Essays on Empirical Asset Pricing and Behavioural Finance

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Declaration

I hereby declare that the thesis is my original work and the work has not been previously submitted to meet requirements for a reward at this or any other higher education institution. I have duly acknowledged all the sources of information which have been used in the thesis.

Yizhi Wang

August 2020

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Abstract

This thesis comprises three chapters. In the first, Digesting the Profitability and Investment Premia: Evidence from the Short-selling Activity', we highlight the different effects of short-selling activity on the profitability and investment premia. We find that the profitability premium disappears among the stocks with high short-selling activity, whereas the short-selling has no impact on the investment premium. We also show that the profitability premium is more likely than the investment premium to be associated with the sentiment-driven mispricing, which is eliminated among the heavily shorted stocks. Collectively, these results suggest that the two new premia have different underlying attributions. Although the profitability premium is more consistent with the mispricing interpretation, the investment premium is not.

The second chapter is titled 'Historical Highs and the Cross-section of Stock Returns'. In this chapter, we examine the return predictability of the historical high in the cross-section of stock returns. We hypothesise that investors anchor on the historical highs and overreact to bad news while stock prices are far below their historical highs. Consistently, a zero-investment strategy by buying stocks with prices far away from, and selling stocks with prices close to, the historical highs achieves significantly positive returns in a holding period of up to five years. We provide evidence that the confusion caused by share splits makes the historical high effect much weaker. In addition, we find that the return persistence can be explained by investors' tendency to hold losers too long and sell winners too soon.

In the third chapter, 'Equity Lending and Stock Returns', we examine the effects of security lending on the US stock markets. Research has shown that the demand side of short-selling activity has significant effects on the stock returns. In this chapter, we focus on the supply

channel and show that a decrease in lendable supply positively predicts stock returns in the cross-section. Further, we find that active institutional investors play an important role in setting the lendable supply. Moreover, the return predictability of the change in the lendable supply is stronger among the underpriced stocks and is unlikely to be caused by the relaxation of short-sale constraints. Lastly, we provide evidence that the return spread is significantly higher following low sentiment, suggesting that the zero-cost strategy offers a great hedge to other sentiment-driven anomalies.

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Chapter 1. Digesting the Profitability and Investment Premia: Evidence from the Short-selling Activity

1.1. Introduction

Motivated by the dividend discount model, Fama and French (2015) extend their well-known three-factor asset pricing model by adding the profitability and investment factors. They provide evidence that the anomaly returns become less anomalous on using their five-factor asset pricing model and that several anomalies share similar factor exposures (Fama and French, 2016). Similarly, Hou, Xue and Zhang (2015) construct a *q*-factor model based on a market factor, a size factor, an investment factor and a profitability factor to explain the cross-section of stock returns. They find that around half of the asset pricing anomalies become insignificant with the *q*-factor model. Although the new factor models capture the prominent patterns in average returns effectively and improve substantially the explanatory power of the previous asset pricing models, the properties of the two new factors are unclear.

Understanding the properties of these two new factors is important for three reasons. First, the profitability and investment premia are two of the most pervasive and robust financial anomalies in the US equity markets, which have captured the attention of academic and professional communications. Second, mispricing and risk both generate return predictability, whereas the new factor asset pricing models themselves do not distinguish the risk-based explanation from the mispricing explanation. Third, research on the profitability and investment premia should have important implications for stock return anomalies because they, to a large extent, share similar phenomena (Fama and French, 2016; Keloharju, Linnainmaa, and Nyberg, 2016).

In this chapter, we investigate the profitability and investment premia from the perspective of short sellers. Short-selling activity plays a unique role in the financial markets because short sellers are skilled at processing information and identifying mispriced securities. For example, Dechow, Hutton, Muelbrook and Sloan (2001) find that short sellers propose their strategies based on the firm's fundamentals, such as its earnings and cash flows, and target firms with overpriced shares relative to their intrinsic value. Because mispricing can be corrected through short-selling activity, whereas risk factor cannot, it is natural to examine whether the underlying drivers of the profitability and investment premia are different with regard to the short-selling activity.

Papers such as Stambaugh, Yu and Yuan (2012) hypothesise that the short-sale constraint is the driving force of many anomalies. However, these papers do not differentiate between various premia, but lump them together as a basket of anomalies, suggesting that mispricing can account for the profitability as well as investment premia. Further, they do not provide direct evidence on whether short sellers can potentially correct for these anomalies. Moreover, Chen, Da and Huang (2019) measure the net arbitrage trading by calculating the difference between abnormal hedge fund holdings and abnormal short interest. They show that 10 well-known anomalies achieve significant abnormal returns only among the stocks with large net arbitrage trading. We take a different and more direct approach. We use short interest as a proxy for the short-selling activity and focus on the following two questions: do short sellers form their trading strategies based on signals embedded in the profitability and the investment characteristics? How would the profitability and investment premia change depending on the short-selling activity?

First, we show that the mispricing has different effects on the profitability premium and investment premium. In regressions of these premia on the mispricing factor of Hirshleifer and Jiang (2010), we find that mispricing contributes to the return predictability of profits-to-assets,

whereas it has little influence on the return predictability power of investment-to-assets. Our evidence also suggests that short arbitrage is more concentrated in the least profitable stocks, whereas short sellers do not engage in the arbitrage of the variation in investment.

Next, we explore whether short positions and abnormal shorting flows affect the profitability and investment premia. Chu, Hirshleifer and Ma (2020) use the pilot program of Regulation SHO as a policy experiment to pin down the effect of short-selling constraints on 11 well-known return anomalies. Their evidence suggests that Regulation SHO affects the profitability premium but not the investment premium. In this chapter, our key insight is that short sellers have significantly different effects on profitability and investment anomalies, which is consistent with Chu, Hirshleifer and Ma (2020). Specifically, we find that the profitability premium disappears among the stocks with a large short position or high abnormal shorting flows, but the investment premium remains highly significant with the differences in short-selling activity. These results reveal that short arbitrageurs target the low profitability firms rather than the high investment firms, and consequently, short arbitrage is only effective in reducing the profitability premium.

Extensive research finds that investor sentiment causes stock prices to depart from their fundamental value (e.g. Baker and Wurgler, 2006; Stambaugh, Yu, and Yuan, 2012). To further examine the different properties of the profitability and investment premia, we investigate whether the variations in these two premia are affected by investor sentiment. If a premium is primarily due to mispricing, the anomaly should be more prevalent when investor sentiment is high. Our results show that investor sentiment has a significant impact on the profitability premium rather than the investment premium. Greater profitability premium follows the periods of high investor sentiment, whereas the portfolios sorted by investment exhibit no significant variation in returns following different levels of investor sentiment. This finding lends further support to the different attributions of the profitability and investment premia.

Lastly, we investigate whether short-selling activity affects the sensitivity of the profitability and investment premia to sentiment variations. We uncover that following a period of low short-selling activity, the profitability premium is significantly higher if it follows a high-sentiment period than if it follows a low-sentiment period, and the difference in premium between the two situations is significantly different from zero. In contrast, we do not find a robust profitability premium following a period of high short-selling activity, regardless of investor sentiment. We also find that investor sentiment has an insignificant impact on the investment premium irrespective of the level of short-selling activity. Time series regressions further confirm that the short sellers are skilled at eliminating the sentiment-related profitability premium.

Thus, we contribute to the literature in several ways. To the best of our knowledge, this is the first study to utilise short interest to examine the different properties of the profitability and investment premia. Prior studies mainly focus on the return predictive powers of the profitability and investment (e.g. Ball, Gerakos, Linnainmaa, and Nikolaev, 2015; Novy-Marx, 2013; Titman, Wei, and Xie, 2004; Xing, 2008), and thus, our research adds to the literature by showing that the underlying attributions of the profitability and investment premia are different from the perspective of short arbitrageurs.

This chapter is also related to the studies that investigate the effects of investor sentiment on stock markets. Stambaugh, Yu and Yuan (2012) find that long–short strategies are more profitable following high sentiment because of short-sale impediments. In this chapter, we show that the profitability premium is more likely than the investment premium to move with investor sentiment. This result suggests that investor sentiment plays a pervasive role in the return anomalies that reflect mispricing but has little impact on the return anomalies that reflect a risk premium.

In addition, we shed new light on the literature about the role of sophisticated investors in stock mispricing. Shorting demand represented by short interest is an equaliser for mispricing characteristics, but not for risk characteristics. In this study, we find that the profitability premium, which is more likely to be associated with investor sentiment, is an anomaly that can be corrected by short-selling activity. However, we do not find evidence about the effects of short-selling activity on the investment premium. These results are consistent with those of previous studies that reveal that short sellers can profit from stock mispricing (e.g. Dechow, Hutton, Muelbrook, and Sloan, 2001).

The remainder of this chapter proceeds as follows. In Section 1.2, we provide a brief review of the literature. In Section 1.3, we describe the data and sample used in this chapter. Section 1.4 contains the empirical results. Section 1.5 concludes the chapter.

1.2. Literature Review

1.2.1. Profitability and investment premia

Motivated by the dividend discount model, Fama and French (2015, 2016) extend their three-factor model to a five-factor asset pricing model by adding the profitability and investment factors. They find that the five-factor asset pricing model improves the description of the cross-section of average returns. Similarly, Hou, Xue and Zhang (2015) construct a *q*-factor model based on the market factor, a size factor, an investment factor and a profitability factor to explain the cross-section of stock returns. They motivate the inclusion of the profitability and the investment factors through the *q*-theory.

In this regard, Novy-Marx (2013) conducts one of the first studies that shows that the profitability premium seems to be the other side of the value premium. He finds that stocks with higher gross profitability earn significantly higher average returns than stocks with lower gross profitability. He argues that gross profitability is a cleaner measure of economic

profitability, and mispricing arises when investors misinterpret the true profitability. Lam, Wang and Wei (2020) also provide consistent evidence that the profitability premium can be primarily attributed to behavioural mispricing. Conversely, Ball, Gerakos, Linnainmaa and Nikolaev (2015) argue that mispricing is unlikely to be the explanation since net income has equal predictive power when properly discounted.

In addition, many studies document the negative relationship between corporate investment and subsequent stock returns with contrasting interpretations. Cooper, Gulen and Schill (2008) suggest that it is due to investors' initial overreaction to changes in future business prospects implied by asset expansions, which is consistent with the mispricing interpretation. Polk and Sapienza (2009) also argue for the mispricing interpretation. They show that managers cater to mispricing by raising investment after substantial discretionary accruals, which leads to lower subsequent returns. By contrast, Xing (2008) interpret the investment premium as discount rate changes from the classical *q*-theory. Similarly, Calson, Fisher and Giammarino (2004) also attribute the investment premium to growth options and therefore the discount rate. Titman, Wei and Xie (2013) examine the relationship between the development of financial markets and the asset growth effect and find that the firms in countries with more developed capital markets exhibit a stronger asset growth effect, which is consistent with the *q*-theory. Lam and Wei (2011) examine whether the asset growth anomaly can be explained by the limits-to-arbitrage hypothesis (behavioural explanation) or the investment friction hypothesis (rational explanation). Their evidence shows significant support for both hypotheses.

1.2.2. Short-selling activity

This chapter is also related to the large stream of literature on the effects of short-selling activity. It is widely accepted that short selling improves the efficiency of security prices. For instance, Dechow, Hutton, Muelbrook and Sloan (2001) investigate the relationship between the trading strategies of short sellers and the ratios of fundamentals to market value. They find that short

sellers achieve superior returns by targeting stocks with low fundamental-to-price ratios, which is temporarily overpriced. In the same spirit, Boehmer, Jones and Zhang (2008) explore the return predictive power of short sales from 2000 to 2004. Their evidence suggests that short-selling activity is quite common in the markets and the lightly shorted stocks outperform the heavily shorted stocks by an annualised risk-adjusted average return of 15.6%. The same conclusion is drawn by Diether, Lee and Wergner (2009), who investigate the trading strategy of short sellers in the US stock markets based on daily short-sale data. Engelberg, Reed and Ringgenberg (2012) examine the ratio of short sales to total volume around public news events. They find that shorting activity increases significantly after news events and a substantial portion of the trading advantage derives from the short seller's superior ability to analyse public information. Israel and Moskowitz (2013) examine the role of shorting in the return premia associated with the firm size, value and momentum and argue that most of the size, value and momentum premia is contributed from the long position rather than the short position in the US stock markets.

Another stream of literature focuses on the negative role of short sellers in financial markets. For example, Goldstein and Guembel (2008) and Khanna and Mathews (2012) conjecture that short sellers induce firms to inefficiently distort their future investments and make the short position profitable. Using an experiment that relaxes short-selling constraints (Regulation SHO), Grullon, Michenaud and Weston (2015) show that the removal of short-selling constraints appears to distort corporate investment flows. In a recent study, De Angelis, Grullon and Michenaud (2017) find that firms perceive short sellers as a threat and Regulation SHO causes pilot firms to increase the convexity of the compensation payoff by granting relatively more stock options to their managers. In this chapter, we regard short sellers as skilled information processors whose short-selling activity can eliminate stock mispricing.

1.2.3. Short interest

Scholars now generally use short interest to investigate the effects of short-selling activity on the stock market. Among the first is Seneca (1967), who uncovers the significantly negative relationship between short interest and expected stock returns, suggesting that short positions can be used as an indication of bearish opinion. Senchack and Starks (1993) argue that future returns are predictively low with unexpected increases in short interest around the announcement date. Desai, Ramesh, Thiagarajan and Balachandran (2002) find that stocks that are heavily shorted experience significantly negative abnormal risk-adjusted returns in the NASDAQ market and that the negative returns increase with the level of short interest. Asquith, Pathak and Ritter (2005) investigate the performance of short-sale constrained stocks by using short interest and institutional ownership as proxies for short-sale constraints. They define these stocks as stocks with high short interest and low institutional ownership. Consistent with Senchack and Starks (1993), they find that stocks with higher short-sale constraints have temporarily higher prices and lower subsequent returns.

Some authors have used short interest to examine whether short sellers can anticipate future announcements and are skilled at eliminating market mispricing. For example, Lamont and Stein (2004) examine the relationship between the aggregate short interest and the market valuations for NASDAQ firms during the dotcom bubble period. They find evidence that short-sale constraints make it difficult for short sellers to correct aggregate mispricing, and the short-selling activity does not stabilise the overall stock market. Akbas, Boehmer, Erturk and Sorescu (2017) argue that short interest can be used to predict bad firm-specific information, such as negative earnings surprises and downgrades in analyst earnings forecasts, and that short sellers improve the price discovery about firm fundamentals. Hwang and Liu (2014) examine the trading activities of short arbitrageurs on market anomalies and find that short interest increases (decreases) disproportionately when a security enters (leaves) the short leg of an anomaly

strategy. In a later study, Rapach, Ringgenberg and Zhou (2016) examine the return predictive power of short interest on the ex-post expected market return and find that the detrended measure of aggregate short interest is the strongest predictor of future excess market return.

This chapter is distinct from these existing studies in that we utilise short interest to proxy for the short-selling activity and investigate the properties of profitability and investment premia from the perspective of short sellers.

1.3. Data Source and Sample

Our sample includes all non-financial firms listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX) and NASDAQ from January 1974 to December 2016. We obtain data on the monthly stock returns from the Center for Research in Security Prices (CRSP). We collect the financial statements and short interest data from Compustat. Data on the market factor ($MKTRF_t$), the size factor (SMB_t) and the book-to-market factor (HML_t) are collected from Kenneth French's website. We obtain the investor sentiment index of Baker and Wurgler (2006, 2007) from Jeffrey Wurgler's website. We download the misvaluation factor (UMO_t) of Hirshleifer and Jiang (2010) from Danling Jiang's website.

1.4. Empirical Results

1.4.1. Profitability and investment premia

Many studies have shown that profitability and investment both have significant return predictive powers (e.g. Ball, Gerakos, Linnainmaa, and Nikolaev, 2016; Titman, Wei, and Xie, 2004). In this subsection, we first replicate previous studies to examine the return predicative powers of profitability and investment from January 1974 to December 2016. Profitability is defined as the total revenues (REVT) minus the cost of goods sold (COGS), divided by total assets (AT), and investment is defined as the annual change in gross property, plant and

equipment (PPEGT) plus the annual change in inventories (INVT) divided by the lagged total assets (AT).

We sort stocks into deciles based on the NYSE decile cut-off of the profits-to-assets or investment-to-assets at the end of June each year, and then calculate the value-weighted average returns for each decile over the next 12 months. The portfolios are rebalanced at the end of each June. We present the average returns for the portfolios sorted by profitability in Panel A of Table 1.1. We also calculate the risk-adjusted alphas by regressing the decile returns on the market factor ($MKTRF_t$) and the Fama–French three factors ($MKTRF_t$, SMB_t, and HML_t).

<Insert Table 1.1 Here>

Consistent with Novy-Marx's (2013) results, the results in Table 1.1 Panel A indicate that the raw returns for the value-weighted portfolios increase across the profits-to-assets deciles. Stocks in the most profitable decile earn a value-weighted average return of 1.16% per month. Conversely, stocks in the least profitable decile have a value-weighted average return of 0.83% per month. The spread between the most profitable and the least profitable stocks is 0.33% (*t*-statistic = 2.22) per month, which is significantly different from zero. The results for the CAPM and the Fama–French three-factor alphas are qualitatively unchanged. The return spread between the most profitable stocks and the least profitable stocks after the controlling of the conventional return factors is significantly positive.

In Table 1.1 Panel B, we report the average returns for the value-weighted portfolios sorted by investment-to-assets. The average profits generally increase with the decreases in investment. The stocks in the lowest investment-to-assets decile outperform those in the highest investment-to-assets decile by 0.34% (*t*-statistic = 2.82) per month. The results are

qualitatively similar after controlling for conventional return factors, which remain significantly different from zero.

Thus far, we have shown that both profitability and investment are useful predictors of future benchmark-adjusted returns. However, these premia may have different underlying attributions. The profitability premium may reflect investors' misinterpretation of the true profitability, whereas the investment premium may reflect the discount rate changes. To analyse whether the profitability and investment premia comove with the mispricing, we regress these two premia on the Fama–French three factors (1993) and the Hirshleifer and Jiang mispricing factor. Hirshleifer and Jiang (2010) construct a financing-based mispricing factor (UMO_t) by using equity and debt financing to identify common misvaluation across firms. They show that the UMO loadings strongly predict the cross-section of returns. We present the regression results in Table 1.2.

<Insert Table 1.2 Here>

Table 1.2 Panel A contains the alphas and factor loadings of the profitability premium. We find that the models that include the mispricing factor explain the average returns on the portfolios sorted by the profits-to-assets. The alphas for the profitability premium drop to insignificance, and the loadings on the mispricing factors are significantly positive at the 1% level. However, in Table 1.2 Panel B, we show that the mispricing factor fails to improve the performance of the three-factor model for the investment premium. The alphas are still significantly positive, and the factor loadings on the mispricing factor are insignificantly different from zero. This simple but powerful test reveals that mispricing contributes to the return predictability of the profits-to-assets rather than the investment-to-assets.

1.4.2. Effects of short selling on the profitability and investment premia

1.4.2.1. Short arbitrage of the profitability and investment premia

The results in Table 1.2 shows that the profitability premium can be partially explained by the mispricing factor of Hirshleifer and Jiang (2010), whereas the investment premium is distinct from this factor. Because short sellers are skilled information processors, we expect the short-selling activity to be associated with the mispricing characteristics, but not the risk characteristics. In this subsection, we employ short interest as the proxy for the short-selling activity and examine the short arbitrage across portfolios sorted by profitability and investment. Short interest is defined as the ratio of shares shorted to the total number of shares outstanding. We present the results in Table 1.3.

<Insert Table 1.3 Here>

To explore whether short sellers capitalise on information related to profitability and investment, we calculate the change in short interest as the difference between the short interest ratio as of the fifth month after the fiscal year-end minus the short interest ratio for the same firm for the previous year divided by the short interest ratio for the previous year. For instance, if the profitability (investment) is calculated as of December 2000, then the corresponding change in short interest is the difference between the short interest ratio as of May 2001 minus the short interest ratio as of May 2000 divided by the short interest as of May 2000. We observe that the change in short interest in the least profitable decile is 1.37 (t-statistic = 10.52), whereas in the most profitable decile it is 0.96 (t-statistic = 12.10). The spread of −0.40 is highly significant (t-statistic = −3.41). However, there is no clear indication that the variation in investment has a substantial effect on the short-selling activity. This result suggests that short sellers are actively engaged in the arbitrage of low profitability firms rather than high

investment firms. We also calculate the difference in short interest as of the seventh month and find quantitatively similar results.

1.4.2.2. Effects of short positions

The results in Table 1.3 suggest that short sellers engage in the arbitrage of the profitability premium but not of the investment premium. Motivated by this finding, we investigate the effects of the short-selling activity on the profitability and investment premia. If short sellers take positions based on signals in the profitability variation, the return predictive power should decrease radically among the stocks with a high level of short interest. Conversely, if short sellers do not capitalise on the variation in investment, the level of short interest should not affect the investment premium.

The stocks with a high level of short interest are more likely to be regarded as overpriced by short sellers. To test for the effects of short positions on these two premia, we first classify all stocks into two groups based on the level of short interest at the end of each month. Specifically, we classify stocks with short interest that is higher than the median value of each month as the large short position group (SI > Median) and the remaining stocks as the small short position group (SI ≤ Median). We then sort stocks independently into deciles based on the NYSE breakpoints of the profits-to-assets or investment-to-assets. We calculate the value-weighted average portfolio returns for each group over the next 12 months. Table 1.4 displays our main findings.

<Insert Table 1.4 Here>

In Panel A of Table 1.4, we present the profits of the decile portfolios sorted by profits-to-assets for stocks with large and small short positions. We find that the level of short interest significantly affects the profitability premium. For the small short position group (SI ≤ Median), the stocks with higher profitability outperform the stocks with lower profitability, and the

return difference between the most profitable stocks and the least profitable stocks is 0.84% (*t*-statistic = 4.38). However, for the large short position group (SI > Median), the return difference between the two extreme profitability deciles disappears. This result shows that profitability has no robust predictability among the stocks with high short interest levels. The profitability premium difference between the stocks with a large short interest position and those with a small short position is 0.72% (*t*-statistic = 3.67), which is significantly different from zero at the 1% level. We also calculate the alphas adjusted by the CAPM and three Fama–French benchmarks and obtain qualitatively similar results. For instance, the CAPM alphas for the profitability premium are 0.83% (*t*-statistic = 4.25) for the small short position group (SI ≤ Median) and 0.14% (*t*-statistic = 0.85) for the large short position group (SI > Median), respectively. The difference between them is 0.68% (*t*-statistic = 3.44), which is economically and statistically significant.

Table 1.4 Panel B reports the investment premium conditional on the short positions. In contrast with the significant effects of short-selling activity on the profitability premium, we observe that investment premium displays no variation with the difference in the short interest levels. Specifically, we find that for the large short position group (SI > Median), the lowest investment stocks outperform the highest investment stocks by 41 bps per month, with a *t*-statistic of 2.57. While for the small short position group (SI ≤ Median), the investment premium is 0.63% per month (*t*-statistic = 3.12), which is significantly positive at the 1% level. The spread between them is 0.22% (*t*-statistic = 1.05), indicating that the short sellers do not engage in the investment anomaly. The results of the CAPM and Fama–French three-factor alphas that both groups earn significant risk-adjusted profits, which further confirms that the short-selling activity has no significant impact on the investment–return relationship.

1.4.2.3. Effects of abnormal shorting flows

Another way to examine whether short sellers do engage in the arbitrage of the profitability and investment premia is to investigate the impact of abnormal shorting flows. If short sellers process information about profitability or investment, we would expect the premia to disappear among the stocks with high abnormal shorting flows. We classify the stocks whose short interest ratio is higher than that in the previous month as the high abnormal shorting group ($\Delta SI > 0$) and the stocks with short interest lower or equal to the value in the previous month as the low abnormal shorting group ($\Delta SI \leq 0$). As in our previous analyses, we then sort stocks independently into deciles based on the NYSE breakpoints of the profits-to-assets or investment-to-assets. We calculate the value-weighted average portfolio returns for each group over the next 12 months.

<Insert Table 1.5 Here>

Table 1.5 presents the results. In Panel A, we show that among the low abnormal shorting group ($\Delta SI \leq 0$), stocks with high profitability achieve a higher monthly return of 0.62% (*t*-statistic = 3.58) than stocks with low profitability. However, profitability has no predictability power for the stocks with high abnormal shorting ($\Delta SI > 0$). The results are qualitatively similar when we examine the CAPM or three-factor alphas. We find no evidence in Table 1.5 Panel B that the abnormal shorting flows affect the return predictability of investment-to-assets. For instance, the low investment decile outperforms the high investment decile by 0.46% per month (*t*-statistic = 2.75) for the low abnormal shorting group ($\Delta SI \leq 0$), and by 0.50% per month (*t*-statistic = 2.78) for the high abnormal shorting group ($\Delta SI > 0$). The investment premium difference between the two groups is −0.05% (*t*-statistic = −0.23), which is insignificantly different from zero.

The combined results of Table 1.4 and Table 1.5 indicate that not only the short positions but also the abnormal shorting flows reduce the profitability premium rather than the investment premium. These findings suggest that short sellers can eliminate the profitability premium that at least partially reflects mispricing whereas they cannot eliminate the investment premium.

1.4.2.4. Short-selling effects in Fama–MacBeth regressions

Table 1.6 evaluates the effects of short-selling activity on the profitability and investment premia by using Fama–MacBeth regressions. To reduce the impact of outliers, we trim the ratios of profits-to-assets and investment-to-assets at their respective 5th and 95th percentile. The dependent variable (R_{it}) is the monthly stock return. GP in Panel A is the profits-to-assets ratio, and INV in Panel B is the investment-to-assets ratio. $D_{\mathrm{SI}>\mathrm{Median}}$ is a dummy variable that takes the value of 1 if the outstanding shares shorted of the stock is over the median value of the short interest at the end of each month, and 0 otherwise. $D_{\Delta \mathrm{SI}>0}$ is a dummy variable that takes the value of 1 if the short interest of the stock is greater than the value in the previous month, and 0 otherwise. The control variables include the logarithm of market capitalisation (Log(Size)), the book-to-market ratio (B/M), the stock return over the last month (Lagret) and the past performance measured at the horizon of 12 to 2 months (Mom). To investigate the importance of short selling, we interact profitability and investment with the two dummy variables that indicate the short positions or the abnormal shorting flows. The interactions allow us to examine the marginal effects of short selling on the return predictability of profitability and investment.

