underlying dynamics. Yu and Yuan (2011) show that a positive mean-variance relation holds only during periods of low sentiment, indicating that beta works when market sentiment is low. Building on this, our work demonstrates that alpha works when market sentiment is high. In a related work to ours, Bordalo et al. (forthcoming) construct a sentiment index based on analyst expectations of long-term expected earnings growth for S&P 500 firms. We share a similar mechanism where return predictability in the time-series stock market as well as cross-section anomalies arises from the non-rational beliefs that lead to systematic pricing errors that are eventually corrected. We believe that our paper is an important complement to their work, as we provide a theoretical underpinning and consider a wide range of anomalies.

Outline: The remainder of the paper is organised as follows: Section 2 introduces our model. Section 3 provides empirical results that support the model. Section 4 discusses

[5] See Section 3.4 for more details.

[6] Antoniou et al. (2013) relate momentum with sentiment, and Stambaugh et al. (2012) uses 11 number of anomalies.

anomalies as a group and justify our reformulation of placing safer (riskier) firm characteristics to long (short) legs. Section 5 concludes.

2 Model

2.1 The toy model

We begin by presenting a simple toy model that captures the essence of our main model. This simple framework contains two agents (rational or sophisticated traders, and irrational or noise traders) and two risky assets, labeled Q and J. Here, Q represents a stock of decent quality, while J is more ”junky.” We assume an economy comprising only these two assets. In such case, as they collectively drive the entire market, the market return is simply the average of their returns: $R^{mkt} = \frac{Q+J}{2}$. Additionally, a cross-sectional strategy can be formed as the difference between the two stocks, $R^{cs} = Q - J$.[7]

When market sentiment is low at time t, demand for both stocks, Q and J, is generally low, depressing prices. This downturn is subsequently corrected, causing R^{mkt}_{t+1} to rise. Conversely, when sentiment is high, demand for both stocks increases, inflating prices temporarily before they revert to fundamental values, leading to a lower R^{mkt}_{t+1}. Notably, J is more sensitive to sentiment changes due to the influence of noise traders, who often gravitate towards riskier assets. This makes the drop in J's returns larger than that of Q, resulting in a positive QMJ (Quality Minus Junk) effect (Asness et al. 2019).

To quantify, a one-unit increase in market sentiment might immediately raise Q by 3% and J by 5%. This aligns with the limits to arbitrage principle (Shleifer and Vishny 1997), which suggests that harder-to-arbitrage stocks, like J, remain mispriced longer. For instance, a one-unit decrease in sentiment (s_t) depresses prices—Q by 3% and J by 5%—which rebounds the following month, generating a +4% market return, $R^{mkt}_{t+1} = \frac{Q_{t+1}+J_{t+1}}{2} = +4$. In high-sentiment periods, prices rise—Q by 3% and J by 5%—but revert next month, yielding a -4% market return ($R^{mkt}_{t+1} = -4$). The heightened sensitivity of J to sentiment changes also enhances the cross-sectional strategy return, as Q declines less than J, producing a +2% cross-sectional return, $R^{cs}_{t+1} = (-3) - (-5) = +2$.

[7] We argue that this is a reasonable assumption; in the empirical section, we demonstrate that the average returns of all anomalies closely mirror overall market returns.

Putting together, our model demonstrates that fluctuations in sentiment drive predictable patterns in both market and cross-sectional returns, generating the contemporaneous negative relationship between the two.

2.2 The baseline model

We now formally describe our theoretical framework, which is based on the noise trader model of De Long et al. (1990) (henceforth DSSW). This original paper draws on a simple overlapping generation (OLG) framework with one risky and one risk-free asset and two types of agents, sophisticated investors and irrational noise traders. Both agents live for two periods and then they die. Rational investors can not take full advantage of arbitrage opportunities because of *noise trader risk* created by the uncertainty of noise traders' stochastic misperception. In particular, sophisticated investors (denoted as "si") are fully rational, in contrast to noise traders (denoted as "nt") whose beliefs are biased and, thus, their trades are polluted with noise. There is a continuum of agents on the interval $[0, 1]$, and the ratio of noise traders is defined as μ. All agents maximize a constant absolute risk aversion (CARA) utility function of wealth, given by

$$U = -\exp^{-(2\gamma)\omega} \tag{1}$$

where γ is the coefficient of absolute risk aversion and ω is wealth. With normally distributed returns of holding a unit of the risky asset, the maximization of equation 1 is equivalent to the maximization of :

$$\overline{\omega} - \gamma\sigma_{\omega}^{2} \tag{2}$$

where $\overline{\omega}$ is the expected final wealth, and σ_{ω}^{2} is the one period ahead variance of wealth.

Our extension is to include two risky assets instead of one as in the original model of DSSW. When a single risky asset explains the entire market, we are not able to form a portfolio strategy. The innovation of our model is to have two risky assets to concurrently explain the general stock market as well as portfolio strategy. We denote them as u_1 and u_2, which are in fixed supply of one unit and bear the price $p_{t,i}$ where $i \in \{1, 2\}$. As we later show, each risky asset represents long- and short-leg of stock returns, respectively. While this setting comes from a simple observation that both time-series and cross-sectional market pattern come from the same set of stock prices, it not only simplifies the notations required to derive the results, but also is highly intuitive.

For instance, assume that operating profitability is the only firm characteristics that matter for investors in this economy. Denoting u_1 as less profitable firm and u_2 as more profitable firm, the aggregate market performance is simply the average of returns of u_1 and u_2, while the cross-sectional signal based on operating profitability is return of u_2 less that of u_1. The risk-free asset is assumed to be in perfectly elastic supply, rendering its priced as fixed. Furthermore, we assume that all assets pay identical dividends at the fixed rate r.

For each period, sophisticated investors maximize their expected utility by optimally choosing to hold $\alpha^{si}_{t,1}$ of the risky asset u_1 and $\alpha^{si}_{t,2}$ of the risky asset u_2. On the other hand, noise traders maximize their expected utility, given their misperception, by choosing to hold $\alpha^{nt}_{t,1}$ of risky asset u_1 and holding $\alpha^{nt}_{t,2}$ of risky asset u_2. We further assume that both agents cannot make unlimited bidding against each other, due to limits of arbitrage (see Shleifer and Vishny 1997).

We also assume that the aggregate market sentiment s_t is a martingale with drift $s^{\star}_t$ and volatility σ^2_s.[8] Finally, we assume that the misperception of noise traders for risky assets u_1 and u_2 is different and is given by:

$$\begin{gathered} s_{t,i} = \beta^m_i s_t + \epsilon_{t,i} \quad \text{for} \quad i \in \{1,2\} \\ \epsilon_{t,i} \sim \mathcal{N}(0,\, \sigma^2_{\epsilon_i}) \quad \text{with} \quad cov(\epsilon_{t,i}, s_t) = 0 \quad \text{and} \quad cov(\epsilon_{t,i}, \epsilon_{t,j}) = 0 \quad \forall\, i \neq j \end{gathered} \tag{3}$$

The idea behind equation 3 is that the misperception of the risky asset includes a systematic as well as an idiosyncratic component $\epsilon_{t,i}$. Intuitively, β^m captures the elasticity of misperception to the systematic sentiment component. What we are interested in is to assess the pricing role of market sentiment, s_t.

2.3 Expected returns conditional on sentiment

The equation 3 above directly imply that $\sigma^2_{s_i} = (\beta^m_i)^2\sigma^2_s + \sigma^2_{\epsilon_i}$ where $i \in \{1,2\}$. Since we do not focus on the idiosyncratic component, we simplify the matter by assuming $\sigma^2_{\epsilon_1} =$

[8]This assumption is crucial for the basic result of the paper and differentiates us with Ding et al. (2019). We empirically validate this assumption in Section 2.4.

$\sigma^2_{\epsilon_2}$. Without loss of generality, assume $\beta_1^m > \beta_2^m > 0$: u_1 has larger exposure to market sentiment than asset u_2 and implies higher noise trader risk $\sigma^2_{s_1} > \sigma^2_{s_2}$. This is exactly the risk that sets limits to arbitrage for rational investors to trade against irrational investors.

Due to equation 2, sophisticated investors maximize the following expected utility:

$$\begin{aligned}\overline{\omega}^{si} - \gamma\sigma^2_{w^{si}} = c_0 &+ \alpha^{si}_{t,1}(r + {}_tp_{t+1,1} - p_{t,1}(1+r)) + \alpha^{si}_{t,2}(r + {}_tp_{t+1,2} - p_{t,2}(1+r)) \\ &- \gamma[(\alpha^{si}_{t,1})^2\, {}_t\sigma^2_{p_{t+1,1}} + (\alpha^{si}_{t,2})^2\, {}_t\sigma^2_{p_{t+1,2}} + 2\alpha^{si}_{t,1}\alpha^{si}_{t,2}\ {}_tcov(p_{t+1,1}, p_{t+1,2})]\end{aligned} \tag{4}$$

c_0 is a function of first-period labor income, and the anterior subscript denotes the time at which an expectation is taken (e.g., ${}_tp_{t+1,1} \equiv E_t[p_{t+1,1}]$) for ease of exposition. Similarly, ${}_t\sigma^2_{p_{t+1,i}}$ denotes the conditional expectation of one-step-ahead variance of $p_{t+1,i}$ and ${}_tcov(p_{t+1,1}, p_{t+1,2})$ is the conditional expectation of the covariance of the one-step-ahead risky assets' prices $p_{t+1,i}$ $\forall i \in \{1,2\}$.

Noise traders likely maximize the following expected utility:

$$\begin{aligned}\overline{\omega}^{nt} - \gamma\sigma^2_{w^{nt}} = c_0 &+ \alpha^{nt}_{t,1}(r + {}_tp_{t+1,1} - p_{t,1}(1+r)) + \alpha^{nt}_{t,2}(r + {}_tp_{t+1,2} - p_{t,2}(1+r)) \\ &- \gamma[(\alpha^{nt}_{t,1})^2\, {}_t\sigma^2_{p_{t+1,1}} + (\alpha^{nt}_{t,2})^2\, {}_t\sigma^2_{p_{t+1,2}} + 2\alpha^{nt}_{t,1}\alpha^{nt}_{t,2}\ {}_tcov(p_{t+1,1}, p_{t+1,2})] \\ &+ \underbrace{\alpha^{nt}_{t,1}(\beta_1^m s_t + \epsilon_{t,1}) + \alpha^{nt}_{t,2}(\beta_2^m s_t + \epsilon_{t,2})}_{\text{misperception}}\end{aligned} \tag{5}$$

Note that noise traders maximization equation 5 has sentiment components, $\alpha^{nt}_{t,1}(\beta_1^m s_t + \epsilon_{t,1}) + \alpha^{nt}_{t,2}(\beta_2^m s_t + \epsilon_{t,2})$. Absence of such sentiment concerns ($\beta_1^m = \beta_2^m = 0$) reduces down to the same trade-off equation in 4. Taking the first order conditions with respect to risky asset holdings yields:

$$\alpha^{si}_{t,1} = \frac{{}_tcov(p_{t+1,1}, p_{t+1,2})R_{t+1,2} - \sigma_2^2 R_{t+1,1}}{2\gamma({}_tcov(p_{t+1,1}, p_{t+1,2})^2 - \sigma_1^2\sigma_2^2)} \tag{6}$$

$$\alpha^{si}_{t,2} = \frac{{}_tcov(p_{t+1,1}, p_{t+1,2})R_{t+1,1} - \sigma_1^2 R_{t+1,2}}{2\gamma({}_tcov(p_{t+1,1}, p_{t+1,2})^2 - \sigma_1^2\sigma_2^2)} \tag{7}$$

where, for ease of notation, we define the excess return from date t to date $t+1$ as $R_{t+1,i} \equiv r + {}_tp_{t+1,i} - p_{t,i}(1+r)$, and the conditional volatility as $\sigma_i^2 \equiv {}_t\sigma^2_{p_{t+1,i}}$ for $i \in \{1,2\}$. For noise traders,

$$\alpha^{nt}_{t,1} = \frac{{}_tcov(p_{t+1,1}, p_{t+1,2})(R_{t+1,2} + \beta^m_2 s_t + \epsilon_{t,2}) - \sigma^2_2(R_{t+1,1} + \beta^m_1 s_t + \epsilon_{t,1})}{2\gamma({}_tcov(p_{t+1,1}, p_{t+1,2})^2 - \sigma^2_1\sigma^2_2)} \tag{8}$$

$$\alpha^{nt}_{t,2} = \frac{{}_tcov(p_{t+1,1}, p_{t+1,2})(R_{t+1,1} + \beta^m_1 s_t + \epsilon_{t,1}) - \sigma^2_1(R_{t+1,2} + \beta^m_2 s_t + \epsilon_{t,2})}{2\gamma({}_tcov(p_{t+1,1}, p_{t+1,2})^2 - \sigma^2_1\sigma^2_2)} \tag{9}$$

