Investor sentiment, firm characteristics and arbitrage risk — the arbitrage factor

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Abstract

This study measures individual stock's arbitrage risk represented by firm speculative appeal. It does this by averaging its rankings on a number of firm characteristics, via which arbitrage against sentiment-driven mispricing varies cross-sectionally. Using the Fama-MacBeth analysis, I find that stock returns and arbitrage risk are negatively correlated following high sentiment periods, whereas the exact opposite occurs following low sentiment periods. Consistent with arbitrage asymmetry at firm level, the premium of arbitrage risk, namely the arbitrage factor, exhibits a strong relation with 11 long-short anomalies that arise from sentiment effects. Moreover, combining arbitrage risk with firm characteristics can explain the idiosyncratic volatility (IVOL) puzzle: the negative IVOL-return relation. Further supporting the explanation, speculative stocks with high arbitrage risk also have high IVOL. Due to short-sale impediments, sentiment is likely to lead to such stocks being overpriced rather than underpriced. Therefore, they earn relatively average low return compared to that of non-speculative ones, so the negative IVOL-return relation prevails.

GEL classification: G12 G14

Key words: Investor sentiment, Arbitrage risk, Idiosyncratic volatility puzzle

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1 Introduction

MODERN ASSET PRICING MODELS do not take account of investor sentiment. However, efforts to integrate investor psychology and sociology into financial markets has led to studies of market-wide sentiment with findings that challenge these models.[1] Investor sentiment can be described as either optimism or pessimism coupled with the propensity to speculate. This is thought to skew investor expectations about asset returns and cause uninformed demand shocks that in the presence of limits to arbitrage have significant effects on cross-sectional returns (Baker and Wurgler (2006)). In particular, sentiment causes that stocks with speculative characteristics, such as youth and small size, to be more likely mispriced than bond-like stocks that have safe rather than speculative appeal (Baker and Wurgler (2006)). Further, due to the existence of the noise trader risk (Delong et al. (1990))[2] and a number of arbitrage costs,[3] mispricing of speculative stocks should also be more risky to arbitrage than that on bond-like ones.

The combined roles of cross-sectional variation of sentiment effect and risky arbitrage imply that the more speculative that stocks are, the higher the arbitrage risk.[4] In this case, the measure of an individual stock's speculative appeal should also reflect the degree of its arbitrage risk. By looking at a set of well-known firm characteristics through which arbitrage against sentiment-driven mispricing varies cross-sectionally, this study investigates how arbitrage risk represented by firm speculative appeal, plays a role in pricing financial assets. Such characteristics examined by this study comprise size, age, beta, dividend yield, operating profitability, return volatility, net stock issues, share price, external finance and sale growth.

Following Stambaugh et al. (2015), who construct a mispricing measure by averaging the

[1]Studies of market-wide sentiment include Delong et al. (1990), Lee et al. (1991), Neal and Wheatley (1998), Brown and Cliff (2005), Baker and Wurgler (2006), Kumar and Lee (2006), Lemmon and Portniaquina (2006), Baker and Wurgler (2007), Yu and Yuan (2011), Baker and Wurgler (2012), Chung et al. (2012), Baker et al. (2012), Stambaugh et al. (2012), Antoniou et al. (2013), Stambaugh et al. (2014), Antoniou et al. (2015), Huang et al. (2015), Stambaugh et al. (2015), Stambaugh and Yuan (2017), Shen et al. (2017) and Han et al. (2018).

[2]It is a risk that irrational investors might divert prices of mis-priced assets further.

[3]Such costs include transaction costs (Pontiff (1996)) and holding costs (Pontiff (2006))

[4]In keeping with previous studies, I refer to the risk of arbitraging on mispricing as arbitrage risk (Pontiff (1996), Shleifer and Vishny (1997),Wurgler and Zhuravskaya (2002), Pontiff (2006) and Stambaugh et al. (2015))

ranking on 11 market anomalies that arise from sentiment, I combine the above characteristics to produce a univariate monthly measure that correlates with the degree of relative arbitrage risk in the cross-section of stocks. While each characteristic is itself a measure of firm speculative appeal that reflects arbitrage risk, my objective for combining them is to develop a single measure that diversifies away some noise in each individual characteristic and thus increases precision when exploring how arbitrage risk affects asset returns. Therefore, the method here is purely cross-sectional and simple. Specifically, for each characteristic I assign a rank to each stock (in percentile), where the more speculative the stock is, the higher percentage of its rank will be. The arbitrage risk for individual stock is the arithmetic average of its ranking on each of the 10 firm characteristics, ranging from 1 to 100.

Having obtained the monthly arbitrage risk for each stock, I then test the trade-off between returns and arbitrage risk by conducting the Fama-MacBeth (Fama and MacBeth (1973)) analysis. The results indicate that returns and arbitrage risk exhibit a strong negative correlation following high sentiment periods, whereas the exact opposite occurs following low sentiment periods. While considering the whole sample period, a positive risk-return trade-off prevails, but becomes insignificant. To the extent that overpricing is more prevalent than underpricing due to short-sale constraints and to the extent that sentiment effects are more prevalent during high sentiment periods than that during low sentiment periods, the above findings are consistent with those of Stambaugh et al. (2012), Antoniou et al. (2015) and Shen et al. (2017), who find stocks that appeal to irrational investors are more likely to be overpriced when sentiment is high. The above findings are also consistent with economic intuition that high sentiment drives up prices and depresses subsequent returns (Yu and Yuan (2011)), especially for those speculative stocks with high arbitrage risk (Baker and Wurgler (2006)). Further supporting these findings, double sorting on arbitrage risk and institutional ownerships into 5x5 portfolios imply that portfolios of high arbitrage-risk stocks tend to have lower institutional ownerships, and thus are more likely to be binding with short-sale constraints.

Thus far, a good question, which is analysed later, is whether the return difference between low-arbitrage-risk stocks and ones with high risk, namely the premium of arbitrage risk, can be a pricing factor. This study applies the 2 x 3 sorting procedure of Fama and French (1993) to construct the pricing factor of arbitrage risk (arbitrage factor hereafter) with a control for size effect. However, unlike other popular pricing factors that are mainly derived from market anomalies, the arbitrage factor does not show a high sharp ratio due to its low average return but high standard deviation. Despite a low sharp ratio (0.04 only), our arbitrage factor is unique but sensible, as it lines up with time-varying sentiment-driven mispricing. Specifically, it can capture time-varying sentiment effects on asset returns: speculative stocks with higher arbitrage risk are more likely to be overpriced during high sentiment periods but perform better when sentiment is low. Such a time-varying pattern implies that the premium of the arbitrage factor, on the time-series average, will not be significant; such a time-varying pattern also indicates that the standard deviation of returns on the arbitrage factor should be prominent, since its premium fluctuates significantly with shifts in investor sentiment.

The success of the arbitrage factor in accommodating to time variation of sentiment effects has also been shown in the regressions of the 11 sentiment-related anomalies with respect to Fama-French three factors (Stambaugh et al. (2012)), in that the arbitrage factor shows strong correlation with these anomalies and the average adjusted R^2 increases from 0.27 to 0.34 after including it.[5] Further supporting this finding, investor sentiment can predict the premium of arbitrage factor, particularly for its short leg where stocks are speculative and susceptible to sentiment influence. Perhaps given the facts that investor sentiment can change investment opportunities and the distribution of future returns,[6] the arbitrage factor that reflects the time-varying sentiment effects should be consistent with the ICAPM (Merton (1973)) which also adds investment horizons and time-varying investment opportunities to the asset pricing picture.[7] Further, numerous studies that find sentiment predicability on asset returns are best supports with regarding sentiment as a state variable and guiding us to create the arbitrage factor that can capture the sentiment-related return comovement.[8]

[5]The return on each of the 11 anomalies is the return spread between stocks in highest-performing decile (long leg) and ones in lowest-performing decile (short leg). Stocks in the short leg are relatively more subject to sentiment effect compared to the long-leg ones.

[6]For example, a positive (negative) shock on investor sentiment drives up (down) demands on those speculative stocks that appeal to sentiment traders

[7]Cochrane (2006) emphasises that in the ICAPM, state variables should be related to expected returns and thus any such variable should be able to forecast future returns: $E_t(R^i_{t+1}) - R^f_t = rra_t Cov_t(R^i_{t+1}, \Delta W_{t+1}/W_t) + \lambda_{zt} Cov_t(R^i_{t+1}, \Delta z_{t+1})$, where Δz_{t+1} is a shock to a state variable.

[8]See Neal and Wheatley (1998), Brown and Cliff (2005), Baker and Wurgler (2006), Lemmon and Portniaquina (2006), Baker and Wurgler (2007), Baker et al. (2012), Chung et al. (2012), Stambaugh et al. (2012), Stambaugh et al. (2014), Huang et al. (2015),Stambaugh et al. (2015), Stambaugh and Yuan (2017), Shen

Lastly, this study combines arbitrage risk with firm characteristics to explain the idiosyncratic volatility (IVOL) puzzle. In a seminal paper, Ang et al. (2006) find that stocks with higher IVOL have lower average returns. Stambaugh et al. (2015) argue that high IVOL indicates high arbitrage risk, and that sentiment leads to stocks with high IVOL being more likely to be overpriced (associated with lower return) than underpriced. Accordingly, the negative relation between IVOL and returns is a consequence of those overpriced stocks. Consistent with this argument, I find that for each of the 10 characteristics, the more speculative decile that stocks are in, the higher IVOL that they have. Note that due to short-sale impediments, those speculative stocks are more likely to be overpriced than underpriced. They typically earn lower average returns than that of non-speculative ones, causing a negative IVOL-return tradeoff.

Perhaps the closest study to this paper is that of Stambaugh and Yuan (2017), who construct two mispricing factors by averaging rankings within two clusters from the 11 anomalies, where assets exist in return comovement. The most striking common feature of our studies is that we do not follow the previous approach of constructing a factor depending on a single variable, but instead, we average the ranking on a set of variables that are subject to sentiment effects. However, the key difference between us is that my approach is based on averaging rankings on the 10 well-documented firm characteristics, through which arbitrage against sentiment-driven mispricing varies cross-sectionally. I further extend the exploration of arbitrage risk by conducting the Fama-MacBeth procedure. The test results indicate that arbitrage risk and stock returns exhibit a significantly negative (positive) correlation following high (low) sentiment.

Another related study is that of Antoniou et al. (2015), who also employ the Fama-MacBeth methodology to examine the tradeoff between beta risk and expected returns in different sentiment regimes. Their study evinces a similar intuition to mine, in that they discover a negative beta-return relation when investor sentiment is high, due to the heavy presence of sentiment traders associated with overconfidence and excessive optimism.

In sum, this study combines cross-sectional arbitrage asymmetry with sentiment regime to develop a deep understanding of the combined roles that arbitrage risk and sentiment

et al. (2017)

effect play in pricing financial assets. Perhaps the biggest contribution here is in creating an arbitrage factor that can capture the co-movement of stocks with close arbitrage risk or speculative appeal. More importantly, the new factor can be incorporated into standard factor models to better fit assets mispricing that arises from sentiment influence. This study also contributes to both behavioural finance and asset pricing literature in explaining the IVOL puzzle.

The rests of this study are organised as follows. Section 2 introduces the motivation. Section 3 presents the data and methodology. Section 4 reports the empirical analyses. Section 5 checks the robustness of the main results. The final section concludes.

2 Motivation

In line with the noise trader risk model (Delong et al. (1990)), I develop a simple model to show how investor sentiment affects speculative stocks.[9] Section 2.2 and 2.3 review the related literature and provide details of implications of the model. Section 2.4 outlines my hypotheses.

2.1 A simple model

The economy contains two groups of two-period-lived agents: irrational investors (denoted i) who have biased expectations about future return and sophisticated ones (denoted s) who have rational expectations. Both types of investors face a wealth constraint of ω_0 at the first period t. For simplicity, there is no first-period consumption.

Two assets are traded in the market. One of them, a, is speculative and risky. Such an asset pays no dividend but appeals to irrational investors. The other one, b, is bond-like and has characteristics of safety, with a fixed dividend of r. In this model, the price of a safe asset is always fixed at one. (One can regard asset b as a bond and r is the risk-free rate r_f).

[9]The model here is similar to the noise trader model. One of the key differences is the identification of two assets traded in the market. I also set capital constraints for agents. In addition, the model's implication that I focus on is different from that of Delong et al. (1990).

Denoting the price of asset a in period t as $P_{a,t}$, irrational traders misperceives the expected price of a by an independent and identically distributed normal variable ρ_t (Delong et al. (1990)).

$$\rho_{a,t} \sim N(\rho*, \sigma_\rho^2) \tag{1}$$

Irrational investors tend to over- or underestimate the price of asset a, depending on their sentiment. Accordingly, if these investors are optimistic (pessimistic), $\rho*$ will be positive (negative). σ_ρ^2 is the variance of their biased beliefs regarding the expected return per unit of the asset a. Each agent's utility is a constant absolute risk aversion function of wealth:

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

where γ is the coefficient of absolute risk aversion, and ω is the wealth. For brevity here, we move to the following equations that express the agents' holding of assets a with maximising their utilities. All derivations are provided in the Appendix.

$$\lambda_{a,t}^s = \frac{P_{a,t+1} - (1 + r_f)P_{a,t}}{2\gamma(\sigma_{P_{a,t+1}}^2)} \tag{3}$$

$$\lambda_{a,t}^i = \frac{P_{a,t+1} - (1 + r_f)P_{a,t}}{2\gamma(\sigma_{P_{a,t+1}}^2)} + \frac{\rho_t}{2\gamma(\sigma_{P_{a,t+1}}^2)} \tag{4}$$

In equations (3) and (4), $\lambda_{a,t}^s$ and $\lambda_{a,t}^i$ denote sophisticated traders' and irrational traders' demands on the speculative asset a respectively. $\sigma_{P_{a,t+1}}^2$ is the one-period variance of price of asset a at t+1. The additional term in equation (4), expressed as $\frac{\rho_t}{2\gamma(\sigma_{P_{t+1}}^2)}$, represents the biased demand of irrational investors. Specifically, when these traders are optimistic, they are apt to overestimate expected returns (ρ_t is positive) and thus demand more of the asset a. If arbitrage is limited, such high demands will drive up the price of a, depressing the subsequent return. In contrast, when pessimistic, irrational traders demand less of asset a, as they tend to underestimate its expected returns (ρ_t becomes negative). Under this view, asset a should yield higher subsequent returns.