<Insert Table 1.6 Here>

Panel A of Table 1.6 presents the results for the profitability premium. We correct the standard errors following the Newey–West (1987) procedure to overcome autocorrelation and heteroscedasticity in the error terms. We note that the coefficient on GP in Column (1) is

significantly positive at the 1% level, suggesting that the profitability has significant power to predict the cross-section of returns for the stocks. Across treatment conditions, the coefficient on GP×$D_{\mathrm{SI}>\mathrm{Median}}$ in Column (2) is −0.69% (*t*-statistic = −.29) and that on GP×$D_{\Delta\mathrm{SI}>0}$ in Column (3) is −0.50% (*t*-statistic = −2.80); both of them are significantly negative at the 1% level. Combining this with the base coefficients on GP, we note that the return predictive powers of the profitability are significantly different for the stocks with different short positions. In other words, the return predictive power of the profitability is significantly lower for the stocks with high short position or high abnormal shorting flows. More control variables are entered into the regressions in Column (4) and Column (5). We observe that the coefficients on GP are still significantly positive at the 1% level, whereas those on GP×$D_{\mathrm{SI}>\mathrm{Median}}$ and GP×$D_{\Delta\mathrm{SI}>0}$ are significantly negative at the 1% level. These results indicate that even after we control for the effects of size, value and stock past performance, the treatment of the short-selling activity still significantly decreases the magnitude of the return predictive power of the profitability.

We then replace the key independent variable of profitability by the ratio of investment-to-assets in Panel B. Consistent with our expectation, INV is significantly negative at the 1% level correlated with the cross-section of stock returns across the five columns. In Column (2), we find that the coefficient on the interaction between INV and $D_{\mathrm{SI}>\mathrm{Median}}$ is −0.03% (*t*-statistic = −0.19), indicating that the short position has no significant effect on the investment premium. We also find the interaction between INV and $D_{\Delta\mathrm{SI}>0}$ is insignificantly different from zero in Column (3). The coefficients are quantitatively unchanged when we control for the effects of size, value and stock past performance. These results are in line with our findings in Table 1.4 and Table 1.5 that the return predictive power of investment seems to be irrelevant to the short-selling activity.

Overall, Table 1.6 confirms that the profitability premium is significantly stronger among the stocks with small short position and low abnormal shorting flows, whereas the relationship between investment and expected returns is irrelevant to the activities of short sellers. Since shorting demand represented by short interest is an equaliser for mispricing characteristics, these results suggest that the primary source of the profitability and investment premia may be different. Although the profitability premium fits the mispricing interpretation, the investment premium does not.

1.4.3. Profitability and investment premia conditional on investor sentiment

Stambaugh, Yu and Yuan (2012) examine the role of investor sentiment in the market anomalies. They do not differentiate between asset pricing anomalies and argue that mispricing is more severe following high levels of investor sentiment because of short-sale impediments. However, in Subsection 1.4.2, we show that the investment premium is less consistent with the mispricing characteristics. In this subsection, we re-examine the effects of investor sentiment on the profitability and investment premia.

To illustrate the association between investor sentiment and the two new factors, Figure 1.1 presents a plot of the profitability premium, the investment premium and investor sentiment. We measure investor sentiment by using the monthly index provided by Baker and Wurgler (2006) orthogonalised to macroeconomic conditions. Periods of high investor sentiment are frequently associated with high levels of profitability premium rather than the investment premium. More formally, we find that the correlation between the profitability premium and orthogonalised investor sentiment is 0.12, which is higher than the correlation between the investment premium and investor sentiment (−0.09). This preliminary result suggests that the profitability premium is more likely than the investment premium to move with investor sentiment.

<Insert Figure 1.1 Here>

Table 1.7 shows the results of the zero-cost strategies based on the profitability and investment conditional on the investor sentiment. We follow Stambaugh, Yu and Yuan (2012) to define a month as a high (low) sentiment month if the investor sentiment index of Baker and Wurgler (2006) in the previous month is above (below) the median value for the sample period. We then calculate the future returns of decile portfolios sorted by the ratio of profits-to-assets or investment-to-assets separately for the different investor sentiment states. Panel A of Table 1.7 shows the average portfolio returns sorted by profits-to-assets following a high- or low-sentiment period and Panel B shows the average portfolio returns sorted by investment-to-assets following a high- or low-sentiment period.

<Insert Table 1.7 Here>

In Table 1.7 Panel A, we find that the stocks in the most profitable decile (long leg) outperform the stocks in the least profitable decile (short leg) only after high-sentiment months. In particular, the return difference between the two decile portfolios is 0.64% (*t*-statistic = 3.11) following high levels of sentiment. In contrast, the return spread following low-sentiment periods is only 0.03% (*t*-statistic = 0.13), which is insignificantly different from zero. The strategy based on the profits-to-assets earns 61 bps more per month following high-sentiment periods, with a *t*-statistic equal to 2.04. However, the results in Table 1.7 Panel B suggest that investor sentiment has no significant effect on the investment premium. We find that the strategy based on the investment-to-assets earns 14 bps (*t*-statistic = 0.07) more per month following low-sentiment periods than high-sentiment periods, which remains insignificantly different from zero. These results seem at odds with the conclusion of Stambaugh, Yu and Yuan (2012) that the anomalies are stronger following high levels of sentiment.

We also calculate the risk-adjusted alphas after controlling for the Market factor ($MKTRF_t$) or the Fama–French three factors ($MKTRF_t$, SMB_t, and HML_t). Specifically, we follow Stambaugh, Yu and Yuan (2012) to estimate the following regressions:

$$R_{i,t} = a_H D_{H,t-1} + a_L D_{L,t-1} + bMKTRF_t + \epsilon_{i,t},$$

$$R_{i,t} = a_H D_{H,t-1} + a_L D_{L,t-1} + bMKTRF_t + cSMB_t + dHML_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the excess return in month *t* on either the long leg, the short leg or the difference. $D_{H,t-1}$ and $D_{L,t-1}$ are dummy variables that indicate high- and low-sentiment periods. The results of the risk-adjusted alphas after controlling for the conventional return factors are qualitatively unchanged: the profitability premium is significantly stronger following high levels of sentiment, whereas the portfolios sorted on the investment-to-assets exhibit no significant variation in returns adjusted by the Fama–French benchmarks following different levels of investor sentiment. These results further confirm that the effect of investor sentiment on the profitability premium is significantly stronger than that on the investment premium.

To resolve the potential problems caused by the binary measure, we conduct an alternative analysis by using predictive regressions. Table 1.8 displays the results of the time series regressions of the profitability and investment premia on the investor sentiment index of Baker and Wurgler (2006). Specifically, we calculate the future returns of the zero-cost strategies based on the ratios of profits-to-assets and investment-to-assets and then regress the returns on the lagged investor sentiment.

<Insert Table 1.8 Here>

In Panel A of Table 1.8, we regress the return difference between the stocks with profitability in the top NYSE decile and those with profitability in the bottom NYSE decile on the investor sentiment in the previous month. The result in Row (1) shows that the coefficient on

$SENTIMENT_{t-1}$ is 0.94 (t-statistic = 3.90), suggesting that investor sentiment indeed has significant positive predictive power for the profitability premium, with high sentiment predicting a high profitability premium. In Row (2) of Panel A, we find that the coefficient on $SENTIMENT_{t-1}$ after the control of the Fama–French three factors ($MKTRF_t$, SMB_t, and HML_t) remains qualitatively unchanged, which is significantly positive at the 1% level.

Panel B of Table 1.8 presents the results of the time series regressions of the investment premium on the lagged sentiment index. We observe that the coefficient on $SENTIMENT_{t-1}$ is insignificantly different from zero, which is consistent with our prior findings that investor sentiment in the previous month has no significant impact on the investment premium. The results after the controlling of the conventional risk factor are qualitatively similar.

To summarise, we find that the return spread based on the profitability is stronger following high-sentiment periods, while the investment premium exhibits no significant variations following different levels of investor sentiment. If mispricing is the primary source of excess returns, the profitability and investment premia should both be stronger following a high-sentiment period. Therefore, our evidence further suggests that the primary source of the two anomalies are different: the profitability premium is more likely than investment premium to be associated with sentiment-driven mispricing.

1.4.4. Effects of short-selling activity on sensitivity of premia to sentiment

We further examine the influence of short-selling activity on the relationship between investor sentiment and these two premia. The literature argues that return anomalies are stronger following a high-sentiment period because the presence of irrational and inexperienced investors causes the stock prices to deviate from their intrinsic value (Stambaugh, Yu, and Yuan, 2012). However, in Subsection 1.4.3 we show that investor sentiment only affects the

profitability premium, indicating that the profitability premium is more likely than the investment premium to be attributable to the sentiment-related mispricing.

As skilled information processors, short sellers are expected to take advantage of mispricing. To explore the role of short sellers in the relationship between investor sentiment and premia based on profitability and investment, we classify our sample period into two categories based on the equal-weighted mean of short interest, and we then investigate the relationship between investor sentiment and these two premia for different categories. Because the equal-weighted mean of short interest exhibits a significant upward trend, we follow Rapach, Ringgenberg and Zhou (2016) to remove a linear trend from the logarithm of the equal-weighted mean of short interest and standardise the detrended mean to have a standard deviation of one. We define a month as a low (high) SI month if the detrended log of the equal-weighted mean of short interest in the previous month is lower (higher) than the median value for the sample period.

The results are presented in Table 1.9. Panel A shows the relationship between the investor sentiment and the profitability premium with different short interest levels. Specifically, after the period of low short interest level (Low SI), the profitability premia following high- and low-sentiment periods are 0.96% (*t*-statistic = 3.07) and 0.03% (*t*-statistic = 0.08), respectively. The results show that the difference in the profitability premium is 0.93% (*t*-statistic = 2.14), which is significantly different from zero. However, we do not find a significant difference in the profitability premium between the high- and low-sentiment states following the period of high short-selling activity (High SI). Indeed, we show that the profitability premium disappears after high- as well as low-sentiment states following the high shorting period (High SI). Consistent with our expectation, the results in Table 1.9 Panel B show that the differences in the investment premium between different sentiment periods are always insignificantly different from zero irrespective of the levels of short-selling activity.

<Insert Table 1.9 Here>

We also report the profits adjusted by the Fama–French three factors in Table 1.10. Specifically, we regress the portfolio excess returns on the dummy variables that indicate investor sentiment states and the risk factors conditional on the level of short-selling activity. Consistent with the findings in Table 1.9, we find that the positive relationship between the profitability premium and investor sentiment only exists following the period of low short interest level (Low SI). We do not observe a significant difference for the investment premium following high- and low-sentiment periods in different short interest level categories.

<Insert Table 1.10 Here>

Next, we conduct a time series analysis to examine whether the short sellers are skilled at eliminating the mispricing attributed by the sentiment investors. Specifically, we run the following regressions,

$$R_t = c + d \cdot SENTIMENT_{t-1} + e \cdot D_{DSI_{t-1}} + f \cdot SENTIMENT_{t-1} \cdot D_{DSI_{t-1}} + g \cdot Controls_{it} + u_t,$$

where R_t is the monthly profitability or investment premium. $SENTIMENT_{t-1}$ is the orthogonalised sentiment index of Baker and Wurgler (2006) in the previous month. $D_{DSI_{t-1}}$ is a dummy variable that equals 1 if the detrended log of the equal-weighted mean of short interest in the previous month is greater than the median value for the sample period, and 0 otherwise. The control variables are the Fama–French three factors ($MKTRF_t$, SMB_t, and HML_t). We report the results in Table 1.11.

<Insert Table 1.11 Here>

Table 1.11 Panel A displays the results of the time series regressions on the profitability premium. We find that the coefficients on $SENTIMENT_{t-1}$ in rows (1) and (2) are significantly positive at the 1% level, suggesting that investor sentiment has significant positive predictive

power for the profitability premium, with high sentiment predicting a high profitability premium. The results also show that the coefficients on the interaction of $SENTIMENT_{t-1}$ and $D_{DSI_{t-1}}$ are −1.24% (t-statistic = −2.47) and −1.48% (t-statistic = −3.39) when we control the Fama–French three factors. This result implies that the ability of investor sentiment to predict the profitability premium is significantly different after the periods with different levels of short-selling activity. Following the period with a high level of short-selling activity, investor sentiment exhibits no relationship with the profitability premium.

We observe a different story for the investment premium in Table 1.11 Panel B. The coefficients on $SENTIMENT_{t-1}$ and the interaction term $SENTIMENT_{t-1} * D_{SI_{t-1}}$ are insignificantly different from zero, which is consistent with our prior findings that short-selling activity and investor sentiment have no significant impact on the investment premium.

Previous studies suggest that the stock market is dominated by irrational and inexperienced investors when investor sentiment is high (Yu and Yuan, 2011). The effects of sentiment on the stock market are due to the mispricing attributed to the sentiment investors and short-sale constraints. The evidence in this subsection appears to suggest that the profitability premium is stronger following high levels of sentiment. However, after the controlling of short-selling activity, we find that investor sentiment exhibits no significant ability to predict the profitability premium after the period of high short-selling activity. Notably, the investor sentiment has no impact on the investment premium regardless of the short-selling activity. These results further confirm that the profitability premium is more likely than the investment premium to be associated with the irrational pricing and that short sellers are skilled at taking advantage of the mispricing patterns generated from the behaviour of irrational and inexperienced investors.

1.5. Conclusion

Motivated by the discount dividend variation model, Fama and French (2015) suggest that profitability and investment are natural choices to describe expected stock returns. However, many studies conjecture that these two factors capture different angles of the variations in the expected returns. In this chapter, we investigate the difference between the profitability and investment premia from the perspective of short sellers. As skilled information processors, short sellers are expected to take advantage of mispricing to form their positions. We find that short sellers capitalise on information related to profitability rather than investment, indicating that the profitability premium is more likely than the investment premium to fit the mispricing interpretation. In addition, the results that the profitability premium disappears among the stocks with a large short position or a high abnormal shorting flow further suggest that short arbitrage is effective in reducing mispricing.

We also show that the profitability premium is more likely than the investment premium to be caused by sentiment-driven mispricing because the investor sentiment has profound effects only on the former. In addition, the results that the short-selling activity mitigates the impact of investor sentiment on the profitability premium confirm that short sellers are skilled at eliminating sentiment-driven mispricing.

Although our research highlights that the primary sources of the profitability and investment factors are different through the effects of short-selling activity, more research is certainly needed to investigate their properties from other angles.

Figures and Tables

Figure 1.1. Profitability premium, investment premium and investor sentiment

This figure depicts the profitability premium, investment premium and investor sentiment from January 1974 to December 2016. The dotted and the solid lines indicate the profitability premium and the investment premium, respectively. The dashed line shows the orthogonalised investor sentiment index of Baker and Wurgler (2006).

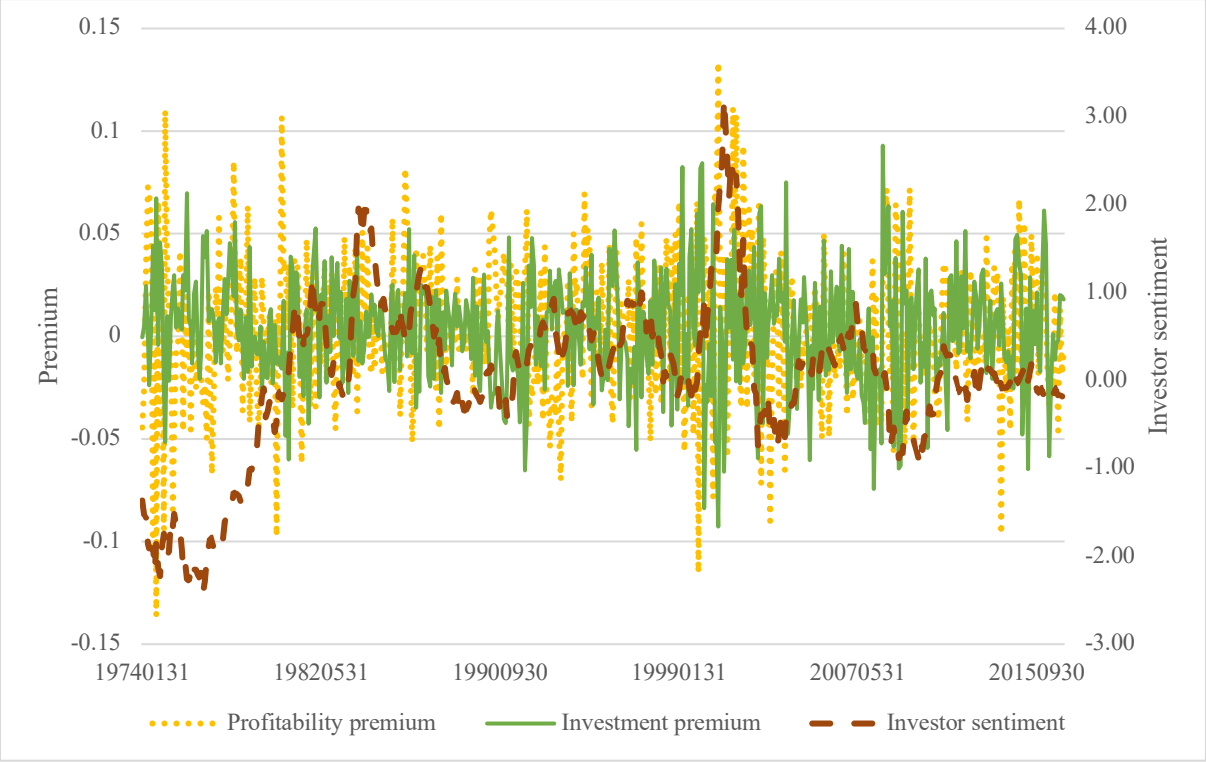


Table 1.1. Future returns predicted by profitability and investment

This table provides the monthly average returns to portfolio sorted by profitability (profits-to-assets) and investment (investment-to-assets), respectively. In June of year *t*, all firms are sorted into 10 portfolios by profitability in Panel A and investment in Panel B using NYSE breakpoints. We obtain the value-weighted monthly returns for these portfolios from July of year *t* to June of year *t* + 1. In Panel A, D1 is the portfolio of stocks in the lowest past profitability decile, and D10 is the portfolio of stocks in the highest past profitability decile. In Panel B, D1 is the portfolio of stocks in the highest past investment decile, and D10 is the portfolio of stocks in the lowest past investment decile. The sample period is January 1974 – December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Difference
Panel A: Profits-to-assets											
Raw return	0.83	0.91	0.93	0.90	1.06	1.01	1.01	0.93	1.04	1.16	0.33**
											(2.22)
CAPM α	−0.13	−0.01	−0.05	−0.07	0.08	0.02	−0.02	−0.07	0.07	0.21	0.34**
											(2.25)
FF3 α	−0.17	−0.15	−0.12	−0.14	0.07	0.02	0.08	0.04	0.21	0.31	0.49***
											(3.24)
Panel B: Investment-to-assets											
Raw return	0.75	0.83	1.06	0.99	1.07	0.97	1.07	1.10	1.09	1.09	0.34***
											(2.82)
CAPM α	−0.35	−0.23	0.08	0.04	0.14	0.05	0.13	0.13	0.12	0.02	0.37***
											(3.00)
FF3 α	−0.31	−0.12	0.19	0.09	0.17	0.06	0.15	0.14	0.00	−0.01	0.30**
											(2.49)

Table 1.2. Regressions of portfolio returns on mispricing factor

This table provides the results of time series regressions of portfolio returns sorted by profitability (profits-to-assets) and investment (investment-to-assets) on the Fama–French three factors ($MKTRF_t$, SMB_t, HML_t) and Hirshleifer and Jiang (2010) mispricing factor (UMO_t). The sample period is January 1974 – December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

	Constant	$MKTRF_t$	SMB_t	HML_t	UMO_t
Panel A: Profits-to-assets					
(1)	0.13	5.50			20.11***
	(0.81)	(1.48)			(3.72)
(2)	0.13	7.84**	−17.07***	−47.27***	43.92***
	(0.84)	(2.22)	(−3.59)	(−8.11)	(7.35)
Panel B: Investment-to-assets					
(1)	0.29**	−1.92			7.13
	(2.24)	(−0.63)			(1.61)
(2)	0.24*	−4.68	22.29***	3.08	8.02
	(1.84)	(−1.56)	(5.51)	(0.62)	(1.58)

Table 1.3. Changes in short interest across decile portfolios sorted by profitability and investment

This table provides the change in short interest in response to the decile rank of profitability and investment. We rank stocks into deciles annually based on the profitability (profits-to-assets) and investment (investment-to-assets). The change in short interest is calculated as the difference between the short interest ratio as of the fifth month after the fiscal year-end minus the short interest ratio for the same firm for the previous year divided by the short interest for the previous year. The sample period is January 1974 – December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

	Short	D2	D3	D4	D5	D6	D7	D8	D9	Long	Difference
Profits-to-assets	1.37***	1.47***	1.43***	1.42***	1.15***	1.14***	1.04***	0.95***	0.92***	0.96***	−0.40***
	(10.52)	(10.03)	(13.16)	(11.80)	(12.56)	(12.36)	(13.57)	(12.84)	(11.81)	(12.10)	(−3.41)
Investment-to-assets	1.23***	1.33***	1.16***	1.13***	1.14***	1.28***	1.21***	1.37***	1.28***	1.14***	−0.09
	(15.63)	(14.84)	(13.85)	(11.82)	(12.05)	(11.98)	(9.33)	(8.69)	(8.96)	(12.36)	(−1.29)

Table 1.4. Effects of short positions

This table provides the effects of shorting activity on the profitability and investment premia. All stocks are sorted independently by the short interest ratio and the ratio of profits-to-assets or investment-to-assets. We classify the stocks with short interest lower than or equal to median value at the end of each month as the small short position group (SI ≤ Median) and the stocks with short interest higher than median value at the end of each month as the large short position group (SI > Median). We then calculate the value-weighted average portfolio returns over the next 12 months. In Panel A, the long leg is the portfolio of stocks in the highest profitability decile, and the short leg is the portfolio of stocks in the lowest profitability decile. In Panel B, the long leg is the portfolio of stocks in the lowest investment decile, and the short leg is the portfolio of stocks in the highest investment decile. The sample period is January 1974 – December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

Anomaly	SI ≤ Median			SI > Median			Difference		
	Long leg	Short leg	Long–short	Long leg	Short leg	Long–short	Long leg	Short leg	Long–short
Panel A: Profits-to-assets									
Raw return	1.40***	0.56**	0.84***	1.06***	0.94***	0.12	0.34**	−0.38**	0.72***
	(5.18)	(2.03)	(4.38)	(5.01)	(4.26)	(0.73)	(1.69)	(−1.97)	(3.67)
CAPM α	0.36**	−0.47***	0.83***	0.14	−0.00	0.14	0.21	−0.47**	0.68***
	(2.27)	(−2.70)	(4.25)	(1.24)	(−0.02)	(0.85)	(1.06)	(−2.45)	(3.44)
FF3 α	0.57***	−0.39**	0.95***	0.19*	−0.14	0.33**	0.38**	−0.24	0.62***
	(4.08)	(−2.50)	(4.92)	(1.64)	(−1.24)	(1.98)	(2.07)	(−1.54)	(3.10)
Panel B: Investment-to-assets									
Raw return	1.37***	0.74**	0.63***	1.18***	0.78***	0.41**	0.19	−0.03	0.22
	(5.18)	(2.14)	(3.12)	(4.67)	(2.93)	(2.57)	(1.12)	(−0.19)	(1.05)
CAPM α	0.33**	−0.43***	0.76***	0.15	−0.31**	0.45***	0.19	−0.12	0.31
	(2.22)	(−2.71)	(3.80)	(1.10)	(−2.55)	(2.79)	(1.15)	(−0.65)	(1.47)
FF3 α	0.22	−0.29**	0.51***	−0.05	−0.32***	0.28*	0.28*	0.04	0.23
	(1.58)	(−2.04)	(2.64)	(−0.48)	(−2.66)	(1.74)	(1.64)	(0.23)	(1.10)

Table 1.5. Effects of abnormal shorting flows

This table provides the effects of shorting activity on the profitability and investment premia. All stocks are sorted independently by the change in short interest and the ratio of profits-to-assets or investment-to-assets. We classify the stocks whose short interest is higher than that in the previous month as the high abnormal shorting group ($\Delta SI > 0$) and the stocks with short interest lower or equal to the value in the previous month as the low abnormal shorting group ($\Delta SI \leq 0$). We then calculate the value-weighted average portfolio returns over the next 12 months. In Panel A, the long leg is the portfolio of stocks in the highest profitability decile, and the short leg is the portfolio of stocks in the lowest profitability decile. In Panel B, the long leg is the portfolio of stocks in the lowest investment decile, and the short leg is the portfolio of stocks in the highest investment decile. The sample period is January 1974 – December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

Anomaly	$\Delta SI \leq 0$			$\Delta SI > 0$			Difference		
	Long leg	Short leg	Long–short	Long leg	Short leg	Long–short	Long leg	Short leg	Long–short
Panel A: Profits-to-assets									
Raw return	1.21***	0.58**	0.62***	1.01***	0.87***	0.14	0.19	−0.29**	0.48***
	(5.23)	(2.55)	(3.58)	(4.75)	(3.96)	(0.77)	(1.39)	(−2.07)	(2.86)
CAPM α	0.22*	−0.39***	0.61***	0.11	−0.03	0.14	0.11	−0.35**	0.46***
	(1.93)	(−3.23)	(3.45)	(0.87)	(−0.25)	(0.77)	(0.80)	(−2.55)	(2.72)
FF3 α	0.37***	−0.40***	0.77***	0.17	−0.17	0.35*	0.20	−0.23*	0.43**
	(3.44)	(−3.41)	(4.46)	(1.40)	(−1.29)	(1.91)	(1.47)	(−1.77)	(2.47)
Panel B: Investment-to-assets									
Raw return	1.28***	0.82***	0.46***	1.17***	0.66**	0.50***	0.11	0.16	−0.05
	(5.36)	(2.97)	(2.75)	(4.41)	(2.47)	(2.78)	(0.72)	(1.04)	(−0.23)
CAPM α	0.27**	−0.31**	0.58***	0.12	−0.41***	0.53***	0.15	0.11	0.05
	(2.30)	(−2.53)	(3.51)	(0.80)	(−3.03)	(2.89)	(1.01)	(0.71)	(0.23)
FF3 α	0.11	−0.23**	0.34**	−0.05	−0.43***	0.39**	0.15	0.20	−0.05
	(1.01)	(−2.05)	(2.18)	(−0.32)	(−3.12)	(2.12)	(1.00)	(1.39)	(−0.24)