Prices are obtained by the following market clearing conditions:

$$(1-\mu)\alpha^{si}_{t,j} + \mu\alpha^{nt}_{t,j} = 1 \quad \forall j \in \ \{1,2\} \tag{10}$$

where the left hand side follows from the assumption that the supply of risky assets is fixed and equal to 1. Thus current prices are given by:

$$p_{t,1} = \frac{1}{1+r}[r + {}_tp_{t+1,1} - 2\gamma({}_tcov(p_{t+1,1}, p_{t+1,2}) + \sigma^2_1) + \mu(\beta^m_1 s_t + \epsilon_{t,1})] \tag{11}$$

$$p_{t,2} = \frac{1}{1+r}[r + {}_tp_{t+1,2} - 2\gamma({}_tcov(p_{t+1,1}, p_{t+1,2}) + \sigma^2_2) + \mu(\beta^m_2 s_t + \epsilon_{t,2})] \tag{12}$$

From equation 8 - 9 it is easy to see that the β^m_1 and β^m_2 have a positive effect on portfolio allocations of $u_1(u_2)$. Since we have assumed that $\beta^m_1 > \beta^m_2$, the current market sentiment will affect investors holding u_1 more. As a result, we get:

$$R_{t+1,i} = \frac{\mu\beta^m_i}{1+r}\left[s_{t+1} - (1+r)s_t - s^*\right] + 2\gamma(k + \sigma^2_i) + \theta_i \tag{13}$$

where θ_i is given by:

$$\theta_i = \frac{\mu\epsilon_{t+1,i}}{1+r} + \mu\epsilon_{t,i} \tag{14}$$

Equation 13 clearly illustrates that the presence of noise traders ($\mu \neq 0$) affects returns. While we remain agnostic about the size of noise traders in the market, their mere presence is sufficient to cause stock prices to deviate significantly from their fundamental values, even in markets with relatively few noise traders (Mendel and Shleifer 2012).

We now present two main theorems using equation 13 for two risky assets ($i = 1, 2$).

Theorem 2.1. *There is a negative relationship between sentiment and future aggregate stock market returns.*

Proof. Using equation 13, the average of aggregate stock market returns are given by:

$$\begin{aligned} R^{mkt}_{t+1} &= \frac{R_{t+1,1} + R_{t+1,2}}{2} \\ &= \frac{\mu(\beta^m_1 + \beta^m_2)}{1+r}\Big[s_{t+1} - (1+r)s_t - s^*\Big] + 2\gamma(\sigma_1^2 + \sigma_2^2) + (\theta_1 + \theta_2) \end{aligned} \tag{15}$$

The expected returns conditional on low or high sentiment period is given by:

$$\begin{aligned} E(R^{mkt}_{t+1} \mid s_t) &= E\Big(\frac{R_{t+1,1} + R_{t+1,2}}{2}\Big| s_t\Big) \\ &= \frac{\mu(\beta^m_1 + \beta^m_2)}{1+r}\Big[E([s_{t+1} - (1+r)s_t \mid s_t)] - s^*\Big] + 2\gamma(\sigma_1^2 + \sigma_2^2) + (\theta_1 + \theta_2) \\ &= \frac{-\mu(\beta^m_1 + \beta^m_2)}{1+r}\Big[rs_t + s^\star\Big] + 2\gamma(\sigma_1^2 + \sigma_2^2) + (\theta_1 + \theta_2) \end{aligned} \tag{16}$$

The last equation follows from the fact that sentiment is assumed to be a martingale.[9] Thus, the higher the sentiment s_t, the lower the aggregate stock market returns in the next period (or β_{mkt}). □

Theorem 2.2. *There is a positive relationship between sentiment and future strategy returns.*

Proof. Consider forming a portfolio strategy where investors long the second risky asset u_2 and short the first risky asset u_1. Taking conditional expectations with respect to the current sentiment s_t, we obtain:

$$\begin{aligned} E(R^{cs}_{t+1} \mid s_t) &= E(R_{t+1,2} - R_{t+1,1} \mid s_t) \\ &= \frac{\mu(\beta^m_2 - \beta^m_1)}{1+r}\Big[E([s_{t+1} - (1+r)s_t \mid s_t)] - s^*\Big] + 2\gamma(\sigma_2^2 - \sigma_1^2) + (\theta_2 - \theta_1) \\ &= \frac{-\mu(\beta^m_2 - \beta^m_1)}{1+r}\Big[rs_t + s^*\Big] + 2\gamma(\sigma_2^2 - \sigma_1^2) + (\theta_2 - \theta_1) \end{aligned} \tag{17}$$

[9]The same results are obtained when sentiment is assumed to be a supermartingale.

Again, the last equation follows from the fact that sentiment is assumed to be a martingale. Since $\beta_2^m - \beta_1^m < 0$, it follows that higher level of sentiment s_t is followed by higher strategy returns in the next period (or α).

□

From Theorems 2.1 and 2.2, the inverse relationship between market anomalies and aggregate stock returns naturally arises.

Corollary 2.2.1. *There is an inverse relationship between aggregate stock market returns (β_{mkt}) and market anomalies (α).*

Proof. Omitted for brevity. □

Following the sentiment beta assumption $\beta_1^m > \beta_2^m > 0$, one can interpret risky asset u_1 as short legs of characteristics-based portfolios, and u_2 as long legs. This is in line with existing literature that short legs are in general more responsive to changes in sentiment (Stambaugh et al. 2012). But the second part of our sentiment beta assumption, $\beta_2^m > 0$, differs from Stambaugh et al. (2012) and Stambaugh et al. (2014) who argue β_2^m is indistinguishable from 0. While our theorems still hold when $\beta_1^m > \beta_2^m = 0$, we show that $\beta_2^m \neq 0$ in the empirical section.

2.4 Is sentiment index a martingale?

A basic assumption driving the main results in Theorems 2.1 and 2.2 is that the sentiment index is a martingale. A sequence of random variables X_t is a martingale process if, for any time t, the following two conditions hold:

(i) $E(| X_t |) < \infty$

(ii) $E(X_{t+1} \mid \mathcal{F}_t) = X_t$

where $\mathcal{F}_t$ is the information set available up to time t. In this section we use the market sentiment index of Huang et al. (2015) (henceforth HJTZ) to show that this sentiment index empirically qualifies to be martingale. We employ three tests. The first one is to consider the increments and assess whether they have zero mean. We find that the average of the increments is 0.002 which is indistinguishable from 0 (t-stat: 0.24). Secondly we run the Ljung-Box test to check whether the index is independently distributed.

In particular, we test the following hypothesis:

- H_0**:** The data are independently distributed, i.e. the correlations in the population from which the sample is taken are 0, so that any observed correlations in the data result from randomness of the sampling process.
- H_a**:** The data are not independently distributed; they exhibit serial correlation.

[INSERT Table 1 HERE]

Panel A in Table 1 presents the results. For $lag = 1$, we find that the χ^2 is equal to 2.52 (p-value: 0.11). Thus, we fail to reject H_0. With $lag = 2$, we find that the χ^2 is equal to 2.54 and the p-value is 0.028. Again, we fail to reject H_0. We also run the Durbin-Watson test, an alternative test statistic used to detect the presence of autocorrelation at lag 1 in the residuals (prediction errors) from a regression analysis. If e_t is the residual given by $e_t = \rho e_{t-1} + \nu_t$ the Durbin-Watson test statistic is

$$d = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2} \tag{18}$$

where T is the number of observations. For large T, d is approximately equal to $2(1 - \hat{\rho})$, where $\hat{\rho}$ is the sample autocorrelation of the residuals. $d = 2$, therefore, indicates no autocorrelation. The value of d always lies between 0 and 4. If the Durbin–Watson statistic is substantially less than 2, there is evidence of positive serial correlation. If $d > 2$, successive error terms are negatively correlated. We find that $DW = 1.88$ with a p-value 0.055 and, therefore, we fail to reject the null hypothesis. From all the above, we can conclude that the assumption that HJTZ sentiment index is a martingale is supported empirically.

Finally, we follow Hall (1978) to estimate the following AR(1) process:

$$s_t = \alpha + \beta s_{t-1} + \epsilon_t \tag{19}$$

Martingales should have $\alpha = 0$ and $\beta = 1$, which leads to $E(s_{t+1} \mid s_t) = s_t$. Panel B in Table 1 presents the results of the regression where the t-statistics are adjusted using Newey-West procedure with 6 lags.

The AR(1) process, reveals that the coefficient of the lagged variable is statistically insignificant different from 1, thus we can infer that s_t is a martingale process.[10]

3 Empirical results

3.1 Data

[INSERT Figure 1 HERE]

We use monthly market-based sentiment series constructed by Huang et al. (2015) (henceforth HJTZ). The HJTZ sentiment index data that we use spans over 55 years, from January 1966 to December 2020 and uses the same six variables[11] as in Baker and Wurgler (2006) (henceforth BW). HJTZ index refines the original sentiment index of BW by extracting information via Principal Least Squares (PLS) regression. We opt for this measure over the widely known BW version of sentiment as it shows to have greater predictive power for the aggregate stock market.[12] Figure 1 examines the time-series behavior of this sentiment index over time. The figure contains two measures, the HJTZ sentiment index (solid red) and the Baker-Wurgler (BW) sentiment index (dotted blue). Both measures are orthogonalized to macroeconomic conditions. The correlation between the two measures is about 70%, and they tend to show a similar trajectory. Closely examining the graph, we find that sentiment tends to spike on a number of occasions. In the late 1960s, investor sentiment rose to a peak around the electronic bubble. During the 1970s, it faced a period of decline, only to witness a remarkable resurgence, reaching its peak once again in the early 1980s amidst the biotech bubble. During the internet bubble in the late 1990s, sentiment met another pinnacle.

[10] If we do not adjust standard errors using the Newey-West procedure with 6 lags, $t(\hat{\beta}-1)$ becomes -1.996 which makes s_t statistically less than 1. In that case, our results still hold since the process is a supermartingale.

[11] The six measures are the closed-end fund discount, the number and the first-day returns of IPOs, NYSE turnover, the equity share in total new issues, and the dividend premium.

[12] Recall that this paper aims to explain the driving factor that explains both the aggregate stock markets and cross-sectional signals. Main empirical results remain unchanged when we use BW sentiment rather than HJTZ sentiment, as shown in the Online Appendix.

For stock market returns, we use log monthly returns of the value-weighted and equal weighted stock market portfolios from the Center for Research in Security Prices (CRSP). We compute excess value weighted (VWR_TBL) and equal weighted stock returns (EWR_TBL) using log of the three-month Treasury bill, also from CRSP.

We use risk anomalies (long-leg, short-leg, and long-short portfolio returns) from the public data repository by Chen and Zimmermann (2022).[13] From the April 2023 release that we use, there are 212 anomalies published in the economics/finance/accounting literature. We trim down this list of anomalies to 100 for a number of reasons. First, we require the anomalies data to match the availability of sentiment data that spans from January 1966 to December 2020. For instance, we do not use a risk factor formed on consensus recommendation (Barber et al. 2001) that is available from 1993 due to analyst recommendation database. Since sentiment reached its highest and lowest level in 1960s and 1970s, missing the first half of our analysis time frame is undesirable. This procedure leaves 147 anomalies. Next, many anomalies contain essentially the same information and are thus duplicates of each other. Moreover, some cross-sectional signals are purely based on performance (for instance, all of momentum-based strategies simply bet on winning stocks, regardless of the underlying fundamentals of firms) or have ambiguous interpretation regarding whether safe firm characteristics are placed on the long-legs or short-legs. For instance, risk factors based on leverage could have different interpretations based on the underlying economy. A firm with strong fundamentals can have high leverage because they perceive the current economic condition as good. A company with poor fundamentals may still maintain high leverage due to its low revenue, which inherently raises the leverage ratio. We therefore pull out these anomalies. This leaves us with 100 anomalies that we use to establish main empirical findings.