However, buying is alway easier than shorting for many investors (Stambaugh et al.

(2015)). In reality, not every sophisticated investor will take the short position if assets are overpriced. In contrast, buying is easier for arbitragers when assts are underpriced.

Incorporating this mechanism into my model, I argue that sentiment-driven mispricing exhibit asymmetry between optimistic and pessimistic periods. Specifically, when optimistic, it is possible for irrational investors to be jointly involved in speculative investment together (Hirshleifer et al. (2006)) and push up the price, as a result of "herding behaviour" (Shiller (2000)) and "group thinking" (Benabou (2012)), while not every sophisticated one will bet against it. Some "smart" arbitragers might short the asset a, but they will face a loss in the short-run if the price of asset a is disturbed further by irrational ones. Such a risk, namely the noise trader risk (Delong et al. (1990)), deters arbitrage activities. As a consequence, overpricing is difficult to arbitrage. However, when the asset a is underpriced by pessimistic investors, sophisticated ones can simply bet all of their wealth and buy asset a without bearing any risk or loss, and thus eliminate underpricing easily.

In addition, the denominator $2\gamma(\sigma^2_{P_{t+1}})$ can also reflect the asymmetric sentiment effect between high (optimistic) and low sentiment (pessimistic) regimes from economic intuitions. Specifically, both the one-period ahead variance $\sigma^2_{P_{t+1}}$ and the coefficient of absolute risk aversion γ tend to be larger in bad times (more uncertainty) than that in good times, as investors are more risk-averse and require higher risk compensation during a recession. (Cochrane (2011)).[10] Note that in bad times, irrational investors are typically pessimistic (Chung et al. (2012)). Under this condition, sentiment effect, represented by ρ_t in the model, should be weaker in low sentiment regime, since the denominator has become larger.

In sum, the above model reflects that speculative asset should be more susceptible to investor sentiment. It also delivers a message that sentiment-driven mispricing should be more prevalent in high sentiment regime than that in low sentiment regime.

[10] Volatility is typically higher after the market falls than after it rises (Campbell and Hentschel (1992)), so the one-period ahead variance $\sigma^2_{P_{t+1}}$ is expected to be larger in a market downturn where irrational investors are pessimistic.

2.2 Cross-sectional sentiment effect and arbitrage asymmetry at firm level

According to Baker and Wurgler (2006, 2007), sentiment-driven mispricing arises from two channels: one is the change of sentiment on irrational investors, and the other is the limits to arbitrage. In the first channel, Baker and Wurgler point out that stocks with higher level of speculative characteristics are more vulnerable to the shift in the sentiment, due to the difficulty to determine their true values. Typically, these speculative stocks are small, young and non-profitable with high growth. Further, the rise of investors' speculative propensity will drive the demand of these stocks, thereby leading to mispricing. In particular, during market craze, such stocks are more compatible with irrational traders' wishful thinking, and thus are more likely to be overpriced. In contrast to speculative traders, sophisticated ones who have less propensity to speculate, prefer stocks with salient characteristics of safety, such as bigger size and higher dividends. Thus, via the first channel of mispricing, stocks that are more speculative are also more prone to sentiment effect, which is consistent with the finding in the equations (3) and (4).

The second channel, namely limits of arbitrage, is also a premise to behavioural finance. In the noise trader model, Delong et al. (1990) attribute the limit of arbitrage to the noise trade risk. Sophisticated investors are risk averse and less likely to bet against this risk, since prices of mis-priced assets might be diverted further. Shleifer and Vishny (1997) suggest that it is costly and risky to arbitrage due to agency problems and capital constraints. According to Barberis and Thaler (2002), transaction costs associated with short-sale constraints also impede the exploitation of mispricing. Moreover, Wurgler and Zhuravskaya (2002) point out that arbitrage risk is high if mispriced assets lack substitutes, particularly for small-cap stocks. Due to limits of arbitrage, rational investors, or arbitragers as they are usually called, cannot eliminate sentiment-driven mispricing quickly.

As to the second channel, Baker and Wurgler (2007) further argue that arbitrage from sophisticated traders varies across different stocks. Specifically, arbitrage tends to be more costly and riskier for those stocks with higher level of speculative characteristics. Combining these two channels, they conclude that "in practice, the same securities that are difficult to value also tend to be difficult to arbitrage." (Baker and Wurgler 2007, P132). In particular, firms with small-cap, young age, no profit, no dividend, high volatility, extreme growth and distress, are hard to value and arbitrage. In contrast, those firms with characteristics of safety as opposed to risk, such as big size and high dividend yields, are less subject to the sentiment effect. In the latter case, Baker and Wurgler (2012) call them as bond-like stocks, which have a strong co-movement with the government bonds. In contrast, speculative stocks are less connected to bonds, and they typically earn lower return than that of bond-like ones.

In sum, due to cross-sectional sentiment effects and limits of arbitrage, arbitrage asymmetry exists at firm level. In our simple model, speculative asset are apt to be affected by sentiment effect, and such mispricing is risky to arbitrage. In particular, if the number of sentiment traders is relatively large compared to that of sophisticated ones, it will be too risky to arbitrage for the latter.

2.3 Mispricing asymmetry between high- and low-sentiment regime

Numerous studies argue that overpricing is more prevalent than underpricing due to short-sale impediments. For instance, Miller (1977) suggests that investors are unwilling to take short positions when their investments are overvalued. According to Ofek and Richardson (2003), due to short-sale constraints, over-optimistic investors inflated prices of Internet stocks, giving rise to the bubble. Moreover, Chang et al. (2007) discover that the existence of short-sale impediments reinforces the overpricing effect.

Drawing on short-sale constraints, many empirical studies discover that stocks that appeal to irrational investors are more likely to be overpriced, especially during the high sentiment regime. In an important paper, Stambaugh et al. (2012) find that 11 long-short strategies are more profitable following a high sentiment month than following a low sentiment month, as short-legs where stocks are susceptible to sentiment effect are overpriced when sentiment is high. In the spirit of Stambaugh et al. (2012), Shen et al. (2017) find that stocks with higher risk exposure to macro-related factors, will have higher expected returns following the low sentiment regime. However, this pattern is exactly opposite following the high sentiment period, since the presence of sentiment traders exert overpricing on stocks with high risk exposure.

In another related study, Yu and Yuan (2011) point out that irrational traders are apt to hold stocks rather than taking short position when they are optimistic. Under this view, sentiment traders have greater impacts on markets in the high sentiment regime and their poor understanding of measuring the risk undermines the mean-variance relation.

2.4 Empirical hypotheses

In a nutshell, the combined roles of sentiment effect and risky arbitrage imply that the more speculative that stocks are, the higher the arbitrage risk. When sentiment is high, irrational traders' high demands on speculative stocks leads to substantial overpricing. However, due to short-sale impediments and arbitrage risk, such overpricing is hard to be arbitraged. Further, sentiment traders associated with poor understanding of risk undermines the risk and return trade-off for those speculative stocks. Under these conditions, one can expect an inverse relation between arbitrage risk and returns following high sentiment periods. In contrast, market tends to be more rational and sentiment effects get attenuated during low sentiment periods. Thus, I conjecture that with less sentiment-driven mispricing, speculative stocks that tend to have small-cap but high growth perform better than those ones have characteristics of safety as opposed to risk. Putting all arguments together motivates me to explore two hypotheses:

Hypothesis 1: *When sentiment is high, stock with higher arbitrage risk are more likely to be overpriced due to short-sale impediments. Thus, arbitrage risk and returns exhibit a significantly negative correlation following high sentiment periods.*

Hypothesis 2: *With less sentiment effects, positive relation between arbitrage risk and returns prevails following low sentiment periods.*

3 Data and Methodology

3.1 Investor sentiment

Investor sentiment is difficult to measure directly but there exist numerous imperfect proxies that contain some information about the level of sentiment in the stock market. Baker and Wurgler (2006, 2007) construct an investor sentiment index as the first principal component of a number of these proxies: the closed-end fund discount, the number and average first-day returns on IPOs, the equity share in new issues, the dividend premium and the NYSE share turnover volume. This study uses monthly investor sentiment index as measured by them (BW sentiment hereafter).[11] Following Stambaugh et al. (2012), a high (low) sentiment month is the one where BW sentiment in previous month is above (below) than its median for the whole sample period.

Figure 1 plots this sentiment index, which spans from July 1965 to Sep 2015. The most striking feature of BW sentiment is its success in capturing anecdotal bubbles and crashes. After the crash of growth stocks, sentiment was low in the middle of 1960s. However, it rose dramatically and reached a peak during the craze of the "concept stocks mania" in the early 1970s. It dropped again in the middle of 1970s but peaked up with the biotech bubble in the early 1980s. For the early period in 1990s, sentiment was more stationary and experienced a small fluctuation. However, during the Dot.com craze, it peaked in the early of 2000 but plummeted after the crash of the Internet bubble. Similarly, sentiment rose again in the mid of 2000s where housing bubble happened, but dropped straightly after the Global Financial Crisis.

3.2 The 10 firm characteristics

This study introduces a number of well-documented firm characteristics, including size, age, dividends yield, operating profitability, beta, return volatility (sigma), external finance, sale growth, net stock issues, and share price, via which arbitrage against sentiment-driven mispricing varies cross-sectionally.

[11] I thank Jeffrey Wurgler for providing the updated sentiment index on his website

Size. Banz (1981) firstly proposes the size effect, where small-cap stocks earn higher return than that of big-cap stocks. Baker and Wurgler (2006) find that small-cap stocks are more susceptible to sentiment influence. According to Wurgler and Zhuravskaya (2002), firms with small size have higher arbitrage risk since they have less substitutions. Under this view, mispricing on small-cap stocks should be more difficult to arbitrage than that on big ones. Here, firm size is measured as the market value of equity (share close price times shares outstanding) in June of each year t.

Age. Baker and Wugler (2006, 2007, 2012) discover that firms that are young are more difficult to value and arbitrage. In particular, during market craze, those start-ups with novel names or concepts are more attractive to excessively optimistic investors. One vivid example is from biotech bubbles in the mid of 1980s. The unrealistic promises released by the biotech start-up, such as producing a wide range of medicine for the treatment of cancer, instil optimism and fancy to speculative investors, which in turn burst the overpricing on biotech stocks Malkiel (1996). Following Baker and Wugrler, this study measures the firms' age as the number of month since they firstly appeared in CRSP.

Dividends Yield. According to Pontiff (1996), stocks with less dividends are more likely to be deviated from their true values. Dividends reduce the holding costs, which in turn promote the arbitrage profitability. However, if firms pay no or small dividends, arbitrage will be costly and difficult. Here, the dividends yield is calculated as the ratio of total dividend divided by share price at the fiscal year-end.

Operating Profitability. Baker and Wugler (2006, 2007, 2012) suggest that those firms with lower profitability are harder to value and arbitrage. In this study, I choose operating profitability and measure it as annual revenues minus cost of goods sold, interest expense and selling, general and administrative expenses, divided by total assets at the fiscal year-end.

Return Volatility (sigma). In the noise trader model, Delong et al. (1990) argue that the presence of irrational traders causes excess volatility. According to Baker and Wurgler (2007), return volatility can be a natural measure of firms' speculative appeal. Further, they discover that stocks with higher volatility are more sensitive to the innovation to sentiment, and thus more difficult to arbitrage. In addition, Yu and Yuan (2011) find that during high sentiment periods where sentiment traders have more impact on stocks, returns are more volatile. Following Baker and Wurgler, in June of each year t, sigma is computed as the standard deviation of returns over last 12 months (with a minimum window of 6 months).

Beta. According to Hong and Sraer (2016), high-beta stocks are more susceptible to speculative overpricing. In addition, Antoniou et al. (2015) discover that firms with high-beta appeal to sentiment traders during high sentiment period. Here, beta is measured by the methodology of Fama and French (1992).

External finance and sale growth. As suggested by Baker and Wurgler (2006, 2012), external finance and sale growth can indicate firm distress and growth opportunities simultaneously. Typically, high levels of external finance and sale growth reflect high growth rates, while low levels are often associated with distress. Both two types of stocks should be prone to sentiment effect. Here, external finance is difference between change in assets and change in retained earnings divided by assets. Sale growth is the change in net sales divided prior-year net sales.

Net stock issues. According to Baker and Wurgler (2004), smart managers tend to issue more shares when share prices are overvalued by irrational investors, namely market timing. Moreover, Stambaugh et al. (2012) argue that stocks with more net issues are more likely to be overpriced, and thus earn lower subsequent return, especially following high sentiment month. Following Fama and French (2008), the net stock issues in fiscal year t is the change of natural log in split-adjusted shares outstanding between fiscal year t-1 and t-2.

Share price. According to Black (1986), stocks values are subject to noisy estimate, and noise traders prefer stocks with lower prices to ones with higher prices. Intuitively, those low-priced stocks deliver an underestimation, and thus may be more compatible to sentiment traders' wishful thinking of extraordinary returns. Moreover, sentiment traders can easily drive low price to an overvalued level, whereas arbitrager can hardly eliminate it. Here, share price is the close price at the end of fiscal year.

3.3 Measuring arbitrage risk

Each month, arbitrage risk for individual stock is measured by averaging its ranking on each of 10 characteristics. Higher ranking indicates higher arbitrage risk. Below are details about the ranking on 10 characteristics and how to measure arbitrage risk.

Sample stocks are chosen from all common stocks (share code 10, 11) listed on NYSE, AMEX and Nasdaq for the period from July 1965 to September 2015 where BW sentiment spans. For all firm characteristics but for age, beta and sigma, the firm-level data is obtained from the merged CRSP-Compustat Database. Following Fama and French (1992), I match and assign the values of these characteristic from the last fiscal year-end (t-1) to months through July at year t to June at year t+1. Since stocks with high distress and high growth are subject to sentiment effect (Baker and Wurgler (2006)), for both external finance and sale growth, stocks are sorted into two groups. Specifically, stocks with lower values of these two characteristics represent distress group while higher ones represent growth group.