Table 1.6. Fama–MacBeth regressions

This table provides the results of Fama–MacBeth regressions for individual stocks. The dependent variable is stock returns. In Panel A, GP is the profits-to-assets ratio. In Panel B, INV is the investment-to-assets ratio. $D_{\text{SI} > \text{Median}}$ is a dummy variable that takes the value of 1 if the outstanding shares shorted of the stock is higher than the median value of the short interest at the end of each month, and 0 otherwise. $D_{\Delta\text{SI} > 0}$ is a dummy variable that takes the value of 1 if the short interest of the stock is greater than the value in the previous month, and 0 otherwise. Log(Size) is the logarithm of market capitalisation. B/M is the book-to-market ratio. Lagret is the stock return over the previous month. Mom is the past cumulative return at the horizon of 12 to 2 months. The sample period is January 1974 – December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

Independent variable	(1)	(2)	(3)	(4)	(5)
Panel A: Profits-to-assets					
Constant	0.97***	0.97***	0.99***	2.14***	2.12***
	(3.20)	(2.89)	(3.11)	(2.84)	(2.77)
GP	1.14***	1.33***	1.19***	1.39***	1.27***
	(5.56)	(5.82)	(5.44)	(6.09)	(5.83)
$D_{SI>\text{Median}}$		0.04		0.29**	
		(0.25)		(2.09)	
GP×$D_{SI>\text{Median}}$		−0.69***		−0.60***	
		(−3.29)		(−2.86)	
$D_{\Delta SI>0}$			−0.03		0.19*
			(−0.25)		(1.92)
GP×$D_{\Delta SI>0}$			−0.50***		−0.51***
			(−2.80)		(−2.88)
Log(Size)				−0.14***	−0.13***
				(−3.07)	(−2.91)
B/M				0.19***	0.19***
				(4.57)	(4.44)
Lagret				−5.12***	−5.12***
				(−11.69)	(−11.67)
Mom				0.16	0.16
				(1.33)	(1.36)
Panel B: Investment-to-assets					
Constant	1.50***	1.59***	1.55***	2.91***	2.90***
	(5.11)	(4.95)	(5.10)	(3.90)	(3.82)
INV	−0.86***	−0.93***	−1.01***	−0.99***	−0.97***
	(−6.63)	(−6.33)	(−7.24)	(−7.23)	(−7.52)
$D_{SI>\text{Median}}$		−0.26*		0.02	
		(−1.89)		(0.17)	
INV×$D_{SI>\text{Median}}$		−0.03		0.07	
		(−0.19)		(0.40)	
$D_{\Delta SI>0}$			−0.27**		−0.02
			(−2.50)		(−0.30)
INV×$D_{\Delta SI>0}$			0.12		0.07
			(0.67)		(0.44)
Log(Size)				−0.14***	−0.14***
				(−3.18)	(−3.12)
B/M				0.14***	0.14***
				(3.23)	(3.05)
Lagret				−5.21***	−5.22***
				(−11.85)	(−11.86)
Mom				0.15	0.16
				(1.33)	(1.35)

Table 1.7. Future returns predicted by profitability and investment conditional on investor sentiment

This table provides the future returns predicted by the profitability and investment conditional on investor sentiment. We define a period as a high (low) sentiment period if the sentiment index of Baker and Wurgler (2006) in the previous month is above (below) its median value for the sample period. In June of year *t*, all firms are sorted into 10 portfolios by profitability in Panel A and investment in Panel B using NYSE breakpoints. We obtain the value-weighted monthly returns for these portfolios from July of year *t* to June of year *t* + 1. In Panel A, the long leg is the portfolio of stocks in the highest profitability decile, and the short leg is the portfolio of stocks in the lowest profitability decile. In Panel B, the long leg is the portfolio of stocks in the lowest investment decile, and the short leg is the portfolio of stocks in the highest investment decile. The sample period is January 1974 – December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

	Long leg			Short leg			Long–short		
	High sentiment	Low sentiment	High-Low	High sentiment	Low sentiment	High-Low	High sentiment	Low sentiment	High-Low
Panel A: Profits-to-assets									
Raw return	1.21***	1.11***	0.10	0.57*	1.08***	−0.52	0.64***	0.03	0.61**
	(4.18)	(3.61)	(0.23)	(1.84)	(3.60)	(−1.20)	(3.11)	(0.13)	(2.04)
CAPM α	0.40***	0.02	0.37**	−0.25*	−0.01	−0.24	0.64***	0.03	0.61**
	(2.97)	(0.17)	(1.98)	(−1.75)	(−0.09)	(−1.18)	(3.03)	(0.16)	(2.03)
FF3 α	0.55***	0.08	0.47***	−0.27*	−0.07	−0.20	0.82***	0.15	0.68**
	(4.23)	(0.61)	(2.59)	(−1.94)	(−0.50)	(−1.03)	(3.94)	(0.72)	(2.30)
Panel B: Investment-to-assets									
Raw return	0.71**	1.48***	−0.77	0.44	1.06***	−0.63	0.27	0.41**	−0.14
	(2.02)	(4.28)	(−1.56)	(1.20)	(2.85)	(−1.20)	(1.59)	(2.38)	(−0.59)
CAPM α	−0.18	0.23*	−0.41**	−0.47***	−0.22	−0.25	0.29*	0.45***	−0.16
	(−1.49)	(1.83)	(−2.36)	(−3.22)	(−1.51)	(−1.21)	(1.67)	(2.59)	(−0.66)
FF3 α	−0.12	0.10	−0.22	−0.36**	−0.26*	−0.11	0.24	0.36**	−0.12
	(−1.20)	(1.06)	(−1.61)	(−2.53)	(−1.80)	(−0.53)	(1.42)	(2.11)	(−0.49)

Table 1.8. Time Series Regressions of Portfolio Returns

This table provides the regressions of profitability and investment premia on the lagged sentiment index ($SENTIMENT_{t-1}$) of Baker and Wurgler (2006) and the Fama–French three factors ($MKTRF_t$, SMB_t, HML_t). In Panel A, we long the stocks with profitability in the top NYSE deciles and short the stocks with profitability in the bottom NYSE deciles. In Panel B, we long the stocks with investment in the bottom NYSE deciles and short the stocks with investment in the top NYSE deciles. Average monthly returns are matched to the sentiment index of Baker and Wurgler (2006) from the previous month. The portfolio is rebalanced at the end of each June. The sample period is January 1974 – December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

	Constant	$SENTIMENT_{t-1}$	$MKTRF_t$	SMB_t	HML_t
			Panel A: Profits-to-assets		
(1)	0.43**	0.94***			
	(1.99)	(3.90)			
(2)	0.79***	0.67***	−22.89***	−69.25***	−9.47
	(4.05)	(3.20)	(−5.19)	(−10.70)	(−1.40)
			Panel B: Investment-to-assets		
(1)	0.52***	−0.17			
	(3.86)	(−1.18)			
(2)	0.42***	−0.23*	−9.60***	9.58**	36.49***
	(3.34)	(−1.71)	(−3.36)	(2.28)	(8.35)

Table 1.9. Future returns predicted by profitability and investment conditional on investor sentiment and short-selling activity

This table provides the future returns predicted by the profitability and investment conditional on investor sentiment and short-selling activity. All stocks are sorted by the ratio of profits-to-assets or investment-to-assets. We define a period as a high (low) sentiment period if the sentiment index of Baker and Wurgler (2006) in the previous month is above (below) its median value for the sample period. We define a month as a low (high) SI month if the detrended log of the equal-weighted mean of short interest in the previous month is lower (higher) than the median value for the sample period. We then calculate the value-weighted average portfolio returns over the next 12 months for each portfolio or the difference. In Panel A, the long leg is the portfolio of stocks in the highest profitability decile, and the short leg is the portfolio of stocks in the lowest profitability decile. In Panel B, the long leg is the portfolio of stocks in the lowest investment decile, and the short leg is the portfolio of stocks in the highest investment decile. The sample period is January 1974 – December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

	Long leg			Short leg			Long–short		
	High sentiment	Low sentiment	High-Low	High sentiment	Low sentiment	High-Low	High sentiment	Low sentiment	High-Low
Panel A: Profits-to-assets									
Low SI	1.23***	1.42***	−0.20	0.27	1.40***	−1.13*	0.96***	0.03	0.93**
	(3.00)	(3.82)	(−0.36)	(0.57)	(3.54)	(−1.85)	(3.07)	(0.08)	(2.14)
High SI	0.86**	1.13**	−0.27	0.58	1.06**	−0.48	0.28	0.07	0.21
	(2.28)	(2.18)	(−0.42)	(1.50)	(2.29)	(−0.79)	(1.14)	(0.21)	(0.51)
Panel B: Investment-to-assets									
Low SI	0.52	1.49***	−0.97	0.29	0.98**	−0.68	0.23	0.51**	−0.29
	(0.99)	(3.77)	(−1.47)	(0.58)	(2.31)	(−1.04)	(0.88)	(2.17)	(−0.82)
High SI	0.63	1.75***	−1.11	0.43	1.31**	−0.88	0.20	0.44*	−0.24
	(1.33)	(3.08)	(−1.52)	(0.80)	(2.15)	(−1.09)	(0.84)	(1.75)	(−0.70)

Table 1.10. Benchmark-adjusted profits predicted by profitability and investment conditional on investor sentiment and short-selling activity

This table provides the Fama–French three-factor alphas following high- and low-sentiment periods predicted by the profitability and investment conditional on short-selling activity. All stocks are sorted by the ratio of profits-to-assets or investment-to-assets. We follow Stambaugh, Yu and Yuan (2012) to define a period as a high (low) sentiment period if the sentiment index of Baker and Wurgler (2006) in the previous month is above (below) its median value for the sample period. We define a month as a low (high) SI month if the detrended log of the equal-weighted mean of short interest in the previous month is lower (higher) than the median value for the sample period. The average alphas in high- and low-sentiment periods are estimates of α_H and α_L from the following regression

$$R_{i,t} = \alpha_H D_{H,t-1} + \alpha_L D_{L,t-1} + bMKT_t + cSMB_t + dHML_t + \varepsilon_{i,t},$$

where $R_{i,t}$ is the excess return in month t of each value-weighted portfolio, and $D_{H,t}$ and $D_{L,t}$ are dummy variables indicating high and low levels of investor sentiment. In Panel A, the long leg is the portfolio of stocks in the highest profitability decile, and the short leg is the portfolio of stocks in the lowest profitability decile. In Panel B, the long leg is the portfolio of stocks in the lowest investment decile, and the short leg is the portfolio of stocks in the highest investment decile. The sample period is January 1974 – December 2016. The t-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

	Long leg			Short leg			Long–short		
	High sentiment	Low sentiment	High-Low	High sentiment	Low sentiment	High-Low	High sentiment	Low sentiment	High-Low
Panel A: Profits-to-assets									
Low SI	0.72***	0.30	0.42	−0.55***	0.00	−0.55**	1.27***	0.30	0.98**
	(3.71)	(1.57)	(1.59)	(−2.68)	(0.02)	(−1.97)	(4.10)	(0.97)	(2.30)
High SI	0.34**	0.03	0.31	−0.09	−0.09	0.00	0.42	0.11	0.31
	(1.96)	(0.15)	(1.28)	(−0.43)	(−0.45)	(0.02)	(1.54)	(0.44)	(0.80)
Panel B: Investment-to-assets									
Low SI	−0.18	−0.03	−0.16	−0.53***	−0.53***	0.00	0.34	0.50**	−0.16
	(−1.29)	(−0.19)	(−0.80)	(−2.66)	(−2.73)	(0.01)	(1.36)	(2.05)	(−0.47)
High SI	−0.06	0.28**	−0.34*	−0.15	−0.07	−0.07	0.09	0.35	−0.27
	(−0.45)	(2.03)	(−1.77)	(−0.75)	(−0.37)	(−0.26)	(0.69)	(1.54)	(−0.82)

Table 1.11. Time series regressions of portfolio returns

This table provides the regressions of profitability and investment premia on the lagged sentiment index ($SENTIMENT_{t-1}$) of Baker and Wurgler (2006), the dummy variable ($D_{DSI_{t-1}}$) that equals 1 if the detrended log of the equal-weighted mean of short interest in the previous month is greater than the median value for the sample period, and 0 otherwise, the interaction between the lagged sentiment index ($SENTIMENT_{t-1}$) and the dummy variable ($D_{DSI_{t-1}}$), and the Fama–French three factors ($MKTRF_t$, SMB_t, HML_t). In Panel A, we long the stocks with profitability in the top NYSE deciles and short the stocks with profitability in the bottom NYSE deciles. In Panel B, we long the stocks with investment in the bottom NYSE deciles and short the stocks with investment in the top NYSE deciles. The average monthly returns are matched to the sentiment index of Baker and Wurgler (2006) from the previous month. The portfolio is rebalanced at the end of each June. The sample period is January 1974 – December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

	Constant	$SENTIMENT_{t-1}$	$D_{SI_{t-1}}$	$SENTIMENT_{t-1} * D_{SI_{t-1}}$	$MKTRF_t$	SMB_t	HML_t
Panel A: Profits-to-assets							
(1)	0.31	1.52***	−0.09	−1.24**			
	(0.96)	(4.35)	(−0.21)	(−2.47)			
(2)	0.61**	1.37***	−0.03	−1.48***	−22.94***	−70.40***	−11.69*
	(2.16)	(4.54)	(−0.08)	(−3.39)	(−2.24)	(−10.95)	(−1.74)
Panel B: Investment-to-assets							
(1)	0.61***	−0.09	−0.24	−0.27			
	(3.07)	(−0.44)	(−0.88)	(−0.87)			
(2)	0.50***	−0.22	−0.18	−0.08	−9.63***	9.57**	36.29***
	(2.72)	(−1.17)	(−0.69)	(−0.27)	(−3.37)	(2.28)	(8.26)

Chapter 2. Historical High and the Cross-section of Stock Returns

2.1. Introduction

Anchoring is a cognitive bias owing to which an individual relies on some observable information that might not be relevant in making decisions. In investment, behavioural-biased investors often apply a reference point to evaluate the potential impact of news. For example, Li and Yu (2012) suggest that investors anchor on the historical high and this anchor generates overreactions. They show that the nearness to the Dow historical high is negatively associated with future aggregate-market returns. In this chapter, we re-examine the anchoring effect of the historical high prices. We provide fresh evidence that the nearness to the historical high of the individual stock price has a significant impact on the cross-section of stock returns.

For any piece of information to act as an anchor, it needs to be readily observable. Unlike the 52-week high of stock price, which is regularly published in the financial press, information about an individual stock's historical high was not easy to obtain before financial tools became widely available to individual investors.[1] The rise of technology changed this situation. Bloomberg Terminal hit the market in December 1982. It was allowed to be installed on personal computers circa 1995.[2] E*Trade Securities, Inc., was founded in 1992.[3] Currently, the historical highs of stocks are readily observable from the internet. In Figure 1, we capture the historical price movements for Cisco System, Inc. (CSCO) from *Yahoo! Finance* on 28 June 2019. From the figure, we can easily note that the historical high price is prominent

[1] Li and Yu (2012) argue that the Dow index and its historical high is one of the most prominent pieces of information in the markets.
[2] Merrill Lynch owned 30% of this company in the early years and benefited from an exclusivity agreement that prevented Bloomberg from selling terminals to its major rivals. In the late 1980s, Bloomberg successfully lobbied Merrill Lynch to end this restriction.
[3] E*Trade was one of the first all-electronic brokerages. It began offering online brokerage services to individual investors in 1992.

information in the picture of price movements. As Barber and Odean (2001) stated, 'The Internet also seems likely to change what information investors focus on, because it reduces the cost of some kinds of information more than others'. Although it is difficult to determine precisely when the historical high of an individual stock becomes easily observable as a pricing reference, we following Barber and Odean (2001, 2002) and choose 1990 as the year to divide the sample because investors began to switch from phone-based to personal computer-based trading in the early 1990s.[4]

Indeed, we find no consistent evidence that nearness to historical highs affects the cross-section of stock returns in the sample before 1990, but find strong evidence that stocks far from their historical highs outperform stocks near their historical highs in the sample after 1990. Unlike many other anomalies, the historical high effect does not diminish in the more recent data.[5] A hedging portfolio formed by buying losers with prices far away from the historical highs and selling winners with prices close to their historical highs yields large abnormal returns in the post-1990 sample; it amounts to 0.69% (t-statistic = 2.70) in CAPM risk-adjusted terms per month in the first 12 months. The anomaly return is also very persistent, and it achieves the highest returns in 24 months and lasts at least up to 60 months.

To differentiate the historical high effect from the long-term return reversal, we exclude the stocks in the return reversal winner and loser portfolios from the historical high winner and loser portfolios, respectively. Our evidence suggests that the historical high strategy achieves significantly positive profits only after 1990. Conversely, if we exclude the historical high

[4] Barber and Odean (2001, 2002) also discuss the possibility that the illusion of knowledge makes investors more overconfident, which is consistent with our finding that anchoring on the historical high becomes prominent after the rise of internet technology.

[5] For example, Green, Hand and Soliman (2011) document that the accruals anomaly has decayed in the US stock markets. Ben-Rephael, Kadan and Wohl (2015) suggest that the characteristic liquidity premium has significantly declined over recent decades.

portfolios from the return reversal portfolios, the stocks that have performed poorly achieve significantly higher returns than the stocks that have performed well both before and after 1990. Consequently, the long-term return reversal is unlikely to account for the cross-sectional return – historical high relationship.

Further, we provide evidence that points to behavioural biases as reasons for the historical high effect. We hypothesise that investors anchor on the historical highs and overreact to bad news while stock prices are far below their historical highs. The anchoring effect is more easily triggered when valuation uncertainty is higher and stocks are more difficult to value (Kumar, 2009). When investors trade difficult-to-value stocks with sparse information, they are more likely to exhibit behavioural biases and rely on the historical high prices to make investment decisions. By employing a set of commonly used proxies for valuation uncertainty, we find strong evidence that the historical high strategy works better when stocks are more difficult to value, which is in line with the anchoring effect.

One prediction, if anchoring on the historical high is at least part of the reason of the observed persistent abnormal returns, is that the anchoring effect will be weaker if some of the investors fail to properly adjust for the historical high following stock splits and reverse splits. We find that the return predictability of the historical high declines and the anchoring effect is much weaker when the (reverse) split-adjusted historical high prices differ from the unadjusted historical high prices. Our finding that behavioural biases in stock returns are less severe when investors fail to split-adjust their reference point is consistent with that of Birru (2015). The splits and reverse splits have asymmetric effects on the historical high winner and loser portfolios. We find that the splits mainly affect the winner portfolio. Failure to properly adjust for splits may make an investor mistake a winner stock as a non-winner. Reverse splits mainly affect the loser portfolio. Failure to properly adjust for reverse splits may make an investor

mistake a loser stock as a non-loser. We find that most of the confusion is owing to reverse splits, that is, when the adjusted historical high price is higher than the unadjusted price. In other words, Confusion occurs when the price is further away from the historical high if investors properly adjust for them. This is consistent with our finding that most of the abnormal returns of the historical high hedging portfolio arises from the positive returns of stocks with prices far away from their historical highs.

The empirical results indicate that the greatest profitability of the historical high strategy derives from loser portfolios. If stocks with prices far away from their historical highs are driven by investors' overreaction to bad news, we should expect the subsequent higher returns of historical high losers to be more prominent following a low-sentiment period. However, if the return predictability is caused by risk, we should find no significant effect of investor sentiment on the historical high strategy. We then adopt Baker and Wurgler's (2006, 2007) sentiment index and examine the profitability of the historical high strategy followed by different investor sentiment levels. The evidence that the historical high strategy achieves significantly higher profits following low-sentiment months further confirms the overreaction hypothesis.

Motivated by Li and Yu's (2012) finding that the historical high is less likely to be an anchor when it equals the 52-week high because the 52-week high is psychologically more recent, we examine whether the 52-week high affects the historical high strategy. The double sort analysis shows that the predictability of the historical high is much stronger among the stocks with prices far away from their 52-week highs. We also consider whether the return predictability of the historical high arises from seasonality and tax-loss trading. Our evidence suggests that the historical high strategy obtains significant returns not only in December and January but

also from February to November. This result indicates that the seasonality and tax-loss trading effects cannot fully explain the profitability of the historical high strategy.

Lastly, we extend our exploration of the return predictability of the historical high by examining investors' trading behaviour. Using the individual trading data of Barber and Odean (2000), we show that investors' trading decisions vary with the distance between the current price and the historical high. Specifically, we find that the tendency to hold losers too long and sell winners too soon is much stronger among the stocks with prices far away from the historical highs. Investors' reluctance to realise losses for a historical high loser pushes its price higher. However, their preference to sell a historical high loser with gains makes it difficult for its price to rise immediately, which results in a slow price adjustment. This tendency explains the persistence of the return predictability of the nearness to the historical high.

This chapter contributes to the literature in the following ways. First, we provide evidence that investors use the historical high as a reference point while evaluating information on the broad cross-section of stocks. The cross-sectional analysis complements the time series regression analysis of Li and Yu (2012). Second, our tests reveal that investors' behavioural biases affect investment decisions, which is consistent with the behavioural finance literature.[6] Third, we provide a profitable strategy based on overreaction in the stock market. Unlike other anomalies that diminish in more recent data, the historical high strategy achieves attractive abnormal returns in recent years.

[6] Many studies examine the effects of behavioural biases on the financial markets (see, for example, Barberis and Huang, 2001; Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999).

The remainder of this chapter is organised as follows. In Section 2.2, we review the relevant literature and develop the hypotheses. In Section 2.3, we describe the data and sample sources. In Section 2.4, we present empirical evidence. We conclude in Section 2.5.

2.2. Literature Review and Hypothesis Development

Anchoring is the initial presented value that can be used to make judgements and decisions (Tversky and Kahneman, 1974). A large body of literature provides evidence about the effects of anchoring on the decision-making process. For example, Genesove and Mayer (2001) investigate the behaviour of real estate sellers and find that they are likely to anchor on the historical price and to be averse to realising losses. Chang, Lin, Luo and Ren (2019) propose an anchoring explanation for the ex-day anomaly and find that investors use the cum-day price as an anchor when determining the ex-day prices.

Numerous studies particularly focus on the effects of past price highs in the financial markets. George and Hwang (2004) find that investors use the 52-week high as an anchor against which they evaluate the potential impact of news. They show that the 52-week high is a proxy for the degree to which investors have underreacted to good news. When the stock price is close to the 52-week high, investors are reluctant to bid the price higher, that is, as high as the information implies. The information eventually prevails, and the price moves up, resulting in a subsequent return continuation. Further, Li and Yu (2012) employ the Dow historical high price to construct a novel proxy for market overreaction. They use the Dow index to perform an empirical test and find that the nearness to the historical high is an anchor that can negatively predict future aggregate-market returns. However, they do not find robust evidence that the nearness to the historical high can predict the future individual stock returns.

In the first hypothesis, we posit that overreaction should apply not only to stock indices but also to individual stocks. Griffin and Tversky (1992) show that individuals might underweight

sporadic news but overweight a prolonged record of good or bad performance. Given that a stock price is far away from the historical high likely owing to consistent bad news in the past, investors tend to overreact to bad news. As a result, stocks with prices far away from the historical high should achieve significantly higher returns than those with prices close to the historical high.

Unlike the Dow historical high, the historical high of an individual stock is less observable. Although newspapers such as the *Wall Street Journal* daily publish the 52-week high price of stocks, investors have less ready access to the historical high prices of individual stocks before the emergence of financial tools. Consequently, our second hypothesis is that investors have begun to use the historical high as a reference point at the stock level only in recent decades.

Our third hypothesis is based on Birru's (2015) argument that investors confuse the winner versus loser status of their holdings because they fail to update their reference prices following share splits. In the case of a forward split, investors may confuse a historical high winner for a historical high non-winner. In the case of a reverse split, investors may confuse a historical high loser for a historical high non-loser. By this logic, we hypothesise that the historical high effect should be weaker when the (reverse) split-adjusted historical high prices differ from the unadjusted historical high prices.

Stambaugh, Yu and Yuan (2012) show that because of short-sale impediments and behavioural biases, overpricing is more prevalent when market-wide sentiment is high. However, in this study, we expect that the stocks with prices far away from the historical highs are undervalued owing to the overreaction to bad news. When the market-wide sentiment is low, investors become overly pessimistic and send stock prices to unjustifiably low levels. Hence, our last hypothesis is that the historical high effect is more pronounced following a low-sentiment period.

2.3. Data

Our initial sample includes all common stocks (with share code 10 or 11) listed on the NYSE, AMEX and NASDAQ. The daily and monthly stock returns are obtained from the CRSP, and the financial statement data are obtained from Compustat. We download institutional holding data from 13F filings of Thomson Reuters. The Fama–French five factors (2015) and Carhart momentum factor (1997) are obtained from Kenneth French's website. We obtain the investor sentiment index of Baker and Wurgler (2006, 2007) from Jeffrey Wurgler's website. The individual trader data are the same as those used by Barber and Odean (2000). We incorporate the delisted returns in the CRSP database and exclude micro-cap stocks by deleting observations in the bottom 10% of the market capitalisation distribution to eliminate the survivorship bias and circumvent the concern of the micro-cap effect.[7] We start our cross-sectional analysis with the data for 1990 because investors switched from phone-based to personal computer-based trading in the 1990s and the internet has been providing investors with far more information (Barber and Odean, 2001, 2002).

2.4. Empirical Results

2.4.1. Returns on the historical high portfolios

In this study, we explore the return predictability of the historical high at the stock level. Most traditional media, such as the *Wall Street Journal*, do not provide investors with the historical prices of individual stocks. However, with the emergence of internet-based stock information providers, investors have been able to access this information in recent years. In Figure 2.1, we capture the historical price movement for Cisco System, Inc. (CSCO) from *Yahoo! Finance* on 28 June 2019. From the figure, we observe the price movement and the historical high price

[7] In the unreported analysis, we find that our results are quantitatively similar when we delete observations in the top 10% of the book-to-market distribution or in the top 10% of O-score distribution.

clearly. Thus, it has been natural for the investors to employ the historical high price as an anchor to predict future stock returns in recent decades.