Our sentiment framework establishes that long-legs contain stocks with (relatively) safe characteristics whereas short-legs include stocks with (relatively) risky characteristics (recall that $\beta_1^m > \beta_2^m > 0$, where β_1^m represents the misperception of noise traders regarding risky asset 1, which we interpret as the short side of portfolio returns, while β_2^m represents the misperception for the long side of portfolio returns). In about 30+ anomalies, we follow this intuition and switch the long-leg returns with short-leg returns. In other words, we reformulate the existing cross-sectional signals to have safe firm characteristics assigned to the long-leg returns and risky characteristics to the short-leg returns.

For example, we switch the legs for the following risk factors: (1) bid-ask spread, (2)

[13] We thank Andrew Chen and Tom Zimmermann for making this data public. This data is available at https://www.openassetpricing.com/.

investment, and (3) firm age, for the following reasons. For the bid-ask spread measure (Amihud and Mendelson 1986a), liquid stocks have lower bid-ask spreads (as liquid stocks tend to have spreads close to zero). For the investment factor (Titman et al. 2004), higher levels of investment expenditures, which are generally viewed favorably due to greater investment opportunities, are originally assigned to the short leg of portfolio returns. For firm age (Barry and Brown 1984), younger firms, which are assigned to the long side of portfolio returns, tend to be riskier due to less public information and smaller size. For other risk factors, such as gross profitability (Novy-Marx 2013), which assigns relatively safer characteristics (higher profitability) to the long side of portfolio returns, we maintain the original assignment. The final set of 100 cross-sectional signals aligns with the relevant literature, including McLean and Pontiff (2016) and Dong et al. (2022). The full list of anomalies considered in our main empirical exercise, along with our decision on whether to flip the long and short sides of returns, is provided in Online Appendix Section A.

3.2 Sentiment and aggregate stock returns

As in Section 2, consider an economy with two risky assets, u_1 and u_2 with returns $R_{t,1}$ and $R_{t,2}$, respectively. Consistent with earlier literature that sentiment has an asymmetric effect on stocks with certain characteristics, we interpret u_2 as the long leg of portfolio strategy, and u_1 as the short leg of portfolio strategy. The representative long-short strategy return would be $R_t^{cs} = R_{t,2} - R_{t,1}$, and aggregate market returns $R_t^{mkt} = (R_{t,2} + R_{t,1})/2$.

We start our analysis by examining the relationship between market sentiment and aggregate stock market returns. We regress the aggregate stock market returns on one month lagged HJTZ sentiment index, following earlier papers such as Baker and Wurgler (2006) and Huang et al. (2015).

$$R_{t+1}^{mkt} = \alpha + \beta s_t + \varepsilon_{t+1} \tag{20}$$

where $mkt = \{\text{VWR\_TBL, EWR\_TBL}\}$ is the aggregate market returns, and s_t is the macroeconomics-orthogonalized version of HJTZ market sentiment index. We are interested in whether we can reject the null hypothesis of $\beta = 0$, that investor sentiment has no predictive ability.

[INSERT Table 2 HERE]

The result, depicted in Table 2, demonstrates a strong negative relationship between market sentiment and aggregate stock returns. A simple forecasting regression model suggests that sentiment negatively predicts market returns (both value-weighted and equal-weighted returns). This holds robust when we divide the available sample into two equal parts (second and third part of Panel A). The low aggregate stock market return following high investor sentiment seems to represent investors' overly optimistic belief about future cash flows that cannot be justified by subsequent economic fundamentals, and aligns well with the prediction stated in Theorem 2.1.

3.3 Sentiment and cross-sectional risk anomalies

We now turn to portfolios formed on firm characteristics that are known to earn strategic profits in the stock market. Because the model framework developed in Section 2 explicitly assumes the presence of long- and short-legs (and henceforth long-minus-short strategy) returns, we separately analyze all of long-leg returns, short-leg returns, and long-short strategy returns.

[INSERT Figure 2 HERE]

Figure 2 plots this result. In this graph, we first categorize months into quintile buckets based on their one-month lagged sentiment level. We calculate the average returns for the 100 long-short strategy returns over a 55-year time frame, conditioned on the sentiment quintile buckets. As the graph suggests, the average returns of the long-short strategy increase as sentiment moves from lower to higher quintile, lending support to Theorem 2.2. Importantly, the average of long-short strategy returns is statistically not different from zero when the sentiment is at its lowest quintile, while that under high sentiment period is positive and statistically significant. This suggests that alpha, or cross-sectional anomalies, is effective when market sentiment is high and ineffective when sentiment is low, complementing earlier findings that market beta works when sentiment is low (Yu and Yuan 2011, Antoniou et al. 2016).

[INSERT Figure 3 HERE]

Figure 3 illustrates the central finding of this paper. Similar to Figure 2, we plot the mean returns of all available long- or short-leg strategy returns across sentiment quintile. This figure provides three empirical patterns that deserve further attention: First, the returns of both the long-leg (represented by a black solid line) and the short-leg (depicted by a red dashed line) portfolios increase as they transition from the highest to the lowest sentiment quintile. Since lower sentiment leads to less demand for securities that results in higher returns for holding risky assets, this is the anticipated direction of the market. Second, the magnitude of this pattern is more severe in the short-leg. The higher the sentiment, more unsophisticated investors arrive at the market, and their demand is concentrated on stocks that are more sentiment-elastic, which tends to be short-legs. The figure illustrates a significant drop in short-leg returns, shrinking from 1.65% to 0.35% per month. This remarkable decrease in short-leg returns in the highest sentiment group is clearly seen in the bootstrapped confidence intervals. When the sentiment is low (sentiment quintile 1 and 2), the upper bootstrapped intervals of short-leg returns intersect much with the lower bootstrapped interval of long-leg returns. But as sentiment increases, moving to sentiment quintile 3 and 4, they overlap significantly less. At the peak of the sentiment, the spread between long-leg returns and short-leg returns is so significant that the boostrapped intervals never intersect. In sum, we establish $\beta_1^m > \beta_2^m > 0$.[14]

The long-short portfolio strategy returns in Figure 2, which is $R_t^{cs} = R_{t,2} - R_{t,1}$, is the gap between black solid line and the red dotted line in Figure 3. Aggregate market returns, $R_t^{mkt} = (R_{t,2} + R_{t,1})/2$, across sentiment quintile is also established using the same figure. Putting together, we arrive at Corollary 2.2.1.

As a robustness check, we use the Baker-Wurgler macroeconomics-orthogonalized sentiment, and alter the sentiment bucket to either median or quartile. We find that results remain robust (see Online Appendix for details).

3.4 The Long-leg results

[INSERT Table 3 HERE]

[14]We obtain the same quantitative result when we use 63 (out of 100) cross-sectional signals that contain safe characteristics in their long-legs and risky characteristics in their short-legs. Since these signals match with our sentiment model, they should provide the upward-sloping pattern of long-short strategy returns as sentiment increases, which we confirm in an unreported exercise. For 37 (out of 100) anomalies that contain safe characteristics in their short-legs and risky characteristics in their long-legs (i.e., they have the 'flipped' legs), the long-short returns are the highest when the sentiment is at the lowest quintile.

In Figure 3, we showed that sentiment also plays a significant role in the variation of long-leg returns. The long-leg returns have shrunk in half moving from the lowest to highest sentiment, from 1.63% to 0.74% per month across sentiment quintile. Bootstrapped intervals also tell us that a wide range of long-leg returns become unprofitable as market sentiment elevates, establishing $\beta_2^m > 0$.

To further validate this finding, we employ a simple regression framework in Table 3. Here, we run predictive regressions with the average returns across 100 anomalies as the dependent variable, separately examining long-side returns (R^{long}), short-side returns (R^{short}), and long-short strategy returns ($R^{\text{long-short}}$). The independent variable is the market sentiment measure from Huang et al. (2015).

[INSERT Figure 4 HERE]

In Panel A, we find that market sentiment negatively predicts composite long-leg returns, with a coefficient of -0.58 and a significant Newey-West adjusted t-statistic of -2.55. The effect on short-leg returns is even stronger, with a coefficient of -0.71 and a Newey-West adjusted t-statistic of -3.10, indicating that sentiment has a more substantial negative predictive power for short-leg returns. As a result, the predictive ability of market sentiment on the long-short strategy return is positive, with a coefficient of 0.13 and a t-statistic of 3.00. In Panel B, we rerun the predictive regressions using our modified methodology, which constructs average returns based on firm characteristics. In this approach, the long side of the portfolio is designed to capture firms with safer characteristics, while the short side represents riskier characteristics, achieved by flipping the long-side and short-side returns for approximately one-third of the anomalies. We denote these modified composite measures with an asterisk (R^{long^*}, R^{short^*}, and $R^{\text{long-short}^*}$). The results in Panel B mirror those in Panel A, reinforcing our main conclusion that long-leg returns are indeed influenced by market sentiment. This finding contrasts with the results of Stambaugh et al. (2014) and Chu et al. (2020). Finally, the distribution of sentiment beta for each anomaly, as shown in Figure 4, confirms that the long side of portfolio returns is also sensitive to market sentiment. This is evidenced by the distribution of sentiment betas for 100 anomalies being significantly different from zero, supporting our regression findings.

4 Exceptions

As discussed in Section 3.1, we are left with an explanation on how some of 100 anomalies have switched signs. We begin this section by noting that the empirical finance literature has generated cross-sectional signals with the aim of consistently producing statistically significant positive returns. This *statistical* approach fails to take into consideration which firm characteristics should be associated with long legs or short legs, an *economic* interpretation that deserves more attention.

The model framework laid out in Section 2 suggests that we identify safer (riskier) firm characteristics as long (short) legs. We find that, among 100 anomalies considered in this work, about 2/3 of them are already constructed in this way. However, the remaining 1/3 of anomalies are in opposite direction. We discuss them in more detail.[15]

4.1 Size and Beta-related anomalies

We find that size and beta-related anomalies work in the opposite direction across the sentiment quintile. Examples for beta related anomalies include beta itself; examples for size related anomalies include firm size (Fama and French 1992) and firm listing age (Barry and Brown 1984), illiquidity (Amihud 2002) and the bid ask spread (Amihud and Mendelson 1986b). This is not surprising that these cross-sectional signals contain risky and harder-to-arbitrage stock in their long-legs (see a related discussion in Birru 2018). In such case, high sentiment environment is associated with low performance in the stocks assigned to the long-legs, generating the inverse relationship.

4.2 Value (BM)-related anomalies

We also find that portfolios sorted on book-to-market (Fama and French 1992 and relevant concepts such as growth in book equity in Lockwood and Prombutr 2010) show a similar pattern. While we did not directly examine Fama-French type risk factor[16], the results here and the above subsection clearly tell us that 'distressed' or riskier stocks are assigned to

[15]See Online Appendix A for full investigation on each anomaly.

[16]SMB and HML are two-way sorts on firm size and book-to-market ratio. A clear test for cross-sectional signals related to firm size and book-to-market would be to do a single sort on firm size and book-to-market ratio, respectively. We use these signals rather than SMB and/or HML.

long-side of the portfolio returns (which are small firms and value firms, respectively), justifying their inverse relationship with sentiment.[17]

4.3 Momentum and aggregate stock returns

Factors based on past stock price, most prominently the past 2-12 months momentum (Jegadeesh and Titman 1993), are simply strategies that bet on past winning stocks. We opt for not including these signals since it is extremely hard to associate past winners and losers with risky and safe legs. In other words, investors simply bet on past winners regardless of their safe or risky traits. In fact, it seems that most momentum strategies do well in both high and low sentiment regimes (undocumented but results are available upon request). We hence pull out 23 number of strategies formed on momentum.

[INSERT Table 4 HERE]

Nevertheless, our explanation can connect the contemporaneous relationship between market anomalies and the aggregate stock market to momentum strategies. Ehsani and Linnainmaa (2022) show that most factors are positively autocorrelated, suggesting that momentum is not a distinct risk factor: rather, it times other factors. Based on our findings, that would suggest a negative relationship between aggregate stock market returns and momentum, a result that we verify in Table 4, in line with the literature (see Daniel and Moskowitz 2016).

5 Conclusion

In this paper, we develop a sentiment-based framework based on De Long et al. (1990) to jointly explain an overall negative contemporaneous relationship between aggregate stock market and cross-sectional strategies. The model suggests that when sentiment is low, the reluctant demand side (long and short legs included) commands higher returns to hold risky assets, giving rise to high aggregate returns. When market sentiment is high, however, the fall in aggregate returns is mainly driven by plummeting high sentiment elasticity stocks (the short leg), generating most anomalies. This framework sheds light

[17] Gârleanu et al. (2012) also propose that value stocks are riskier since they are harder to hedge against "displacement risk".

on the current practice of creating portfolio strategy returns as the model suggests that a firm characteristic that is deemed safer (riskier) to the equity market sentiment should be placed on the long-legs (short-legs).