As for beta, to allow for its variation that is unrelated to size, this study follows the methodology of Fama and French (1992) to estimate it, namely Fama-French Betas (FF-beta hereafter). Specifically, in June of each year t, all firms are sorted into 10 size deciles based on the NYSE breakpoints. Each size decile is further subdivided into 10 portfolios on the basis of individual stocks' pre-ranking betas, which are calculated by using 24-60 monthly return (as available) before July of year t. Again, only NYSE stocks are used to decide the beta breakpoints for each size decile. In total, this procedure generates 100 size-beta portfolios in June of year t. I then calculate the equal-weighted return of these portfolios for the next twelve months. Thus, I have post-ranking monthly returns for each of 100 size-beta portfolios, spanning the whole sample periods. Post-ranking betas are calculated as the sum of the slopes in the regression of the return on each portfolio on the current and the prior month's CRSP value-weighted market return. Finally, the post-ranking beta of each size-beta portfolio is assigned back to individual stocks.Table 1 reports the time-series averages of post-ranking FF-beta for 100 portfolios. In sum, betas vary significantly in each size decile, and they tend to become larger with firm being smaller.

Having obtained values of firm characteristics, I now rank sample stocks into percentile on each characteristic.[12] The more speculative the stock is, the higher percentage of its rank will be. The arbitrage risk of each firm is the arithmetic average of its ranking on each of 10 firm characteristics, ranging from 1 to 100. To exclude the situation where few characteristic decides the arbitrage risk, this study requires that a stock must have no less than five non-missing values of firm characteristics for each month.

Table 2 provides the summary statistics of arbitrage-risk measure, size, book-to-market ratio and FF-beta, and their pooled cross-sectional time-series correlations. Size is measured as firm's market equity, ME (closed price x share outstanding) at June of each fiscal year t. The book value, BE, is measured as the book value of stockholders' equity, B, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, I use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. The book-to-market ratio is calculated as the BE at June in calendar year t, divided by ME at the end of December of t-1. Following Fama and French (1992), this study takes the natural logarithm of arbitrage risk rank, size and book-to-market ratio to exclude the influence of some extreme outliers. Panel B in table 2 indicates that stocks with smaller size and higher betas tend to have higher arbitrage risk. In addition, the correlations between these variables are modest, implying that the multicollinearity is not a material issue here.

To check the robustness of arbitrage-risk measure, each month sample stocks are broken into 10 deciles by sorting on arbitrage risk: stocks in the top decile have higher arbitrage risk than those in the bottom decile. Table 3 shows the properties of portfolios formed on arbitrage risk. Specifically, it reports the time-series monthly average values of 10 characteristics within each arbitrage-risk sorted portfolio. Consistent with the relation between sentiment effects and firm speculative appeal, portfolios with higher arbitrage risk also have smaller size, higher beta, younger age, lower dividend yield, lower operating profitability, higher sigma, higher net stock issues and lower share prices. In particular, stocks in the highest decile experience extreme growth rates —the average external finance increases by 109.61% annually, and the annual average growth rate of sales is 138.58%.[13]

[12]Note that both external finance and sale growth have two groups that represent distress and growth respectively. I rank both of two type of groups into percentile.

[13]Note that these characteristics are measured at fiscal year end and reported in the annual financial

Panel A of Table 4 reports the average monthly return on value-weighted portfolios formed on arbitrage risk. In the whole sample period, portfolios with lower arbitrage risk perform slightly better than those with higher arbitrage risk. However, after dividing sentiment into high and low periods, I find a strong two-regime pattern. Specifically, the average monthly return declines dramatically and monotonously with the increase of arbitrage risk following high sentiment periods, indicating a strong negative relation between arbitrage risk and return. In particular, the spread between the portfolio with highest risk and the one with lowest risk is -1.98% with a t-statistic of -3.83. In contrast, speculative stocks perform better than less speculative ones following low sentiment month. The top decile that contains the most speculative stocks earn 1.14% higher average return (t-statistic is 2.45) than the bottom decile. Perhaps, with less sentiment effects, speculative stocks that tend to have small-cap but high growth yield higher return than those ones have characteristics of safety as opposed to risk. Overall, the above findings are consistent with that of Shen et al. (2017), who discover that firms with higher exposure to sentiment changes (more prone to sentiment effects) earn average lower (higher) return than ones with lower exposure to sentiment changes following high (low) sentiment periods.

More interestingly, the difference between return following high sentiment and the one following low sentiment also declines monotonouslythe with the increase of arbitrage risk. Such differences are small and insignificant for the first four deciles but become significant negative for the last four deciles where stocks have relatively high arbitrage risk. In particular, the portfolio with highest arbitrage risk earns 2.83% lower average return (t-statistic is -3.41) following high sentiment than that following low sentiment. This finding is consistent with economic intuition that high sentiment drives up the price and depresses the return, especially for speculative stocks with high arbitrage risk.

Panel B of Table 4 reports the average monthly volatility for each portfolio, with two important findings emerging.[14] First, volatility is generally larger for portfolios with higher arbitrage risk. In particular, when sentiment is high, the volatility of the top decile is two times and a half as that of the bottom decile. Second, for the first four deciles, the volatility

statement.

[14]Here, the volatility is calculated from within-month daily value-weighted return.

difference between different regimes is not prominent. In contrast, volatilities of the last four deciles are much higher during high-sentiment periods than those during low sentiment periods. Both two findings are consistent with the implication from behavioural literature that sentiment traders can cause excess volatility.[15]

4 Empirical Analysis

4.1 Fama-Macbeth regression

To give a more direct evidence to a negative trade-off between arbitrage risk and stock returns, this study employs the Fama-Macbeth analysis. Specifically, at the end of each month t, I run the cross-sectional regression of individual stock' return on their arbitrage risk, with controlling for firm size, book-to-market ratio and beta (Fama and French (1992)), returns on recent and intermediate horizon past performances (Novy-Marx (2012)). The factor loadings are the time-series average of slope coefficients on each variable, and the t-statistics are the ratios between average slopes and standard errors of sample means.[16] To get a two-regime pattern, I repeat the test for high- and low-sentiment regimes separately.

Table 5 reports the regression results. Panel A looks at the whole sample period. Panel B and C presents the result for high- and low- sentiment periods respectively. The results indicate that following high sentiment, returns and arbitrage risk exhibit a strong negative correlation. The slope coefficient of -0.68 (t-statistic is -2.12) suggests that the premium in expected return is -0.68% for per unit of arbitrage risk, after controlling other explanatory variables. In contrast, the relation between arbitrage risk and return becomes significantly positive following low sentiment: per unit of arbitrage risk is associated with 1.03% premium in expected return (t-statistic is 3.17). While considering the whole sample, this relation becomes insignificant (the factor loading is 0.16 with a t-statistic of 0.66). Thus, all of these

[15] For example, Delong et al. (1990) point out that noise trading can make asset prices more volatile. Yu and Yuan (2011) find that the volatility of market return is much higher during high sentiment periods where sentiment traders largely present.

[16] For example, if $\widehat{\lambda}$ is the estimated cross-sectional slope coefficients, its average slope is $\overline{\lambda}=\frac{1}{T}\sum_{t=1}^{T}\widehat{\lambda}_t$, and the standard error is $\sigma^2(\lambda)=\frac{1}{T}var(\widehat{\lambda}_t)=\frac{1}{T^2}\sum_{t=1}^{T}(\widehat{\lambda}_t-\overline{\lambda})$ if $\widehat{\lambda}_t$ are not correlated. To solve the issue of autocorrelated $\widehat{\lambda}_t$, I correct the standard errors by using the Newey-West method (Newey and West (1987)).

findings are consistent with the hypotheses in section 2.4 .

The explanation to these findings is organised as follows. When sentiment is high, speculative stocks that are susceptible to sentiment effect should be more likely to be overpriced. However, due to short-sale constraints, such a overpricing is hard to be eliminated, especially for those speculative stocks with high arbitrage risk. The combined effects of sentiment-driven overpricing and short-sales impediments imply that following high sentiment the expected return and arbitrage risk should be significantly negatively correlated, since overpriced stocks earn lower subsequent return. In contrast, during low sentient periods where the market becomes more rational, speculative stocks that tend to have small-cap but high growth perform better than those ones have characteristics of safety as opposed to risk, and thus earn higher returns. Under this setting, arbitrage risk and returns should exhibit a negative relation.

In addition, other results presented in Table 5 line up with previous studies. Specifically, β is not significantly priced (Fama and French (1992)). However, after considering sentiment effect, I find that β loading is slightly negative during high sentiment periods but becomes significantly positive when sentiment is low (Antoniou et al. (2015)). Such pattern also appears on size loading —size effect only present in low sentiment periods (Baker and Wurgler (2006)). In addition, I also find a strong value effect (Fama and French (1992)) and monthly return reversal (Jegadeesh and Titman (1993) and Novy-Marx (2012)). Moreover, the coefficient on cumulative returns of past 12 to seven months is more significant than that on cumulative returns of past 6 to 2 months, indicating that momentum profit is primarily driven by returns of 12 to seven months prior to portfolio formation (Novy-Marx (2012)).

4.2 The arbitrage factor

Baker and Wurgler (2012) discover a strong co-movement between bond-like stocks with government bonds, while speculative stocks are less connected to bonds. In particular, during high sentiment periods, those speculative stocks represent higher risk but earn less return than that of bond-like stocks. Following Baker and Wurgler, this study conjectures that stocks with higher (lower) arbitrage risk have more (less) exposure to sentiment-driven mispricing, so one should expect strong co-movement among stocks with close arbitrage risk. The premium between those bond-likes stocks and speculative stocks, namely arbitrage factor, can capture such a co-movement.

To calculate the arbitrage factor, I follow the 2 x 3 sorting procedure of Fama and French (1993). At In June of each year t, NYSE stocks are sorted into two groups by firm size. All sample stocks are broken into small and big size portfolios based on NYSE breakpoints. They are also broken into three groups (bottom 30%, middle 40% and top 30%) based on the breakpoints of arbitrage risk for NYSE stocks. By interacting two size groups and three arbitrage-risk groups, six portfolios (B/L, B/M, B/H, S/L, S/M, S/H) are constructed. Finally, the premium of arbitrage risk or arbitrage factor, is the difference between the equally average of the returns on two low arbitrage-risk groups (B/L and S/L), and the equally average of the returns on two high arbitrage-risk groups (B/H and S/H). Thus, the new factor should be free from the size effect.

4.2.1 The arbitrage factor and cross-sectional anomalies

In a seminal paper, Stambaugh et al. (2012) introduce 11 well-documented cross-sectional anomalies including asset growth, composite stock issues, failure probability, gross profitability, investments-to-assets, momentum, net operating assets, financial distress (Ohlson's O score), total accruals, return on assets and net stock issues, that arise from sentiment effects.[17] The return on each of the 11 anomalies is the return spread between stocks in the highest-performing decile (long leg) and ones in the lowest-performing decile (short leg).

Table 6 reports the results of regressing the 11 anomalies' returns on the arbitrage factor with controlling for Fama-French three factors (FF-3 hereafter).[18] For all anomalies but total accruals, their returns are significantly positive correlated with arbitrage factor (t-statistics range from 1.59 to 9.88). In particular, there is a strong positive relation exists in arbitrage factor and the equally combination of these long-short strategies (slope coefficient is 0.31 with a t-statistic of 10.63) In addition, after including arbitrage factor into FF-3 model, the average adjusted R^2 increases from 0.27 to 0.34. It implies that the augmented factor model performs better than the FF-3 model in explaining 11 cross-sectional anomalies.

[17] I thank Yuan Yu for providing these data online.
[18] I thank Ken French for providing these factors.

Consistent with sentiment-driven overpricing on short-legs that contain lowest-performing stocks, the arbitrage factor exhibits a strong negative correlation with returns on short-legs. 10 of their slopes coefficients are significant (t-statistics range from -3.03 to -11.53). Moreover, return on the equally combination of short legs shows a more significantly negative relation to arbitrage factor (slope coefficient is -0.26 with t-statistic of -12.46). However, this relation gets ambiguous and weak for long-legs. Specifically, for anomalies of composite stock issues, failure probability, gross profitability, return on assets and net stock issues, returns on those highest-performing deciles are positively related to arbitrage factor. As to the other 6 anomalies, this relation gets either negative or insignificant.

As become clear below, one must grasp the intuition behind these 11 anomalies to understand their relation with arbitrage factor. According to Stambaugh et al. (2012), stocks in short legs are relatively susceptible to sentiment-driven mispricing compared to those in long legs. In particular, during high sentiment periods where short-sales are constrained, stocks in short-legs are more overpriced than ones in long-legs. Thus, they discover that long-short strategies of these anomalies are particularly profitable following high sentiment month. This profitability mainly come from the lower return of short legs, since sentiment does not greatly affect on long legs. Analogously, arbitrage factor also reflects the cross-sectional asymmetric of sentiment-driven mispricing. In particular, when sentiment is high, stocks with lower arbitrage risk are less overpriced compared to those with higher arbitrage risk. Under this condition, one can understand the spread between them as a premium that price the exposure to sentiment effect. Since 11 anomalies are also built on stocks' different exposure to sentiment effect, the arbitrage factor can explain these anomalies very well. Thus, arbitrage factor is positively correlated with returns on each of the 11 long-short strategies, but negatively correlated with returns on their short legs. In contrast, long legs are less likely subject to sentiment effect, so they do not show a strong relation with arbitrage factor.

4.2.2 Investor sentiment and the arbitrage factor

In a related study, Stambaugh and Yuan (2017) average rankings within two clusters from the 11 anomalies for individual stock. Within each cluster, they follow 2 x 3 sort procedures to construct long legs of highest-performing stocks (top 80th percentiles) and short legs of lowest-performing stocks (bottom 20th percentiles). The long-short spreads are premium of two mispricing factors. Consistent with the relation between investor sentiment and the 11 anomalies, Stambaugh and Yuan (2017) find that BW sentiment can predict premiums of two mispricing factors and returns on their short legs. However, BW sentiment does not exhibit predictability on returns of long legs.