<Insert Figure 2.1 here>

To investigate the return predictability of the nearness to the historical high, we follow previous studies to construct a zero-investment strategy. Beginning from January 1990, at the end of each month, we rank stocks according to the ratio of the current price over the historical high price ($\frac{Current\ price}{Historical\ high}$). For each month, we adjust the historical high price for forward split and reverse split by using the cumulative factor to adjust price (CFACPR) for each stock. Our sample dates back to December 1925, the period when CRSP first began to provide monthly return data. Then, we form an equal-weighted winner portfolio comprising stocks in the top 30%, and a loser portfolio of stocks in the bottom 30%. We expect that stocks with prices far away from the historical high overreact to bad news and that a return reversal will follow. Therefore, we construct a long–short portfolio by *buying the stocks with prices far away from their historical high (losers) and selling the stocks with prices close to their historical high (winners)*. We skip one month to mitigate the possible impact of the bid–ask bounce and other market microstructure effects and then hold the positions from 6 to 60 months to investigate the return predictability of the nearness to the historical high at the stock level. We follow Jegadeesh and Titman (1993) to calculate the equal-weighted portfolio returns by using the overlapping period approach. The results of the monthly average return of the historical high strategy from January 1990 to December 2016 are reported in Panel A of Table 2.1.

<Insert Table 2.1 here>

In Table 2.1 Panel A, we observe that the loser portfolios outperform the winner portfolios, and their differences are economically and statistically significant. These results are consistent with Li and Yu's (2012) findings that the nearness to the historical high negatively predicts

future aggregate-market returns. Specifically, we find that the zero-investment portfolio of the historical high strategy by buying stocks with prices far away from their historical high and selling the stocks with prices close to their historical high earns an average profit of 0.76%, with a *t*-statistic of 2.50 if we hold portfolios for six months. We also calculate the monthly profits with different holding periods. We find that even if we hold the positions for 60 months, the average monthly returns of the historical high strategy are still economically and statistically significant. After incorporating transaction costs, the historical high strategy is preferable because we do not have to rebalance portfolios frequently.

We also calculate the risk-adjusted alphas by regressing the winner and loser portfolio returns on conventional return factors, which includes the market factor (MKTRF), the Fama–French three factors (FF3), Fama–French three factors and Carhart momentum factor (Carhart4), and the Fama–French five factors (FF5). We find that the historical high strategy cannot be fully explained by the conventional return factors, and most of the risk-adjusted profits come from the loser portfolio, which is strong evidence of overreaction to bad news. These results suggest that because of the overreaction effect, stocks with prices far away from the historical highs tend to outperform those with prices close to the historical highs, and the overreaction effect is rather persistent over time. Overall, the evidence provides strong support for our first hypothesis.

We next consider the second hypothesis, which suggests that since the historical high prices of individual stocks are not readily available before 1990, anchoring is not expected to take effect. Unlike the 52-week high, the historical high prices of individual stocks have been less readily accessible to investors before the emergence of internet-based stock information providers in recent decades. As a result, we expect that the return predictability of the historical high before 1990 is much weaker since anchoring on the historical high was difficult. To investigate the differences in anchoring due to the availability of the information regime, we examine the

profitability of the historical high strategy for the period of January 1965 to December 1989. We report the results in Table 2.1 Panel B.

Consistent with our expectation, we find the predictability of the nearness to the historical high prices before 1990 is insignificant. The return difference between the winner and loser groups after adjusting for the conventional risk factors is quantitatively similar. The result that the historical high strategy achieves significant abnormal profits only after 1990 is consistent with the fact that investors have been finding it easier to access the historical prices of the individual stocks in recent years.

Thus far, we have shown that the stocks with prices far away from their historical highs outperform the stocks with prices close to their historical highs. However, it is worth investigating the stock characteristics associated with the ratio of the current stock price to the historical high price. We calculate the average of a variety of stock characteristics for the winner, middle and loser portfolios of the historical high strategy. The results are reported in Table 2.2.

<Insert Table 2.2 here>

Row (1) of Table 2.2 suggests that the average $\frac{Current\ price}{Historical\ high}$ in the loser portfolio is, as expected, significantly lower than that in the winner portfolio by 0.71, and Row (2) suggests that the historical high winners have a higher $\frac{Current\ price}{52-week\ high}$. Row (3) shows that firm size slightly increases with $\frac{Current\ price}{Historical\ high}$, and Row (4) suggests that the book-to-market ratio decreases with $\frac{Current\ price}{Historical\ high}$. Row (5) and Row (6) show that the historical high winners are large and well-established firms with low idiosyncratic volatility, indicating that the zero-cost historical high strategy is less affected by short-sale constraints as we long historical high losers and sell historical high winners. Row (7) shows that the Ohlson (1980) O-score for the historical high

winners is lower than that for the historical high losers. In Row (8), we find that the average distance between the historical high month and the ranking month is 64.13 months for the loser portfolio and 12.68 months for the winner portfolio, suggesting that losers are much further away from the time that the historical high was achieved. Row (9) and Row (10) show the past performance measured at the horizons of past cumulative returns from 12 to two months ($R_{-12,-2}$) and past cumulative returns from 60 to 13 months ($R_{-60,-13}$), respectively. Consistent with our expectation, the stocks with prices far away from the historical high tend to be undervalued.

Next, we conduct additional statistical tests based on the Fama and MacBeth (1973) regressions to investigate whether the return predictability of the historical high is robust after the consideration of additional stock characteristics. Table 2.3 reports the time series averages of the estimated coefficients and their *t*-statistics from the cross-sectional regressions. The dependent variables are the cumulative monthly stock returns for different holding periods. The independent variable of interest is the ratio of the current price to the historical high price (HH). We also follow prior studies to control for the firm size (Log(ME)), book-to-market (BE/ME), share price (PRC), institutional ownership (IO), idiosyncratic volatility (IVOL), firm age (AGE), Ohlson's O (O-score) and past performance measured at the horizons of the past one month returns ($R_{-1,0}$), the past cumulative returns from 12 to two months ($R_{-12,-2}$) and the past cumulative returns from 60 to 13 months ($R_{-60,-13}$) in our analysis.

<Insert Table 2.3 here>

We observe that the coefficients on HH are all significantly negative for the entire 5-year period after the formation and none of the control variables subsumes the significant relationship between HH and the stock returns. These results indicate that the nearness to the historical high contains information on future stock returns that is not captured by other return predictors.

2.4.2. Historical high and return reversal

A large body of literature has shown that the stocks that have performed poorly achieve significantly higher returns than the stocks that have performed well (e.g. see Baytas and Cakici, 1999; De Bondt and Thaler, 1985). Unlike the return reversal that occurs for fixed-period returns and applies equally on past return winners and losers, the historical high effect occurs for variable periods and is mainly concentrated on historical high losers. To address the concern whether the return predictability of the historical high is driven by the long-term return reversal, we exclude the reversal effect from the historical high effect and vice versa. Specifically, we first sort stocks based on the ratio of the current price to the historical high and the cumulative abnormal returns over the past five years.[8] The winner, middle and loser portfolios for the historical high and return reversal portfolios are classified based on a 30%–40%–30% cut-off. We then exclude stocks in the reversal winner portfolio from the historical high winner portfolio and stocks in the reversal loser portfolio from the historical high loser portfolio. The performance of the historical high strategy after the exclusion of return reversal effect is presented in Table 2.4.

<Insert Table 2.4 here>

We observe from Table 2.4 Panel A that the historical high losers achieve significantly higher returns than the historical high winners after 1990. However, in Panel B of Table 2.4, we do not find robust return predictability of the nearness to the historical high at the stock level from 1965 to 1989. These results indicate that the historical high effect is distinguished from the long-term return reversal.

<Insert Table 2.5 here>

[8] To exclude the momentum effect, the return reversal portfolios are classified based on the cumulative abnormal returns from month *t*-60 to month *t*-13. The results are similar if we include the cumulative abnormal returns from month *t*-12 to month *t*-1.

In Table 2.5, we present the profitability of return reversal after excluding the historical high effect. We remove the historical high winners from the return reversal winner portfolio and the historical high losers from the return reversal loser portfolio. Unlike the historical high, which has return predictability only after 1990, return reversal losers achieve significantly higher returns than the return reversal winners in both subperiods. Interestingly, when we compare the results in Table 2.4 and 2.5, we find that the historical high strategy achieves higher monthly profits than the return reversal in the recent subperiod. Overall, the results in Subsection 2.4.2 suggest that the historical high effect is unlikely to be driven by the well-documented long-term return reversal.

2.4.3. Is the historical high effect behavioural?

In this subsection, we investigate whether the return predictability of the historical high is associated with investors' behavioural biases. Specifically, we focus on the effects of valuation uncertainty, share split and investor sentiment on the historical high strategy.

2.4.3.1. Historical high and valuation uncertainty

Previous studies suggest that behavioural biases increase when there is more uncertainty (Daniel, Hirshleifer, and Subrahmanyam, 2001; Hirshleifer, 2001). The anchoring effect is more easily triggered when valuation uncertainty is higher and stocks are more difficult to value (Kumar, 2009). We now use a set of standard proxies for valuation uncertainty to investigate how the historical high strategy varies with the increase in valuation. Our proxies for valuation uncertainty include institutional ownership, share turnover, the number of institutional investors, PPE (property, plant, and equipment), R&D expenses, firm age and idiosyncratic volatility. First, we separate stocks into two groups by a given measure of stock characteristics. We then adopt a 30%–40%–30% cut-off to construct the winner, middle and loser portfolios for the historical high strategy within each group. We hold the positions from

6 months to 60 months and report the Fama–French five-factor alphas in Table 2.6 for the sake of brevity.

<Insert Table 2.6 here>

In Table 2.6 Panel A we show that the profits of the historical high strategy are significantly higher among the stocks with low institutional ownership. For instance, the Fama–French five-factor alpha of the historical high strategy is 1.32% (*t*-statistic = 4.35) in the low institutional ownership group and 0.19% (*t*-statistic = 0.92) in the high institutional ownership group when we hold the position for 6 months. The difference in the risk-adjusted alpha between the high and low institutional ownership groups is 1.13% (*t*-statistic = 6.68), which is significantly different from zero at the 1% level.

In the remaining rows, we repeat our analysis by using other measures of valuation uncertainty. Similar patterns can be observed in the results of alternative proxies. We find that the historical high strategy achieves higher risk-adjusted alphas among the stocks with higher valuation uncertainty. These results provide strong evidence that investors exhibit stronger behavioural biases on the historical highs when it is more difficult to value stocks.

2.4.3.2. Historical high and share split

Birru (2015) documents that investors may fail to properly adjust their reference point following stock splits, confusing the winner versus loser status of their holdings. If investors apply the historical high as an anchor to evaluate the effects of the news, we expect that the share split and limited attention lead to investor confusion regarding the historical high winner versus loser status and affect the return predictability. To directly test whether stock splits affect the historical high effect, we compare the adjusted historical high price with the unadjusted historical high price for each stock and classify the stocks into two groups at the end of each month. One group contains all stocks with the split-adjusted historical highs equal to the

unadjusted historical highs. The other group contains all stocks with the split-adjusted historical highs different from the unadjusted historical highs. We then examine the return predictability of the historical high within each group. Intuitively, if the split-adjusted historical high equals the unadjusted historical high, investors should have no confusion, and such predictability should be stronger. However, if the stock splits make the split-adjusted historical high differ from the unadjusted historical high, investors may confuse a historical high winner (loser) for a historical high non-winner (non-loser), resulting in weaker predictability.

Panel A of Table 2.7 presents the profits of the historical high strategy for the group of stocks with the split-adjusted historical high prices that are the same as the unadjusted historical high prices and Panel B of Table 2.7 presents the strategy profits for the group of stocks with different historical highs. In our sample, approximately 45% of stocks are in the latter group. We find that when the split-adjusted historical high prices are different from the unadjusted historical highs, the return spread between the winner and loser portfolios tend to be much smaller. For example, when we hold the portfolios for 12 months, the historical high strategy achieves raw returns of 1.20% (*t*-statistic = 4.11) among the stocks with same historical highs and 0.68% (*t*-statistic = 2.62) among the stocks with different historical highs. The results are similar for the risk-adjusted profits.

<Insert Table 2.7 Here>

In Table 2.8, we present the results of cross-sectional regressions that include one additional dummy variable (CON), to confirm our findings in the portfolio analysis. HH is the ratio of the current stock price to the historical high price. CON equals 1 if the adjusted historical high price is different from the unadjusted historical high price and 0 otherwise. We interact HH with the dummy variable to examine whether the confusion caused by share splits affects the return predictability after the controlling of firm characteristics.

<Insert Table 2.8 Here>

The regressions show that the predictability of the ratio of the current price to the historical high is significantly lower among the stocks with different historical highs. For example, the coefficients on HH and HH×CON for the 6-month holding period are −0.03 (*t*-statistic = −2.62) and 0.02 (*t*-statistic = 2.22), respectively. The results remain similar when we increase the holding horizon to five years. These findings further support that investors fail to adjust their reference point properly following stock splits. Overall, the results in Table 2.7 and Table 2.8 provide strong support for the third hypothesis.

These empirical results are consistent with Birru's (2015) finding that investors may determine gains or losses based on a comparison of the current price with an unadjusted reference price. However, the effects of forward and reverse splits on the winner and loser statuses of the stock are different. A forward split often makes investors confuse a winner for a non-winner, whereas a reverse split often makes them confuse a loser for a non-loser. For example, suppose an investor holds a stock with a current price of US$10 and a historical high price of US$15, which undergoes a 5:4 split. In this case, the winner/loser status of the historical high strategy should be determined by US$12 rather than US$15. If the investor fails to consider the forward split, she may view a winner stock with the current price to historical high price ratio of 2:3 as a non-winner stock with a wrong ratio of 8:15. By contrast, investors may confuse a loser for a non-loser in the case of a reverse split. To develop a better understanding of the split effects, we separate our sample into winner and loser portfolios and examine their performance with and without the split effects respectively.

<Insert Table 2.9 Here>

The results in Table 2.9 show that the effects of forward and reverse splits are asymmetric. If the difference in the split-adjusted historical high and the unadjusted historical high is due to a forward (reverse) split, we should expect a lower (higher) split-adjusted historical high. Panel A of Table 2.9 shows the effect of a forward spit on the winner portfolio. We classify the stocks in the winner portfolio into two categories, the stocks with the adjusted historical highs equal to the unadjusted historical high (Same) and the stocks with adjusted historical highs lower than the unadjusted historical high (Adj < Raw), and then examine their performance from 6 months to 60 months. We find no significant difference in the return performance for these two categories. In Table 2.9 Panel B, we examine the effect of a reverse split on the historical high losers. Consistent with our expectation, we find that the historical high losers achieve significantly higher returns for the stocks with the same historical high prices.

This evidence suggests that investors may not properly account for changes in their reference point arising from share splits, which is in line with the growing literature on the limited attention of investors.

2.4.3.3. Historical high and investor sentiment

We now consider the fourth hypothesis, which predicts that the historical high effect is more prominent following low sentiment than following high sentiment. Stambaugh, Yu and Yuan (2012) examine the relationship between investor sentiment and a broad set of anomalies in cross-sectional stock returns. They show that because of the short-sale constraints, overpricing is more difficult to eliminate and share prices reflect the valuation of investors who are too optimistic. As a result, the profitability of the long–short strategies tends to be greater following periods of high investor sentiment because of the short-sale impediments. Unlike most of the anomalies in Stambaugh, Yu and Yuan (2012) that are driven by the sentiment-related overpricing, most abnormal returns of the historical high hedging portfolio are from the

positive returns of historical high losers. If the return prediction is from the overreaction to bad news following pessimistic investor sentiment, we should expect the subsequent higher returns of historical high losers to be more prominent following low-sentiment periods. However, if the historical high losers are risker than the historical high winners, we should find no effect of investor sentiment on the historical high strategy.

To investigate whether the level of investor sentiment affects the profitability of the historical high strategy, we follow Stambaugh, Yu and Yuan (2012) to calculate the average returns following high and low levels of investor sentiment. We adopt Baker and Wurgler's (2006, 2007) sentiment index to identify whether the ranking month *t* is optimistic or pessimistic and construct the historical high strategy. We define the ranking month as an optimistic (pessimistic) month if the sentiment in month *t* is above (below) the median value of the time series sentiment index. We calculate the monthly profits of the historical high strategy following high- and low-sentiment periods and report the results in Table 2.10.

<Insert Table 2.10 here>

We observe from Table 2.10 Panel A that the historical high strategy works well following low-sentiment periods. For example, this strategy achieves a monthly average return of 1.47% (*t*-statistic = 3.54) after a low-sentiment month if we hold the positions for six months. In Panel B of Table 2.10, we show the average returns of the historical high strategy following high-sentiment (optimistic) months. We observe that contrary to the results in Table 2.10 Panel A, the historical high losers slightly outperform the historical high winners following optimistic months. Further, the results of the risk-adjusted alphas are qualitatively unchanged. These results are consistent with our prior findings that the profits of the stocks with prices far away from the historical highs are driven by the overreaction effect.

2.4.4. Robustness checks

2.4.4.1. Historical high and 52-week high

The results in Table 2.1 Panel A show that the difference in risk-adjusted alphas between the winner and loser portfolios are insignificantly different from zero if we hold the positions for six months. This can be partially explained by the 52-week high effect identified by George and Hwang (2004), who argue that the stocks with prices close to their 52-week high tend to outperform those with prices far below their 52-week high in the subsequent short-term period. Because the stocks in the winner portfolio of the historical high strategy are likely to be the winner portfolio classified by the 52-week high criterion and these two anchors have opposite directions for the return prediction, the historical high strategy works relatively worse if we hold the zero-cost portfolio for six months after the ranking period. [9]

In this subsection, we explore whether the nearness to the 52-week high affects the return predictability of the historical high in the cross-section. We expect that a conditional historical high strategy for the stocks with prices far away from the 52-week highs achieves higher profits since the 52-week high is less likely to be an anchor among those stocks. Specifically, first we sort stocks into two groups by the ratio of their current price to their 52-week high and then bin them based on the ratio of their current price to their historical high with a 30%–40%–30% cut-off. We calculate the portfolio returns of such a conditional historical high strategy in 6 months to 60 months and report the results in Table 2.11.

<Insert Table 2.11 here>

We observe that the historical high strategy achieves much higher profits among the loser portfolios classified by the 52-week high criterion. For instance, if we hold the positions for

[9] In the unreported analysis, we find that the return predictability of the 52-week high is weaker in recent years.

six months, the historical high strategy generates monthly returns of 1.48% (*t*-statistic = 4.18) in the 52-week high losers and 0.41% (*t*-statistic = 3.03) in the 52-week high winners, respectively. These results suggest that the nearness to the historical high should have a much stronger predictive power among the stocks far away from their 52-week high, which is consistent with Li and Yu (2012) that the historical high anchor has an opposite effect to that of the 52-week high anchor.

We also report the risk-adjusted alphas by regressing the portfolio returns on conventional risk factors. We discover that the risk-adjusted profits of the historical high strategy are qualitatively unchanged. The historical high strategy achieves the highest risk-adjusted alphas within the loser portfolio classified by the 52-week high.

2.4.4.2. Seasonality patterns and tax-loss trading

We now analyse the effects of seasonality and tax-loss trading on the historical high strategy. Many studies show that the seasonal patterns and tax-loss trading significantly affect the cross-section of stock returns. Dyl (1977) posits that investors sell their losing stocks in late December to obtain tax savings and restore their position by purchasing the losing stocks in January. As a result, the losing stocks underperform in December and outperform in January. Similarly, Grinblatt and Moskowitz (2004) show that returns are strongly negative in December for losing firms. Thus, we are concerned whether the profitability of the historical high strategy is entirely attributable to the seasonality effect associated with tax-loss trading. To address this concern, we examine the profits of the historical high strategy in and out of December and January in this subsection. We report the results in Table 2.12.

<Insert Table 2.12 here>

Table 2.12 Panel A shows the average portfolio profits of the historical high strategy in December and January, and Table 2.12 Panel B presents the average portfolio returns from

February to November. Although the historical high strategy seems overwhelmingly successful in December and January, we can still achieve substantial positive profits by utilising the historical high strategy from February to November. The risk-adjusted alphas are also economically and statistically significant. These results indicate that the profitability of the historical high strategy is not fully attributable to the seasonality effect and tax-loss trading.

2.4.5. Why is the historical high effect so persistent?

Odean (1998) tests the disposition effect and finds that investors realise their gain more readily than their losses. If they use the historical high as a reference point, they might become more reluctant to realise their losses when the stock prices are far below the historical highs, since they may believe that the prices will eventually rise. However, investors become more risk-averse in the gain frame. Consequently, they are more likely to sell their winners when the stock prices are far away from the historical highs. To examine whether individual investors exhibit behavioural biases when stock prices are far away from the historical highs, we follow Odean (1998) to calculate the proportion of gains realised (PGR) and the proportion of losses realised (PLR) for the historical high winner and loser portfolios. The PGR is the number of realised gains divided by the number of realised gains plus the number of unrealised gains. The PLR is the number of realised losses divided by the number of realised losses plus the number of unrealised losses. The results are reported in Table 2.13.

<Insert Table 2.13 here>

In Table 2.13, we find that investors sell a significantly higher proportion of their gains than of their losses for historical high winners as well as losers, which is consistent with Odean's (1998) assertion that investors exhibit a significant preference for selling winners and holding losers. Moreover, our evidence further shows that individual investors are less likely to realise their losses and more likely to sell their gains among the historical high losers, suggesting that the

historical high is an important reference point for trading behaviour. Investors' reluctance to realise the losses for the historical high losers indicates that they apply the historical high as a reference to make investment decisions and further push the prices of the historical high losers to be higher. However, their tendency to sell the historical high losers with gains makes it difficult for the prices of the historical high losers to rise immediately, resulting in long-term predictability.

2.5. Conclusion

In this chapter, we show that investors use the historical high as a reference point while evaluating information in the broad cross-section of stocks. The nearness to the historical high captures the extent of overreaction. We find that a historical high strategy by buying stocks with prices far away from their historical highs and selling stocks with prices approaching their historical highs achieves long-run positive returns. We also find that the historical high effect is robust to the fixed-period return reversal.

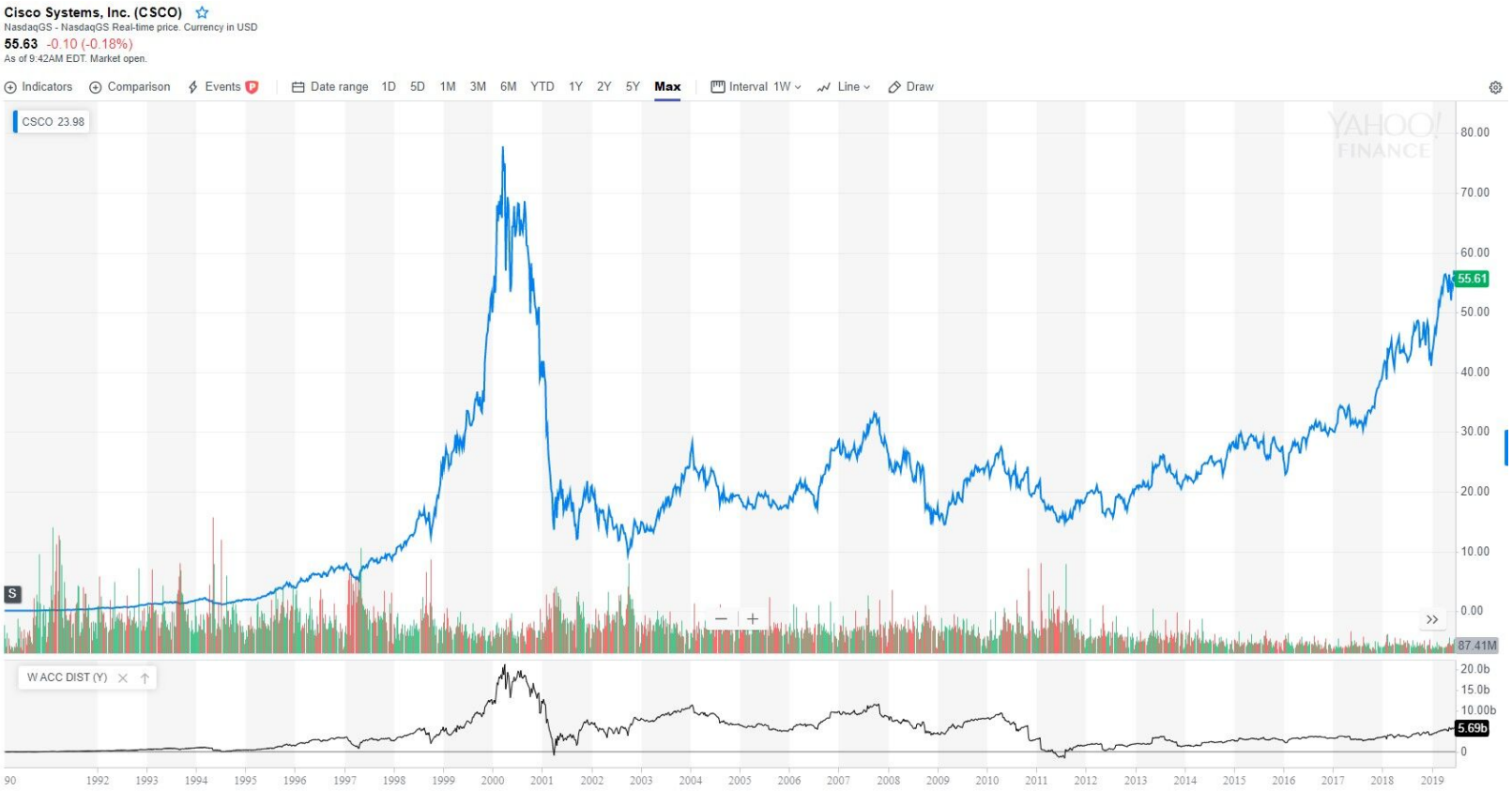
We offer evidence that the historical high effect is associated with behavioural biases. First, we find strong evidence that the historical high strategy works better among stocks with higher valuation uncertainty, which is in line with the anchoring explanation. Second, we show that the confusion caused by share splits makes the historical high effect much weaker, indicating that share splits and limited attention affect investors' anchoring biases. Last, the evidence that the historical high strategy achieves significantly higher returns following low-sentiment periods confirms that our findings are primarily driven by the overreaction effect. These results have important implications for the literature on the impact of behavioural biases on asset pricing.