The model predictions are supported using U.S. aggregate stock market returns as well as numerous published risk anomalies. Some risk factors that do not follow this sentiment pattern are indeed those who place firms with riskier characteristics to the long-legs and (relatively) safer characteristics to the short-legs, which is opposite to our framework. Putting together, this paper argues that sentiment is an important element that jointly explains the market beta and strategy alpha.

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List of Figures

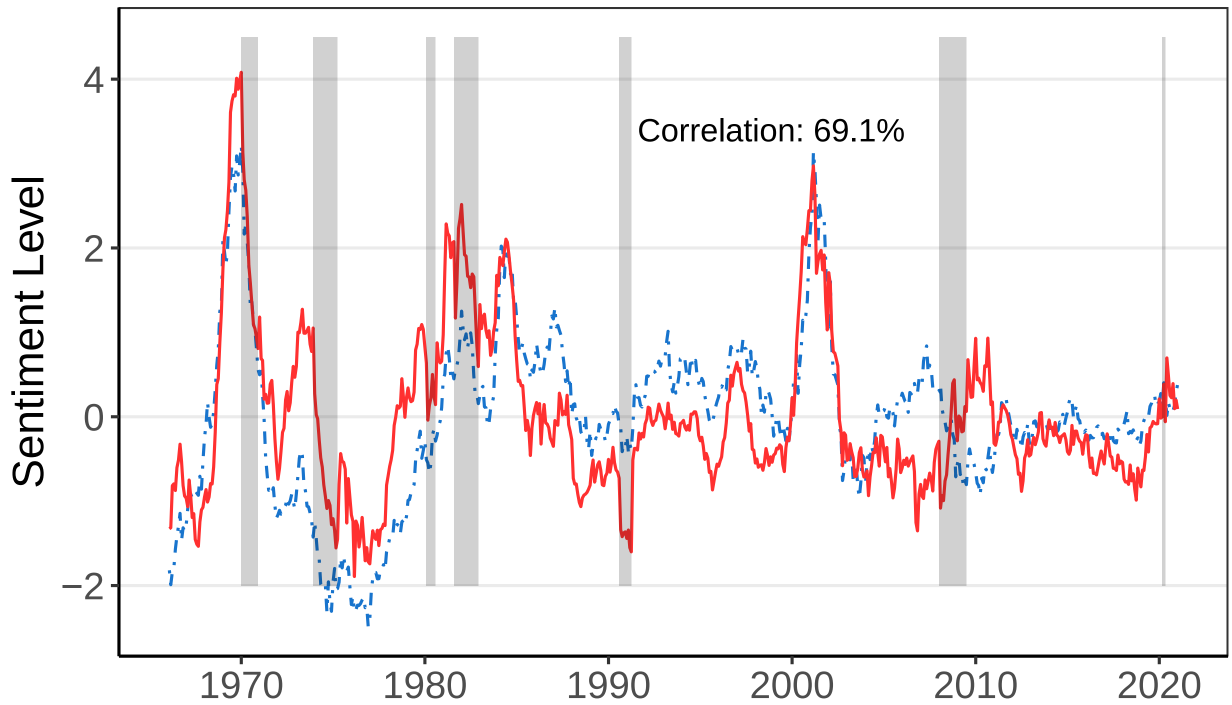


Figure 1: This figure illustrates sentiment index over time. Red solid line is the HJTZ sentiment index that we use in the main analysis. We also plot Baker-Wurgler index in dotted blue line. Both sentiment measures are macroeconomics variables-orthogonalized version. Shaded areas are NBER recessions.

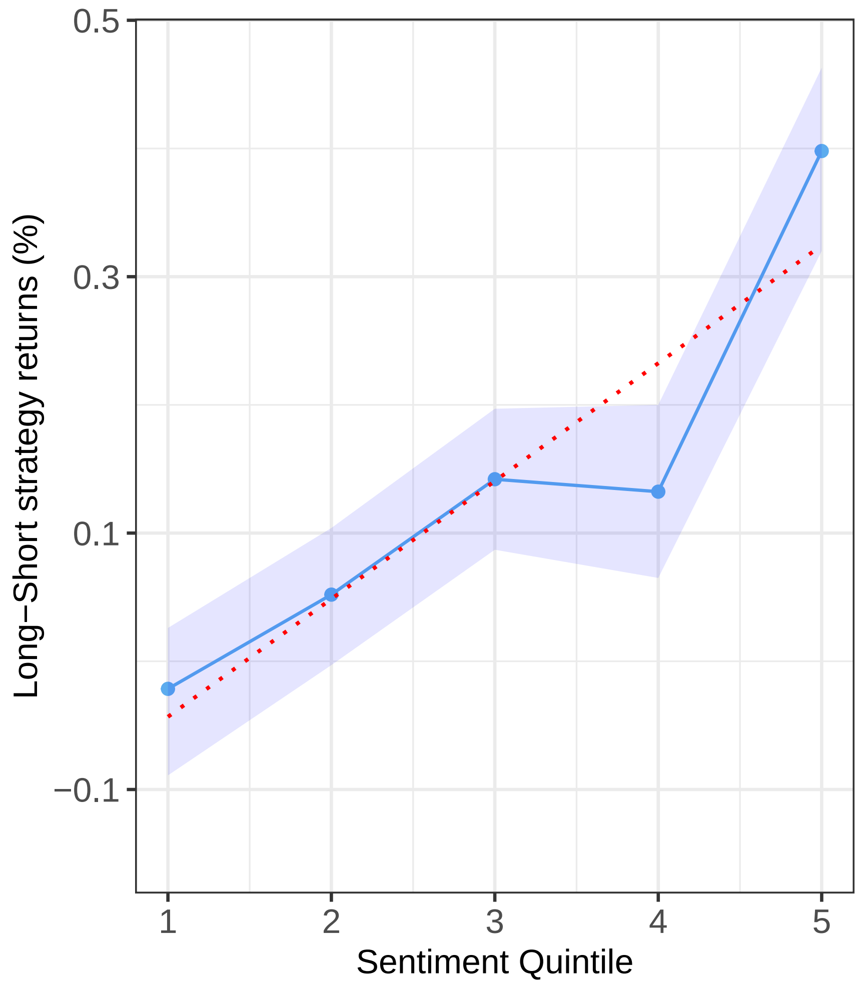


Figure 2: This figure illustrates the average monthly returns of 100 number of long-short portfolio strategy. We take average monthly return of cross-sectional signals across sentiment quintiles (Quintile 1: lowest sentiment, Quintile 5: highest sentiment). Sentiment measure is one month lag of equity market sentiment (see Section 3.1). The shaded areas are 95% Confidence Intervals using 1,000 boostrapped samples with replacement, and the red dotted line is the regression line that fits the graph. Approximately 40% of anomalies switch long-leg characteristics with short-leg characteristics in order to assign safe (risky) firm characteristics to the long- (short-) legs: see Section 4 for details.

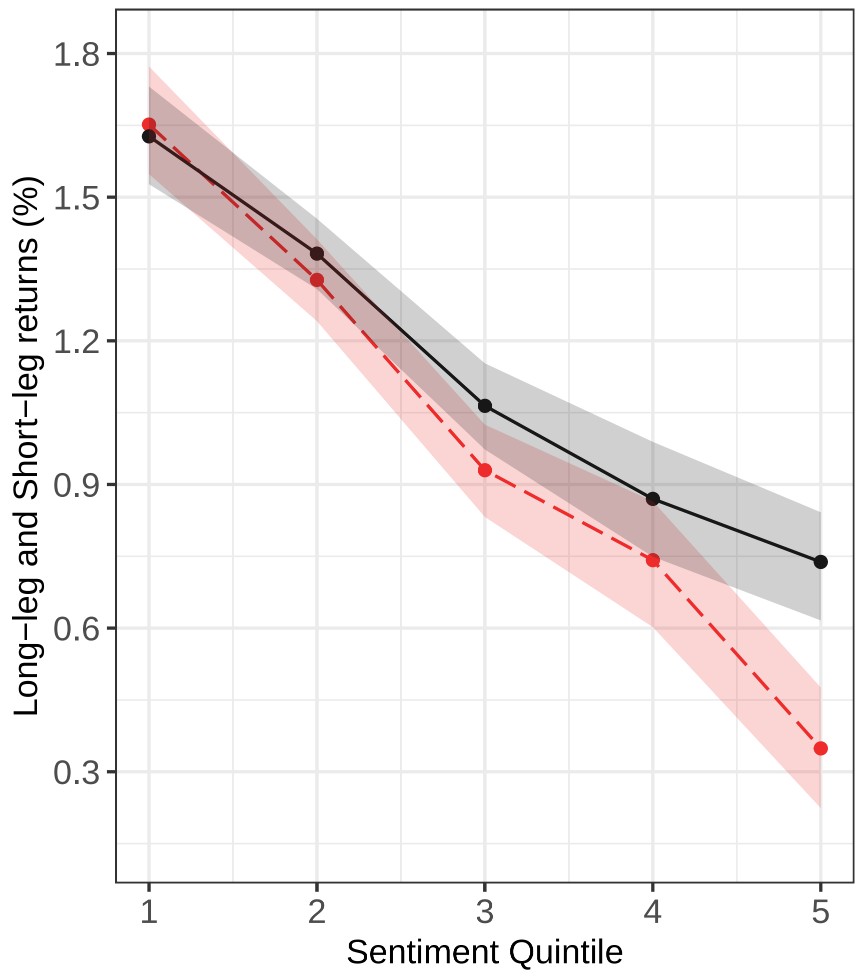


Figure 3: This figure illustrates the average monthly returns of 100 number of long-leg returns and short-leg returns. We take average monthly return of cross-sectional signals' long-leg returns or short-leg returns across sentiment quintiles (Quintile 1: lowest sentiment, Quintile 5: highest sentiment). The solid black line indicates average of long-leg returns, and the red dotted line indicates average of short-leg returns. Sentiment measure is one month lag of equity market sentiment (see Section 3.1). The shaded areas are 95% Confidence Intervals using 1,000 boostrapped samples with replacement. Approximately 40% of anomalies switch long-leg characteristics with short-leg characteristics in order to assign safe (risky) firm characteristics to the long- (short-) legs: see Section 4 for details.

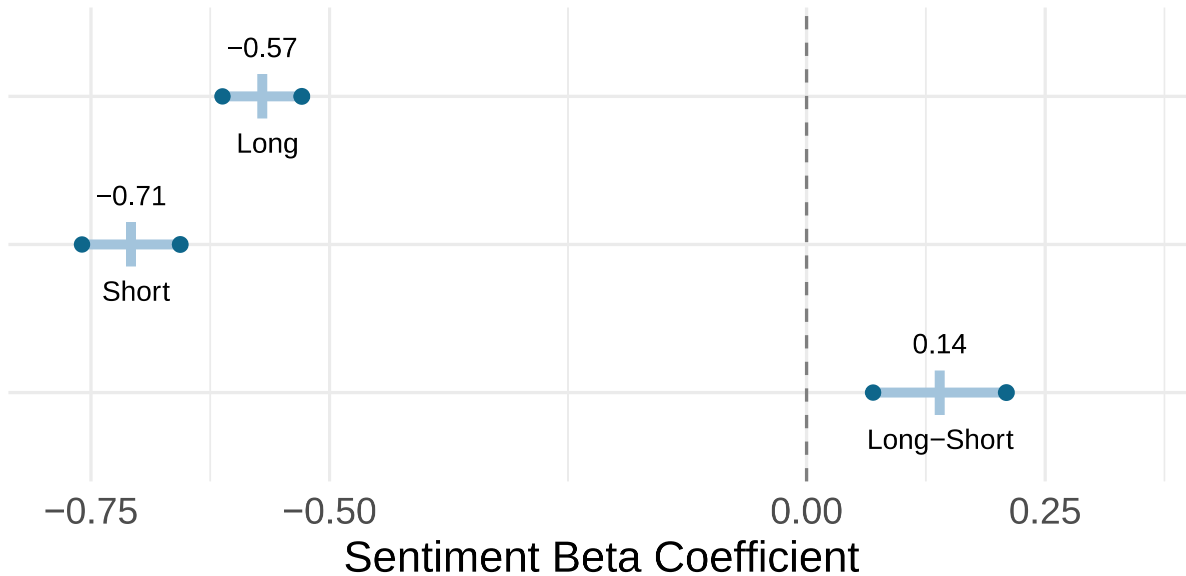


Figure 4: This figure illustrates the distribution of sentiment beta for 100 anomalies: the long side of portfolio returns (Long), the short side of portfolio returns (Short), and the long-short strategy portfolio returns (Long-Short). The numbers in each dumbbell plot represent the mean of the sentiment beta estimate, and the distribution is shown with a 95% confidence interval.