As discussed earlier, the arbitrage factor arises from cross-sectional variation of sentiment effect, and its premium is the return difference between stocks with low arbitrage risk (long leg) and stocks with high arbitrage risk (short leg). Thus, in the spirit to Stambaugh et al. (2012) and Stambaugh and Yuan (2017), we should also find forecasting power of sentiment on arbitrage factor and the short leg's return.

Table 7 reports the sentiment predictability. BW sentiment negatively predicts the return on the short leg portfolio. The slope coefficient of -1.04 (t-statistic is -2.98) suggests that one standard deviation increase of sentiment (BW sentiment is standardised) leads to 1.04% lower subsequent return. It confirms my conjecture that speculative stocks are overpriced when sentiment is high. In contrast, this study does not find a relation between sentiment and the long leg portfolio. For the long-short spread —arbitrage factor, sentiment exhibits a strong positive predictability (t-statistic is 4.21), and one standard deviation rise in sentiment is associated with 0.98% higher return in next month.

4.2.3 A deep look at the arbitrage factor

In the mean-variance framework, a factor can explain any pattern of returns if and only if it is the ex-post mean-variance portfolio. In other words, it should have a maximum sharp ratio so that any asset or portfolio return can lie in the span of it. Table 8 summarises the sharp-ratio of the arbitrage factor as well as a set of factors that have been well-studied in the empirical asset-pricing literature. These factors comprise the market excess return, size and value factors proposed by Fama and French (1993); the momentum factor proposed by Carhart (1997); the liquidity factor proposed by Pastor and Stambaugh (2003); the value, momentum and gross profitability proposed by Novy-Marx (2013); the size, investment and profitability proposed by Hou et al. (2015); two additional factors based on Fama-French's three factors:

profitability and investment proposed by Fama and French (2015); three mispricing factors proposed by Stambaugh and Yuan (2017) and two behavioural factors proposed by Daniel et al. (2017).

Comparing these factors, the arbitrage factor has lower average return but high standard deviation, and thus lower sharp ratio (0.04). As a consequence, it is not a mean-variance efficient portfolio and might not be able to explain other asset returns. Despite the lowest sharp ratio, our arbitrage factor shows its uniqueness by capturing a time-varying return pattern: stocks with high arbitrage risk are more likely to be overpriced during high sentiment periods but perform better when sentiment is low. Note that in our previous result as described in Table 4, the top decile with high arbitrage risk earns significant lower return following high sentiment and higher return following low sentiment than that of the bottom decile with lower arbitrage risk. Such a time-varying pattern implies that the premium of the arbitrage factor, on time-series average, will not be significant. It also indicates that the standard deviation of the arbitrage factor should be prominent, since its premium fluctuates significantly with shifts in investor sentiment.

In short, unlike other factors that are mainly derived from market anomalies, our arbitrage factor does not show a significant premium and high sharp ratio. Thus, it might not be suitable for inclusion in a parsimonious factor model to capture abnormal returns of market anomalies.[19] However, such a factor is unique but sensible, as it lines up with time-varying sentiment-driven mispricing. Accordingly, it can better capture the time variation of return patterns that are correlated with sentiment effects. These have been shown in the regressions of the 11 market anomalies as described in the Section 4.2.1, in that the average R^2 increases from 0.27 to 0.34 after including the arbitrage factor.

Investor sentiment can change the distribution of future returns and investment opportunities (e.g. a positive (negative) shock on investor sentiment drive up (down) demands on those speculative stocks that appeal to sentiment traders). Perhaps, therefore, the arbitrage factor that reflects the time-varying sentiment effects should be consistent with ICAPM (Merton (1973)), which also adds investment horizons and time-varying investment opportunities

[19] In time-series factor models, $R_t^i = a_i + \beta_i f_i + \epsilon_t^i$. Taking the expectation, we have $E(R^i) = E(a^i) + \beta_i E(f)$. Since the arbitrage factor is not developed as a anomaly and it does not show a high premium, one should not expect it work well in factor models to cover all pricing errors. ($E(a^i)$=0 here)

to the asset pricing picture. Further, numerous studies that find sentiment predicability on asset returns are best supports with regarding sentiment as a state variable and guiding us to create the arbitrage factor that can capture the sentiment-related return comovement.

4.3 Institutional ownership and arbitrage risk

Many studies have used institutional ownership as proxy for arbitrage costs or short-sale constraints.[20] For instance, Nagel (2005) suggests that stocks with lower IO are more likely to be binding with short-sales constraints through two channels. First, a low IO suggests that sophisticated investors could have sold their shares and are unable to exert further selling pressure. Second, low IO stocks may have characteristics that institutions do not like (Gompers and Metrick (2001)), indicating that the number of sophisticated sellers is lower than that of irrational investors. Since low IO is associated with little stock loan supply, Nagel (2005) further argues that short-sale is hard and costly for stocks with low IO, which is consistent with the finding of D'Avolio (2002), in that stock loan fees are negatively correlated with IO.

Recall from Section 2 that arbitrage asymmetry exists at firm level and short sale are constrained on overpriced stocks. If speculative stocks are more likely to be overpriced as a consequence of sentiment effects and short-sale impediments, one should expect that these stocks have higher level of short-sale constraints and thus lower IO. To provide more evidence to this intuition, I construct the 5x5 double sorted portfolios with respect to arbitrage risk and IO. Th latter is measured as the fraction of shares outstanding held by institutional investors (Nagel (2005)).[21] Panel A in Table 9 presents the monthly average IO for double-sorted portfolios. Within each level of IO, the IO almost rises monotonically from the portfolio with lowest arbitrage risk to the one with highest arbitrage risk. In particular, given the independent sorting on arbitrage risk, the top quantile with highest arbitrage risk only has a average of 18.78% IO, while the bottom decile has a average of 47.85%.

To the extent that number of institutional owners might reflect whether a stock appeal

[20]See Ali et al. (2003), Asquith et al. (2005), Nagel (2005), Duan et al. (2010) and Stambaugh et al. (2015)

[21]The data on institutional holdings is obtained from Thomson Financial Institutional Holdings, covering the period from April 1980 to September 2015.

to sophisticated investors and thus less speculative, I also examine the average number of institutional owners within each portfolio. Panel B of Table 9 present the result. Consistent with the finding of IO, I find that the higher arbitrage risk that stock have, the lower the number of institutional owners, indicating that stocks with high arbitrage risk are speculative and less appeal to sophisticated traders. Finally, Panel C of Table 9 and Figure 3 reports the average number of stocks in each portfolio, with a emerging finding: high (low) IO stocks aggregate in the portfolios with high (low) arbitrage risk. Such a pattern envisions a vivid intuition to us in that stocks with higher arbitrage risk tend to have lower IO.

4.4 Firm characteristics, arbitrage risk and idiosyncratic volatility puzzle

Ang et al. (2006) find that stocks with higher Idiosyncratic volatility (IVOL) earn lower average returns, namely IVOL puzzle. In a well-cited study, Shleifer and Vishny (1997) point out that IVOL is a big arbitrage risk for arbitragers. Specifically, arbitragers are highly specialised in trading a few assets and are far from diversified. Thus, IVOL cannot be diversified away, so it is a risk that deters arbitrage against noise trading. In particular, they argue that stocks with high IVOL are more likely to be overpriced, and thus earn lower return. Following Sheifer and Vishny, Ali et al. (2003) argue that the value premium is an anomaly that is stronger among stocks with high IVOL. Further, according to Pontiff (2006), idiosyncratic risk is the largest holding cost that prevent arbitrager from exploiting mispricing. In addition, Stambaugh et al. (2015) argue that higher IVOL indicates higher arbitrage risk. They find stocks with high IVOL that are more likely to be overpriced (associated with lower return) than underpriced as a result of investor sentiment. Accordingly, the negative relation between IVOL and return is the consequence of those overpriced stocks.

Drawing on a well-documented relation between IVOL and arbitrage risk, this study analyses the IVOL puzzle by combining firm characteristics with arbitrage risk. As reported in the section 3.3, portfolios with higher arbitrage risk yield lower return than those with lower arbitrage risk over the whole sample period. In particular, when sentiment is high, the average monthly spread between the top decile and the bottom decile is -1.98%, with a t-statistic of -3.83. Note that speculative stocks that have high arbitrage risk, should also have higher IVOL. Under this condition, one should observe a negative relation between IVOL and average return.

To make my point clear here, I compute the IVOL of portfolios formed on arbitrage risk and also the 11 firm characteristics as described above.[22] Specifically, for arbitrage risk and each of 11 characteristics, sample stocks are ranked into 10 decile.[23] Following Ang et al. (2006), the monthly IVOL for individual stock is calculated as the standard deviation of the residuals from the regression of the most recent month's daily returns on the Fama- French three factors. Each month, the portfolios' IVOL is the average IVOL of individual stocks within each decile.

Table 10 shows the main result. I find that IVOL increase monotonously with the increase of arbitrage risk, which is consistent the argument of Pontiff (2006) and Stambaugh et al. (2015)—high IVOL indicate high arbitrage risk. Further, IVOL is generally higher for the portfolio with higher beta, younger age, lower dividends, higher net stock issues, lower operating profitability, lower share price, higher return volatility and smaller size. Partial of these findings appeal in Bali and Cakici (2008), who also discover that stocks with high IVOL have small size, high beta and low price.

Interestingly, IVOL of portfolios formed on external finance, sale growth and book-to-market ratio display intriguing patterns. Specifically, both bottom and top deciles have relative high IVOL compared that of middle deciles—a "U" shape. As discussed previously, stocks with the smallest external finance, the lowest sale growth and highest book-to-market ratio imply highest distress, and ones with largest external finance, the highest growth experience and lowest book-to-market ratio experience extreme growth. Both two types of firms are more subject to sentiment effect than those with middle value.

Figure 2 plots the IVOL graphically. IVOL of arbitrage risk, beta, return volatility and

[22]I add book-to-market ratio here. According to Baker and Wurgler (2006), book-to-market ratio has two hats—low value indicate high growth, while high value indicate distress.

[23]Beta is calculated monthly by using the methodology of Fama and French (1992). Sigma is computed as standard deviation of returns over last 12 months (with a minimum window of 6 months). Firms' age is measured as the number of month since they firstly appear in CRSP. Other firm characteristics are obtained from merged CRSP-Compustat Database. For all characteristics but for age and beta, I match the firm level data from the last fiscal year-end to months through July at year t to June at year t+1.

net stock issues, rises with the increase of values in each characteristic, which is opposite to the trend of age, dividends yield, share price, operating profitability and size. U-shaped patterns appear in the IVOL of portfolios sorted by external finance, sale growth and book-to-market ratio. Overall, all evidences imply that the higher arbitrage risk or speculative level, the higher IVOL.

To further explain the IVOL effect, this study constructs the 5x5 double sorted portfolios with respect to IVOL and arbitrage risk. Each month, sample stocks are firstly sorted into quintile portfolios based on their individual IVOL, and then ranked into quintile portfolios by independently sorting on arbitrage risk. By interacting five IVOL groups and five arbitrage-risk groups, 25 portfolios are generated. Panel A of Table 11 reports the average monthly IVOL for each double sorted portfolio. Within each level of IVOL, the IVOL rises monotonically from the portfolio with lowest arbitrage-risk to the one with highest arbitrage-risk. Panel B of Table 11 reports the average number of stocks in each portfolio, and I find that stocks with high arbitrage risk tend to be those ones with high IVOL. Such pattern has been further illustrated by Figure 4, in that high (low) IVOL stocks aggregate in the portfolios with high (low) arbitrage risk.

Panel C of Table 11 shows the average monthly value-weighted return within each portfolio. Given the independent sorting on IVOL, a strong IVOL effect, reported in the last column, appears. Figure 5 plots the return on double-sorted portfolios graphically. I find that the IVOL effect mainly comes from the segments of high arbitrage risk: stocks with both high arbitrage risk and high IVOL earn particularly low return. However, within the the level of lowest arbitrage risk, a exact opposite appeals: stocks with highest IVOL earn higher return than that of ones with lowest IVOL. As analysed below, understanding the relation between sentiment influence and arbitrage risk is important. Typically, stocks with high arbitrage risk are speculative. They have features of high IVOL and high exposure to sentiment-driven mispricing. However, arbitrage against this mispricing is costly and risky. In particular, due to the short-sale impediments, stocks associated with high arbitrage risk are more likely to be overpriced as a result of sentiment effects. Thus, negative IVOL-return relation prevails.

5 Robustness Checks

5.1 Investor sentiment and time-varying factor loading on arbitrage risk

Fama-MacBeth procedure is an important and widely used methodology in asset pricing, and it shows its importance by allowing changing betas (Cochrane (2006)). Thus, by running the cross-sectional regression for each period, one should expect a time-varying coefficient estimates on the rank of arbitrage risk in our case. Further, if sentiment effect does determine the cross-sectional relation between stock return and arbitrage risk, one should also expect that the rise (decline) of investor sentiment in current period will bring a negative (positive) effect on this relation in subsequent period.

Following this intuition, I firstly obtain the two kinds of factor loadings on arbitrage rank (in time series) from the Fama-MacBeth regressions as described in Section 4.1: one is estimated without control variables and the other one is estimated with most control variables, and then regress them on the one-month lagged BW sentiment. Table 12 reports the regression results. Consistent with the sentiment predictability on the premium of arbitrage risk, sentiment shows a strong negative predictability on these factor loadings. For the estimates without control variables, the slope coefficient of -1.29 (t-statistic is -4.40) suggests that a unit increase of sentiment drive down the subsequent factor loading on arbitrage rank by -1.29. In the later case, a unit increase of sentiment is associated with -0.94 (t-statistic is -4.36) more negative factor loading on arbitrage rank in the subsequent month.

In sum, the above findings are consistent with our hypotheses: a negative (positive) relation between stock return and arbitrage risk following high (low) sentiment periods.

5.2 Alternative sentiment index

This subsection checks the robustness of sentiment predictability on the arbitrage factor by using the survey-based sentiment —University of Michigan Consumer Sentiment Index (MCSI). According to Lemmon and Portniaquina (2006), the MCSI can be a potential measure of how optimistic that investors are. Following Baker and Wurgler (2006), I remove business cycle components including the growth in industrial production, durable consumption, non-durable consumption, service consumption, employment and a dummy for NBER economic recessions, from the MCSI. Residuals are saved and standardised as the proxy of investor sentiment.