The robustness test results indicate that the return predictability of the historical high is opposite to the effect of 52-week high and such profitability cannot be fully explained by the seasonality effect. Besides, we show that the disposition effect explains the return persistence.

Figures and Tables

Figure 2.1. Historical price movement

This figure shows the historical price movements for Cisco System, Inc. (CSCO). The chart is captured from *Yahoo! Finance* on 28 June 2019.



Source: Yahoo! Finance

Table 2.1. Monthly portfolio returns of historical high strategy

This table presents the monthly profits for the historical high strategy. We adopt a 30%–40%–30% cut-off to construct the winner, middle and loser portfolios. Firms in the bottom 10% of the market capitalisation distribution are excluded. We skip one month between the ranking and holding periods and hold the portfolios from 6 months to 60 months. We report the monthly average returns of the zero-cost portfolios in this table. The monthly sample period is January 1990 to December 2016 in Panel A and January 1965 to December 1989 in Panel B. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

Holding period		6 months	12 months	24 months	36 months	48 months	60 months
Panel A: From January 1990 to December 2016							
Raw return	Winner	1.16	1.09	1.06	1.08	1.12	1.14
	Loser	1.92	2.06	2.17	2.16	2.12	2.10
	Winner−Loser	−0.76**	−0.97***	−1.11***	−1.08***	−1.00***	−0.96***
		(−2.50)	(−3.54)	(−4.38)	(−4.52)	(−4.50)	(−4.56)
CAPM α	Winner	0.36	0.28	0.24	0.26	0.30	0.32
	Loser	0.81	0.97	1.10	1.10	1.08	1.06
	Winner−Loser	−0.45	−0.69***	−0.86***	−0.84***	−0.78***	−0.74***
		(−1.57)	(−2.70)	(−3.62)	(−3.77)	(−3.75)	(−3.81)
FF3 α	Winner	0.30	0.21	0.15	0.15	0.17	0.18
	Loser	0.68	0.83	0.97	0.98	0.96	0.95
	Winner−Loser	−0.38	−0.62***	−0.82***	−0.83***	−0.79***	−0.77***
		(−1.46)	(−2.74)	(−4.10)	(−4.61)	(−4.78)	(−4.96)
Carhart4 α	Winner	0.21	0.20	0.22	0.24	0.27	0.28
	Loser	1.13	1.21	1.26	1.24	1.22	1.19
	Winner−Loser	−0.92***	−1.01***	−1.05***	−1.00***	−0.94***	−0.91***
		(−4.57)	(−5.17)	(−5.51)	(−5.68)	(−5.83)	(−6.04)
FF5 α	Winner	0.24	0.19	0.13	0.12	0.13	0.14
	Loser	1.06	1.16	1.26	1.25	1.21	1.18
	Winner−Loser	−0.82***	−0.98***	−1.13***	−1.14***	−1.09***	−1.04***
		(−3.27)	(−4.58)	(−6.23)	(−6.93)	(−7.17)	(−7.37)
Panel B: From January 1965 to December 1989							
Raw return	Winner	1.48	1.40	1.29	1.27	1.25	1.24
	Loser	1.40	1.51	1.62	1.64	1.65	1.66
	Winner−Loser	0.09	−0.12	−0.33*	−0.37**	−0.40***	−0.42***
		(0.41)	(−0.61)	(−1.94)	(−2.45)	(−2.87)	(−3.18)
CAPM α	Winner	0.53	0.44	0.33	0.31	0.29	0.28
	Loser	0.36	0.48	0.59	0.61	0.63	0.63
	Winner−Loser	0.17	−0.04	−0.26	−0.30**	−0.34**	−0.35***
		(0.88)	(−0.19)	(−1.59)	(−2.12)	(−2.56)	(−2.88)
FF3 α	Winner	0.40	0.32	0.19	0.14	0.10	0.08
	Loser	−0.23	−0.10	0.02	0.06	0.09	0.11
	Winner−Loser	0.63***	0.42***	0.17	0.08	0.01	−0.03
		(4.18)	(3.17)	(1.51)	(0.81)	(0.14)	(−0.40)
Carhart4 α	Winner	0.22	0.22	0.18	0.18	0.16	0.16
	Loser	0.04	0.11	0.17	0.19	0.20	0.20
	Winner−Loser	0.18	0.11	0.01	−0.01	−0.03	−0.04
		(1.48)	(0.88)	(0.07)	(−0.12)	(−0.39)	(−0.51)
FF5 α	Winner	0.38	0.30	0.20	0.17	0.14	0.11
	Loser	−0.11	−0.00	0.09	0.11	0.12	0.13
	Winner−Loser	0.49***	0.30**	0.11	0.06	0.02	−0.02
		(3.05)	(2.17)	(0.91)	(0.62)	(0.25)	(−0.19)

Table 2.2. Historical high and stock characteristics

This table presents the average stock characteristics of portfolios sorted by the ratio of the current stock price to their historical high price. We adopt a 30%–40%–30% cut-off to construct the winner, middle and loser portfolios. Firms in the bottom 10% of the market capitalisation distribution are excluded. We examine the ratio of the current price to the highest price achieved with in the past 12 months ($\frac{Current\ price}{52-week\ high}$), firm size (Log(ME)), book-to-market (BE/ME), idiosyncratic volatility (IVOL), firm age (AGE), Ohlson's O (O-score), the average distance between the current month and the month with the historical high achieved (Distance), past performance measured at horizons of past cumulative returns from 12 to two months ($R_{-12,-2}$) and past cumulative returns from 60 to 13 months ($R_{-60,-13}$) across the portfolios. The sample is from January 1990 to December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

	Winner	Middle	Loser	Winner−Loser
(1) $\frac{Current\ price}{Historical\ high}$	0.89	0.58	0.18	0.71***
				(133.38)
(2) $\frac{Current\ price}{52-week\ high}$	0.88	0.77	0.65	0.23***
				(32.79)
(3) Log(ME)	13.97	12.99	11.67	2.30***
				(36.73)
(4) BE/ME	0.65	0.77	0.96	−0.32***
				(−16.20)
(5) IVOL	0.02	0.02	0.04	−0.02***
				(−29.66)
(6) AGE	23.70	21.02	16.88	−6.82***
				(−34.73)
(7) O-score	−1.08	−0.73	−0.71	−0.37***
				(−4.97)
(8) Distance	12.68	40.80	64.13	51.45***
				(557.96)
(9) $R_{-12,-2}$	0.32	0.15	0.04	0.28***
				(14.38)
(10) $R_{-60,-13}$	1.16	0.94	0.31	0.84***
				(21.27)

Table 2.3. Historical high in Fama–MacBeth regression

This table shows the results from Fama–MacBeth regressions of returns on the ratio of the current price to the historical high price. Firms in the bottom 10% of the market capitalisation distribution are excluded. HH is ratio of the current price to the historical high price. We include firm size (Log(ME)), book-to-market (BE/ME), share price (PRC), institutional ownership (IO), idiosyncratic volatility (IVOL), firm age (AGE), Ohlson's O (O-score) and past performance measured at horizons of past one month returns ($R_{-1,0}$), past cumulative returns from 12 to two months ($R_{-12,-2}$) and past cumulative returns from 60 to 13 months ($R_{-60,-13}$) as control variables. The monthly sample period is January 1990 to December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

Explanatory variable	Regression					
	6 months	12 months	24 months	36 months	48 months	60 months
Constant	0.17***	0.31***	0.59***	0.90***	1.72***	1.50***
	(9.18)	(9.88)	(11.27)	(10.54)	(9.62)	(9.04)
HH	−0.02**	−0.05***	−0.12***	−0.21***	−0.33***	−0.50***
	(−2.32)	(−3.83)	(−6.67)	(−11.23)	(−13.44)	(−14.56)
Log(ME)	−0.01***	−0.01***	−0.01***	−0.02***	−0.02***	−0.02***
	(−6.33)	(−6.24)	(−5.62)	(−4.68)	(−3.32)	(−2.60)
BE/ME	0.01***	0.01***	0.04***	0.07***	0.10***	0.14***
	(3.04)	(4.53)	(8.15)	(9.10)	(10.76)	(12.22)
PRC	0.00**	0.00***	0.00***	−0.00	−0.00	−0.00
	(2.45)	(2.60)	(2.85)	(−1.24)	(−1.58)	(−1.38)
IO	0.02***	0.02***	0.05***	0.09***	0.12***	0.18***
	(4.98)	(4.22)	(6.69)	(9.30)	(9.94)	(10.88)
IVOL	0.21	0.96***	2.19***	3.21***	3.93***	5.39***
	(1.50)	(4.31)	(6.69)	(8.26)	(9.03)	(9.34)
AGE (%)	−0.01**	−0.03***	−0.09***	−0.16***	−0.26***	−0.41***
	(−1.98)	(−3.45)	(−5.94)	(−7.17)	(−7.32)	(−7.77)
O-score (%)	0.00	0.11***	0.26***	0.35***	0.33***	0.56***
	(0.33)	(4.53)	(6.90)	(7.48)	(4.54)	(6.25)
$R_{-1,0}$	0.02**	0.03*	−0.02	−0.08***	−0.11***	−0.08
	(2.33)	(1.82)	(−0.68)	(−2.59)	(−2.65)	(−1.31)
$R_{-12,-2}$	−0.01*	−0.03***	−0.09***	−0.11***	−0.15***	−0.16***
	(−1.74)	(−4.26)	(−7.34)	(−8.01)	(−8.42)	(−5.74)
$R_{-60,-13}$	−0.00***	−0.01***	−0.01***	−0.02***	−0.02***	−0.02***
	(−6.53)	(−7.36)	(−6.58)	(−8.02)	(−5.99)	(−4.75)

Table 2.4. Historical high excluding return reversal

This table presents the monthly profits for the historical high strategy after the controlling of return reversal. We adopt a 30%–40%–30% cut-off to construct the winner, middle and loser portfolios. We exclude stocks in the reversal winner portfolio from the historical high winner portfolio and stocks in the reversal loser portfolio from the historical high loser portfolio. Firms in the bottom 10% of the market capitalisation distribution are excluded. We skip one month between the ranking and holding periods and hold the portfolios from 6 months to 60 months. We report the monthly average returns of the zero-cost portfolios in this table. The monthly sample period is January 1990 to December 2016 in Panel A and January 1965 to December 1989 in Panel B. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

Holding period		6 months	12 months	24 months	36 months	48 months	60 months
Panel A: From January 1990 to December 2016							
Raw return	Winner	1.17	1.10	1.07	1.10	1.14	1.17
	Loser	1.82	1.99	2.16	2.16	2.13	2.10
	Winner−Loser	−0.65**	−0.89***	−1.09***	−1.06***	−0.98***	−0.94***
		(−2.06)	(−3.20)	(−4.27)	(−4.44)	(−4.37)	(−4.42)
CAPM α	Winner	0.38	0.30	0.25	0.28	0.32	0.35
	Loser	0.70	0.90	1.09	1.10	1.08	1.07
	Winner−Loser	−0.32	−0.60**	−0.83***	−0.82***	−0.75***	−0.72***
		(−1.09)	(−2.33)	(−3.50)	(−3.68)	(−3.60)	(−3.65)
FF3 α	Winner	0.32	0.23	0.16	0.17	0.20	0.21
	Loser	0.61	0.80	0.99	1.01	0.99	0.98
	Winner−Loser	−0.30	−0.57**	−0.82***	−0.84***	−0.79***	−0.77***
		(−1.07)	(−2.39)	(−3.99)	(−4.57)	(−4.68)	(−4.87)
Carhart4 α	Winner	0.23	0.22	0.23	0.27	0.30	0.32
	Loser	1.11	1.21	1.30	1.28	1.25	1.24
	Winner−Loser	−0.89***	−0.99***	−1.07***	−1.02***	−0.95***	−0.92***
		(−4.32)	(−4.99)	(−5.49)	(−5.68)	(−5.82)	(−6.05)
FF5 α	Winner	0.28	0.23	0.17	0.16	0.17	0.18
	Loser	1.06	1.18	1.31	1.32	1.27	1.24
	Winner−Loser	−0.78***	−0.95***	−1.15***	−1.16***	−1.10***	−1.06***
		(−2.91)	(−4.20)	(−6.10)	(−6.95)	(−7.19)	(−7.44)
Panel B: From January 1965 to December 1989							
Raw return	Winner	1.50	1.41	1.31	1.30	1.29	1.27
	Loser	1.35	1.48	1.61	1.64	1.65	1.66
	Winner−Loser	0.15	−0.07	−0.29*	−0.34**	−0.37***	−0.39***
		(0.73)	(−0.36)	(−1.80)	(−2.33)	(−2.77)	(−3.10)
CAPM α	Winner	0.56	0.46	0.36	0.34	0.33	0.32
	Loser	0.32	0.45	0.58	0.61	0.63	0.64
	Winner−Loser	0.24	0.02	−0.22	−0.27**	−0.30**	−0.32***
		(1.26)	(0.09)	(−1.43)	(−1.98)	(−2.43)	(−2.79)
FF3 α	Winner	0.41	0.32	0.19	0.15	0.12	0.09
	Loser	−0.24	−0.11	0.03	0.08	0.10	0.12
	Winner−Loser	0.64***	0.42***	0.16	0.07	0.01	−0.03
		(4.25)	(3.18)	(1.44)	(0.79)	(0.16)	(−0.38)
Carhart4 α	Winner	0.22	0.21	0.18	0.18	0.17	0.16
	Loser	0.04	0.12	0.20	0.21	0.22	0.22
	Winner−Loser	0.18	0.09	−0.02	−0.03	−0.05	−0.06
		(1.46)	(0.73)	(−0.19)	(−0.35)	(−0.63)	(−0.77)
FF5 α	Winner	0.38	0.30	0.20	0.18	0.15	0.13
	Loser	−0.10	0.01	0.13	0.14	0.15	0.15
	Winner−Loser	0.47***	0.28**	0.07	0.04	0.01	−0.03
		(2.98)	(2.00)	(0.63)	(0.37)	(0.07)	(−0.32)

Table 2.5. Return reversal excluding historical high

This table presents the monthly profits for the return reversal strategy after the controlling of the historical high. We adopt a 30%–40%–30% cut-off to construct the winner, middle and loser portfolios. We exclude stocks in the historical high winner portfolio from the reversal winner portfolio and stocks in the historical high loser portfolio from the reversal loser portfolio. Firms in the bottom 10% of the market capitalisation distribution are excluded. We skip one month between the ranking and holding periods and hold the portfolios from 6 months to 60 months. We report the monthly average returns of the zero-cost portfolios in this table. The monthly sample period is January 1990 to December 2016 in Panel A and January 1965 to December 1989 in Panel B. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

Holding period		6 months	12 months	24 months	36 months	48 months	60 months
Panel A: From January 1990 to December 2016							
Raw return	Winner	1.00	1.08	1.24	1.28	1.31	1.33
	Loser	1.92	1.77	1.67	1.65	1.64	1.63
	Winner−Loser	−0.92***	−0.69***	−0.43***	−0.36***	−0.36***	−0.30***
		(−5.65)	(−4.84)	(−3.78)	(−4.10)	(−4.26)	(−4.27)
CAPM α	Winner	−0.01	0.08	0.26	0.32	0.34	0.37
	Loser	1.01	0.87	0.77	0.75	0.75	0.74
	Winner−Loser	−1.03***	−0.79***	−0.51***	−0.44***	−0.41***	−0.37***
		(−6.50)	(−5.63)	(−4.61)	(−5.08)	(−5.41)	(−5.45)
FF3 α	Winner	−0.13	−0.05	0.12	0.18	0.21	0.23
	Loser	0.86	0.71	0.60	0.57	0.57	0.55
	Winner−Loser	−0.99***	−0.77***	−0.48***	−0.40***	−0.36***	−0.32***
		(−6.31)	(−5.49)	(−4.34)	(−4.70)	(−4.99)	(−5.02)
Carhart4 α	Winner	0.20	0.24	0.35	0.38	0.40	0.43
	Loser	0.90	0.79	0.71	0.70	0.69	0.67
	Winner−Loser	−0.70***	−0.54***	−0.37***	−0.33***	−0.29***	−0.25***
		(−5.42)	(−4.44)	(−3.43)	(−3.93)	(−4.17)	(−4.12)
FF5 α	Winner	−0.08	−0.01	0.13	0.20	0.24	0.27
	Loser	0.90	0.77	0.64	0.58	0.55	0.52
	Winner−Loser	−0.98***	−0.78***	−0.50***	−0.38***	−0.31***	−0.25***
		(−5.98)	(−5.31)	(−4.40)	(−4.41)	(−4.29)	(−4.03)
Panel B: From January 1965 to December 1989							
Raw return	Winner	0.92	0.89	0.94	0.99	1.04	1.08
	Loser	1.84	1.70	1.58	1.54	1.49	1.47
	Winner−Loser	−0.92***	−0.81***	−0.64***	−0.55***	−0.46***	−0.39***
		(−5.97)	(−5.63)	(−4.98)	(−4.92)	(−4.50)	(−4.41)
CAPM α	Winner	−0.10	−0.12	−0.07	−0.02	0.03	0.08
	Loser	0.87	0.73	0.60	0.57	0.52	0.50
	Winner−Loser	−0.97***	−0.86***	−0.67***	−0.58***	−0.49***	−0.42***
		(−6.49)	(−6.08)	(−5.32)	(−5.32)	(−4.93)	(−4.87)
FF3 α	Winner	−0.34	−0.37	−0.34	−0.31	−0.28	−0.25
	Loser	0.53	0.42	0.30	0.26	0.20	0.18
	Winner−Loser	−0.87***	−0.79***	−0.64***	−0.56***	−0.48***	−0.42***
		(−5.75)	(−5.55)	(−4.99)	(−5.08)	(−4.83)	(−4.91)
Carhart4 α	Winner	−0.11	−0.15	−0.12	−0.10	−0.08	−0.06
	Loser	0.49	0.39	0.30	0.28	0.21	0.19
	Winner−Loser	−0.60***	−0.54***	−0.43***	−0.38***	−0.29***	−0.25***
		(−4.11)	(−3.94)	(−3.41)	(−3.48)	(−3.07)	(−3.10)
FF5 α	Winner	−0.16	−0.20	−0.18	−0.17	−0.17	−0.17
	Loser	0.53	0.43	0.28	0.23	0.18	0.17
	Winner−Loser	−0.69***	−0.63***	−0.46***	−0.41***	−0.35***	−0.34***
		(−4.32)	(−4.20)	(−3.42)	(−3.52)	(−3.43)	(−3.79)

Table 2.6. Profits of historical high strategy conditional on stock characteristics

This table presents the Fama–French five-factor alphas of the historical high strategy conditional on stock characteristics. We first separate stocks into two groups by a given measure of stock characteristics. The variables are defined in the Appendix. We then adopt a 30%–40%–30% cut-off to construct the winner, middle and loser portfolios for the historical high strategy within each group. Firms in the bottom 10% of the market capitalisation distribution are excluded. We buy winners and sell losers to construct a zero-cost portfolio. We skip one month between the ranking and holding periods and hold the portfolios from 6 months to 60 months. The monthly sample period is January 1990 to December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

	6 months	12 months	24 months	36 months	48 months	60 months
Panel A: Grouped by institutional ownership						
Low	−1.32***	−1.47***	−1.58***	−1.55***	−1.46***	−1.39***
	(−4.35)	(−5.54)	(−6.76)	(−7.12)	(−7.20)	(−7.29)
High	−0.19	−0.35**	−0.55***	−0.61***	−0.60***	−0.60***
	(−0.92)	(−2.03)	(−4.03)	(−5.28)	(−5.79)	(−6.10)
Difference	−1.13***	−1.12***	−1.03***	−0.94***	−0.86***	−0.80***
	(−6.68)	(−7.25)	(−7.21)	(−6.91)	(−6.69)	(−6.55)
Panel B: Grouped by share turnover						
Low	−1.19***	−1.30***	−1.36***	−1.32***	−1.25***	−1.20***
	(−5.31)	(−6.43)	(−7.46)	(−7.76)	(−7.85)	(−7.93)
High	−0.46	−0.66***	−0.88***	−0.91***	−0.88***	−0.86***
	(−1.53)	(−2.65)	(−4.44)	(−5.30)	(−5.68)	(−6.00)
Difference	−0.73***	−0.64***	−0.48***	−0.41***	−0.37***	−0.34***
	(−3.82)	(−3.94)	(−3.73)	(−3.67)	(−3.65)	(−3.59)
Panel C: Grouped by number of institutional investors						
Low	−1.38***	−1.53***	−1.63***	−1.59***	−1.49***	−1.41***
	(−4.85)	(−6.14)	(−7.33)	(−7.67)	(−7.67)	(−7.77)
High	−0.12	−0.26	−0.46***	−0.53***	−0.53***	−0.53***
	(−0.51)	(−1.33)	(−3.01)	(−4.09)	(−4.59)	(−4.86)
Difference	−1.25***	−1.27***	−1.17***	−1.06***	−0.95***	−0.88***
	(−7.75)	(−8.35)	(−8.44)	(−8.40)	(−8.09)	(−8.03)
Panel D: Grouped by PPE (property, plant and equipment)						
Low	−0.84***	−1.06***	−1.20***	−1.19***	−1.13***	−1.07***
	(−3.11)	(−4.56)	(−6.12)	(−6.68)	(−6.80)	(−6.92)
High	−0.87***	−0.97***	−1.03***	−1.01***	−0.96***	−0.91***
	(−3.85)	(−4.87)	(−5.87)	(−6.30)	(−6.42)	(−6.46)
Difference	0.03	−0.09	−0.18*	−0.18*	−0.17*	−0.16*
	(0.18)	(−0.72)	(−1.67)	(−1.85)	(−1.78)	(−1.72)
Panel E: Grouped by R&D expenses						
High	−1.41***	−1.51***	−1.46***	−1.38***	−1.25***	−1.18***
	(−4.53)	(−5.42)	(−5.86)	(−6.01)	(−5.77)	(−5.80)
Low	−0.52**	−0.72***	−0.85***	−0.83***	−0.79***	−0.76***
	(−2.27)	(−3.54)	(−4.98)	(−5.46)	(−5.66)	(−5.81)
Difference	−0.89***	−0.79***	−0.61***	−0.56***	−0.46***	−0.43***
	(−4.33)	(−4.27)	(−3.57)	(−3.43)	(−2.95)	(−2.82)
Panel F: Grouped by firm age						
Low	−0.85***	−1.09***	−1.35***	−1.36***	−1.28***	−1.22***
	(−2.78)	(−4.21)	(−6.30)	(−7.15)	(−7.43)	(−7.71)
High	−0.73***	−0.85***	−0.95***	−0.98***	−0.97***	−0.95***
	(−3.43)	(−4.43)	(−5.49)	(−6.00)	(−6.25)	(−6.40)
Difference	−0.12	−0.24*	−0.40***	−0.38***	−0.31***	−0.27***
	(−0.76)	(−1.74)	(−3.41)	(−3.62)	(−3.22)	(−2.99)
Panel G: Grouped by idiosyncratic volatility						
High	−1.46***	−1.61***	−1.62***	−1.48***	−1.32***	−1.22***
	(−4.65)	(−6.20)	(−7.67)	(−7.97)	(−7.94)	(−8.06)
Low	0.07	−0.03	−0.19**	−0.26***	−0.31***	−0.31***
	(0.58)	(−0.24)	(−2.17)	(−3.23)	(−3.89)	(−4.13)
Difference	−1.53***	−1.58***	−1.43***	−1.22***	−1.02***	−0.91***
	(−6.52)	(−8.04)	(−8.81)	(−8.70)	(−8.35)	(−8.24)

Table 2.7. Split effects on profits of historical high strategy

This table presents the split effects on the profits of the historical high strategy. We adopt a 30%–40%–30% cut-off to construct the winner, middle and loser portfolios. Firms in the bottom 10% of the market capitalisation distribution are excluded. We buy winners and sell losers to construct a zero-cost portfolio for the historical high strategy. We skip one month between the ranking and holding periods and hold the portfolios from 6 months to 60 months. In Panel A, we show the strategy's monthly profits for stocks with adjusted historical high prices that are the same as the unadjusted historical high prices. In Panel B, we show the strategy's monthly profits for the stocks with adjusted historical high prices that are different from the unadjusted historical high prices. The sample period is January 1990 to December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