List of Tables

Panel A: Test Statistics

Test	Value	t-stat	Result
Average of Increments	0.002	0.24	Fail to Reject
Ljung-Box	2.52	0.11	Fail to Reject
Durbin-Watson	1.88	0.055	Fail to Reject

Panel B: AR(1) test

The equation is $s_t = \alpha + \beta s_{t-1} + \epsilon_t$

	$\hat{\alpha}$	$t(\hat{\alpha})$	$\hat{\beta}$	$t(\hat{\beta})$	$t(\hat{\beta}-1)$
Results	0.0009	0.1018	0.9886	77.39	-0.8935

Table 1: HJTZ Sentiment index is a martingale

Note: This table records test results to check whether HJTZ sentiment index is a Martingale.

Panel A: Predictive regression results

Regression is of the form $R^{mkt}_{t+1} = \alpha + \beta s_t + \varepsilon_{t+1}$

1. Full Sample (1966:01 - 2020:12)

Dep. Variable (R^{mkt}_{t+1})	β	$t(\beta)$	R-squared	Constant?
VWR_TBL	**-0.61*** **	**-4.07**	0.02	Yes
EWR_TBL	**-0.84*** **	**-4.45**	0.02	Yes

2. First-half (1966:01 - 1993:06)

Dep. Variable (R^{mkt}_{t+1})	β	$t(\beta)$	R-squared	Constant?
VWR_TBL	**-0.48*** **	**-2.69**	0.01	Yes
EWR_TBL	**-0.93*** **	**-3.82**	0.03	Yes

3. Second-half (1993:07 - 2020:12)

Dep. Variable (R^{mkt}_{t+1})	β	$t(\beta)$	R-squared	Constant?
VWR_TBL	**-0.96*** **	**-3.68**	0.02	Yes
EWR_TBL	**-0.56** **	**-2.14**	0.01	Yes

Panel B: Market Returns Conditional on Sentiment Levels

	VWR_TBL			EWR_TBL		
Sentiment Sorts	(1) mean returns	(2) t-stat	(3) n	(4) mean returns	(5) t-stat	(6) n
Above Median	-0.37	-0.10	330	1.10	0.23	330
Below Median	**9.59*** **	**3.70**	330	**11.94*** **	**3.14**	330
Difference	**9.96** **	**2.29**	-	**10.84* **	**1.71**	-
Top decile	**-19.10*** **	**-3.86**	66	**-23.20*** **	**-3.40**	66
Bottom decile	**11.64* **	**1.95**	66	**28.57*** **	**3.26**	66
Difference	**30.76*** **	**3.96**	-	**51.78*** **	**5.27**	-

Table 2: Forecasting aggregate market returns with sentiment

Note: This table records stock market returns conditional on sentiment levels. We use one-month lagged value of Huang et al. (2015), and value-weighted excess stock returns (VWR_TBL) as well as equally-weighted excess stock returns (EWR_TBL) in both panels. Panel A presents predictive regression results. Panel B provides average stock returns, t-statistics, and number of months that fall into each sentiment levels. Above/Below Median indicates that the sentiment during the full-sample is above/below the median value. We similarly define quintile/decile sorts on sentiment levels. In both Panel A and B, we adjust t-statistics using Newey-West procedure with 6 lags.

Panel A: Using the anomalies as they are

Regression is of the form $R_{t+1}^{\text{portfolio}} = \alpha + \beta s_t + \varepsilon_{t+1}$
where portfolio $= \{\text{long}, \text{ short}, \text{ long-short}\}$

Dep. Variable	β	$t(\beta)$	Adj. R-squared (%)	Constant?
R_{t+1}^{long}	**-0.58****	**-2.55**	0.9	Yes
R_{t+1}^{short}	**-0.71*****	**-3.10**	1.2	Yes
$R_{t+1}^{\text{long-short}}$	**0.13*****	**3.00**	2.5	Yes

Panel B: Using the anomalies as proposed in this paper

Regression is of the form $R_{t+1}^{\text{portfolio}^*} = \alpha + \beta s_t + \varepsilon_{t+1}$
where portfolio$^* = \{\text{long}^*, \text{ short}^*, \text{ long-short}^*\}$

Dep. Variable	β	$t(\beta)$	Adj. R-squared (%)	Constant?
R_{t+1}^{long}	**-0.56****	**-2.57**	0.9	Yes
R_{t+1}^{short}	**-0.73*****	**-3.10**	1.3	Yes
$R_{t+1}^{\text{long-short}}$	**0.18*****	**4.55**	2.7	Yes

Table 3: Sentiment affects all of long-leg, short-leg and long-short strategy returns

Note: This table examines the impact of sentiment on the performance of long-leg, short-leg, and long-short strategy returns. We use a one-month lagged sentiment measure based on Huang et al. (2015) and analyze the average returns across 100 anomalies, focusing separately on long-side returns, short-side returns, and the combined long-short strategy returns. In Panel A, we calculate a composite measure by averaging the long-leg returns, short-leg returns, and long-short strategy returns across all 100 anomalies, resulting in R^{long}, R^{short}, and $R^{\text{long-short}}$, respectively. In Panel B, we repeat this procedure, but with one-third of the anomalies' long- and short-legs reversed to ensure that the long side of the portfolio represents safer firm characteristics. The resulting composite measures are indicated with an asterisk (*). Each panel presents the estimated coefficients and corresponding t-statistics, adjusted for autocorrelation using Newey-West standard errors with six lags.

Regression is of the form $R_t^{mkt} = \alpha + \beta mom_t + \varepsilon_{t+1}$

1. Full Sample (1927:01 - 2020:12)

Dep. Variable	α	$t(\alpha)$	β	t(β)
VWR_TBL	**11.18*****	**6.15**	**-4.71*****	**-12.33**
EWR_TBL	**12.95*****	**5.66**	**-7.25*****	**-15.07**

Table 4: The relationship between momentum and aggregate returns

Note: This table records relationship between momentum and aggregate returns.

Bibliography

Huang, D., Jiang, F., Tu, J. and Zhou, G.: 2015, Investor Sentiment Aligned: A Powerful Predictor of Stock Returns, *Review of Financial Studies* **28**(3), 791–837.

On the Time Variation of Aggregate Stock Returns and Cross-Sectional Anomalies

Online Appendix

Author(s) details removed for EFMA Submission

A List of Anomalies

This section enumerates the full list of published risk factors used in the empirical section in the main body of the paper. The 100 number of anomalies are listed in an alphabetical order of their factor label, followed by their description. The asset pricing literature has generated anomalies that are exclusively focused on generating statistically significant positive returns (i.e., firm characteristics that are associated with future positive returns go to the long-legs, while those associated with future negative returns go to the short-legs). However, there has been less focus on identifying the placement of safe or risky characteristics in the long or short positions. We add to the empirical asset pricing literature by assigning an economic interpretation to them: cross-sectional signals identified with a check mark (✓) contain risky (safe) firm characteristics in the long (short) positions, which we ultimately interchange in our main analysis.

1. ✓ **Accruals (accruals, Sloan 1996)**: firms with relatively high (low) levels of accruals (defined as net income (IB) minus operating cash flow (oancf) scaled by lagged total assets) experience negative (positive) future abnormal stock returns. This means that firms with safe characteristics (high accruals) are placed in the short-legs. **(mispricing)**

2. ✓ **Accruals-BM (book-to-market and accruals, Bartov and Kim 2004)**: Firms with low accruals and high B/M ratio goes to long-legs, while high accruals and low B/M ratio goes to short-legs. Since the former characteristics (both accruals and B/M ratio) are associated with risky characteristics, long-legs are risky legs. **(mispricing)**

3. ✓ **Beta (CAPM beta, Fama and MacBeth 1973)**: firms with higher market beta are more influenced by the market movement, hence riskier. Since they tend to obtain higher returns, they are placed in the long-legs. **(risk)**

4. ✓ **Beta-Liquidity-PS (Pastor-Stambaugh Liquidity beta, Pastor and Stambaugh 2003)**: firms with low liquidity tends to earn high future returns. This indicates that high liquidity firms, which are well-known corporate identities with strong fundamentals, are placed in the short-legs. **(risk)**

5. ✓ **Beta-Tail-Risk (tail risk beta, Kelly and Jiang 2014)**: firms with high loadings on past tail risk (hence riskier) earn high returns. In this vein, long-legs are risky legs. **(risk)**

6. ✓ **Bid-Ask-Spread (bid-ask spread, Amihud and Mendelson 1986)**: liquid stocks would have bid-ask spread close to zero. Hence, more illiquid and riskier stocks are placed in the long-legs. **(mispricing)**

7. ✓ **BM (book-to-market ratio, Rosenberg et al. 1985)**: B/M ratio can be considered as a distress measure, so firms with higher B/M (that goes to the long-legs) are riskier firms. **(agnostic)**

8. ✓**BM-Dec (book-to-market ratio where book assets used are from December last year, Fama and French 1992)**: Same as above. **(agnostic)**

9. ✓ **Brand-Invest (brand capital investment, Belo, Lin and Vitorino 2014)**: Brand capital, an intangible asset, *"helps firms increase sales through, for example, increased customer loyalty or visibility* [...] [,] *allows firms to differentiate their goods and services from those of competitors and thus it is a potential source of competitive advantage."* Since firms with low brand capital investment rates have higher average stock returns and go to long-legs, risky traits are placed to the long-legs. **(risk)**

10. ✓ **Cash-Prod (cash productivity, Chandrashekar and Rao 2006)**: productivity of cash is defined as firm's economic rents per dollar of cash holdings. The authors argue that cash productivity is negatively related to future returns, so a portfolio strategy would place firms with less cash productivity to the long-legs. **(agnostic)**

11. **CB-Oper-Prof (cash-based operating profitability, Ball et al. 2016)**: This measure is created by purging accruals from operating profitability. Since higher cash-based operating profitability relates to stronger firm performance, and higher stock returns, long-legs are firms with safe characteristic. **(agnostic)**

12. **CF (cash flow to market, Lakonishok et al. 1994)**: Higher cash flows produce higher returns, and this is a good sign for company management. **(mispricing)**

13. **CFP (operating cash flow to price, Desai et al. 2004)**: operating cash flow, defined as earnings plus depreciation minus working capital accruals, positively predicts future abnormal returns. Since higher operating cash flow firms are equipped with safe characteristics, long-legs are safe legs. **(mispricing)**

14. **Ch-Asset-Turnover (change in asset turnover, Soliman 2008)**: Asset Turnover (ATO) is defined as sales divided by net operating assets. The asset turnover ratio can be used as an indicator of the efficiency with which a company is using its assets to generate

revenue. The paper documents that higher asset turnover predicts positive returns. Hence, long-legs contain safe assets.