Table 13 reports the regression of arbitrage factor on the one-month lagged MCSI. Consistent with the report in table 6, the MCSI can positively predict the premium of arbitrage risk and negatively predict the return on the short leg. However, it does not show any relation to the return on the long leg.

5.3 Controlling for macro-related variables

One might be apt to seek a risk-based explanation to the relation between the arbitrage factor and the 11 market anomalies. In particular, if some omitted macro-related risk premiums coincide with the premium of arbitrage risk, part of the finding can also be obtained. To exclude these alternatives, this study follows Stambaugh et al. (2012) and Shen et al. (2017) to control for additional macro-variables, including the real interest rate, the inflation rate (Fama (1981)), the term and default premium (Chen et al. (1986)), and the consumption-wealth ratio (cay) defined in Lettau and Ludvigson (2001).[24]

Table 14 presents the regression after controlling for additional macro-variables. The overall result is almost identical to that reported in table 7. In sum, if risk-based explanation of macro-variables can drive the result, the arbitrage factor might not be connected to sentiment effect. By controlling for five macro-related risk factors in the analysis, this probability is removed, and the arbitrage factor is robust to explain the 11 market anomalies.

[24]The real interest rate is the difference between return on the 30-day T-bill and inflation rates. The term premium is defined as spread between 20-year T-bill and 1-year T-bill. The default premium is the difference between BAA and AAA bonds. The inflation rate and T-bill return are obtained from CRSP. The default premium comes from the St.louis Federal Reserve and cay is obtained from Martin Lettau's website

6 Conclusion

Stocks that are more susceptible to investor sentiment are also more risky to arbitrage. To explore the combined roles of sentiment effects and arbitrage risk in pricing financial assets, this study measures the individual stocks' arbitrage risk represented by firm speculative appeal, by averaging their ranking on 10 firm characteristics through which arbitrage against sentiment effect varies cross-sectionally. Consistent with that overpricing is more prevalent than underpricing due to short constraints, I find that during high sentiment periods, stocks with high arbitrage risk earn significantly lower average returns than ones with lower risk. Further supporting this finding, the Fama-Macbeth analysis implies a negative factor loading on arbitrage risk.

Popular factors are generally constructed by sorting on a single firm characteristic. Note that averaging stocks' rank on each firm characteristic will yield a less noisy measure than does it rank on any single characteristic. Thus, this study constructs the arbitrage factor based on the average ranking on the 10 firm characteristics. Unlike other factors that are mainly derived from market anomalies, our arbitrage factor does not show a significant premium and high sharp ratio. However, it shows its uniqueness and success by not only reflecting the common elements of stocks with close arbitrage risk but also accommodating to the time variation of return patterns that are correlated with sentiment effects. These have been shown in the regressions of the 11 market anomalies, in that the average adjusted R^2 increases from 0.27 to 0.34 after including the arbitrage factor. Further supporting this explanation, investor sentiment exhibits a strong positive predictability on arbitrage factor. Intuitively, a positive innovation to sentiment brings less overpricing on stocks with lower arbitrage risk than that on ones with higher risk, and thus boosts their return spread.

Lastly, this study combines arbitrage risk with sentiment-driven overpricing to explain the idiosyncratic volatility (IVOL) puzzle. Stocks with high arbitrage risk also have high IVOL. Due to short-sale impediments, speculative stocks are more likely to be overpriced than underpriced as a consequence of investor sentiment. Therefore, they earn lower average returns than that of non-speculative ones, so the negative IVOL-return relation prevails.

In sum, this study develops a deep understanding of how arbitrage risk plays a role in pricing financial assets. The main objective here is in quantifying the sentiment effect as a risk factor and incorporating it into standard factor models, to contribute to explaining stock returns as well as numerous market anomalies that arise from investor sentiment.

Appendix

Appendix A. Derivations of Equations (3) and (4)

Giving the normal distribution of expected return on holding a unit of the speculative asset a, maximising the utility in equation (2) is equivalent to maximising:

$$U = -e^{-(2\gamma)\overline{\omega}+2\gamma^2\sigma_\omega^2} \tag{A1}$$

(*Note that* $E(e^z) = e^{E(z)+0.5\sigma_z^2}$)

Denote numbers of asset a and b that sophisticated investors buy are $\lambda_{a,t}^s$ and $\lambda_{b,t}^s$ respectively, that irrational ones buy are $\lambda_{a,t}^i$ and $\lambda_{b,t}^i$ respectively. Due to wealth constraints ω_0 at period t, we have:

$$\lambda_{a,t}^s(P_{a,t}) + \lambda_{b,t}^s \leqslant \omega_0 \qquad \text{and} \qquad \lambda_{a,t}^i(P_{i,t}) + \lambda_{b,t}^i \leqslant \omega_0 \tag{A2}$$

(*Note that the price of asset* b *is fixed at one*)

By forming the Lagrangean, we transform this constrained maximisation problem into an unconstrained one. Thus, for sophisticated investors, maximising the utility is also equivalent to maximising the value:

$$U_(\lambda_{s,t}, L) = -e^{-(2\gamma)\overline{\omega}_s+2\gamma^2\sigma_\omega^2} - L[\lambda_{a,t}^s(P_{a,t}) + \lambda_{b,t}^s - \omega_0] \tag{A3}$$

(L *is the Lagrangean Multiplier*)

where $\overline{\omega}_s$=$\lambda_{a,t}^s(P_{a,t+1}) + \lambda_{b,t}^s + \lambda_{b,t}^s(r_f)$, representing the expected final wealth for sophisticated investors in period t+1. Note that only the price of asset b is volatile, the variance of final wealth σ_ω^2 is $(\lambda_t^s)^2\sigma_{P_{a,t+1}}^2$, where $\sigma_{P_{a,t+1}}^2$ is the one-period variance of $P_{a,t+1}$.

To maximise the utility, taking the first derivatives of equations (A3) on $\lambda_{a,t}^s$ and $\lambda_{b,t}^s$

respectively, and such derivatives must equal zero:

$$\frac{\partial U_(\lambda_{s,t},L)}{\partial \lambda^s_{a,t}} = [-2\gamma(P_{a,t+1}) + 4\gamma^2(\lambda^s_{a,t})\sigma^2_{P_{t+1}}](-e^{-(2\gamma)\overline{\omega}_s+2\gamma^2\sigma^2_\omega}) - L(P_{a,t}) = 0$$
$$\frac{\partial U_(\lambda_{s,t},L)}{\partial \lambda^s_{b,t}} = -2\gamma(1+r_f)(-e^{-(2\gamma)\overline{\omega}_s+2\gamma^2\sigma^2_\omega}) - L = 0 \tag{A4}$$

Solving equations in A(4), we get equation (3):

$$\lambda^i_{a,t} = \frac{P_{a,t+1} - (1+r_f)P_{a,t}}{2\gamma(\sigma^2_{P_{a,t+1}})} \tag{3}$$

Repeating the above procedure for the irrational investors, we have:

$$U_(\lambda_{i,t}, L) = -e^{-(2\gamma)\overline{\omega}_i+2\gamma^2\sigma^2_\omega} - L[\lambda^i_{a,t}(P_{a,t}) + \lambda^i_{b,t} - \omega_0]$$

$$\frac{\partial U_(\lambda_{i,t},L)}{\partial \lambda^i_{a,t}} = [-2\gamma(P_{a,t+1}) + 4\gamma^2(\lambda^i_{a,t})\sigma^2_{P_{t+1}}](-e^{-(2\gamma)\overline{\omega}_i+2\gamma^2\sigma^2_\omega}) - L(P_{a,t}) = 0 \tag{A5}$$

$$\frac{\partial U_(\lambda_{i,t},L)}{\partial \lambda^i_{b,t}} = -2\gamma(1+r_f)(-e^{-(2\gamma)\overline{\omega}_i+2\gamma^2\sigma^2_\omega}) - L = 0$$

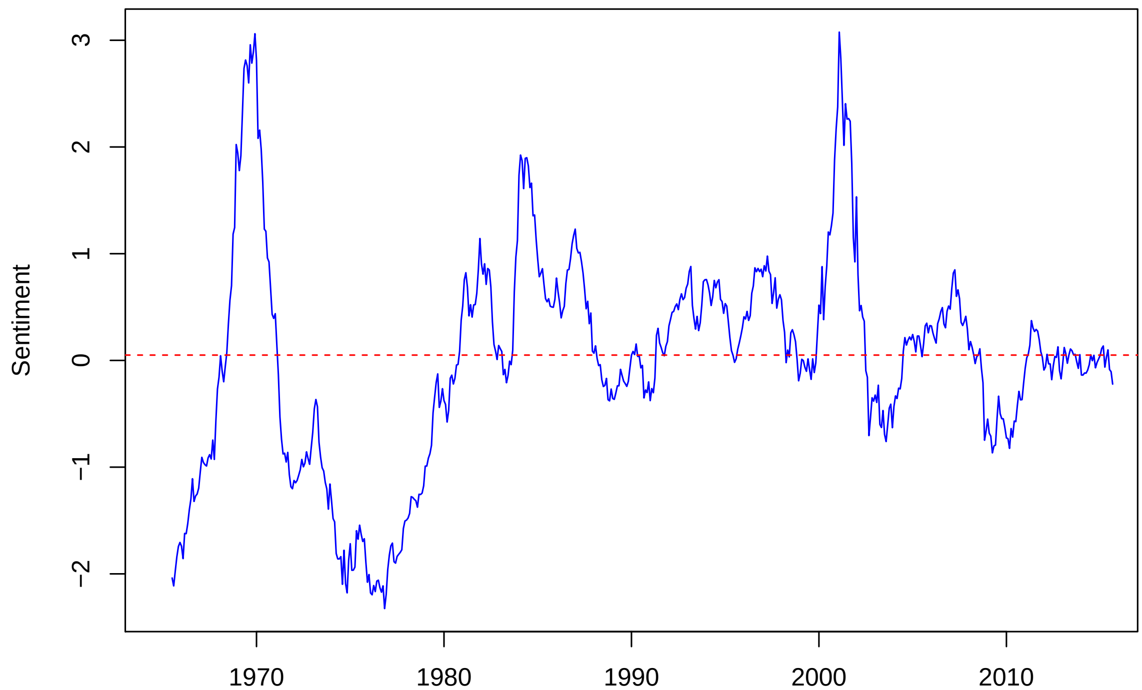
where $\overline{\omega}_i$=$\lambda^i_{a,t}(P_{a,t+1}) + \lambda^i_{b,t} + \lambda^i_{b,t}(r_f) + \rho_t$, representing the expected final wealth for irrational investors in period t+1. (Note that ρ_t is sentiment traders' biased believes about future return)

Solving equations in A(5), we get equation (4):

$$\lambda^i_{a,t} = \frac{P_{a,t+1} - (1+r_f)P_{a,t}}{2\gamma(\sigma^2_{P_{a,t+1}})} + \frac{\rho_t}{2\gamma(\sigma^2_{P_{a,t+1}})} \tag{4}$$