Holding period		6 months	12 months	24 months	36 months	48 months	60 months
Panel A: Same historical highs							
Raw return	Winner	1.19	1.10	1.06	1.10	1.16	1.20
	Loser	2.11	2.30	2.44	2.43	2.38	2.35
	Winner−Loser	−0.91***	−1.20***	−1.38***	−1.33***	−1.22***	−1.15***
		(−2.77)	(−4.11)	(−5.10)	(−5.16)	(−5.07)	(−5.10)
CAPM α	Winner	0.36	0.25	0.20	0.24	0.30	0.34
	Loser	0.96	1.17	1.33	1.33	1.29	1.28
	Winner−Loser	−0.59*	−0.92***	−1.13***	−1.09***	−0.99***	−0.94***
		(−1.92)	(−3.34)	(−4.41)	(−4.47)	(−4.38)	(−4.40)
FF3 α	Winner	0.32	0.21	0.13	0.14	0.18	0.22
	Loser	0.87	1.07	1.25	1.26	1.22	1.21
	Winner−Loser	−0.54*	−0.87***	−1.12***	−1.11***	−1.04***	−0.99***
		(−1.86)	(−3.45)	(−5.02)	(−5.50)	(−5.63)	(−5.80)
Carhart4 α	Winner	0.22	0.19	0.22	0.26	0.31	0.34
	Loser	1.35	1.47	1.55	1.53	1.48	1.46
	Winner−Loser	−1.14***	−1.28***	−1.34***	−1.26***	−1.18***	−1.12***
		(−5.03)	(−5.88)	(−6.22)	(6.31)	(−6.45)	(−6.64)
FF5 α	Winner	0.33	0.25	0.18	0.18	0.21	0.24
	Loser	1.34	1.48	1.62	1.61	1.56	1.53
	Winner−Loser	−1.01***	−1.23***	−1.44***	−1.43***	−1.35***	−1.29***
		(−3.55)	(−5.16)	(−7.06)	(−7.74)	(−7.97)	(−8.24)
Panel B: Different historical highs							
Raw return	Winner	1.15	1.11	1.08	1.08	1.09	1.10
	Loser	1.71	1.80	1.87	1.87	1.85	1.84
	Winner−Loser	−0.56**	−0.68***	−0.79***	−0.79***	−0.76***	−0.74***
		(−2.00)	(−2.62)	(−3.29)	(−3.52)	(−3.59)	(−3.67)
CAPM α	Winner	0.40	0.35	0.31	0.30	0.31	0.32
	Loser	0.65	0.75	0.84	0.86	0.85	0.85
	Winner−Loser	−0.25	−0.40*	−0.54**	−0.56***	−0.54***	−0.53***
		(−0.96)	(−1.67)	(−2.41)	(−2.67)	(−2.75)	(−2.83)
FF3 α	Winner	0.30	0.25	0.19	0.17	0.17	0.17
	Loser	0.47	0.57	0.66	0.68	0.68	0.68
	Winner−Loser	−0.16	−0.31	−0.47**	−0.51***	−0.51***	−0.51***
		(−0.72)	(−1.52)	(−2.56)	(−3.09)	(−3.32)	(−3.49)
Carhart4 α	Winner	0.24	0.25	0.24	0.24	0.25	0.24
	Loser	0.86	0.91	0.94	0.93	0.92	0.91
	Winner−Loser	−0.62***	−0.66***	−0.70***	−0.69***	−0.68***	−0.66***
		(−3.42)	(−3.71)	(−4.13)	(−4.40)	(−4.55)	(−4.72)
FF5 α	Winner	0.16	0.14	0.08	0.06	0.05	0.04
	Loser	0.71	0.78	0.84	0.84	0.83	0.80
	Winner−Loser	−0.55**	−0.65***	−0.76***	−0.79***	−0.78***	−0.76***
		(−2.54)	(−3.34)	(−4.48)	(−5.13)	(−5.38)	(−5.48)

Table 2.8. Split effects in Fama–MacBeth regressions

This table shows the results from Fama–MacBeth regressions of returns on the dummies indicate whether the past performance of stock *i* falls into the winner or loser portfolios of the historical high strategies. Firms in the bottom 10% of the market capitalisation distribution are excluded. HH is the ratio of the current price to the historical high price. CON is a dummy that equals 1 if the adjusted historical high price is different from the unadjusted historical high price, and 0 otherwise. We include firm size (Log(ME)), book-to-market (BE/ME), share price (PRC), institutional ownership (IO), idiosyncratic volatility (IVOL), firm age (AGE), Ohlson's O (O-score) and past performance measured at horizons of past one month returns ($R_{-1,0}$), past cumulative returns from 12 to two months ($R_{-12,-2}$) and past cumulative returns from 60 to 13 months ($R_{-60,-13}$) as control variables. The monthly sample period is January 1990 to December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

	6 months	12 months	24 months	36 months	48 months	60 months
Intercept	0.17***	0.33***	0.65***	1.00***	1.29***	1.68***
	(9.24)	(10.51)	(12.58)	(11.78)	(10.36)	(9.95)
HH	−0.03***	−0.09***	−0.21***	−0.35***	−0.49***	−0.76***
	(−2.62)	(−4.93)	(−7.39)	(−11.10)	(−12.66)	(−13.45)
HH×CON	0.02**	0.06***	0.12***	0.19***	0.21***	0.33***
	(2.22)	(5.83)	(6.92)	(7.90)	(7.23)	(8.08)
CON	−0.00	−0.02***	−0.06***	−0.10***	−0.11***	−0.18***
	(−0.84)	(−3.12)	(−4.04)	(−5.19)	(−5.86)	(−7.26)
Log(ME)	−0.01***	−0.01***	−0.02***	−0.02***	−0.02***	−0.02***
	(−6.41)	(−6.57)	(−5.99)	(−5.06)	(−3.64)	(−2.89)
BE/ME	0.01***	0.01***	0.04***	0.07***	0.10***	0.14***
	(3.13)	(4.71)	(8.40)	(9.28)	(10.84)	(12.34)
PRC	0.00**	0.00***	0.00***	−0.00	−0.00	−0.00
	(2.47)	(2.62)	(2.82)	(−1.12)	(−1.05)	(−0.35)
IO	0.02***	0.02***	0.05***	0.09***	0.13***	0.18***
	(5.14)	(4.48)	(6.98)	(9.59)	(10.19)	(11.24)
IVOL	0.21	0.94***	2.11***	3.07***	3.80***	5.19***
	(1.58)	(4.42)	(6.81)	(8.18)	(8.77)	(9.07)
AGE (%)	−0.01***	−0.03***	−0.10***	−0.18***	−0.27***	−0.42***
	(−12.59)	(−4.13)	(−6.55)	(−7.55)	(−7.49)	(−7.72)
O-score (%)	0.00	0.00***	0.26***	0.35***	0.32***	0.55***
	(0.26)	(4.42)	(6.70)	(7.33)	(4.42)	(6.22)
$R_{-1,0}$	0.02**	0.03*	−0.01	−0.07**	−0.10**	−0.07
	(2.29)	(1.84)	(−0.56)	(−2.33)	(−2.45)	(−1.15)
$R_{-12,-2}$	−0.01*	−0.03***	−0.09***	−0.11***	−0.14***	−0.15***
	(−1.73)	(−4.12)	(−7.05)	(−7.60)	(−8.12)	(−5.44)
$R_{-60,-13}$	−0.00***	−0.01***	−0.01***	−0.02***	−0.02***	−0.01***
	(−6.22)	(−6.75)	(−5.99)	(−7.41)	(−5.37)	(−3.85)

Table 2.9. Split effects on winner and loser portfolios

This table presents the split effects on the winner and loser portfolio profits of the historical high strategy. Firms in the bottom 10% of the market capitalisation distribution are excluded. We buy winners and sell losers to construct a zero-cost portfolio for the historical high strategy. We skip one month between the ranking and holding periods and hold the portfolios from 6 months to 60 months. In Panel A, we show the split effects on the profits of the winner portfolio. In Panel B, we show the reverse split effects on the profits of the loser portfolio. We adopt a 30%–40%–30% cut-off to construct the winner, middle and loser portfolios. The sample period is January 1990 to December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

Holding period		6 months	12 months	24 months	36 months	48 months	60 months
Panel A: Split effects on the winner portfolio							
Raw return	Same	1.19	1.10	1.06	1.10	1.16	1.20
	Adj < Raw	1.15	1.11	1.08	1.08	1.09	1.10
	Difference	0.05	−0.02	−0.02	0.02	0.06	0.10
		(0.46)	(−0.15)	(−0.21)	(0.18)	(0.68)	(1.07)
CAPM α	Same	0.36	0.25	0.20	0.24	0.30	0.34
	Adj < Raw	0.40	0.35	0.31	0.30	0.31	0.32
	Difference	−0.03	−0.10	−0.11	−0.06	−0.01	0.02
		(−0.31)	(−0.99)	(−1.12)	(−0.69)	(−0.16)	(0.26)
FF3 α	Same	0.32	0.21	0.13	0.14	0.18	0.22
	Adj < Raw	0.30	0.25	0.19	0.17	0.17	0.17
	Difference	0.02	−0.05	−0.06	−0.03	0.01	0.05
		(0.35)	(−0.68)	(−0.92)	(−0.43)	(0.23)	(0.76)
Carhart4 α	Same	0.22	0.19	0.22	0.26	0.31	0.34
	Adj < Raw	0.24	0.25	0.24	0.24	0.24	0.24
	Difference	−0.02	−0.05	−0.02	0.02	0.06	0.10
		(−0.31)	(−0.75)	(−0.33)	(0.36)	(0.99)	(1.50)
FF5 α	Same	0.33	0.25	0.18	0.18	0.21	0.24
	Adj < Raw	0.16	0.13	0.07	0.05	0.05	0.04
	Difference	0.17**	0.12*	0.10*	0.13**	0.16***	0.19***
		(2.52)	(1.81)	(1.70)	(2.10)	(2.68)	(3.16)
Panel B: Reverse split effects on the loser portfolio							
Raw return	Same	2.11	2.30	2.44	2.43	2.38	2.35
	Adj > Raw	1.70	1.81	1.91	1.97	1.98	1.99
	Difference	0.40**	0.49***	0.53***	0.45***	0.39***	0.36**
		(2.27)	(2.99)	(3.40)	(2.94)	(2.63)	(2.52)
CAPM α	Same	0.96	1.17	1.33	1.33	1.29	1.28
	Adj > Raw	0.73	0.83	0.94	1.01	1.03	1.03
	Difference	0.23	0.33**	0.39***	0.32**	0.26*	0.24*
		(1.38)	(2.16)	(2.64)	(2.17)	(1.86)	(1.74)
FF3 α	Same	0.87	1.07	1.25	1.26	1.22	1.21
	Adj > Raw	0.63	0.74	0.85	0.92	0.93	0.94
	Difference	0.23	0.33**	0.40***	0.34**	0.29**	0.27**
		(1.43)	(2.22)	(2.90)	(2.53)	(2.22)	(2.11)
Carhart4 α	Same	1.36	1.47	1.55	1.53	1.48	1.46
	Adj > Raw	0.85	0.94	1.04	1.10	1.12	1.13
	Difference	0.51***	0.53***	0.51***	0.42***	0.37***	0.33**
		(3.60)	(3.87)	(3.74)	(3.13)	(2.75)	(2.56)
FF5 α	Same	1.34	1.48	1.62	1.61	1.56	1.53
	Adj > Raw	0.89	0.99	1.10	1.16	1.16	1.16
	Difference	0.45***	0.49***	0.52***	0.45***	0.40***	0.37***
		(2.70)	(3.23)	(3.73)	(3.28)	(2.94)	(2.80)

Table 2.10. Profits of historical high strategy conditional on investor sentiment

This table presents the profits of the historical high strategy following different investor sentiment. Firms in the bottom 10% of the market capitalisation distribution are excluded. We define the ranking month *t* as optimistic (pessimistic) subperiod if the sentiment in month *t* is above (below) the middle point of the time series sentiment index. Then, we construct three equal-weighted portfolios based on the historical high strategy. In particular, we adopt a 30%–40%–30% cut-off to construct winner, middle and loser portfolios. We buy winners and sell losers to construct a zero-cost portfolio. We skip one month between the ranking and holding periods and hold the portfolios from 6 months to 60 months. We report the monthly average returns following low-sentiment months in Panel A and the monthly average returns following high-sentiment months in Panel B. The monthly sample period is January 1990 to December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

Portfolios	6 months	12 months	24 months	36 months	48 months	60 months
Panel A: Low investor sentiment						
Winner	1.14	1.12	1.12	1.16	1.20	1.20
Loser	2.61	2.69	2.74	2.67	2.60	2.54
Winner−Loser	−1.47***	−1.56***	−1.61***	−1.51***	−1.40***	−1.34***
	(−3.54)	(−4.03)	(−4.58)	(−4.84)	(−5.05)	(−5.23)
CAPM α	−0.94***	−1.07***	−1.18***	−1.13***	−1.07***	−1.04***
	(−2.61)	(−3.17)	(−3.80)	(−4.10)	(−4.33)	(−4.54)
FF3 α	−0.91***	−1.02***	−1.09***	−1.04***	−0.98***	−0.95***
	(−2.70)	(−3.27)	(−3.95)	(−4.35)	(−4.63)	(−4.88)
Carhart4 α	−0.99***	−1.08***	−1.13***	−1.07***	−1.00***	−0.97***
	(−3.72)	(−4.08)	(−4.43)	(−4.66)	(−4.92)	(−5.20)
FF5 α	−1.06***	−1.17***	−1.24***	−1.18***	−1.10***	−1.07***
	(−3.62)	(−4.48)	(−5.62)	(−5.98)	(−6.23)	(−6.55)
Panel B: High investor sentiment						
Winner	1.17	1.06	0.99	1.00	1.04	1.08
Loser	1.23	1.44	1.60	1.65	1.65	1.65
Winner−Loser	−0.06	−0.38	−0.61*	−0.65*	−0.61*	−0.57*
	(−0.13)	(−0.99)	(−1.68)	(−1.80)	(−1.76)	(−1.73)
CAPM α	0.09	−0.26	−0.50	−0.53	−0.49	−0.45
	(0.20)	(−0.70)	(−1.42)	(−1.53)	(−1.46)	(−1.42)
FF3 α	0.09	−0.20	−0.50*	−0.61**	−0.61**	−0.58**
	(0.22)	(−0.58)	(−1.68)	(−2.17)	(−2.28)	(−2.33)
Carhart4 α	−0.87***	−0.83***	−0.83***	−0.88***	−0.87***	−0.82***
	(−2.76)	(−2.79)	(−2.83)	(−3.13)	(−3.29)	(−3.33)
FF5 α	−0.55	−0.71**	−0.96***	−1.06***	−1.04***	−0.98***
	(−1.39)	(−2.16)	(−3.33)	(−3.95)	(−4.10)	(−4.11)

Table 2.11. Profits of historical high strategy conditional on 52-week high effect

This table presents the monthly profits of the historical high strategy conditional on the 52-week high effect. Firms in the bottom 10% of the market capitalisation distribution are excluded. We first separate stocks into two groups according to the ratio of the current price to 52-week high price. We then report the monthly profits of the historical high strategy for the two groups for different holding periods. We buy winners and sell losers to construct a zero-cost portfolio. We skip one month between the ranking and holding periods and hold the portfolios from 6 months to 60 months. We report the profits of the historical high strategy for the stocks with prices close to 52-week high in Panel A and the profits of the historical high strategy for the stocks with prices far away from 52-week high in Panel B. The monthly sample period is from January 1990 to December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

Portfolios	6 months	12 months	24 months	36 months	48 months	60 months
Panel A: Close to 52-week high						
Winner	1.24	1.15	1.07	1.07	1.09	1.10
Loser	1.65	1.58	1.57	1.57	1.59	1.60
Winner−Loser	−0.41***	−0.43***	−0.50***	−0.50***	−0.50***	−0.51***
	(−3.03)	(−3.28)	(−3.99)	(−4.27)	(−4.51)	(−4.62)
CAPM α	−0.30**	−0.33***	−0.40***	−0.41***	−0.41***	−0.41***
	(−2.31)	(−2.60)	(−3.32)	(−3.60)	(−3.84)	(−3.94)
FF3 α	−0.21**	−0.25***	−0.35***	−0.37***	−0.39***	−0.40***
	(−2.00)	(−2.59)	(−3.92)	(−4.52)	(−4.94)	(−5.16)
Carhart4 α	−0.33***	−0.31***	−0.38***	−0.40***	−0.42***	−0.43***
	(−3.43)	(−3.29)	(−4.24)	(−4.81)	(−5.30)	(−5.50)
FF5 α	−0.31***	−0.34***	−0.44***	−0.47***	−0.48***	−0.50***
	(−3.09)	(−3.77)	(−5.36)	(−5.92)	(−6.34)	(−6.56)
Panel B: Far away from 52-week high						
Winner	0.93	0.93	1.02	1.11	1.15	1.19
Loser	2.40	2.61	2.69	2.60	2.51	2.60
Winner−Loser	−1.48***	−1.68***	−1.67***	−1.50***	−1.36***	−1.27***
	(−4.18)	(−5.11)	(−5.46)	(−5.26)	(−5.13)	(−5.12)
CAPM α	−1.23***	−1.45***	−1.46***	−1.30***	−1.17***	−1.09***
	(−3.57)	(−4.53)	(−4.88)	(−4.67)	(−4.54)	(−4.52)
FF3 α	−1.21***	−1.44***	−1.48***	−1.34***	−1.23***	−1.15***
	(−3.80)	(−4.98)	(−5.76)	(−5.80)	(−5.75)	(−5.77)
Carhart4 α	−1.66***	−1.74***	−1.66***	−1.49***	−1.38***	−1.29***
	(−5.71)	(−6.26)	(−6.50)	(−6.46)	(−6.53)	(−6.58)
FF5 α	−1.69***	−1.85***	−1.87***	−1.73***	−1.60***	−1.48***
	(−5.55)	(−6.84)	(−7.89)	(−8.06)	(−8.05)	(−8.02)

Table 2.12. Profits of historical high strategy conditional on seasonality patterns

This table presents the monthly profits of the historical high strategy conditional on seasonality patterns and tax-loss trading. We adopt a 30%–40%–30% cut-off to construct the winner, middle and loser portfolios for the historical high strategy. Firms in the bottom 10% of the market capitalisation distribution are excluded. We buy winners and sell losers to construct a zero-cost portfolio. We skip one month between the ranking and holding periods and hold the portfolios from 6 months to 60 months. We report the monthly average returns of the historical high strategy for December and January in Panel A and the monthly average returns of the historical high strategy from February to November in Panel B. The monthly sample period is January 1990 to December 2016. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

Portfolios	6 months	12 months	24 months	36 months	48 months	60 months
Panel A: December and January						
Winner	1.69	1.65	1.56	1.55	1.61	1.67
Loser	4.48	4.57	4.63	4.55	4.43	4.30
Winner−Loser	−2.79**	−2.92***	−3.07***	−3.00***	−2.82***	−2.63***
	(−2.45)	(−3.00)	(−3.41)	(−3.50)	(−3.51)	(−3.50)
CAPM α	−2.65**	−2.80***	−2.93***	−2.87***	−2.70***	−2.52***
	(−2.26)	(−2.79)	(−3.16)	(−3.25)	(−3.62)	(−3.26)
FF3 α	−1.84*	−2.02**	−2.20***	−2.17***	−2.06***	−1.93***
	(−1.80)	(−2.37)	(−2.87)	(−3.05)	(−3.11)	(−3.14)
Carhart4 α	−2.50***	−2.48***	−2.53***	−2.46***	−2.34***	−2.19***
	(−3.44)	(−3.58)	(−3.69)	(−3.83)	(−3.96)	(−3.98)
FF5 α	−2.00**	−2.09***	−2.23***	−2.20***	−2.09***	−1.96***
	(−2.21)	(−2.84)	(−3.44)	(−3.64)	(−3.69)	(−3.72)
Panel B: February to November						
Winner	1.05	0.98	0.96	0.99	1.02	1.03
Loser	1.41	1.56	1.68	1.68	1.66	1.66
Winner−Loser	−0.36	−0.58**	−0.72***	−0.69***	−0.64***	−0.62***
	(−1.27)	(−2.24)	(−3.01)	(−3.11)	(−3.08)	(−3.17)
CAPM α	−0.04	−0.30	−0.47**	−0.46**	−0.42**	−0.41**
	(−0.15)	(−1.31)	(−2.21)	(−2.33)	(−2.29)	(−2.38)
FF3 α	−0.00	−0.27	−0.48***	−0.50***	−0.48***	−0.48***
	(−0.00)	(−1.35)	(−2.78)	(−3.32)	(−3.49)	(−3.72)
Carhart4 α	−0.46***	−0.59***	−0.63***	−0.58***	−0.55***	−0.54***
	(−2.60)	(−3.35)	(−3.70)	(−3.82)	(−3.93)	(−4.19)
FF5 α	−0.33	−0.53***	−0.71***	−0.74***	−0.71***	−0.70***
	(−1.53)	(−2.88)	(−4.68)	(−5.53)	(−5.86)	(−6.10)

Table 2.13. PGR and PLR

This table compares the aggregate proportion of gains realised (PGR) and the aggregate proportion of losses realised (PLR) for the winner and loser portfolios of the historical high. Firms in the bottom 10% of the market capitalisation distribution are excluded. The PGR is the number of realised gains divided by the number of realised gains plus the number of unrealised gains. The PLR is the number of realised losses divided by the number of realised losses plus the number of unrealised losses. The monthly sample period is January 1991 to November 1996. The *t*-statistics are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

	PGR	PLR	Difference
Winner	0.122***	0.104***	0.018***
	(49.03)	(40.80)	(8.22)
Loser	0.139***	0.083***	0.056***
	(46.64)	(39.30)	(19.69)
Winner−Loser	−0.017***	0.021***	−0.038***
	(−5.51)	(8.15)	(−10.39)

Chapter 3. Equity Lending and Stock Returns

3.1. Introduction

Short-selling activity plays an important role in financial markets. The literature that examines short-selling activity focuses more on the demand channel. For example, Boehmer, Jones and Zhang (2008) show that shorting constraints are not widespread and that short-selling activity is quite common in the stock markets. Their finding that the lightly shorted stocks outperform the heavily shorted stocks suggests that short sellers are well informed about future stock price moves. However, the role of the suppliers of lendable securities in relation to stock markets is yet to be explored intensively because it is much more difficult to measure their activities by using traditional databases.

In this chapter, we focus on the suppliers of lendable securities and provide evidence about the effects of equity lending on stock markets. To understand how securities lenders affect the cross-section of stock returns in the US stock market, we apply the *Markit Securities Finance* database and measure their activities by the change in the lendable supply. The change in the lendable supply reflects their opinions. For instance, a decrease in the lendable supply implies that securities lenders believe that the underlying securities are underpriced, and they want to reduce the possibility that the securities will be shorted by decreasing the lendable supply in the equity lending market. This novel yet simple identification allows us to measure their opinions regarding individual stocks.

Our results show that the activities of securities lenders strongly predict future stock returns in the cross-section. Specifically, we sort stocks into quintiles based on the change in the lendable supply and calculate the subsequent portfolio returns. We find that the stocks with the most decreased lendable supply outperform the stocks with the most increased lendable supply. A

long–short hedging strategy generates a monthly average return of 0.65% per month, which is significantly different from zero at the 1% level (t-statistic = 4.00). Our evidence shows that the return spread mainly comes from the outperformance of the stocks with decreased lendable supply, indicating that the limits to arbitrage of Shleifer and Vishny (1997) cannot explain the return predictability. We also show that such return predictability is not subsumed by other well-known return determinants and displays no long-term return reversal. This evidence suggests that securities lenders bring their information about equity mispricing to the stock markets.

We also provide evidence to show the effects of active institutional investors on the securities lending program. Institutional investors are an important source of lending inventory, and securities lenders can be either active or passive institutions. Traders often borrow securities to establish a short position, and short selling predicts future negative abnormal returns. Passive institutions attempt to replicate the market performance and take advantage of the equity lending market to generate additional profits. We expect that active institutional investors should be less willing to lend shares for fear of underperformance. Consistently, our evidence suggests that the willingness to lend shares decreases for the stocks with relative increased active institutional ownership or increased active mutual fund holdings. This finding indicates that active institutional investors play an important role in the security lending decision and the return predictability of the change in the lendable supply is likely to be attributable to their participation in the lending market.

Following Rhodes-Kropf, Robinson and Viswanathan (2005), we calculate the intrinsic value of individual stocks and define stock misvaluation, or $Mis_{i,t}$, as the difference between the stock's observed market value and its intrinsic value. We then examine whether securities lenders apply stock misvaluation information in equity lending. We provide direct evidence that they reduce the lendable supply for underpriced securities. Specifically, we show that the

average of the change in the lendable supply among the most underpriced stocks is lower than that among the most overpriced stocks by 0.18 (t-statistic = 6.61), which is significantly different from zero at the 1% level. Moreover, we find that the effects of securities lenders on the future stock returns are stronger among the underpriced stocks. These findings suggest that they are informed about stock mispricing and contribute to the price discovery process.

Next, we examine whether the return predictability originates from the relaxation of short-sale constraints. Stocks with high lending fees are more subject to short-sale constraints. If the increased lendable supply relaxes short-sale constraints and affects share prices, the return predictability of change in the lendable supply should be most evident among high-fee stocks. Our evidence suggests that stocks with decreased lendable supply do not outperform stocks with increased lendable supply among high-fee stocks, suggesting that such return predictability is unlikely to be caused by the relaxation of short-sale constraints.

Lastly, we examine the impact of investor sentiment on the return predictability of the change in the lendable supply. In contrast to Stambaugh, Yu and Yuan (2012), who find that most return anomalies are stronger following high-sentiment periods, we find that the zero-investment portfolio by buying stocks with decreased lendable supply and selling stocks with increased lendable supply generates significantly higher profits following low-sentiment periods. Time series regressions confirm the effects of investor sentiment on the return spread. These results indicate that sentiment-driven mispricing and short-sale constraints fail to explain the return predictability, and the strategy based on the change in the lendable supply provides a hedge to the other anomaly-based strategies.

This chapter contributes to the literature from three different perspectives. First, we uncover the effects of equity lending activities on future stock returns. While most prior studies focus on the demand channel of short-selling activity and show the effects of short sellers on the

stock markets (e.g. Boehmer and Wu, 2013; Dechow, Hutton, Meulbroek, and Sloan, 2001; Rapach, Ringgenberg, and Zhou, 2016), we analyse the supply channel in the securities lending markets and find that the change in the lendable supply has significant effects on the share prices in the US stock markets.

Second, we contribute to the understanding of the role of active institutional investors, especially active mutual funds, in the lendable supply. The change in the lendable supply is from two possible channels. The availability and the willingness both affect the lendable supply. That is, more shares become available for lending with the increase in the institutional ownership. Conversely, active institutions should be less willing to lend shares in which they execute information-based transaction. We suggest that the availability of lending shares increases with the institutional ownership while the willingness to lend shares decreases for the stocks with relative increased active institutional ownership or (informed) mutual fund holdings.

Third, this chapter provides evidence that the hedging strategy based on the change in the lendable supply achieves significantly higher profits following low-sentiment periods. Stambaugh, Yu and Yuan (2012) suggest that return anomalies are more profitable following high sentiment because of sentiment-driven mispricing and short-sale constraints. Our evidence suggests that the long–short strategy provides a great complement to other return anomalies.

The remainder of this chapter is organised as follows. In Section 3.2, we provide an overview of the main features of the securities shorting and lending markets and briefly review the related literature. In Section 3.3, we introduce our data source and discuss our research framework. We describe our main empirical analysis in Section 3.4. In Section 3.5, we provide concluding remarks.