Net Non-Current Operating Assets (NNCOA) is defined as change in total assets (COMPUSTAT ITEM #6) - current assets (#4) - investment and advances (#32). Net Working Capital (NWC) is the change in current operating assets minus current operating liabilities; see Table 3 of the paper. **(mispricing)**

15. ✓ **Ch-EQ (growth in book equity, Lockwood and Prombutr 2010)**: high sustainable growth firms (measured by ratio of book equity to book equity in the previous year) tend to have low default risk, low BM ratios, and low subsequent returns. This indicates that high sustainable growth firms, which are safer than low sustainable growth firms, are placed in the short-legs. **(risk)**

16. ✓ **Ch-Inv (inventory growth, Thomas and Zhang 2002)**: change in inventory, defined as 12 month change in inventory over average total assets, negatively predicts future stock returns. The paper documents a profitability reversal argument based on shift in demand, which indicates that past high performing firms suffer from profitability reversals and hence are placed in the short-legs. **(mispricing)**

17. ✓ **Ch-Inv-IA (change in capital investment, industry adjusted, Abarbanell and Bushee 1998)**: Change in Investment with industry adjustment, which the article denotes as RCAPX, is constructed to test the notion that it is good news for future earnings when firm-specific capital expenditures outpace industry average capital expenditures. The result is the opposite, indicating that firms with higher capital investment relative to given industry earns negative subsequent returns. **(mispricing)**

18. **Ch-NNCOA (change in net noncurrent operating assets, Soliman 2008)**: see discussions in Ch-Asset-Turnover **(mispricing)**

19. **Ch-NWC (change in net working capital, Soliman 2008)**: see discussions in Ch-Asset-Turnover **(mispricing)**

20. **Ch-Tax (change in taxes, Thomas and Zhang 2011)**: firms with high seasonally differenced quarterly tax expense earn positive future returns. Since firms with strong fundamentals tend to pay high tax, long-legs are safe legs. **(mispricing)**

21. **Comp-Equ-Iss (composite equity issuance, Daniel and Titman 2006)**: *"composite share issuance variable measures the amount of equity the firms issues (or retires) in exchange for*

cash or services. Thus, seasoned issues, employee stock option plans, and share-based acquisitions increase the issuance measure, while repurchases, dividends, and other actions that take cash out of the firm reduce the issuance measure." The paper argues that composite equity issuance captures intangible information. Since composite share issuance variable is significantly negatively related to future returns, and firms tend to place themselves in a riskier position by conducting share issuance at the sacrifice of, for instance, dilution of ownership stake, short-legs contain riskier firms. **(agnostic)**

22. ✓ **Coskew-ACX (coskewness using daily returns, Ang, Chen and Xing 2006)**: see below for coskewness. The logic works the same way. **(risk)**

23. ✓ **Coskewness (coskewness, Harvey and Siddique 2000)**: *"Everything else being equal, investors should prefer portfolios that are right-skewed to portfolios that are left-skewed. This is consistent with the Arrow-Pratt notion of risk aversion. Hence, assets that decrease a portfolio's skewness are less desirable and should command higher expected returns."* Since higher skewness produces low future returns, short-legs contain firms with relatively safe characteristics. **(risk)**

24. ✓ **Del-COA (change in current operating assets, Richardson et al. 2005)**: Table 1 and 2 of the paper describes variables in details. Changes in current operating assets negatively predicts stock returns. Since higher operating assets indicate positive signals for the future activity, short-legs are safe legs. **(mispricing)**

25. **Del-COL (change in current operating liabilities, Richardson et al. 2005)**: see Del-COA. Changes in current operating liabilities negatively predicts stock returns. Higher operating liabilities indicates riskier business activities, so firms with riskier characteristics are placed in the short-legs. **(mispricing)**

26. **Del-FIN-L (change in financial liabilities, Richardson et al. 2005)**: see Del-COA. Changes in financial liabilities (Del-FIN-L) negatively predicts future stock returns. So, firms with more liabilities (hence riskier) are placed in the short-legs. **(mispricing)**

27. **Del-LT-I (change in long term investment, Richardson et al. 2005)**: see Del-COA. Changes in long term investment negatively predicts stock returns. Since higher investment results in negative subsequent returns, risky characteristics are placed in the short-legs. **(mispricing)**

28. **Del-Net-Fin (change in net financial assets, Richardson et al. 2005)**: see Del-COA. Increases in net financial assets positively predicts returns. Since higher financial as-

sets provide greater investment opportunities as well as firm fundamentals, long-legs contain safe firms. **(mispricing)**

29. **Div-Init (dividend initiation, Michaely et al. 1995)**: Changes in dividends can provide insight into a company's future prospects. Dividend initiations is good news, whereas dividend omissions is bad news. The paper documents that firms with dividend initiations have positive future returns, so that long-legs contain firms with stronger future prospects. **(mispricing)**

30. **Div-Omit (dividend omission, Michaely et al. 1995)**: similar to Div-Init above, firms that omit dividend payments earn negative future returns. Since firms that are not omitting dividends go to long-legs, firms with safe characteristics are placed in the long-legs. **(mispricing)**

31. **Div-Season (dividend seasonality, Hartzmark and Solomon 2013)**: firms predicted to issue a dividend earn positive abnormal returns. Since dividend-paying firms tend to have better future prospects, long-legs contain safe characteristics. **(mispricing)**

32. **Div-Yield-ST (predicted dividend yield next month, Litzenberger and Ramaswamy 1980)**: higher predicted dividend yield next month would indicate firms with better future prospects, so long-legs would have firms with stronger future prospects. **(risk)**

33. ✓**Dol-Vol (past trading volume, Brennan et al. 1998)**: stocks with higher trading volume indicate higher liquidity and thus are associated with safer features. Since these stocks produce negative returns, they are placed in the short-legs. **(mispricing)**

34. ✓ **Earnings-Consistency (earnings consistency, Alwathainani 2009)**: Firms consistently ranking in the lowest 30% of past financial growth (risky firms) have greater rates of future returns. So, riskier firms go to the long-legs. **(mispricing)**

35. **Earnings-Surprise (earnings surprise, Foster et al. 1984)**: firms with positive earnings surprise are those associated with better (safer) future prospects, so long-legs contain firms with safe characteristics. **(agnostic)**

36. **Earn-Sup-Big (earnings surprise of big firms, Hou 2007)**: same logic as above. **(mispricing)**

37. **Ent-Mult (enterprise multiple, Loughran and Wellman 2011)**: firms with low Enterprise Multiple (EM is defined as equity value plus debt plus preferred stock less cash, divided by EBITDA) outperform high EM firms. So, long-legs contain firms with safer characteristics. **(mispricing)**

38. **EP (earnings-to-price ratio, Basu 1977)**: in a given industry, high E/P ratio firms compared to low E/P ratio firms typically indicates that the former are well-performing in the market. Since EP positively predicts stock market returns, long-legs contain firms with safe characteristics. **(mispricing)**

39. **Equity-Duration (equity duration, Dechow et al. 2004)**: long duration equities that tend to be sensitive (thus riskier) generate lower average returns. This indicates that firm with long equity duration are placed in the short-legs. **(risk)**

40. **Exch-Switch (exchange switch, Dharan and Ikenberry 1995)**: stocks that move trading platform generally earn poor returns. Since firms with strong fundamentals will generally not switch their listings, short-legs are risky legs. **(agnostic)**

41. ✓ **Firm-Age (firm age based on CRSP listings, Barry and Brown 1984)**: firm age, proxied as a period of listing, negatively predicts future stock returns. Since firms that spent less time in CRSP have less public information, hence riskier, long-legs contain firms that are relatively riskier. **(risk)**

42. **GP (gross profits-to-total assets, Novy-Marx 2013)**: profitable firms generate significantly higher returns than unprofitable firms, although the are less prone to distress, have longer cash flow durations, and have lower levels of operating leverage. Hence, firms with safe feature (highly profitable) go to long-legs. **(agnostic)**

43. ✓ **Gr-LT-NOA (growth in long term operating assets, Fairfield et al. 2003)**: The paper argues that, after controlling for current profitability, growth in long-term net operating assets has negative associations with future returns, consistent with conservative accounting and diminishing marginal returns on investments. Hence, safe characteristic is assigned to the short-legs. **(mispricing)**

44. **Gr-Sale-To-Gr-Inv (sales growth over inventory growth, Abarbanell and Bushee 1998)**: Percentage growth in sales less percentage growth in inventory positively predicts subsequent stock returns. Since higher sales relative to industry signals safe traits, long-legs are safe legs. **(mispricing)**

45. **Gr-Sale-To-Gr-Overhead (sales growth over overhead growth, Abarbanell and Bushee 1998)**: Similar to above, Gr-Sale-To-Gr-Overhead (defined as percentage growth in sales relative to average sales of past two years, minus percentage growth in administrative expenses relative to average administrative expenses of last two years) positively predicts stock returns. **(mispricing)**

46. ✓ **Herf (Herfindahl industry concentration using sales, Hou and Robinson 2006)**: firms in more concentrated industries earn lower returns, as highly concentrated industries are less risky because they engage in less innovation. This indicates that firms that go to long-legs are those in industries with high herfindahl index (less concetrated industry) and riskier. **(risk)**

47. ✓ **Herf-Asset (Herfindahl industry concentration using assets, Hou and Robinson 2006)**: see Herf. **(risk)**

48. ✓ **Herf-BE (Herfindahl industry concentration using book equity, Hou and Robinson 2006)**: see Herf. **(risk)**

49. **Hire (employment growth, Belo, Lin and Bazdresch 2014)**: firms with high hiring rates are expanding firms that incur high adjustment costs, hence riskier firms. Since the paper documents that hiring rate is negatively associated with future stock returns, risky legs are short-legs. **(risk)**

50. **Idio-Vol-3F (idiosyncratic risk using Fama-French 3 factor model, Ang, Hodrick, Xing and Zhang 2006)**: stocks with high idiosyncratic volatility receive low average returns. Hence, short-legs are risky legs. **(agnostic)**

51. **Idio-Vol-AHT (idiosyncratic risk using AHT model, Ali et al. 2003)**: similar to above (Idio-Vol-3F), reciprocal of Ivolatility, defined as standard deviation of residuals from CAPM regression using daily data, positively predicts future stock returns. Since low volatility stocks earn higher returns than high volatility counterparts, long-legs are safe legs. **(mispricing)**

52. ✓ **Illiquidity (Amihud's illiquidity, Amihud 2002)**: stock returns increase in illiquidity (daily ratio of absolute stock return to its turnover average over the past 12 months). Since illiquid assets tend to be risky, long-legs are risky legs. **(mispricing)**

53. **Ind-IPO (initial public offerings, Ritter 1991)**: firms that go through initial public offerings underperform for the next three years. Since IPO firms are riskier than mature firms in the secondary market, short-legs are risky legs. **(mispricing)**

54. **Ind-Ret-Big (industry return on big firms, Hou 2007)**: intra-industry lead-lag effects where top 30% size firms take the long-legs. Since these firms tend to come with strong and stable characteristics, long-legs are safe legs. **(mispricing)**

55. **Intan-CFP (intangible return using cash-flow-to-price, Daniel and Titman 2006)**: see discussions in Comp-Equ-Iss **(agnostic)**

56. **Intan-EP (intangible return using earnings price, Daniel and Titman 2006)**: see discussions in Comp-Equ-Iss **(agnostic)**

57. **Intan-SP (intangible return using sales-to-price, Daniel and Titman 2006)**: see discussions in Comp-Equ-Iss **(agnostic)**

58. ✓ **Investment (investment to revenue, Titman et al. 2004)**: higher investment expenditures should be viewed favourably as they are likely to be associated with greater investment opportunities. Since higher investment expenditures result in negative future returns, safe characteristics are assigned to the short-legs. **(mispricing)**

59. ✓ **Invest-PPE-Inv (change in PPE and investment-to-assets, Lyandres et al. 2008)**: investment factor that longs low-investment firms and shorts high-investment firms earn significantly positive average returns. The logic is similar to above. **(risk)**

60. ✓ **Inv-Growth (inventory growth, Belo and Lin 2012)**: similar to Ch-Inv, inventory growth negatively predicts future stock returns. **(risk)**

61. **Mean-Rank-Rev-Growth (revenue growth rank, Lakonishok et al. 1994)**: The anomaly is defined as mean rank based on firms' annual revenue growth in the past 5 years. Since higher revenue indicates firms performing well, which earns higher stock returns, long-legs are firms with safe characteristics. **(mispricing)**

62. **MS (mohanram G-score, Mohanram 2005)**: GSCORE is a combination of 8 existing signals related to earnings and cash flow fundamentals, extrapolation, and accounting conservatism. Since higher values of individual signals generally indicate firms with stronger performance, and since firms with higher GSCORE earn higher returns, long-legs contain firms with safe characteristics. **(mispricing)**

63. ✓ **Net-Debt-Price (net debt to price, Bradshaw et al. 2006)**: $\Delta DEBT$, defined as #111 - #114 + #301 (COMPUSTAT annual data item) negatively predicts future stock returns. This indicates that firms with less debt are placed in the long-legs (so that safe firm characterstics goes to the long-legs). **(mispricing)**

64. **Net-Payout-Yield (net payout yield, Boudoukh et al. 2007)**: payout yields (dividends plus repurhcases) as well as net payout yields (dividends plus repurchases minus issuances) mirror firms' performance. Since higher payout yields (as well as net payout yields) predicts positive future returns, safe firms are assigned to long-legs. **(agnostic)**

65. **Num-Earn-Increase (earnings streak length, Loh and Warachka 2012)**: a consistent earnings (streak) positively predicts future stock returns. Since a series of positive earnings indicate good performance, hence associated with safe features of a given firm, long-legs are safe legs. **(mispricing)**

66. **Oper-Prof (operating profits to book equity, Fama and French 2006)**: firms with higher operating profitability predict higher stock returns. Since firms with higher profitability tends to be those with strong fundamentals, long-legs are safe legs. **(agnostic)**