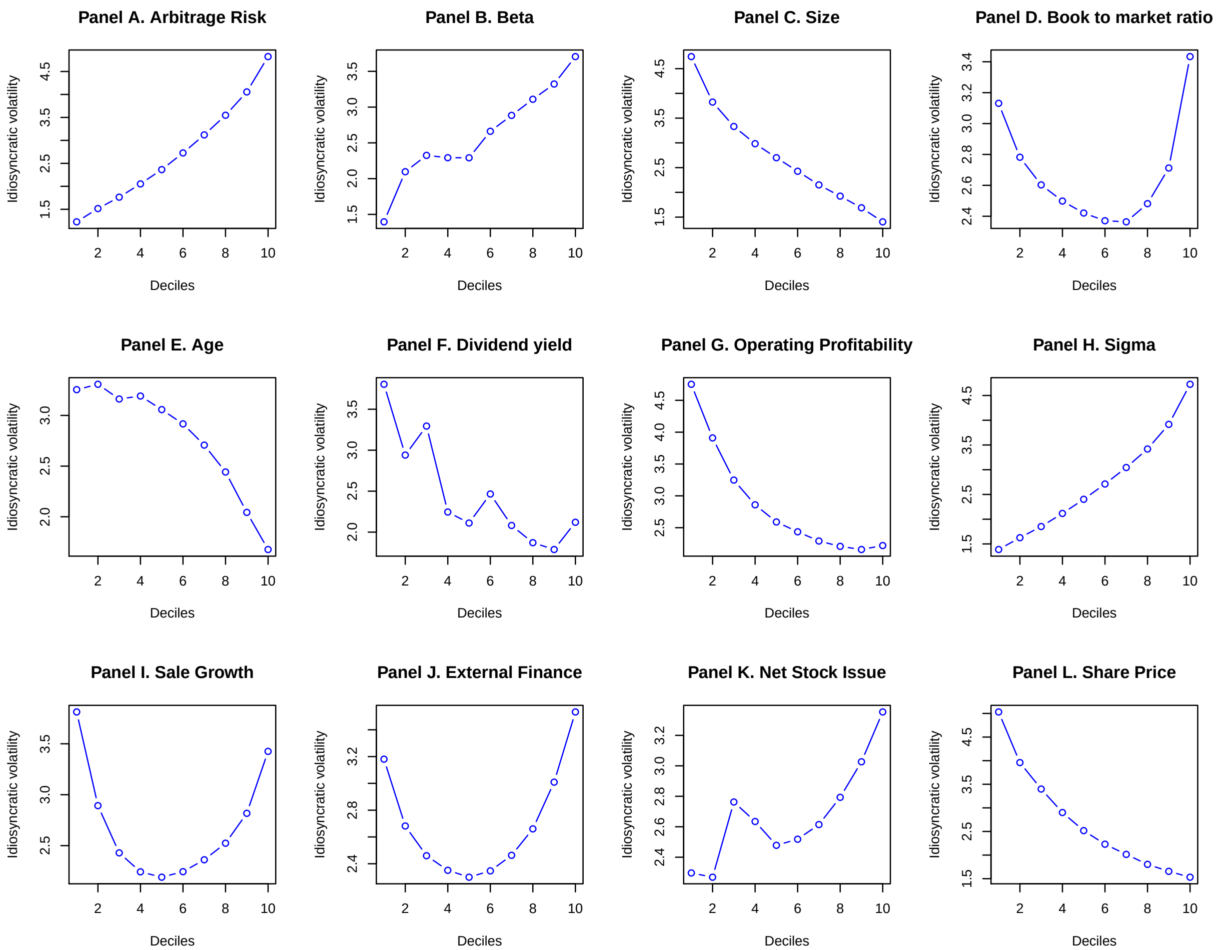
Appendix B. Figures

Figure 1: BW sentiment



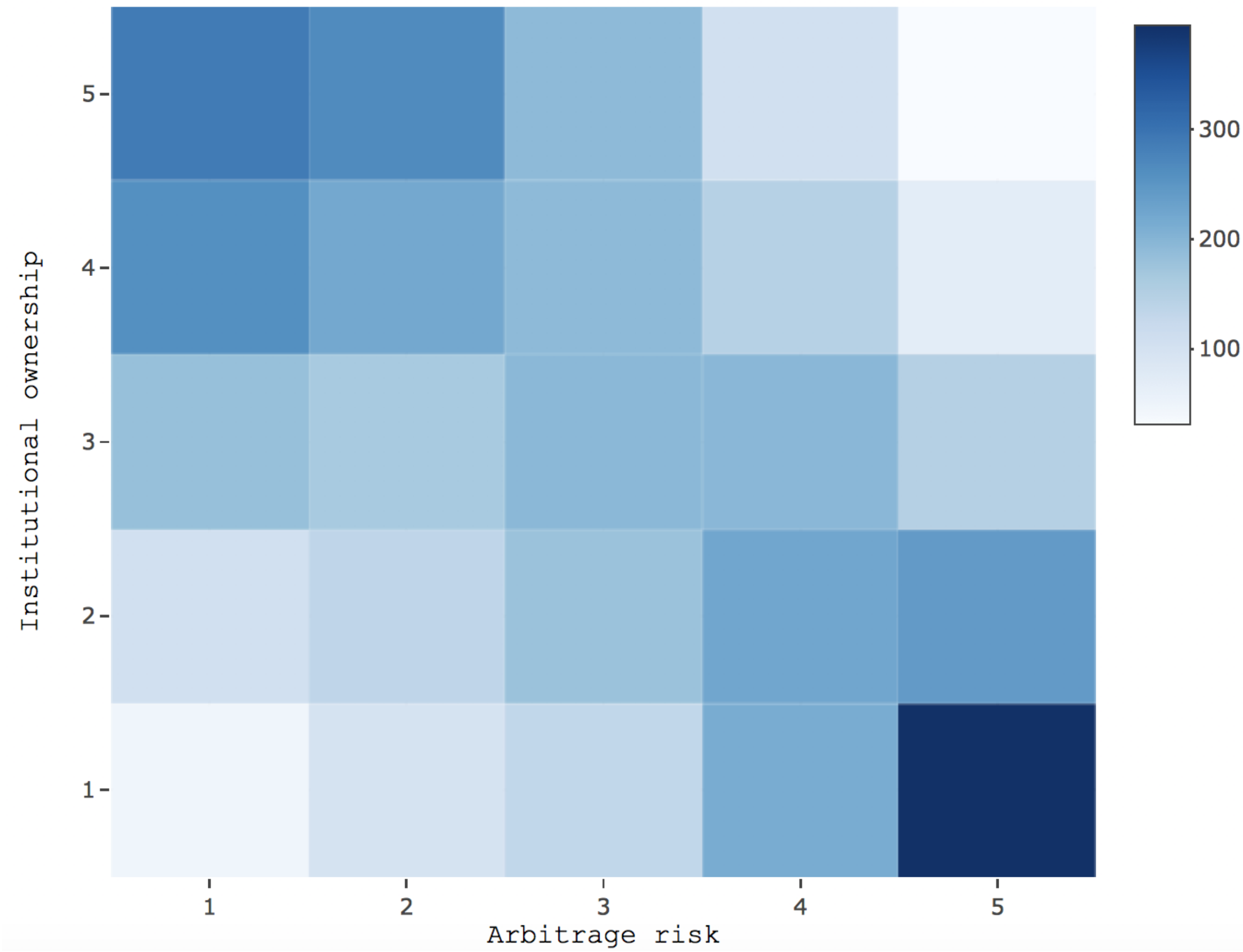
Notes: The BW sentiment spans from 1965:07 to 2015:09. The red dash line represents its median. To control for the business-cycle effects, Baker and Wurgler (2006) firstly regress five sentiment proxies, including discount of closed-end fund, the number of IPOs and the mean 1st-day IPO return, the premium for dividend-paying stocks and equity share in new issues, against the growth in industrial production, durable consumption, non-durable consumption, service consumption, employment and a dummy for NBER economic recessions. They save the residuals and use the first principle component analysis to pick up the common sentiment component from residuals. The standardised first principle component score is the market-wide sentiment index.

Figure 2: Firm characteristics and idiosyncratic volatility



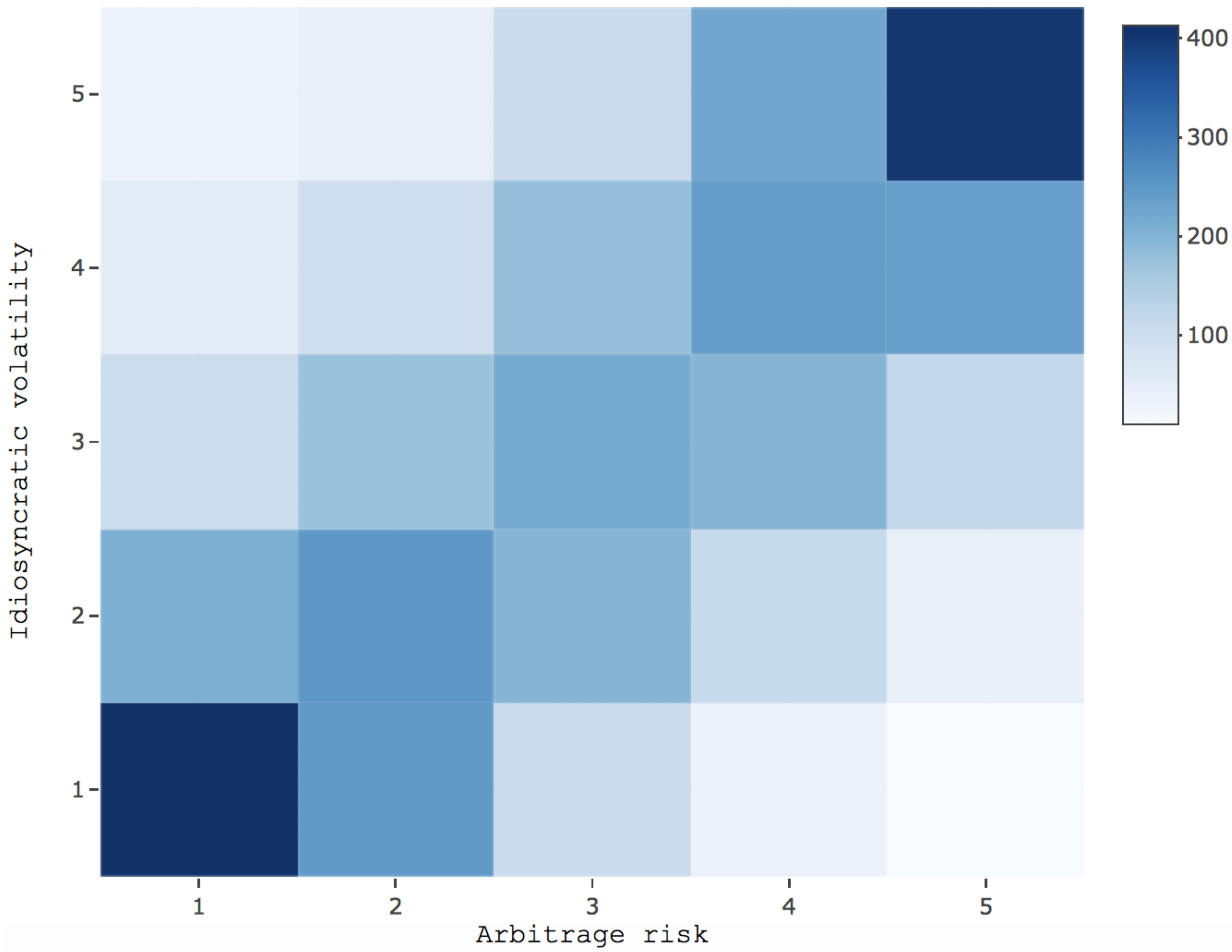
Notes: This figure illustrates the average monthly idiosyncratic volatility (IVOL) in percentage of portfolios sorted by different firm characteristics. The sample period spans from 1965 July to 2015 September. For each characteristic, sample stocks are ranked into 10 deciles. Following Ang et al. (2006), the monthly IVOL for individual stock is calculated as the standard deviation of the residuals from the regression of the most recent month's daily returns on the Fama-French three factors. Each month, the portfolios' IVOL is the average IVOL of individual stocks within each decile. I then take the average of portfolios' IVOL for the whole sample period and plot them in the graph.

Figure 3: Number of stocks within the double-sorted portfolios formed on institutional ownerships and arbitrage risk



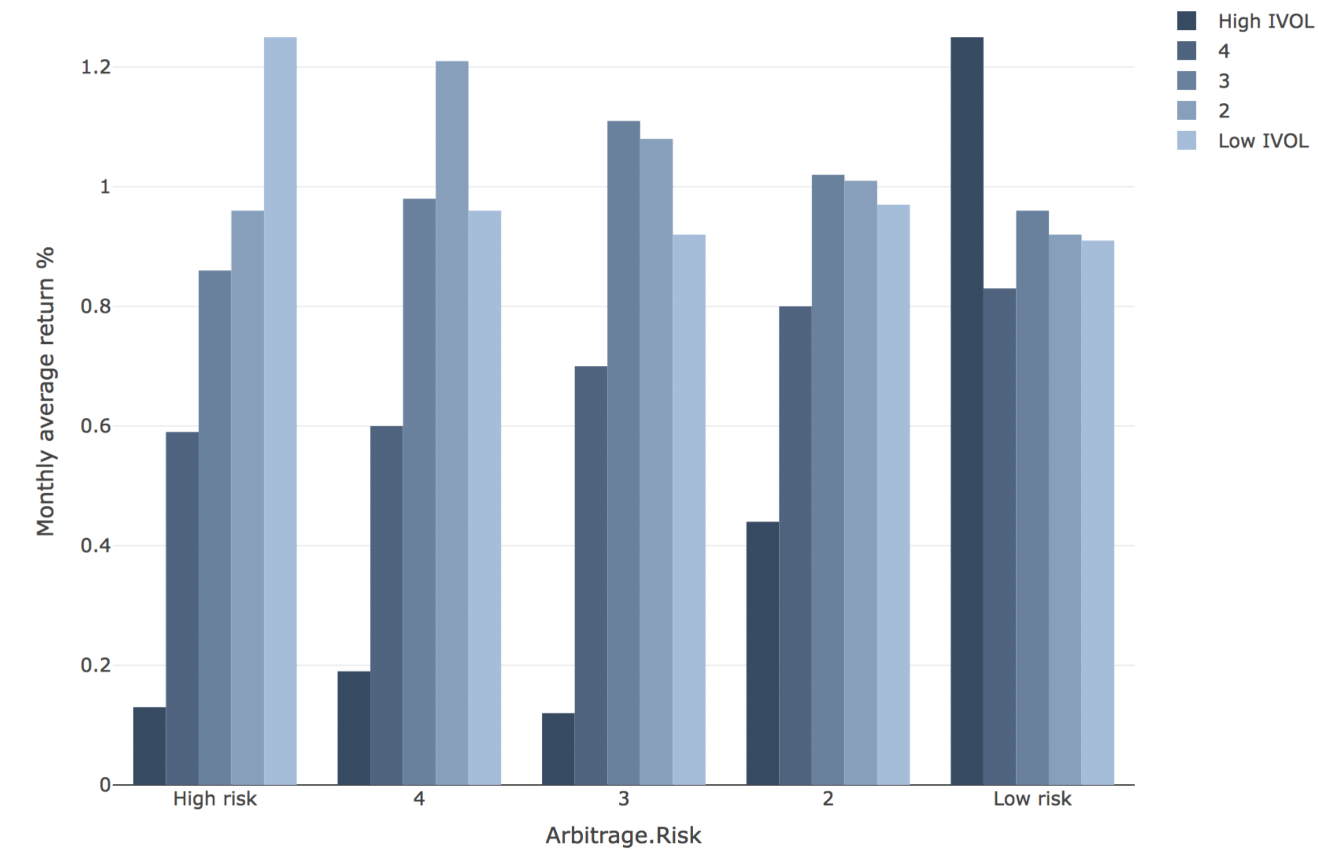
Notes: This graph illustrates the monthly average number of stocks within the 5x5 double sorted portfolios formed on IO and arbitrage risk. For each stock, IO is measured as the ratio between stocks hold by institutional investors and shares outstanding. Each month, sample stocks are firstly ranked into five groups by sorting on their individual IO, and then ranked into five groups by independently sorting on arbitrage risk. The data on institutional holdings comes from the Thomson Financial Institutional Holdings database and covers the period from April 1980 to September 2015. 1 to 5 denotes the bottom quantile to top quantile.

Figure 4: Number of stocks within the double-sorted portfolios formed on IVOL and arbitrage risk



Notes: This graph illustrates the monthly average number of stocks within the 5x5 double sorted portfolios formed on idiosyncratic volatility (IVOL) and arbitrage risk. Following Ang et al. (2006), the monthly IVOL of individual stocks is calculated as the standard deviation of the residuals from the regression of the most recent month's daily returns on the Fama-French three factors. Each month, sample stocks are firstly ranked into five groups by sorting on their individual IVOL, and then ranked into five groups by independently sorting on arbitrage risk. The sample period spans from 1965 July to 2015 September.