3.2. Securities Lending Markets

3.2.1. Overview of the securities lending market

The securities lending market involves a temporary transfer of underlying securities from one party to another party for collaterals or fees, and it has grown dramatically in recent years. According to the Markit Group, Ltd., the market value of securities on loan worldwide is about US$1.0 trillion at the end of June 2015 (Baklanova, Copeland, and McCaughrin, 2015). Figure 3.1 plots the time series of the equal-weighted lendable supply ratio (as a percentage of shares outstanding) from January 2006 to December 2016. We observe there is a strong upward trend of the lendable supply over the sample period, suggesting that the equity lending market has become much more popular over the past decade. In addition, we find that the level of lendable supply remains stable during the global financial crisis from 2007 to 2009. The steady lendable supply during this period suggests that securities lenders were concerned about the further underperformance or outright losses on cash collateral reinvestment portfolios. This finding is also consistent with the fact that the ability to short sell was restricted during the global financial crisis.

<Insert Figure 3.1 Here>

There are usually three main parties in the securities lending market: ultimate owners, third-party intermediaries and securities borrowers. The ultimate owners of the securities, referred to as securities lenders, are typically large institutional investors, such as mutual funds, central banks and insurance companies. Although ultimate owners with large portfolios may conduct their own lending programs, the securities lending of smaller lenders is usually facilitated by third-party intermediaries, such as custodian banks or asset managers. The primary users of the borrowed securities are normally hedge funds and securities dealers, who borrow securities for various reasons. Their common motivations include establishing short positions, managing inventories and facilitating market-marking activity. The ultimate owners of securities enhance

their yield by receiving lending fees from the borrowers. If securities lending intermediaries are involved, they execute lenders' instructions, and both share the fees.

The securities lending activity can be regarded as the collection of rental fees on idle assets through fully collateralised loans (Baklanova, Copeland, and McCaughrin, 2015). Although securities lenders decide the securities that will be available for lending and receive additional income from the interest and appreciation on the collaterals by the temporary transfer of lending equities, they may suffer losses because securities borrowers often utilise these shares in establishing short positions. Despite the importance of the securities lending market, little evidence is available on whether securities lenders are informed players in financial markets. Hence, it is essential that academics and practitioners both understand securities lenders' process of lending decision-making and their effects on the stock market.

3.2.2. Studies on the securities shorting and lending market

3.2.2.1. Short selling and stock returns

The literature mainly focuses on the demand channel of the securities lending market and proxies for the demand of securities lending as short-selling activity. Studies provide novel evidence that short sellers are skilled information processors. For example, Cohen, Diether and Malloy (2007) find that the increases in shorting demand significantly negative predict future stock returns and suggest that short selling is important for private information revelation. Diether, Lee and Wergner (2009) find that short sellers are well informed and their trading strategies achieve attractive abnormal returns. Lynch, Nikolic, Yan and Yu (2014) suggest that short sellers possess superior market-wide information and the aggregate shorting predicts market returns. In the same spirit, Rapach, Ringgenberg and Zhou (2016) examine the return predictive power of the short-selling activity of the ex-post expected market return and find that the aggregate short interest is the strongest predictor of the future market excess return.

Purnanandam and Seyhun (2018) employ insider trading as an instrument for the availability of private information and confirm that short sellers improve the informational efficiency of the market.

Another stream of studies examines the effects of short-sale impediments on financial markets. Jones and Lamont (2002) suggest that stock overvaluation is driven by the short-sale constraints bind. Similarly, Boehme, Danielsen and Sorescu (2006) find that stock price overvaluation only exists among stocks with high short-sale constraints as well as high dispersion. Chang, Chen and Yu (2007) employ the addition of a stock to a pilot list of designated securities that can be shorted as an exogenous shock to short-sale constraints in the Hong Kong stock market. They find that short-sale constraints contribute to stock overvaluation. Saffi and Sigurdsson (2011) provide evidence that stocks with higher short-sale constraints have lower price efficiency. Stambaugh, Yu and Yuan (2012) find that overpricing is more prevalent than underpricing and that the anomalies are stronger following periods of high sentiment because of short-sale impediments. Liu and Wang (2018) suggest that short-sale constraints decrease bid prices, increase ask prices and drive up the bid–ask spread volatility in imperfectly competitive markets. Engelberg, Reed and Ringgenberg (2018) examine the costs of short selling and show that the uncertainty about the loan fee is associated with lower returns, more mispricing and less short selling.

3.2.2.2. Securities lending and stock returns

The supply channel of the securities lending market has attracted considerable attention in recent years because of the data availability. Miller (1977) proposes a model and suggests that the supply increase in the shorting market creates negative price pressure for the underlying securities. Duong, Huszar, Tan and Zhang (2017) suggest that higher stock lending fees negatively predict future stock returns. However, Kaplan, Moskowitz and Sensoy (2013) find

contradictory evidence by conducting a randomised stock lending experiment for an anonymous money manager and indicate that the returns to stocks with lending supply are no different from the stocks not available for lending.

Aggarwal, Saffi and Sturgess (2015) investigate the institutional investors' voting preference and find that they are more likely to restrict lendable shares before the proxy record date to exercise their voting right and affect corporate governance. Prado, Saffi and Sturgess (2016) examine the effects of institutional investors' lending activities on the stock returns by using the equity lending data from 2006 to 2010. Their evidence suggests that stocks with lower, more concentrated, short-term and less passive ownership have lower lending supply, higher costs of shorting and higher arbitrage risk. Evans, Ferreira and Prado (2017) examine why mutual fund managers lend, rather than sell, stocks with short-selling demand. Their evidence suggests that the investment restrictions and the fund family profit maximisation considerations can be used to explain security lending decisions.

Other recent studies explore the determinants of short-sale supply by using equity lending data. For example, Beneish, Lee and Nichols (2015) suggest that the lendable supply is positively correlated with borrowing costs and negatively associated with financial statement constructs that indicate overvaluation. In this chapter, we focus on the supply channel of the equity lending market and examine whether securities lenders affect share prices in the US stock markets.

3.3. Data

Our sample covers all common stocks (share code 10 and 11) listed on the NYSE, AMEX and NASDAQ. The stock returns are downloaded from the CRSP. We collect the accounting information and the short interest data from Compustat. The equity lending data are downloaded from the *Markit Securities Finance* database, and the institutional investor ownership (13F) data are obtained from Thomson Reuters. Mutual fund data are from Thomson

Reuters and the CRSP. We also download the investor sentiment index of Baker and Wurgler (2006, 2007) from Jeffrey Wurgler's website. The sample consists of stocks with lendable supply from January 2006 to December 2016. In total, we have 294,990 firm-month observations. We obtain the market factor ($MKTRF_t$), the size factor (SMB_t), the book-to-market factor (HML_t), the profitability factor (RMW_t) and the investment factor (CMA_t) from Kenneth French's website.

Prior studies have employed institutional ownership to proxy for the lendable supply (e.g. Asquith, Pathak, and Ritter, 2005; Nagel, 2005). However, the percentage of institutional holdings is only a rough indicator and cannot measure the lendable shares precisely (Prado, Saffi, and Sturgess, 2016). Because of the availability of equity lending data in recent years, we can observe the equity lending market with increased precision. Specifically, we obtain this data from the *Markit Securities Finance* database, which collects daily equity lending supply and loans information from more than 100 custodians and prime brokers. The Markit data, which captures the lending market conditions of individual stocks, has been employed by several studies on asset pricing as well as corporate finance (e.g. Ashcraft and Santos, 2009; Bali, Bodnaruk, Scherbina, and Tang, 2018; Kim, Shroff, Vyas, and Wittenberg-Moerman, 2018). Because borrowing fees are insensitive to changes in demand when demand is moderate (Kolasinski, Reed, and Ringgenberg, 2013), we employ the lendable shares to measure the activities of securities lenders. We define the lendable shares for security *i* at time *t* as the fraction of the lendable quantity relative to its shares outstanding. This direct measure allows us to examine the effects of equity supply on the stock markets. Because the equity lending data are reported daily, we follow Beneish, Lee and Nichols (2015) and only consider the last available observation of equity lendable supply for each firm in each month. The results are quantitatively unchanged if we use the average lendable supply of individual stocks for each

month. To the best of our knowledge, our study is one of the first that examines such a long time series of equity lending data.

3.4. Empirical Results

3.4.1. Proxy for the activities of securities lenders

To examine whether securities lenders affect the cross-section of stock returns, we construct a simple proxy to measure their activities by using the shocks in the lendable supply. Specifically, we calculate the change in the lendable supply as follows:

$$\Delta\text{Lendable supply}_{t} = \left(\frac{\text{Lendable quantity}}{\text{Share outstaing}}\right)_{t} - \left(\frac{\text{Lendable quantity}}{\text{Share outstaing}}\right)_{t-1}$$

We winsorise ΔLendable supply at the top and bottom one percentiles and divide our sample into quintiles based on ΔLendable supply. A set of stock characteristics calculated for each quintile group is reported in Table 3.1.

<Insert Table 3.1 Here>

Table 3.1 Row (1) shows that the Δlendable supply in the smallest quintile (Low) is as low as −1.45 and in the largest quintile (High) is as high as 1.63. The results from Row (2) and Row (3) indicate that the stocks with increased ΔLendable supply have higher short interest and lower lending fees. Row (4) shows that the stocks with increased lendable supply tend to have a slightly larger size. The book-to-market ratio in Row (5) exhibits an inverted U-shaped pattern across the Δlendable supply quintiles. Row (6) and Row (7) show the past performance measured at horizons of past one month returns ($R_{1,1}$) and past cumulative returns from 12 to two months ($R_{12,2}$), respectively. We observe that the stocks with increased lendable supply perform better than those with decreased lendable supply.

3.4.2. Return predictability of ΔLendable supply

Our analysis in this subsection proceeds as follows. First, we empirically test the return predictability of the activities of securities lenders. Our interest is in understanding whether their actions affect the cross-section of stock returns in the US stock markets. Following the previous research, we construct a zero-cost strategy and investigate the return spread. Starting with January 2006, we classify our sample into quintiles based on the change in the lendable supply (ΔLendable supply) and then calculate the equal-weighted average returns of portfolios in the subsequent month. To take risks into account, we also analyse the risk-adjusted alphas by regressing portfolio returns on the Fama–French three- and five-factor models (Fama and French, 2015). The results are provided in Table 3.2 Panel A.

<Insert Table 3.2 Here>

We observe that the average returns of the portfolios decrease with the increase in the lendable supply. Specifically, the stocks with the most decreased lendable supply achieve an average return of 1.36% in the next month and the stocks with the most increased lendable supply achieve a monthly average return of 0.71%. A long–short hedge portfolio generates an average monthly return of 0.65%, which is economically large and statistically significant at the 1% level (*t*-statistic = 4.00). The results for the risk-adjusted alphas are quantitatively unchanged, and the return spreads relative to the Fama–French three- and five-factor models are 0.65% (*t*-statistic = 3.91) and 0.68% (*t*-statistic = 3.93), respectively. Moreover, the positive abnormal returns from the long leg indicate that the return predictability of the change in the lendable supply is unlikely to be explained by the limits to arbitrage.

In Panel B of Table 3.2, we also examine the cross-sectional relationship between the level of lendable supply and stock returns. We sort stocks into quintiles based on the level of lendable supply and calculate the subsequent portfolio returns. Our findings show that the long–short

strategy by buying the bottom lendable supply quintile and selling the top lendable supply quintile does not generate significant return spread. The results suggest that the change in the lendable supply predicts future stock returns beyond the level of lendable supply.

In Figure 3.2, we plot the time series of the return spread between the stocks in the highest and lowest change in the lendable supply quintile. The long–short portfolio generates significant profits in our sample period, but the return spread is substantially higher during 2008–2009. An unreported table shows that the long–short hedge portfolio experiences significant abnormal returns both in and out of National Bureau of Economic Research (NBER) recession periods and the return spread is significantly higher during NBER recession dates.[10] These results suggest that the effects of securities lenders on the stock markets are much stronger during bad times.

<Insert Figure 3.2 Here>

We also examine the factor loadings of the quintile portfolio returns sorted by the change in the lendable supply. The results are reported in Table 3.3. We observe from the last column that the return predictability pattern has no significant loading on any of the Fama–French five factors. These results indicate that the return spread sorted by the change in the lendable supply is distinct from the traditional asset pricing factors.

<Insert Table 3.3 Here>

The results in Table 3.2 suggest that the decrease in lendable supply positively predicts future stock returns. We then conduct additional statistical tests based on the Fama and MacBeth (1973) regressions to investigate whether the results are robust after the consideration of additional risk characteristics. Table 3.4 shows the results of the Fama–MacBeth regressions

[10] The NBER recession dates are defined as December 2007 to June 2009.

of firms' returns in the subsequent months on the change in the lendable supply. We include the short interest, lending fee, firm size, book-to-market ratio and past performance measured at horizons of past one month returns ($R_{1,0}$) and past cumulative returns from 12 to two months ($R_{12,2}$) in the regressions. To overcome autocorrelation and heteroscedasticity in the error terms, we correct the standard errors following the Newey–West (1987) procedure.

<Insert Table 3.4 Here>

The dependent variable from Column (1) to (3) is the stock return in the subsequent one month. We find that the coefficient for ΔLendable supply in Column (1) is −0.15 (*t*-statistic = −3.19), which is significantly different from zero at the 1% level. The results of regressions (2) and (3) are quantitatively unchanged when we control for other stock characteristics. We also find that the coefficient for short interest is insignificantly different from zero, whereas the coefficient for the lending fee is negative and significant, suggesting that the predictability of the shorting demand declines in our sample period. These findings are consistent with the portfolio analysis that the change in lendable supply contains predictive information beyond other well-known return determinants.

We then examine whether the price impact of the change in the lendable supply is permanent or transitory by testing whether there is return reversal for a longer holding period. Allen and Gale (1992) and Purnanandam and Seyhun (2018) suggest that stock price manipulation will result in a return reversal. Motivated by their argument, we hypothesise that if the price impact of securities lenders is transitory, the result that the change in the lendable supply negatively predicts future stock returns is more likely to be associated with the stock price manipulation of securities lenders. However, if they are acting on their private information about the stock valuation, then their price impact should be permanent. To test these hypotheses, we extend the holding period to three months and perform Fama–MacBeth regression analysis. The results

from Column (4) to Column (6) show that there is no long-term return reversal for the portfolios sorted by the change in lendable supply, suggesting that securities lenders bring additional information about equity mispricing to the stock markets.[11]

3.4.3. Lendable shares and active institution investors

The securities lending program provides institutional investors with an important avenue to generate additional income. The lending income is negligible compared with the potential losses from the price decline, and we expect that active institutions are less willing to lend out shares when they increase their holdings. In this subsection, we first use panel regressions with time-fixed effects and cross-sectional regressions as follows to investigate the effects of active institutional investors on the lendable supply:

$$\Delta Lendable\ supply = \alpha + \beta_1 \Delta \frac{INS}{Shrout} + \beta_2 \Delta \frac{INS}{Shrout} \times D \frac{ActINS}{INS} + \beta_3 Controls + \epsilon$$

where the dependent variable, $\Delta Lendable\ supply$, is the change in the lendable supply ratio. $\Delta \frac{INS}{Shrout}$ is the change in the institutional ownership, $D \frac{ActINS}{INS}$ is a dummy variable that equals 1 if the relative active institutional ownership increases, and 0 otherwise. The active institutions are classified based on the institution's potential business ties with the invested firm (Chen, Harford, and Li, 2007). Specifically, investment companies (type 3) and investment advisors (type 4) are defined as active institutional investors. It can be argued that this measure for active institutional holdings includes passive mutual funds. To address this concern, we exclude passive mutual funds from active institutional investors.[12] Control variables (Controls) include short interest, lending fee, firm size (Log(ME)), book-to-market (BE/ME) and past performance measured at horizons of past one month returns ($R_{1,0}$) and past cumulative returns

[11] In the unreported analysis, we find that a long–short hedge portfolio by buying stocks with the most decreased lendable supply and selling stocks with the most increased lendable supply also generates a significantly positive return for a three-month holding period.

[12] The passive mutual fund is defined as a fund whose name contains a text string that identifies it as an index fund or is classified in the CRSP mutual fund database as an index fund (Appel, Gormley, and Keim, 2016).

from 12 to two months ($R_{12,2}$). All institutional holdings are measured as of the previous quarter-end. We present the results in Table 3.5.

<Insert Table 3.5 Here>

Table 3.5 Column (1) shows that the change in the lendable supply is positively related to the change in the institutional ownership, indicating that more shares are available to lend out among stocks with greater institutional holdings. Column (2) shows that stocks with increased relative active institutional holdings exhibit a relatively lower increase in the lendable supply. The significantly negative coefficient on the interaction term $\Delta \frac{INS}{Shrout} \times D \frac{ActINS}{INS}$ indicates that the active institutional investors are less willing to lend out shares than are the passive institutional investors. The results in Columns (3) and (4) for the cross-sectional regressions are qualitatively similar.

We take a further step and focus on the role of active mutual funds in securities lending by using the following model:

$$\Delta Lendable\ supply = \alpha + \beta_1 \Delta \frac{Mutual}{Shrout} + \beta_2 \Delta \frac{Mutual}{Shrout} \times D \frac{ActMutual}{Mutual} + \beta_3 Controls + \epsilon$$

where the dependent variable is the change in the lendable supply ratio. $\Delta \frac{Mutual}{Shrout}$ is the change in the mutual fund holdings, $D \frac{ActMutual}{Mutual}$ is a dummy variable that equals 1 if the relative active mutual fund ownership increases, and 0 otherwise. We classify the non-passive funds that can be matched to the CRSP mutual fund database as active mutual funds. Our regression results are presented in Table 3.6 Panel A.

<Insert Table 3.6 Here>

In Column (1), we find that the coefficient for the change in the mutual fund holdings is significantly positive at the 1% level, which is consistent with Evans, Ferreira and Prado's

(2017) finding that the percentage of active funds lending securities has increased dramatically. When we interact the change in the mutual fund holdings with the dummy variable $D\frac{ActMutual}{Mutual}$ in Column (2), the interaction variable $\Delta\frac{Mutual}{Shrout} \times D\frac{ActMutual}{Mutual}$ is negative and significant. This result implies the willingness to lend out shares is much lower for the stocks with increased active mutual fund holdings. Columns (3) and (4) show that these findings remain robust when we use cross-section regression analysis: stocks with increased actively managed equity fund holdings exhibit a relatively lower lending supply.

We also analyse the relationship between active fund stock selection skills and securities lending. To measure fund stock selection skills, we estimate alpha from the Carhart (1997) four-factor asset pricing model by using data for the prior 12 months. The active funds with positive alphas are defined as informed active funds and those with negative alphas are defined as uninformed active funds. We classify the stocks into two groups based on the change in the ratio of informed active fund holdings to the shares held by mutual funds ($\Delta\frac{MPActive}{Mutual}$). Lastly, we calculate the change in lendable supply for these two groups and report the findings in Table 3.6 Panel B.

As reported in Panel B of Table 3.6, the stocks with increased informed active fund holdings exhibit a significantly lower increase in the lendable supply. This result suggests that stocks with increased portfolio weights by active funds with better performance in the past are less likely to be lent out. The evidence is also consistent with the return predictability of the change in the lendable supply.

Overall, this subsection provides evidence consistent with that of Duong, Huszar, Tan and Zhang (2017), namely, that active institutional investors play an important role in the stock lending market. Our findings also imply that the return predictability of the change in the

lendable supply arises from the participation of active institutional investors in the lending program.

3.4.4. Stock valuation and securities lending

Subsection 3.4.2 provides evidence on the stocks with decreased lendable supply outperforming those with increased lendable supply. Prior studies show that securities lenders have some monopoly power to decide which securities will be available for lending, especially when the search frictions are high (Kolasinski, Reed, and Riggenberg, 2013). If they are informed about the equity mispricing and consider the possible effects of the change in the lendable supply on the stock returns, we expect that securities lenders are less likely to lend the underpriced securities and avoid the further loss from the underperformance of the loaned securities. Motivated by the effects of securities lenders on the stock markets, we hypothesise that they tend to decrease the lendable supply if they believe that they will suffer further losses on the underpriced securities. As a result, there should be a negative relationship between the share underpricing and lendable supply.

To examine this hypothesis, we first follow Rhodes-Kropf, Robinson and Viswanathan (2005) to estimate the intrinsic value of each firm by estimating the following cross-sectional regression on an annual basis:

$$M = \beta_{0jt} + \beta_{1jt}B + \beta_{2jt}Abs(NI) + \beta_{3jt}I_{(<0)} \times Abs(NI) + \beta_{4jt}LEV + \epsilon.$$

where *M* is the logarithm of a firm's market capitalisation three months after the fiscal year-end and *j* is the industry that is based on the Fama–French industry classification system. *B* is the logarithm of a firm's book value of the common equity in the same period. *Abs(NI)* is the logarithm of a firm's net income in absolute value. $I_{(<0)}$ is an indicator that takes the value of 1 if a firm's net income is negative and 0 otherwise. *LEV* is a firm's leverage ratio that calculated as one minus common equity over the total asset. We delete the firm observations

with leverage ratio greater than 1 or less than 0. Rhodes-Kropf, Robinson and Viswanathan (2005) suggest that the accounting variables in this valuation model explain more than 86% of the within-industry variation in firm value and the fitted value $\widehat{M}$ from this regression is a fair proxy for the firm's intrinsic value. We then define the firm's monthly mispricing ($Mis_{i,t}$) as the difference between a firm's market capitalisation from July of year $t + 1$ to June of year $t + 2$, scaled by the intrinsic value of $\widehat{M}$:

$$Mis_{i,t} = (MV_{i,t} - \widehat{M})/\widehat{M}.$$

Intuitively, a positive (high) $Mis_{i,t}$ indicates that stock i at month t is overpriced, while a negative (low) $Mis_{i,t}$ suggests stock i at month t is underpriced.

<Insert Table 3.7 Here>

To examine whether securities lenders rely on the stock misvaluation information, we sort all stocks into quintiles based on the stock mispricing ($Mis_{i,t}$) and then calculate the change in the lendable supply in month $t + 1$ for each quintile in Table 3.7 Panel A. We observe that the average change in the lendable supply among the most underpriced (overpriced) stocks is −0.04 (0.14). The difference between the two quintiles is 0.18 (t-statistic = 6.61), which is significantly different from zero at the 1% level. This result indicates that stock misvaluation has a substantial effect on the change in the lendable supply. In other words, securities lenders are informed about stock mispricing, and they decrease the lendable supply for the underpriced stocks because of the concern about further underperformance of underpriced securities.

We then conduct a double sorting analysis to examine the effects of stock mispricing on the relationship between the change in the lendable supply and future stock returns. Unlike the short sellers, who typically target overpriced stocks, securities lenders are more likely to be concerned about the further underperformance of the underpriced stocks. As a result, we expect that the effects of securities lenders on the stock returns should be stronger for the stocks with

prices under their intrinsic value. To test this expectation, we sort all stocks into two groups based on the level of stock mispricing and then calculate the portfolio returns sorted by the change in the lendable supply in the next month. The results are reported in Panel B of Table 3.7.

Table 3.7 Panel B shows that the stocks with decreased lendable supply outperform those with increased lendable supply in both groups. We observe that for the underpriced stocks, the return spread between the stocks with most decreased lendable supply and those with most increased lendable supply is 0.82% (*t*-statistic = 4.03). However, the return spread between these two quintiles among the overpriced stocks is only 0.38% (*t*-statistic = 3.08), which is lower by 0.44%. We also find that the results of the risk-adjusted alphas are quantitatively unchanged. These findings indicate that the effects of securities lenders are stronger among the underpriced securities and securities lending activities contribute to the stock price efficiency.

We further conduct a Fama–MacBeth (1973) style cross-sectional analysis to examine the return predictability of the change in the lendable supply for the underpriced and overpriced stocks. The results are reported in Table 3.8. Consistent with the portfolio analysis, we find that the return predictability of the change in the lendable supply is stronger among the underpriced stocks. The coefficient for ΔLendable supply is much lower in magnitude for the overpriced stocks. This finding remains similar after the consideration of other stock characteristics.

<Insert Table 3.8 Here>

Overall, the results in Subsection 3.4.4 suggest that securities lenders are informed about stock mispricing: they reduce the lendable supply for the underpriced stocks to avoid further losses from potential short-selling activities, and the effects of securities lenders on the future stock returns are much stronger for the underpriced stocks.

3.4.5. Short-sale constraints and securities lending

We have shown that the return predictability of the change in the lendable supply is caused by the participation of active institutional investors. In this subsection, we examine whether such return predictability arises from the relaxation of short-sale constraints. With the increase of lendable supply, short-sale constraints are relaxed as short sellers can borrow stocks more easily. Conversely, the decrease in the lendable supply tightens short-sale constraints and indicates the target stock is less likely to be shorted. Thus, the underperformance of the stocks with increased lendable supply can also be attributed to the relaxation of short-sale constraints.

We classify all stocks into two groups based on the relative cost of borrowing by using the daily cost of borrowing score (DCBS). The DCBS is a measure of the relative cost of borrowing for each stock, which ranges from 1 (low cost) to 10 (high cost). Specifically, we follow Beneish, Lee and Nichols (2015) to categorise stocks with a DCBS value of 3 or more as special and those with a DCBS value of 1 or 2 as general collateral. We then calculate the long–short portfolio returns in the high-cost (special) and low-cost (general collateral) groups, respectively. Duffie, Garleanu and Pedersen (2002) suggest that short-sale constraints mostly affect stocks with high demand. Thus, if the return predictability arises from the relaxation of short-sale constraints, the effects of the lendable supply shocks on the share prices should be stronger among the special group (difficult-to-borrow stocks). Table 3.9 reports the empirical findings.

<Insert Table 3.9 Here>

In Table 3.9 Panel A, we find that the return predictability of the change in the lendable supply is insignificant among the special group. We also control for traditional risk factors and do not find that the change in the lendable supply predicts future stock returns for the stocks with high borrowing costs. This finding is also consistent with that of Kaplan, Moskowitz and Sensoy (2013): there is no adverse effect on stock prices from lendable supply shocks among the

difficult-to-borrow stocks. In contrast, the results in Table 3.9 Panel B suggest that the stocks with decreased lendable supply outperform those with increased lendable supply among the low-cost (general collateral) group, and the alpha spreads are significantly different from zero at the 1% level. These results indicate that the return predictability of the change in the lendable supply is unlikely to be caused by the relaxation of short-sale constraints.