67. **Oper-Prof-RD (operating profitability, R&D adjusted, Ball et al. 2016)**: This is the operating profitability less Research and Development Expenses, which bears the same meaning as CB-Oper-Prof. See discussions there. **(agnostic)**

68. **OP-Leverage (operating leverage, Novy-Marx 2011)**: firms with levered assets earn higher returns than non-levered assets. The leverage in this context is operating leverage, defined as (COGS + XSGA)/AT (note that this is not financial leverage. In fact, page 110 says that operating leverage and financial leverage are negatively correlated). Since firms that sell more are generally viewed as those performing well, long-legs contain safe firms. **(risk)**

69. ✓ **Org-Cap (organizational capital, Eisfeldt and Papanikolaou 2013)**: firms with more organization capital (defined as a durable input in production that is distinct from physical capital) earn higher average returns than firms with less organization capital. *"Since shareholders can appropriate only a fraction of the cash flows from organization capital, investing in firms with high organization capital exposes them to additional risks."* In this sense, long-legs are risky-legs. **(risk)**

70. **Payout-Yield (payout yield, Boudoukh et al. 2007)**: see Net-Payout-Yield. **(agnostic)**

71. ✓ **Pct-Acc (percent operating accruals, Hafzalla et al. 2011)**: from the standard definition of accruals (where the numerator is earnings less operating cash, and the denominator is the total assets), percent accruals replace the denominator with earnings. Since the predicted patterns remain the same, the same logic as mentioned earlier in the anomaly Accruals apply here. **(mispricing)**

72. ✓**Price (stock price, Blume and Husic 1973)**: similar to firm size, log of absolute value of stock price negatively predicts stock returns. **(agnostic)**

73. **QMJ (quality of a stock, Asness et al. 2019)**: quality characteristics, including profitability, growth, and safety, are a safe characteristics that *"investors should be willing to*

pay a higher price for." Since they earn positive future returns, long-legs are safe legs. **(agnostic)** - not part of chen zimmermann list but I can confirm that paper mentions both possibilities

74. **RD-Ability (R&D ability, Cohen et al. 2013)**: long-short portfolio strategy that longs the past R&D winners and that shorts the past R&D losers earns significant profits. R&D activities can be viewed as risky behavior, but this paper focuses on R&D winners and losers . In that manner, past R&D winners who produce positive returns are safe firms. **(mispricing)**

75. **RD-IPO (IPO and no R&D spending, Guo et al. 2006)**: firms that do not spend on R&D activity nor who went through IPO earn higher returns. Since these are relatively stable firms than their counterparts (i.e., those that invested in R&D or those that were recently IPO-ed), long-legs are safe legs. **(mispricing)**

76. **Realized-Vol (realized total volatility, Ang, Hodrick, Xing and Zhang 2006)**: see Idio-Vol-3F. **(agnostic)**

77. **Return-Skew (return skewness, Bali et al. 2016)**: **(agnostic)**

78. **Return-skew-3F (idiosyncratic skewness based on Fama-French 3 factor model, Bali et al. 2016)**: See above. **(agnostic)**

79. **Revenue-Surprise (revenue surprise, Jegadeesh and Livnat 2006)**: revenues reported during preliminary earnings announcement positively predicts future stock returns. Since these are firms with better fundamentals and prosperous future prospects, long-legs contain firms with safe characteristics. **(agnostic)**

80. **RIO-MB (institutional ownership and market to book, Nagel 2005)**: institutional ownership (Residual Institutional Ownership, or RIO, defined as the percentage of shares held by institutions controlling for firm size, see equation 2 of the paper) is used as a supporting proxy for short-sale constraints hypothesis. For a given level of institutional ownership, high market to book firms are relatively safer firms and go to long-legs. **(mispricing)**

81. **RIO-Turnover (institutional ownership and turnover, Nagel 2005)**: similar logic to RIO-MB. For a given level of institutional ownership, high turnover firms are relatively safer firms and go to long-legs. **(mispricing)**

82. **RIO-Volatility (institutional ownership and idiosyncratic volatility, Nagel 2005)**: similar logic to RIO-MB. For a given level of institutional ownership, low idiosyncratic volatility firms are relatively safer firms and go to long-legs. **(mispricing)**

83. **RoE (net income to book equity, Haugen and Baker 1996)**: return on equity positively predicts stock returns, which is a safe characteristic placed in the long-legs. **(mispricing)**

84. **Share-Iss-1Y (share issuance 1 year, Pontiff and Woodgate 2008)**: annual share issuance, defined as log difference between month t adjusted shares less month $t-11$ adjusted shares, negatively predicts future stock returns. Since share issues tend to be related to the demand for cash at the sacrifice of dilution of ownership stake, it indicates that firms are riskier. So, short-legs are risky legs. **(agnostic)**

85. **Share-Iss-5Y (share issuance 5 years, Daniel and Titman 2006)**: same as above. **(agnostic)**

86. **Share-Repurchase (share repurchases, Ikenberry et al. 1995)**: When the management team believes their firm is undervalued, they would choose to buy back their own stocks to signal economic agents that the firm is a good investment. Since firms that repurchase their own shares earn significant subsequent returns, long-legs contain firms that are undervalued, hence (relatively) safe characteristics than the firms in the short-legs. **(mispricing)**

87. **Share-Vol (share volume, Datar et al. 1998)**: the statement *"The negative sign on the turnover rate variable confirms that illiquid stocks offer higher average returns than liquid stocks."* (page 210) indicates that more risky (illiquid) firms are assigned to long-legs. **(mispricing)**

88. ✓ **Size (firm size, Fama and French 1992)**: small size firms tend to be risky for many reasons. Hence, long-legs are risky legs. **(agnostic)**

89. **SP (sales-to-price, Barbee et al. 1996)**: since higher annual sales (per share) would lead to stable firm performance, long-legs are safe legs. **(agnostic)**

90. ✓ **Spinoff (spinoffs, Cusatis et al. 1993)**: the paper shows that *"both the spinoffs and their parents offer significantly positive abnormal returns for up to three years beyond the spinoff announcement date."* Since spinoff-ed firms relative to their parent firms are new and risky, long-legs contain firms with riskier characteristics. **(mispricing)**

91. **Std-turn (share turnover volatility, Chordia et al. 2001)**: the paper documents a negative cross-sectional relationship between stock returns and volatility of share turnover (as well as dollar trading volume). Since higher liquidity volatility is associated with riskier characteristic, long-legs are safe assets that have lower liquidity volatility. **(agnostic)**

92. **Tang (tangibility, Hahn and Lee 2009)**: The paper examines the marginal effect of tangibility on stock returns. The empirical measure of tangibility is debt capacity since *"a firm's debt capacity increases with asset tangibility as higher tangibility implies higher value of collateral for lenders."* While the paper shows that tangibility positively affect stock returns to constrained firms only, this still suggests that long-legs contain firms with safe characteristics relative to firms in the short-legs. **(risk)**

93. **Tax (taxable income to income, Lev and Nissim 2004)**: firms with higher tax ratio, which produces higher subsequent returns, tend to be big, less volatile, and growth firms. Hence, firms that go to long-legs are relatively safer. **(mispricing)**

94. ✓ **Total-Accruals (total accruals, Richardson et al. 2005)**: see Del-COA. **(mispricing)**

95. **Vol-Mkt (volume to market equity, Haugen and Baker 1996)**: trading volume over market equity negatively predicts mean returns. This indicates riskier firms with higher trading volume are placed in the short-legs. **(mispricing)**

96. **Vol-SD (volume variance, Chordia et al. 2001)**: See the anomaly Std-turn. **(agnostic)**

97. **Volume-Trend (volume trend, Haugen and Baker 1996)**: similar to Vol-Mkt, five-year time trend in monthly trading volume, which is a risky firm characteristic, is negatively related to stock returns. **(mispricing)**

98. ✓ **Zero-trade (days with zero trades, Liu 2006)**: The paper defines turnover-adjusted number of zero daily trading volumes over the prior n months. $n = 1$. Since firms with more number of no trading records (zero trades) are those accompanied with more illiquidity and higher future stock returns, long-legs contain more risky firms. **(risk)**

99. ✓ **Zero-trade-Alt-1 (days with zero trades, alternative specification, Liu 2006)**: Same as above, but $n = 6$. **(risk)**

100. ✓ **Zero-trade-Alt-2 (days with zero trades, alternative specification, Liu 2006)**: Same as above, but $n = 12$. **(risk)**

B Additional results

This section provides additional results that substantiate empirical findings in the main body of the paper. In Figure A.1 and Figure A.2, we change the sentiment measure from Huang et al. (2015) (HJTZ) to Baker and Wurgler (2006) (BW) and confirm that we can successfully replicate Figure 2 and Figure 3. The surge in strategy returns moving from sentiment quintile 3 to 4 presented in Figure A.2 addresses a concern, and we thus change the sentiment bucket from quintile to median for further robustness. The results shown in Figure A.3 show that the change of sentiment bucket does not affect our results. Finally, we return to the Huang et al. (2015) (HJTZ) sentiment measure and recast the same exercise using quartile sentiment buckets, shown in Figure A.4.

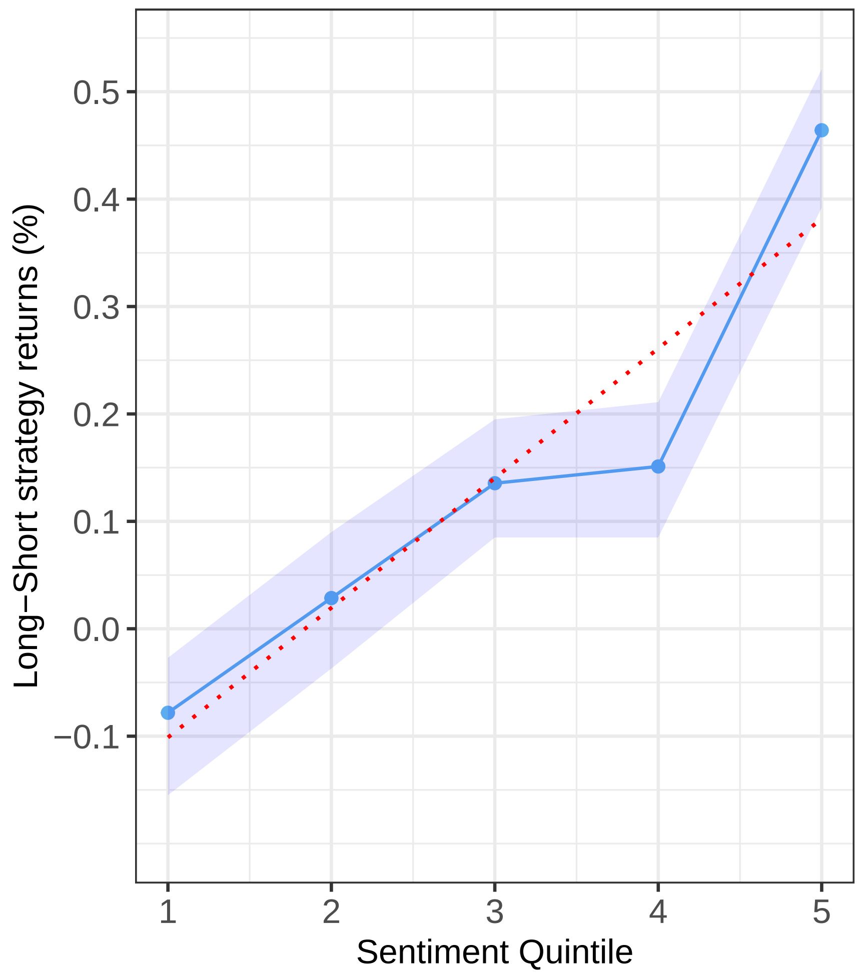


Figure A.1: This appendix figure illustrates the average monthly returns of 100 number of long-short portfolio strategy. We take average monthly return of cross-sectional signals across sentiment quintiles (Quintile 1: lowest sentiment, Quintile 5: highest sentiment). Sentiment measure is one month lag of Baker-Wurgler equity market sentiment. The shaded areas are 95% Confidence Intervals using 1,000 boostrapped samples with replacement, and the red dotted line is the regression line that fits the graph. Approximately 40% of anomalies switch long-leg characteristics with short-leg characteristics in order to assign safe (risky) firm characteristics to the long- (short-) legs: see Section 4 for details.