Figure 5: Monthly return on the double-sorted portfolios formed on IVOL and arbitrage risk



Notes: This figure shows the value-weighted return on the 5x5 double sorted portfolios ranked by idiosyncratic volatility (IVOL) and arbitrage risk. Following Ang et al. (2006), the monthly IVOL of individual stocks is calculated as the standard deviation of the residuals from the regression of the most recent month's daily returns on the Fama-French three factors. Each month, sample stocks are firstly ranked into five groups by sorting on their individual IVOL, and then ranked into five groups by independently sorting on arbitrage risk. The sample period spans from 1965 July to 2015 September.

Appendix C. Tables

Table 1: Postformation of Fama-French Betas

In June of each year t, all NYSE/AMEX/NASDAQ stocks are sorted into 10 size deciles based on the NYSE breakpoints. I further subdivide each size decile into 10 portfolios on the basis of individual stocks' pre-ranking betas, which are calculated by using 24-60 monthly return (as available) before July of year t. Only NYSE stocks are used to decide the beta breakpoints for each size decile. In total, this procedure generates 100 size-beta portfolios in June of year t. I then calculate the equal-weighted return of these portfolios for the next twelve months. Thus, I have post-ranking monthly returns on for each of 100 size-beta portfolios, spanning the whole sample periods. Post-ranking betas are calculated as the sum of the slopes in the regression of the return on each portfolio on current and prior month's CRSP value-weighted market return. Finally, the post-ranking beta of each size-beta portfolio is assigned back to individual stocks. The sample period is from July 1965 to September 2015.

	Low beta	2	3	4	5	6	7	8	9	High beta
Small size	1.01	1.11	1.23	1.29	1.40	1.45	1.52	1.65	1.72	1.89
2	0.90	1.02	1.11	1.22	1.35	1.34	1.50	1.63	1.64	1.92
3	0.89	0.92	1.07	1.16	1.22	1.26	1.33	1.47	1.62	1.86
4	0.75	0.89	0.94	1.16	1.19	1.28	1.42	1.42	1.65	1.86
5	0.73	0.85	0.98	1.09	1.21	1.25	1.31	1.35	1.51	1.76
6	0.65	0.74	0.87	1.06	1.19	1.21	1.26	1.33	1.41	1.75
7	0.69	0.75	0.89	1.06	1.15	1.18	1.22	1.29	1.40	1.71
8	0.55	0.70	0.90	1.04	1.05	1.08	1.24	1.25	1.36	1.66
9	0.54	0.67	0.82	0.92	1.02	1.00	1.10	1.22	1.25	1.57
Big size	0.50	0.64	0.70	0.86	0.90	0.99	1.02	1.07	1.22	1.49

Table 2: Descriptive statistics and correlation coefficients

Panel A presents the descriptive statistics of firm arbitrage risk, size, book-to-market ratio and beta. Q1 and Q3 represent the first and third quantile respectively. Panel B reports the pooled cross-sectional time-series correlations. The sample period is from 1965 July to 2015 September. Arbitrage-rank that is measured as the rank percentile by averaging ranking on 10 firm chracteristics represents arbitrage risk. Size is measured as firm's market equity, ME (closed price x share outstanding) at June of each fiscal year t. The book value, BE, is measured as the book value of stockholders' equity, B, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, this study uses the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. The book-to-market ratio is calculated as the BE at June in fiscal year t, divided by ME at the end of December of t-1. Beta is calculated monthly by using the methodology of Fama-French (1992). $ret_{1,0}$ is the past month return. $ret_{6,2}$ and $ret_{12,7}$ are measured as the cumulative returns at horizons past 12 to seven months and six to two months respectively. Following Fama and French (1992), I take the natural logarithm of arbitrage risk rank, size and book-to-market ratio to exclude influences from some extreme outliers. * denotes the significance level at 5%.

Panel A: Descriptive statistics					
	Mean	Std	Median	Q1	Q3
ln[arbitrage]	3.89	0.37	3.96	3.66	4.18
Beta	1.29	0.33	1.25	1.02	1.52
ln[size]	4.68	2.17	4.51	3.10	6.14
ln[BM]	−0.45	0.95	−0.37	−0.98	0.15

Panel B: Correlation coefficients							
	ln[arbirtage]	β	ln[size]	ln[BM]	$ret_{1,0}$	$ret_{6,2}$	$ret_{12,7}$
ln[arbirtage]	1.00						
Beta	0.62*	1.00					
ln[size]	−0.58*	−0.27*	1.00				
ln[BM]	−0.07*	−0.09*	−0.30*	1.00			
$ret_{1,0}$	0.00	0.00	−0.017 *	0.032*	1.00		
$ret_{6,2}$	0.003*	0.006*	−0.012	0.086*	−0.018*	1.00	
$ret_{12,7}$	0.006*	0.023*	0.048*	−0.006*	−0.001	−0.027*	1.00

Table 3: Characteristics of portfolios formed on arbitrage risk

This table presents the average monthly values of firm characteristics of portfolios formed on arbitrage risk. The sample period spans from 1965 July to 2015 September. Arbitrage-rank represents arbitrage risk. It is calculated as the rank percentile by averaging ranking on each of 10 firm characteristics. Each month, all sample stocks are broken into 10 deciles on the basis of their arbitrage rank. The stocks in the top decile have relatively high arbitrage risk compared to those in the bottom decile.

Size is measured as firm's market equity, ME (closed price x share outstanding) at June of each fiscal year t. The book value, BE, is measured as the book value of stockholders' equity, B, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, this study uses the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. The book-to-market ratio is calculated as the BE at June in fiscal year t, divided by ME at the end of December of t-1. Following Fama and French (1992), I take the natural logarithm of arbitrage risk rank, size and book-to-market ratio to exclude influences from some extreme outliers. Beta is calculated monthly by using the methodology of Fama-French. Sigma is computed as standard deviation of returns over last 12 months (with a minimum window of 6 months). Firms' age is measured as the number of month since they firstly appear in CRSP. Other firm characteristics are obtained from merged CRSP-Compustat Database. For all characteristics but for age and beta, the firm level data are matched from the last fiscal year-end to months through July at year t to June at year t+1.

	Low risk	2	3	4	5	6	7	8	9	High risk
ln[Arbitrage]	3.13	3.47	3.65	3.79	3.90	4.00	4.09	4.17	4.26	4.38
ln[size]	7.15	6.10	5.52	5.03	4.62	4.24	3.90	3.59	3.26	2.85
ln[BM]	−0.46	−0.40	−0.37	−0.35	−0.33	−0.34	−0.37	−0.42	−0.52	−0.75
Beta	0.89	1.06	1.16	1.24	1.31	1.38	1.43	1.47	1.52	1.61
Age	28.62	20.53	17.04	14.51	12.57	11.50	10.40	8.96	7.78	5.75
Dividend yield (%)	4.48	3.68	3.29	2.81	2.22	1.85	1.52	1.17	0.89	0.52
Operating profitability (%)	18.63	16.58	15.45	14.24	12.99	11.29	9.01	5.51	-1.33	-19.50
Sigma %	6.28	7.66	8.84	10.16	11.54	13.17	15.16	17.13	20.31	25.65
Sale Growth	8.91	9.93	10.49	13.19	16.46	19.59	24.40	34.54	50.04	109.61
External Finance	5.65	6.32	7.60	8.66	11.25	13.76	19.37	32.36	53.94	138.58
Net Stock Issue	−0.56	0.00	1.18	1.82	3.46	4.81	6.29	9.09	13.48	27.65
Price	99.90	59.34	45.26	25.72	20.57	16.30	13.04	10.85	8.06	5.32
Number	408	409	409	409	409	409	409	409	409	409

Table 4: Return and volatility of arbitrage-risk sorted portfolios

This table presents the average monthly raw return (percentage) arbitrage-risk sorted portfolios in months following high- and low-sentiment periods and their volatility in high and low periods. Each month, sample stocks are broken into 10 deciles on the basis of their arbitrage rank. The stocks in the top decile have relatively high arbitrage risks compared to those in the bottom decile. Panel A reports the average monthly value-weighted return.Panel B looks at the average monthly variance of each arbitrage-risk sorted portfolio. The volatility is calculated from within-month daily value-weighted return. The sample period spans from 1965 July to 2015 September. The parentheses report t-statistics. (In the whole sample periods, t-statistics are corrected by Newey-West heteroscedasticity and autocorrelation robust standard errors)

	Low risk	2	3	4	5	6	7	8	9	High risk	H−L risk
Panel A: Average monthly return $\times 10^2$											
All	0.93	0.93	0.92	0.91	0.83	0.94	0.80	0.64	0.55	0.49	-0.44
	(5.85)	(4.55)	(3.94)	(3.41)	(2.85)	(2.90)	(2.21)	(1.68)	(1.25)	(1.04)	(1.41)
High sentiment	1.08	0.95	0.83	0.62	0.42	0.46	0.08	−0.18	−0.54	−0.90	−1.98
	(4.95)	(3.50)	(2.70)	(1.70)	(1.06)	(1.05)	0.17	(−0.35)	(−0.98)	(−1.53)	(−3.83)
Low sentiment	0.79	0.91	1.02	1.21	1.26	1.45	1.54	1.48	1.67	1.93	1.14
	(3.38)	(3.18)	(3.21)	(3.49)	(3.29)	(3.47)	(3.25)	(2.97)	(3.17)	(3.30)	(2.45)
H−L sentiment	0.29	0.04	−0.19	−0.58	−0.84	−0.99	−1.46	−1.66	−2.21	−2.83	
	(0.90)	(0.09)	(−0.44)	(−1.16)	(−1.52)	(−1.65)	(−2.18)	(−2.36)	(−2.90)	(−3.41)	
Panel B: Average volatility $\times 10^4$											
All	0.89	1.16	1.41	1.69	1.84	2.06	2.44	2.67	2.76	2.31	1.44
High sentiment	0.86	1.07	1.42	1.82	1.96	2.18	2.69	3.01	3.19	2.37	1.51
Low sentiment	0.93	1.25	1.39	1.55	1.71	1.94	2.19	2.31	2.32	2.24	1.31
H−L sentiment	-0.07	-0.18	0.04	0.27	0.25	0.24	0.49	0.70	0.87	0.13	

Table 5: Arbitrage risk and Fama-MacBeth regressions

This table reports the Fama-Macbeth regression results. Panel A looks at the whole sample period. Panel B and C presents results following high- and low- sentiment periods respectively. The whole sample period spans from 1965 July to 2015 September. Arbitrage risk is measured as the rank percentile by averaging ranking on 10 firm characteristics. Beta is calculated monthly by using the methodology of Fama and French (1992). Size is measured as firm's market equity, ME (closed price x share outstanding) at June of each fiscal year t. The book value, BE, is measured as the book value of stockholders' equity, B, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Depending on availability, I use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock. The book-to-market ratio is calculated as the BE at June in fiscal year t, divided by ME at the end of December of t-1. $ret_{1,0}$ is the past month return. $ret_{6,2}$ and $ret_{12,7}$ are measured as the cumulative returns at horizons past 12 to seven months and six to two months respectively. N is the number of months in the sample. Following Fama and French (1992), this study takes the natural logarithm of arbitrage-risk rank, size and book-to-market ratio to exclude influences from some extreme outliers. The parentheses report the Newey-West heteroscedasticity and autocorrelation consistent t-statistics.

ln[arbitrage]	β	ln[ME]	ln[BE/ME]	$ret_{1,0}$	$ret_{6,2}$	$ret_{12,7}$
Panel A: Full sample period (N=603)						
0.20						
(0.67)						
	0.20					
	(0.69)					
0.36	-0.04					
(1.42)	(-0.26)					
	0.01	−0.13	0.25			
	(0.06)	(−3.46)	(4.06)			
0.17			0.37	−0.06		
(0.54)			(5.71)	(−14.09)		
		−0.17			0.003	0.006
		(−3.99)			(1.33)	(3.99)
0.16	0.03		0.36	−0.06	0.001	0.006
(0.66)	(0.18)		(5.97)	(−14.86)	(0.31)	(4.24)
Panel B: High sentiment (N=306)						
−0.96						
(−2.47)						
	−0.72					
	(−2.06)					

Table 5 – continued from previous page

−0.56	−0.32					
(-1.68)	(-1.44)					
	−0.60	−0.05	0.39			
	(−1.96)	(−1.00)	(4.99)			
−0.89			0.48	−0.05		
(−2.35)			(5.58)	(−10.25)		
		−0.06			0.004	0.005
		(−1.14)			(1.72)	(3.14)
−0.68	−0.11		0.44	−0.05	0.002	0.005
(−2.12)	(−0.57)		(5.61)	(−11.24)	(0.80)	(3.31)
Panel C: Low sentiment (N=297)						
1.41						
(3.33)						
	1.15					
	(2.71)					
1.31	0.23					
(3.86)	(0.83)					
	0.65	−0.21	0.10			
	(1.74)	(−4.08)	(1.14)			
1.26			0.26	−0.07		
(2.90)			(2.73)	(−10.06)		
		−0.27			0.001	0.007
		(−4.68)			(0.40)	(2.73)
1.03	0.17		0.28	−0.07	0.000	0.007
(3.17)	(0.69)		(3.14)	(−10.57)	(−0.17)	(2.97)

Table 6: Arbitrage factor and 11 anomalies

$$R_t = \alpha + \beta_1 \text{Arbitrage}_t + \beta_2 \text{Mkt}_t + \beta_3 \text{SMB}_t t + \beta_4 \text{HML}_t + \epsilon_t$$

This table reports the results of regression of return of 11 anomalies on the augmented 4-factor model—arbirtrage factor and Fama-French three factors including market premium (Mkt), size effect (SMB), value effect (HML). The 11 anomalies are asset growth, composite stock issues, failure probability, gross profitability, investments-to-assets, momentum, net operating assets, financial distress (Ohlson's O score), total accruals, return on assets and net stock issues. The return on each of the 11 anomalies is the return spread between stocks in the highest-performing decile (long leg) and ones in the lowest-performing decile (short leg).The sample period spans from 1965 July to 2015 September. I follow Stambaugh et al. (2012) and uses the White's robust standard errors to control for heteroskedasticity. Adjusted R^2_{FF} measures the goodness of fit in the regression of long-short spreads on FF-3 factors. Adjusted R^2_A measures the goodness of fit in the regression of long-short spreads on the augmented four factors.