3.4.6. Investor sentiment and securities lending

Stambaugh, Yu and Yuan (2012) show that many return anomalies are more profitable following high investor sentiment periods owing to sentiment-driven mispricing and short-sale impediments. They conjecture that the most optimistic views about the market are overly optimistic following periods of high sentiment, and hence, stocks tend to be overpriced during such periods. In this subsection, we explore how investor sentiment affects the return predictability of the change in the lendable supply.

We use the monthly sentiment index of Baker and Wurgler (2006, 2007) to measure investor sentiment. A high-sentiment month is the one in which the value of the sentiment index is higher than the median value for the sample period, and a low-sentiment month is the one with below-median value. We then calculate the average monthly returns and risk-adjusted alphas following high- and low-sentiment months, respectively. The risk-adjusted alphas based on the Fama–French three and five factors are estimated from the following regressions:

$$R_{i,t} = a_H D_{H,t-1} + a_L D_{L,t-1} + bControls_{i,t} + \epsilon_{i,t},$$

where $R_{i,t}$ is the excess return in month t on either the long leg, short leg or the difference between the two legs. $D_{H,t-1}$ and $D_{L,t-1}$ are dummy variables that indicate high and low-sentiment months, and the control variables are the Fama–French risk factors ($MKTRF_t$, SMB_t, HML_t, RMW_t, CMA_t). The results are reported in Table 3.10.

<Insert Table 3.10 Here>

Table 3.10 reveals that the hedging strategy based on the change in the lendable supply exhibits significantly higher average profits following a low-sentiment period. Specifically, the long–short strategy earns 0.65% more per month following a low-sentiment period, with a *t*-statistic of 2.04. Moreover, we find that the return on the stocks with decreased lendable supply is higher following a low-sentiment period, which contradicts Stambaugh, Yu and Yuan (2012). These results are consistent with Section 3.4.5 that the return predictability is unlikely to be caused by the short-sale constraints.

We then regress excess returns on the lagged sentiment index as well as the contemporaneous Fama–French factors to investigate whether investor sentiment predicts returns in a way consistent with the portfolio analysis. Table 3.11 reports the results of the predictive regression analysis.

<Insert Table 3.11 Here>

In Panel A of Table 3.11, we find that there is a significant negative relationship between investor sentiment and the long–short spread. The results in Panel B and Panel C remain qualitatively unchanged after adjusting for benchmark exposures, indicating that the sentiment-driven mispricing of Stambaugh, Yu and Yuan (2012) is unlikely to be the explanation for the return predictability. Overall, the evidence in Table 3.10 and Table 3.11 suggests that the long–short strategy based on the change in the lendable supply is a complement to the other anomaly-based strategies.

3.5. Conclusion

The equity lending market provides a unique opportunity for securities lenders to generate additional profits. In this chapter, we show that the change in the lendable supply contains their

information, which predicts future stock returns in the cross-section. Specifically, we find that the stocks with decreased lendable supply outperform those with increased lendable supply.

We link the return predictability to the activities of active institutional investors and provide evidence that the securities lenders are informed about stock mispricing. We also show that this return predictability is unlikely to arise from the relaxation of short-sale constraints. Lastly, our empirical results show that the hedging strategy achieves significantly higher profits following a low-sentiment period, which offers a complement to other sentiment-driven trading strategies.

Figures and Tables

Figure 3.1. Lendable supply ratio

The figure shows the time series of equal-weighted lendable shares relative to total shares outstanding from January 2006 to December 2016.

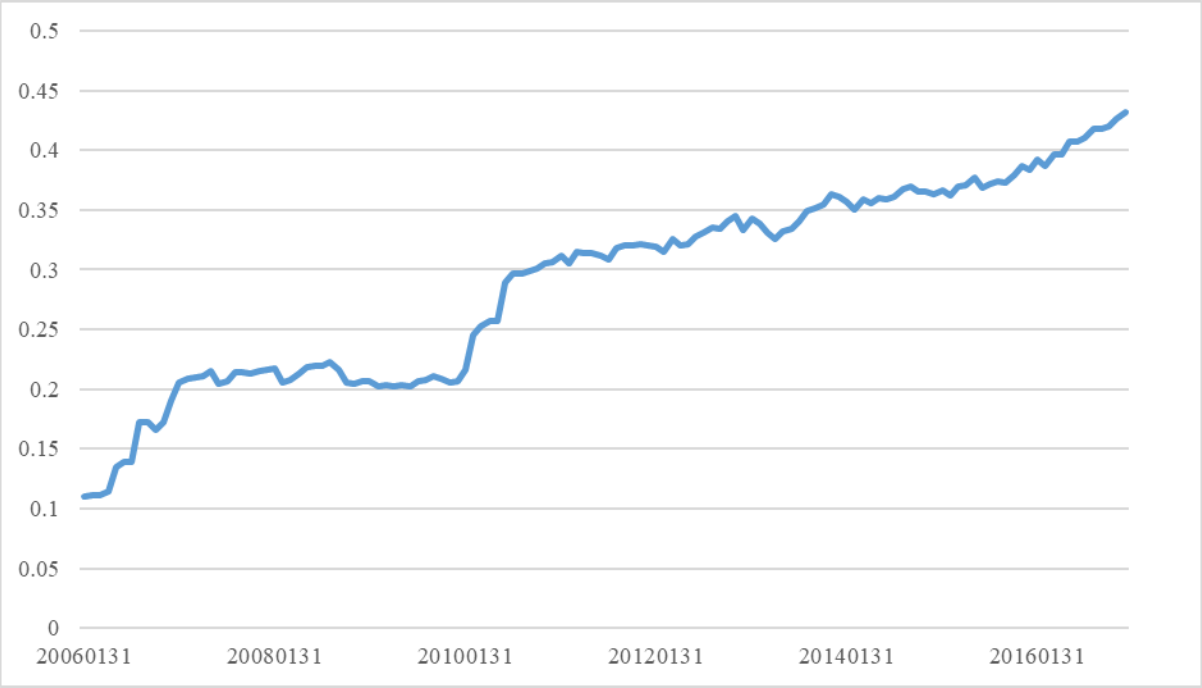


Figure 3.2. Time series of return predictability of change in the lendable supply

The figure shows the time series of the return spread between the stocks in the highest change in the lendable supply quintile and the lowest change in the lendable supply quintile from January 2006 to December 2016.

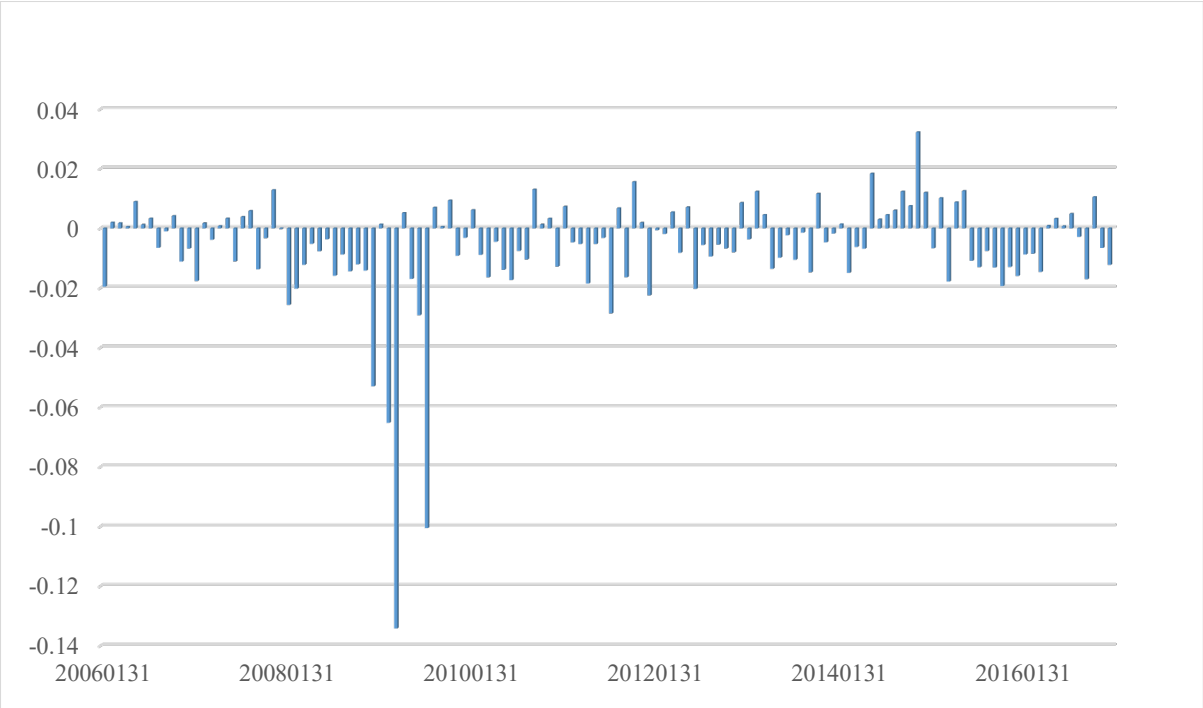


Table 3.1. Lendable supply and stock characteristics

This table shows the average stock characteristics of quintile portfolios sorted by the change in the lendable supply. Short interest (%) is the ratio of shares shorted to total shares outstanding. Lending fee (%) is the average loan fee. Log(ME) is the logarithm of the firm's market value. BE/ME is the firm's book-to-market ratio. $R_{1,0}$ is the stock return over the last month and $R_{12,2}$ represents the stock's past cumulative returns from 12 to two months. The numbers in parentheses are *t*-statistics, and the sample period is from January 2006 to December 2016.

	Low	2	3	4	High	Difference
(1) ΔLendable supply (%)	−1.45	−0.25	0.08	0.46	1.63	3.08***
						(29.71)
(2) Short interest (%)	5.65	4.05	3.32	4.61	6.41	0.77***
						(6.83)
(3) Lending fee (%)	1.21	1.39	1.62	1.14	0.95	−0.26***
						(−5.33)
(4) Log(ME)	13.63	13.46	13.02	13.67	13.83	0.20***
						(3.08)
(5) BE/ME	0.79	0.80	0.87	0.80	0.75	−0.04**
						(−2.42)
(6) $R_{1,0}$ (%)	0.21	0.44	0.86	1.36	2.08	1.87***
						(11.44)
(7) $R_{12,2}$ (%)	8.04	7.33	7.18	11.39	16.66	8.62***
						(12.90)

Table 3.2. Returns of portfolios sorted on Δlendable supply and lendable supply

This table shows the average monthly raw and risk-adjusted returns for the portfolios sorted by the change in lendable supply in Panel A and the lendable supply ratio in Panel B. We sort stocks into quintile portfolios and hold the portfolios for one month. The numbers in parentheses are *t*-statistics, and the sample period is from January 2006 to December 2016.

	Low	2	3	4	High	Difference
Panel A: Sorted by Δlendable supply						
Raw Return	1.36**	1.17**	0.71	0.84*	0.71	−0.65***
	(2.48)	(2.43)	(1.60)	(1.75)	(1.39)	(−4.00)
FF3 α	1.09**	0.89*	0.55	0.57	0.44	−0.65***
	(2.01)	(1.89)	(0.88)	(1.21)	(0.88)	(−3.91)
FF5 α	1.27**	1.09**	0.55	0.70	0.59	−0.68***
	(2.23)	(2.22)	(1.28)	(1.42)	(1.12)	(−3.93)
Panel B: Sorted by lendable supply						
Raw Return	0.90**	1.02*	0.97*	1.04**	0.84	−0.07
	(2.08)	(1.95)	(1.93)	(2.13)	(1.57)	(−0.22)
FF3 α	0.52	0.68	0.73	0.82*	0.59	0.07
	(1.30)	(1.35)	(1.47)	(1.70)	(1.13)	(0.25)
FF5 α	0.71*	0.87	0.86*	1.00**	0.76	0.06
	(1.69)	(1.63)	(1.64)	(1.96)	(1.39)	(0.19)

Table 3.3. Factor loadings on portfolios sorted on change in lendable supply

This table shows the factor loadings for the portfolios sorted by the change in lendable supply. We sort stocks into quintile portfolios and hold the portfolios for one month. Alphas are the intercepts of the regressions of monthly excess portfolio return on the Fama–French five factors (2016). The numbers in parentheses are *t*-statistics, and the sample period is from January 2006 to December 2016.

	Low	2	3	4	High	Difference
Alphas (%)	1.27	1.09	0.55	0.70	0.59	−0.68***
						(−3.93)
MKT	0.33	0.32	0.37	0.34	0.35	0.02
						(0.49)
SMB	−0.59	−0.52	−0.40	−0.54	−0.64	−0.06
						(−0.73)
HML	0.09	0.11	0.13	0.12	−0.01	−0.10
						(−1.24)
RMW	−0.49	−0.52	−0.48	−0.37	−0.46	0.03
						(0.21)
CMA	0.07	0.02	0.02	0.10	0.22	0.15
						(1.05)

Table 3.4. Cross-sectional regressions

This table shows results from Fama–MacBeth regressions of returns on the change in lendable supply. The dependent variable is the future 1-month and 3-month cumulative holding period returns, respectively. ΔLendable supply is the change in the lendable supply. We include short interest, lending fee, firm size (Log(ME)), book-to-market (BE/ME) and past performance measured at horizons of past one month returns ($R_{1,0}$) and past cumulative returns from 12 to two months ($R_{12,2}$) as control variables. The numbers in parentheses are *t*-statistics based on Newey–West (1987) standard errors. The sample period is from January 2006 to December 2016.

Explanatory variable	Model					
	(1)	(2)	(3)	(4)	(5)	(6)
	1-month return			3-month return		
Constant	0.01*	0.01*	0.02***	0.03**	0.03**	0.03
	(1.64)	(1.80)	(2.69)	(1.96)	(2.19)	(1.46)
ΔLendable supply	−0.15***	−0.15***	−0.14***	−0.37***	−0.39***	−0.36***
	(−3.19)	(−3.47)	(−3.90)	(−3.34)	(−3.58)	(−4.49)
Short interest		0.00	0.01		−0.02	0.01
		(0.05)	(1.01)		(−0.74)	(0.31)
Lending fee		−0.09***	−0.10***		−0.25***	−0.28***
		(−4.20)	(−5.84)		(−5.86)	(−7.27)
Log(ME)			−0.00**			−0.00
			(−2.41)			(−0.95)
BE/ME			−0.00			0.00
			(−0.30)			(1.12)
$R_{1,0}$			−0.00			−0.01
			(−0.42)			(−1.01)
$R_{12,2}$			−0.00			−0.02
			(−0.83)			(−1.19)

Table 3.5. Lendable supply and institutional investors

This table shows the results of regressions of the change in the lendable supply on the change in the institutional ownership. $\Delta \frac{INS}{Shrout}$ is the change in the institutional ownership, $D \frac{ActINS}{INS}$ is a dummy variable that equals 1 if the relative active institutional ownership increases, and 0 otherwise. We include short interest, lending fee, firm size, book-to-market and past performance measured at horizons of past one month returns and past cumulative returns from 12 to two months as control variables. The numbers in parentheses are *t*-statistics, and the sample period is from January 2006 to December 2016.

	(1)	(2)	(3)	(4)
	Panel regressions		Cross-sectional regressions	
Constant	1.92***	1.91***	−0.06	−0.06
	(55.74)	(55.60)	(−0.55)	(−0.61)
$\Delta \frac{INS}{Shrout}$	3.50***	3.84***	5.24***	5.67***
	(43.72)	(38.10)	(12.41)	(11.41)
$\Delta \frac{INS}{Shrout} \times D \frac{ActINS}{INS}$		−0.71***		−0.75
		(−5.54)		(−1.59)
Controls	Yes	Yes	Yes	Yes
Time-fixed effect	Yes	Yes	-	-
Adj. R^2	0.17	0.17	0.05	0.05
Observations	253,943	253,943	253,943	253,943

Table 3.6. Lendable supply and mutual funds

This table shows the effects of active mutual funds on the change in the lendable supply. Panel A shows the regression results of the change in the lendable supply on the change in the active mutual fund holdings. $\Delta\frac{Mutual}{Shrout}$ is the change in the mutual fund holdings. $D\frac{ActMutual}{Mutual}$ is a dummy variable that equals 1 if the relative active fund holding increases, and 0 otherwise. We include short interest, lending fee, firm size, book-to-market and past performance measured at horizons of past one month returns and past cumulative returns from 12 to two months as control variables. Panel B shows the change in the lendable supply for the stocks with increased and decreased informed active fund holding. $\Delta\frac{MPActive}{Mutual}$ is the change in the ratio of informed active fund holding to the shares held by mutual funds. The numbers in parentheses are *t*-statistics, and the sample period is from January 2006 to December 2016.

Panel A: Lendable supply and active mutual funds				
	(1)	(2)	(3)	(4)
	Panel regressions		Cross-sectional regressions	
Constant	−0.11***	−0.10**	−0.06	−0.06
	(−3.02)	(−2.56)	(−0.58)	(−0.65)
$\Delta\frac{Mutual}{Shrout}$	5.26***	7.92***	7.36***	11.41***
	(36.14)	(35.52)	(12.14)	(12.40)
$\Delta\frac{Mutual}{Shrout}\times D\frac{ActMutual}{Mutual}$		−4.37***		−5.40***
		(−15.73)		(−5.59)
Controls	Yes	Yes	Yes	Yes
Time-fixed effect	Yes	Yes	-	-
Adj. R^2	0.16	0.16	0.05	0.05
Observations	248,901	248,901	248,901	248,901

Panel B: Lendable supply and active fund stock selection skills			
	$\Delta\frac{MPActive}{Mutual}>0$	$\Delta\frac{MPActive}{Mutual}<0$	Difference
ΔLendable supply	0.056	0.097**	−0.041***
	(1.10)	(2.19)	(−2.86)

Table 3.7. Effects of stock mispricing

This table shows the effects of stock mispricing on the relationship between the change in the lendable supply and future stock returns. In Panel A, we report the ΔLendable supply for the quintile portfolios sorted by the stock mispricing. In Panel B, we first sort our sample into two groups based on the stock mispricing and then calculate the return spread on the quintile portfolio sorted based on the change in lendable supply. The numbers in parentheses are *t*-statistics, and the sample period is from January 2006 to December 2016.

Panel A: ΔLendable supply sorted by stock mispricing						
$Mis_{i,t}$	Low	2	3	4	High	Difference
ΔLendable supply	−0.04	0.04	0.07	0.08	0.14	0.18***
						(6.61)

Panel B: Portfolio returns sorted by ΔLendable supply								
	Low	2	3	4	High	Difference	FF3 α	FF5 α
Underpriced	1.67	1.23	0.91	1.00	0.84	−0.82***	−0.81***	−0.84***
($Mis_{i,t} < 0$)						(−4.03)	(−3.87)	(−3.81)
Overpriced	0.96	0.86	0.69	0.77	0.58	−0.38***	−0.39***	−0.42***
($Mis_{i,t} > 0$)						(−3.08)	(−3.13)	(−3.15)

Table 3.8. Cross-sectional regressions for underpriced and overpriced stocks

This table shows results from Fama–MacBeth cross-sectional regressions of returns on the change in the lendable supply for the underpriced and overpriced stocks. ΔLendable supply is the change in the lendable supply. We include utilisation, lending fee, firm size (Log(ME)), book-to-market (BE/ME) and past performance measured at horizons of past one month returns ($R_{1,0}$) and past cumulative returns from 12 to two months ($R_{12,2}$) as control variables. The numbers in parentheses are *t*-statistics based on Newey–West (1987) standard errors. The sample period is from January 2006 to December 2016.

Explanatory variable	Model					
	(1)	(2)	(3)	(4)	(5)	(6)
	Underpriced ($Mis_{i,t} < 0$)			Overpriced ($Mis_{i,t} > 0$)		
Constant	1.09*	1.18*	1.95***	0.73	0.78*	2.01***
	(1.74)	(1.91)	(2.62)	(1.51)	(1.64)	(2.64)
ΔLendable supply	−21.03***	−22.13***	−20.85***	−8.95**	−9.36**	−9.48***
	(−3.07)	(−3.37)	(−3.60)	(−2.06)	(−2.19)	(−2.58)
Utilisation		−0.19	0.88		0.39	0.56
		(−0.19)	(0.85)		(0.39)	(0.59)
Indicative fee		−8.21***	−9.05***		−8.61***	−9.84***
		(−3.32)	(−4.69)		(−3.40)	(−4.54)
Log(ME)			−0.10**			−0.09**
			(−2.07)			(−2.40)
BE/ME			−0.05			−0.08
			(−0.44)			(−0.30)
$R_{1,0}$			−0.55			0.22
			(−0.64)			(0.26)
$R_{12,2}$			−0.13			−0.33
			(−0.17)			(−1.11)

Table 3.9. Returns of portfolios sorted on Δlendable supply for special and general collateral
This table shows the average monthly raw and risk-adjusted returns for the portfolios sorted by the change in lendable supply. We sort stocks into quintiles and hold the portfolios for one month. We show the long–short portfolio returns in the high-cost stocks (special) in Panel A and that in the low-cost stocks (general collateral) in Panel B. The numbers in parentheses are *t*-statistics, and the sample period is from January 2006 to December 2016.

	Low	2	3	4	High	Difference
Panel A: Special						
Raw Return	−0.17	−0.45	−0.77	0.05	−0.57	−0.40
						(−0.70)
FF3 α	−0.71	−0.75	−1.08	−0.31	−0.86	−0.15
						(−0.26)
FF5 α	−0.63	−0.53	−0.82	0.09	−0.62	−0.01
						(−0.01)
Panel B: General collateral						
Raw Return	1.46	1.28	0.83	0.92	0.83	−0.62***
						(−4.00)
FF3 α	1.20	1.01	0.53	0.66	0.57	−0.62***
						(−3.92)
FF5 α	1.39	1.22	0.81	0.78	0.72	−0.67***
						(−4.01)

Table 3.10. Investor sentiment and securities lending: portfolio analysis

The table provides the average excess returns and benchmark-adjusted returns following high and low level of investor sentiment. We define period as a high (low) sentiment period if the sentiment index of Baker and Wurgler (2006) in the previous month is above (below) its median value for the sample period. The sample period is from January 2006 to December 2016. The *t*-statistics are in parentheses.

ΔLendable supply	Low			High			Difference		
	High sentiment	Low sentiment	High-Low	High sentiment	Low sentiment	High-Low	High sentiment	Low sentiment	High-Low
Raw Return	0.50	2.03**	−1.54	0.18	1.06	−0.88	−0.32**	−0.97***	0.65**
	(0.88)	(2.18)	(−1.40)	(0.32)	(1.25)	(−0.86)	(−2.26)	(−3.41)	(2.04)
FF3 α	0.24	1.92**	−1.68	−0.09	0.97	−1.06	−0.33	−0.95***	0.62**
	(0.31)	(2.54)	(−1.56)	(−0.13)	(1.38)	(−1.06)	(−1.43)	(−4.15)	(1.96)
FF5 α	0.42	2.13***	−1.70	0.09	1.10	−1.01	−0.33	−1.03***	0.70**
	(0.54)	(2.70)	(−1.56)	(0.12)	(1.49)	(−0.99)	(−1.41)	(−4.33)	(2.11)

Table 3.11. Investor sentiment and securities lending: predictive regression analysis

The table provides estimates in the regression,

$$R_t = a + bS_{t-1} + cControls_t + \epsilon_t,$$

where R_t is the excess return in month t on either the stocks with decreased lendable supply (low), stocks with increased lendable supply (high) or the difference between the two legs. S_{t-1} is the sentiment index of Baker and Wurgler (2006). The control variables are the Fama–French risk factors ($MKTRF_t$, SMB_t, HML_t, RMW_t, CMA_t). The sample period is from January 2006 to December 2016. The *t*-statistics are in parentheses.

ΔLendable supply	Constant	S_{t-1}	$MKTRF_t$	SMB_t	HML_t	RMW_t	CMA_t
Panel A: $R_t = a + bS_{t-1} + \epsilon_t$							
Low	1.13**	−4.44***					
	(2.10)	(−3.12)					
High	0.53	−3.01**					
	(1.03)	(−2.23)					
Difference	0.60***	−1.43***					
	(3.84)	(−3.42)					
Panel B: $R_t = a + bS_{t-1} + cMKTRF_t + dSMB_t + eHML_t + \epsilon_t$							
Low	0.97*	−4.47***	36.55***	−60.96**	12.85		
	(1.85)	(−3.18)	(2.71)	(−2.52)	(0.62)		
High	0.36	−3.06**	38.41***	−64.12***	7.21		
	(0.73)	(−2.31)	(3.02)	(−2.81)	(0.37)		
Difference	0.61***	−1.40***	1.86	3.16	5.64		
	(3.82)	(−3.29)	(−0.45)	(0.43)	(0.90)		
Panel C: $R_t = a + bS_{t-1} + cMKTRF_t + dSMB_t + eHML_t + fRMW_t + gCMA_t + \epsilon_t$							
Low	1.17**	−4.48***	29.38**	−66.99***	15.27	−43.93	−12.56
	(2.12)	(−3.16)	(1.98)	(−2.70)	(0.62)	(−1.13)	(−0.28)
High	0.52	−2.99**	32.86**	−69.94***	3.43	−42.93	8.73
	(1.00)	(−2.23)	(2.35)	(−2.98)	(0.15)	(−1.17)	(0.20)
Difference	0.65***	−1.49***	−3.49	2.95	11.84	−1.01	−21.28
	(3.88)	(−3.88)	(−0.78)	(0.39)	(1.58)	(−0.09)	(−1.56)

Appendix: Variable Definition

1. Institutional ownership: the percentage of outstanding shares held by institutional investors.
2. Share turnover: the number of shares traded in a month as a percentage of the number of outstanding shares.
3. Number of institutional investors: the number of institutional investors holding a firm's shares.
4. PPE (Property, plant and equipment): the property, plant and equipment over total assets.
5. R&D expenses: the research and development expense over total assets.
6. Firm age: the number of years since a stock's first appearance on CRSP.
7. Idiosyncratic volatility: the standard deviation of the residual values from Fama and French (2015) five-factor regression.
8. Relative active institutional ownership: the ratio of number of shares held by active institutions to the total shares held by all institutions.
9. Relative active mutual fund ownership: the ratio of number of shares held by active mutual funds to the total shares held by active and passive mutual funds.

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