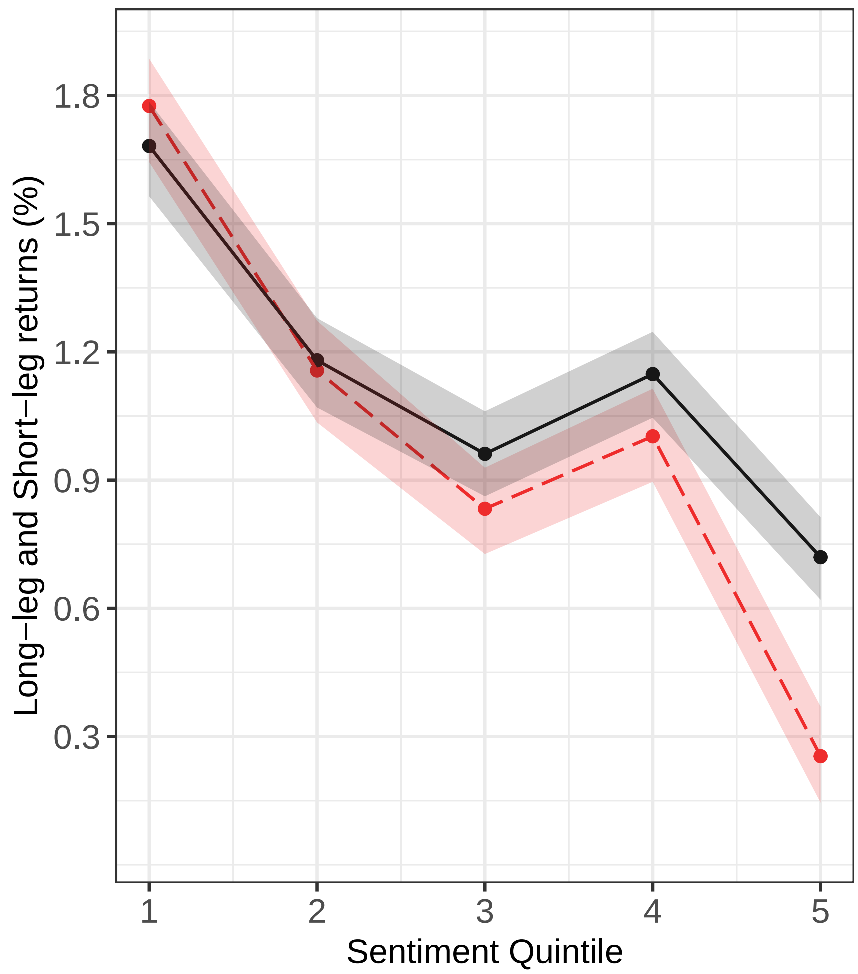
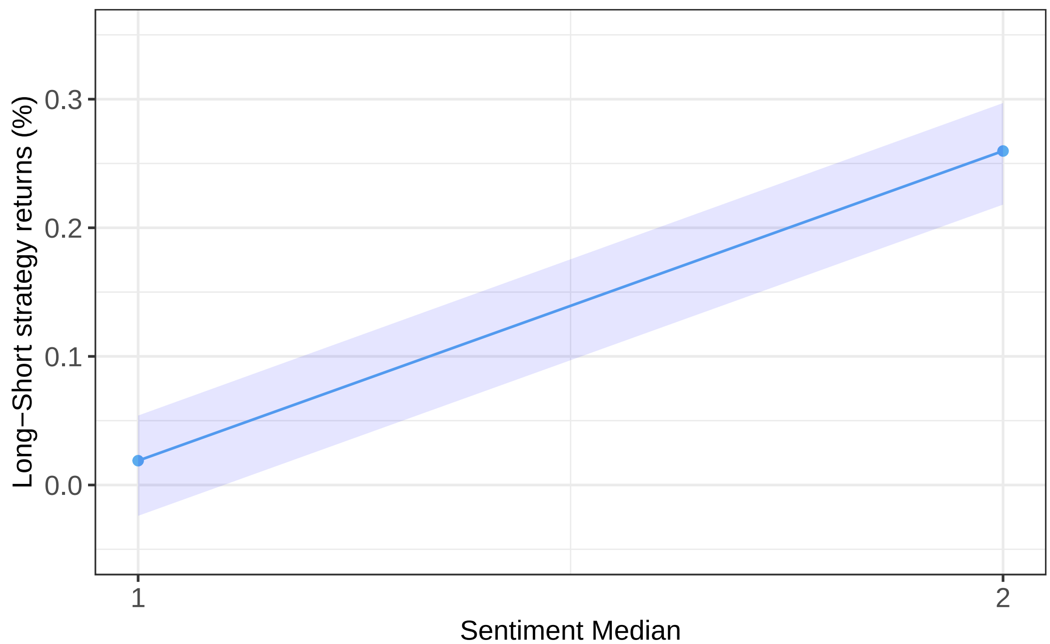


Figure A.2: This appendix figure illustrates the average monthly returns of 100 number of long-leg returns and short-leg returns. We take average monthly return of cross-sectional signals' long-leg returns or short-leg returns across sentiment quintiles (Quintile 1: lowest sentiment, Quintile 5: highest sentiment). The solid black line indicates average of long-leg returns, and the red dotted line indicates average of short-leg returns. Sentiment measure is one month lag of Baker-Wurgler equity market sentiment. The shaded areas are 95% Confidence Intervals using 1,000 boostrapped samples with replacement. Approximately 40% of anomalies switch long-leg characteristics with short-leg characteristics in order to assign safe (risky) firm characteristics to the long- (short-) legs: see Section 4 for details.



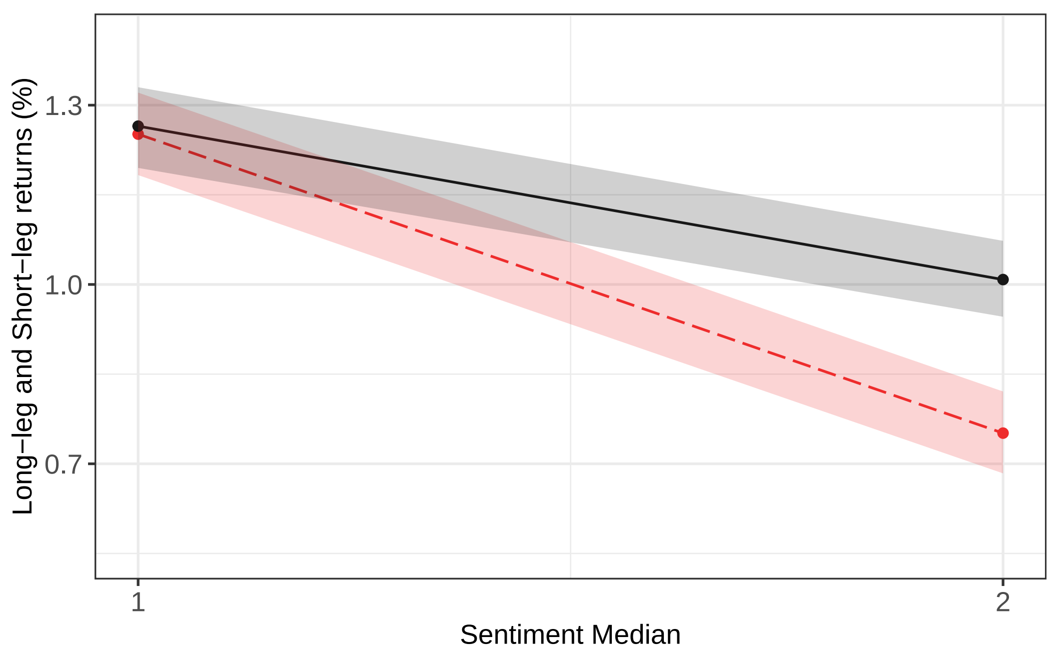


Figure A.3: This appendix figure illustrates the average monthly returns of 100 number of long-short portfolio strategy. We take average monthly return of cross-sectional signals across sentiment median (lowest 50% Percentile: below-median sentiment, highest 50% Percentile: above-median sentiment). Sentiment measure is one month lag of Baker-Wurgler equity market sentiment. The shaded areas are 95% Confidence Intervals using 1,000 boostrapped samples with replacement, and the red dotted line is the regression line that fits the graph. Approximately 40% of anomalies switch long-leg characteristics with short-leg characteristics in order to assign safe (risky) firm characteristics to the long- (short-) legs.

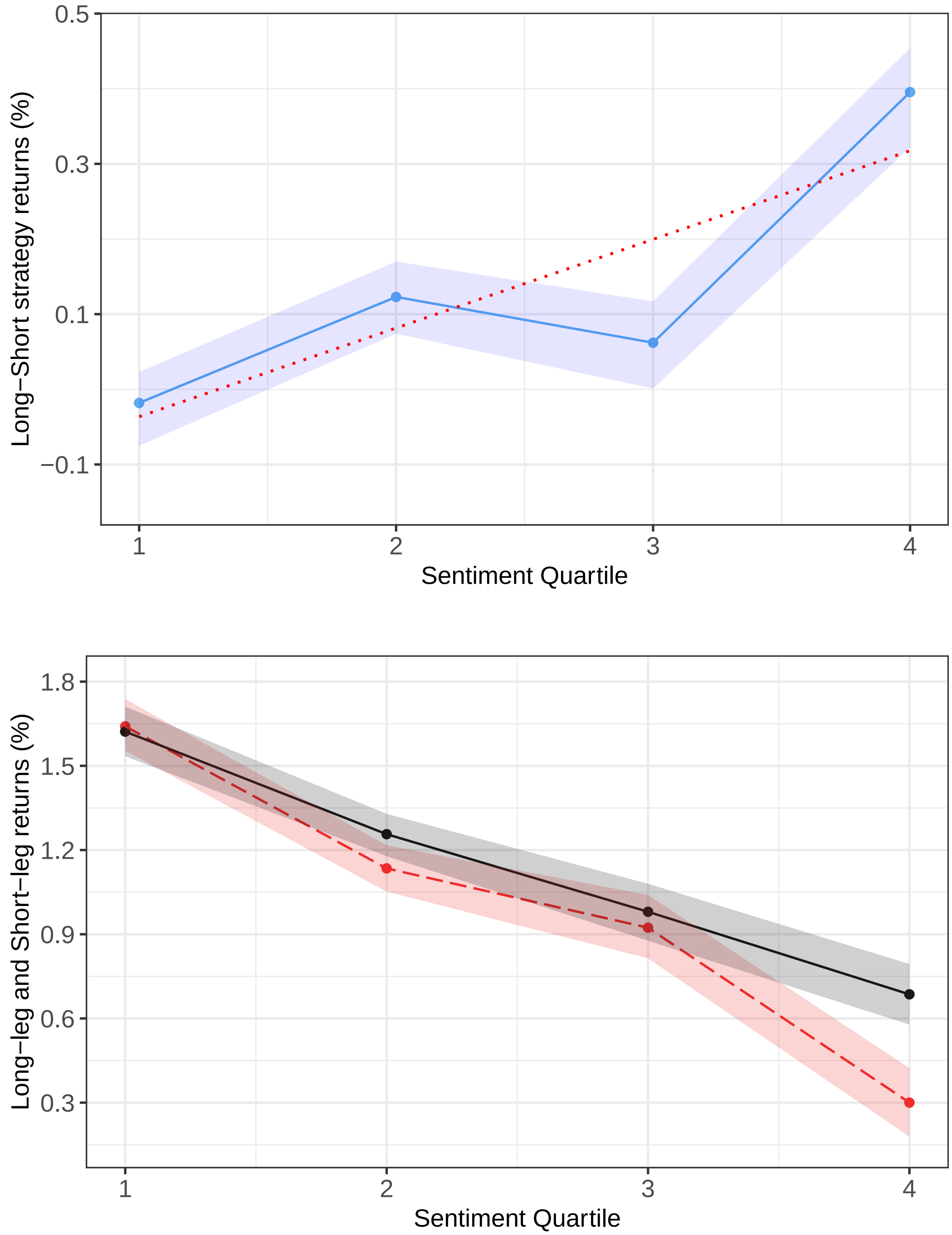


Figure A.4: This appendix figure illustrates the average monthly returns of 100 number of long-short portfolio strategy. We take average monthly return of cross-sectional signals across sentiment quartile (Quartile 1: lowest sentiment; Quartile 4: highest sentiment). Sentiment measure is one month lag of Huang et al. (2015) equity market sentiment. The shaded areas are 95% Confidence Intervals using 1,000 boostrapped samples with replacement, and the red dotted line is the regression line that fits the graph. Approximately 40% of anomalies switch long-leg characteristics with short-leg characteristics in order to assign safe (risky) firm characteristics to the long- (short-) legs.

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