Anomaly	Long−short		Long leg		Short leg		Long−short	
	$\hat{\beta}_1$	t-satistic	$\hat{\beta}_1$	t-satistic	$\hat{\beta}_1$	t-satistic	R^2_{FF}	R^2_A
Asset growth	0.21	3.58	0.00	−0.04	−0.21	−5.90	0.36	0.39
Composite equity issues	0.25	5.08	0.06	2.01	−0.19	−5.33	0.48	0.53
Failure probability	0.88	9.88	0.23	4.42	−0.64	−11.53	0.35	0.52
Gross profitability	0.20	3.79	0.22	6.10	0.02	0.47	0.32	0.34
Investment-to-assets	0.14	2.89	−0.01	−0.42	−0.15	−3.50	0.15	0.17
momentum	0.70	4.58	0.03	0.36	−0.67	−8.07	0.06	0.15
Net Operating asset	0.17	3.62	0.03	1.22	−0.14	−4.12	0.04	0.07
Ohlsons O score	0.08	1.59	−0.09	−3.68	−0.17	−4.37	0.50	0.51
Total accruals	−0.17	−2.87	−0.30	−7.58	−0.12	−3.03	0.13	0.15
Return on assets	0.50	8.39	0.10	3.97	−0.40	−8.13	0.23	0.36
Net stock issue	0.31	7.33	0.11	6.16	−0.20	−5.73	0.30	0.41
Combination	0.29	10.67	0.03	1.93	−0.26	−12.93	0.38	0.53

Table 7: BW sentiment predicability on the arbitrage factor

$$\text{Arbitrage}_t = \alpha + b\text{Sentiment}_{t-1} + \epsilon_t$$

This table reports the regression of arbitrage risk premium on the one-month lagged BW sentiment index. The sample period spans from 1965 July to 2015 September. t-statistics are adjusted by the Newey-West heteroscedasticity and autocorrelation consistent standard errors.

	Long−short		Long leg		Short leg	
	$\hat{b}$	t-satistic	$\hat{b}$	t-satistic	$\hat{b}$	t-satistic
Arbirtage factor	0.98	4.21	−0.06	−0.34	−1.04	−2.98

Table 8: Summary statistics of pricing factors

This table presents the mean, standard deviation and sharp ratio of monthly factors returns. These factors include MKT-R_f, SMB (size) and HML (value) proposed by Fama and French (1993) (FF3); momentum factor proposed by Carhart (1997); liquidity factor proposed by Pastor and Stambaugh (2003); HML* (value), UMD* (momentum) and PMU* (gross profitability) proposed by Novy-Marx (2013) (NM4); SMB, I/A (investment to assets) and ROE (return on equity) proposed by Hou et al. (2015) (HXZ4); two additional factors based on FF3, RMW (profitability) and CMA (investment) proposed by Fama and French (2015) (FF5); three mispricing factors, SMB, MGMT and PERF proposed by Stambaugh and Yuan (2017) (SY4); two behavioural factors, FIN and PEAD proposed by Daniel et al. (2017) (DHS3). The arbitrage factor which is the difference between the return on portfolios of stocks with high and low arbitrage risk is from this study.

SR and N represent sharp ratio and the number of monthly observations respectively. The sample period spans 1965:07 to 2015:09 for all factors but liquidity factor (1968:01−2015:09), NM4 (1965:07−2012:12), HXZ4 and DHS3 (1972:07−2014:12),

	Arbitrage	Liquidity	Momentum	FF3		
	Factor	Factor	Factor	MKT-R_f	SMB	HML
Mean	0.21	0.40	0.73	0.48	0.23	0.34
Std	5.44	3.37	4.21	4.51	3.13	2.85
SR	0.04	0.12	0.17	0.11	0.07	0.12
N	603	588	603	603	603	603

	NM4			HXZ4		
	HML*	UMD*	PMU*	SMB	I/A	ROE
Mean	0.38	0.62	0.26	0.29	0.43	0.56
Std	1.41	2.83	1.16	3.14	1.86	2.59
SR	0.27	0.22	0.22	0.09	0.23	0.22
N	570	570	570	510	510	510

	FF5		SY3			DHS3	
	RMW	CMA	SMB	MGMT	PERF	FIN	PEAD
Mean	0.26	0.31	0.47	0.59	0.72	0.80	0.65
Std	2.27	2.04	2.90	2.89	3.79	3.92	1.85
SR	0.11	0.15	0.16	0.20	0.19	0.20	0.35
N	603	603	603	603	603	510	510

Table 9: Arbitrage risk and institutional ownership

This table reports the average monthly institutional ownership (IO), number of Institutional owners and number of stocks for the 5x5 double sorted portfolios formed on IO and arbitrage risk. For each stock, IO is measured as the ratio between stocks hold by institutional investors and shares outstanding. The data on institutional holdings comes from the Thomson Financial Institutional Holdings database and covers the period from April 1980 to September 2015.

Each month, sample stocks are firstly ranked into five groups by sorting on their individual IO, and then ranked into five groups by independently sorting on arbitrage risk. Panel A reports the average monthly IO within each quantile portfolio. Panel B shows average number of Institutional owners in each quantile portfolio. Panel C looks at the average number of stocks in each quantile portfolio.

	High Risk	4	3	2	Low Risk	All Stocks
			Panel A: Institutional ownership %			
Low IO	3.83	4.24	4.60	4.79	5.35	4.25
2	16.85	17.11	17.25	17.28	17.45	17.35
3	32.84	33.38	33.57	34.10	34.39	33.68
4	49.76	50.43	51.02	51.49	51.52	51.08
High IO	72.74	72.52	72.65	72.74	72.52	72.59
All stocks	18.78	30.19	38.34	43.79	47.85	
			Panel B: Number of Institutional owners			
Low IO	8	8	8	8	10	9
2	21	22	23	29	68	29
3	35	40	48	74	177	81
4	50	63	81	119	225	128
High IO	68	86	104	135	212	145
All stocks	22	38	57	88	187	
			Panel C: Number of stocks			
Low IO	395	214	132	99	48	889
2	243	224	179	136	107	889
3	149	197	195	166	183	889
4	71	147	192	221	259	889
High IO	31	106	192	267	291	889
All stocks	889	889	889	889	889	

Table 10: Arbitrage risk, firm characteristics and IVOL

This table reports the average monthly idiosyncratic volatility (IVOL) in percentage of portfolios sorted by different firm characteristics. The sample period spans from 1965 July to 2015 September. For each characteristic, sample stocks are ranked into 10 deciles. Following Ang et al. (2006), monthly IVOL for individual stocks is calculated as the standard deviation of the residuals from the regression of the most recent month's daily returns on the Fama-French three factors. Each month, the portfolios' IVOL is the average IVOL of individual stocks within each decile. I then take the average of portfolios' IVOL for the whole sample period, as reported in the table.

Decile	Low risk	2	3	4	5	6	7	8	9	High risk
Arbitrage risk	1.23	1.52	1.76	2.05	2.36	2.73	3.12	3.55	4.06	4.82
Beta	1.40	2.10	2.33	2.29	2.29	2.66	2.88	3.11	3.32	3.71
Size	4.74	3.82	3.33	2.98	2.70	2.43	2.15	1.92	1.69	1.40
Book-to-market ratio	3.13	2.78	2.60	2.50	2.42	2.37	2.36	2.48	2.71	3.43
Age	3.25	3.31	3.16	3.19	3.06	2.92	2.71	2.44	2.04	1.68
Dividend yield	3.80	2.94	3.29	2.25	2.11	2.47	2.08	1.87	1.79	2.12
Operating profitability	4.75	3.91	3.25	2.86	2.59	2.44	2.29	2.21	2.16	2.22
Sigma	1.39	1.63	1.85	2.12	2.40	2.71	3.04	3.42	3.92	4.73
Sale Growth	3.81	2.89	2.43	2.24	2.19	2.24	2.36	2.52	2.82	3.43
External Finance	3.18	2.68	2.46	2.35	2.30	2.35	2.46	2.66	3.01	3.53
Net Stock Issue	2.30	2.27	2.76	2.63	2.48	2.52	2.61	2.79	3.03	3.35
Price	5.03	3.96	3.40	2.90	2.52	2.23	2.01	1.80	1.66	1.53

Table 11: IVOL, number of stocks and return in the double sorted portfolios formed on IVOL and arbitrage risk

This table reports the average monthly IVOL, number of stocks and value-weighted return for the 5x5 double sorted portfolios formed on IVOL and arbitrage risk. Each month, sample stocks are firstly ranked into five groups by sorting on their individual IVOL, and then ranked into five groups by independently sorting on arbitrage risk. The sample period spans from 1965 July to 2015 September. Following Ang et al. (2006), the monthly IVOL of individual stocks is calculated as the standard deviation of the residuals from the regression of the most recent month's daily returns on the Fama-French three factors. Panel A reports the average monthly IVOL within each portfolio. Panel B reports the average number of stocks in each portfolio. Panel C shows the average monthly value-weighted return on each portfolio.

	High Risk	4	3	2	Low Risk	All Stocks
			Panel A: IVOL			
High IVOL	6.43	5.79	5.37	5.11	4.98	6.00
4	3.12	3.08	3.03	2.99	2.94	3.06
3	2.19	2.17	2.14	2.11	2.08	2.14
2	1.56	1.55	1.53	1.51	1.48	1.51
Low IVOL	0.74	0.83	0.88	0.91	0.90	0.88
All stocks	4.44	3.33	2.54	1.91	1.37	
			Panel B: Number of stocks			
High IVOL	404	238	119	44	10	816
4	223	241	199	115	38	816
3	109	181	219	199	108	816
2	45	100	174	251	246	816
Low IVOL	34	56	105	207	413	816
All stocks	816	816	816	816	816	
			Panel C: Value-weighted return			
High IVOL	0.13	0.19	0.12	0.44	1.25	0.27
4	0.59	0.60	0.70	0.80	0.83	0.71
3	0.86	0.98	1.11	1.02	0.96	0.96
2	0.96	1.21	1.08	1.01	0.92	0.96
Low IVOL	1.25	0.96	0.92	0.97	0.91	0.92
High−Low	−1.12	−0.77	−0.80	−0.53	0.34	−0.65
All stocks	0.49	0.72	0.86	0.91	0.92	

Table 12: BW sentiment and factor loadings on the arbitrage risk

$$\text{FactorLoading}_t = \alpha + b\text{Sentiment}_{t-1} + \epsilon_t$$

This table reports the regression of factor loadings on arbitrage risk (in time-series) obtained from Fama-MacBeth tests on the one-month lagged BW sentiment index. Panel A looks at the factor loadings without control variables, and Panel B looks at the factor loadings with most control variables as indicated in Table 5. The sample period spans from 1965 July to 2015 September. t-statistics are adjusted by the Newey-West heteroscedasticity and autocorrelation consistent standard errors.

	Panel A		Panel B	
	$\hat{b}$	t-satistic	$\hat{b}$	t-satistic
FactorLoading	−1.29	−4.40	−0.94	−4.36

Table 13: Michigan sentiment predicability on arbitrage factor

$$\text{Arbitrage}_t = \alpha + b\text{Sentiment}_{t-1} + \epsilon_t$$

This table reports the regression of arbitrage risk premium on the one-month lagged Michigan sentiment index. The sample period spans from 1965 July to 2015 September. t-statistics are adjusted by the Newey-West heteroscedasticity and autocorrelation consistent standard errors.

	Long−short		Long leg		Short leg	
	$\hat{b}$	t-satistic	$\hat{b}$	t-satistic	$\hat{b}$	t-satistic
Arbitrage factor	0.80	3.18	−0.18	−1.21	−0.98	−2.91

Table 14: Controlling for macro-related variables

$$\mathrm{R}_t = \alpha + \beta_1 \mathrm{Arbitrage}_t + \beta_2 \mathrm{Mkt}_t + \beta_3 \mathrm{SMB}_t + \beta_4 \mathrm{HML}_t + \sum_{i=1}^{5} \alpha_i \mathrm{M}_{i,t} + \epsilon_t$$

This table checks the robustness of the results in table 6, with controlling for additional five macro-related variables including the real interest rate, the inflation rate, the term premium, the default premium and the consumption-wealth ratio (cay). The real interest rate is the difference between return on the 30-day T-bill and inflation rates. The term premium is defined as spread between 20-year T-bill and 1-year T-bill. The default premium is the difference between BAA dn AAA bonds. The inflation rate and T-bill return are obtained from CRSP. The default premium comes from the St.louis Federal Reserve and cay is obtained from Sydney Ludvigson's website. The sample period spans from 1965 July to 2015 September. This study follows Stambaugh et al. (2012) and use the White's robust standard errors to control for heteroskedasticity.

Anomaly	Long−short		Long leg		Short leg	
	$\hat{\beta}_1$	t-satistic	$\hat{\beta}_1$	t-satistic	$\hat{\beta}_1$	t-satistic
Asset growth	0.21	3.60	0.00	−0.07	−0.12	−2.54
Composite equity issues	0.24	4.69	0.05	1.55	−0.16	−2.73
Failure probability	0.88	9.89	0.24	4.41	−0.65	−9.46
Gross profitability	0.21	3.82	0.22	5.91	−0.02	−0.30
Investment-to-assets	0.12	2.44	−0.02	−0.65	−0.18	−2.69
momentum	0.72	4.80	0.05	0.58	−0.76	−7.54
Net Operating asset	0.17	3.47	0.03	0.92	−0.15	−2.85
Ohlsons O score	0.08	1.51	−0.09	−3.50	−0.20	−4.13
Total accruals	−0.15	−2.31	−0.28	−6.67	−0.08	−1.45
Return on assets	0.50	8.33	0.10	3.95	−0.40	−8.22
Net stock issue	0.32	7.41	0.11	6.12	−0.19	−3.29
Combination	0.31	10.42	0.04	2.60	−0.26	−8.04

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