ESSAYS ON EMPIRICAL ASSET PRICING

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PhD

The Hong Kong Polytechnic University

2020

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Essays on Empirical Asset Pricing

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A thesis submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy

March 2020

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This humble work is dedicated to my parents,

for their endless love.

Essays on Empirical Asset Pricing

Abstract

This thesis contains two essays on empirical asset pricing. The first essay investigates profitability of multiple trading strategies in foreign exchange market. We find that the proximity of current spot exchange rates to their 52-week extremes explains a significant portion of carry and momentum returns in the foreign exchange market. Anchored carry strategies go long high interest rate currencies that are closest to their 52-week highs and short low interest rate currencies that are closest to their 52-week lows. Anchored momentum strategies go long past winner currencies that are closest to their 52-week highs and short past loser currencies that are closest to their 52-week lows. These "anchored" strategies earn significantly higher returns than their corresponding "residual" strategies—where currencies that are near their 52-week extremes are excluded. These results are robust to simultaneously controlling for the carry spread (i.e. difference between interest rate for long and short portfolio) and the momentum spread (i.e. difference between lagged excess returns for long and short portfolio)—and are thus not driven simply by currencies closer to their 52-week extremes having higher interest differentials or lagged excess returns. We also find that the exposure to various macroeconomic and stock market risk factors cannot account for the outperformance of the anchored strategies.

The second essay studies investor sentiment and the crash risk of anomalies in the stock market. We document that the majority of stock market anomalies exhibit significantly negative skewness following low-sentiment periods and significantly positive skewness following high-sentiment periods. The more negative standardized CVaR of these strategies following low sentiment suggests that crashes are more likely during these times. Thus, left-tail risks cannot account for these strategies' higher returns following high-sentiment periods. In tests of co-exceedances of extreme returns, we find that co-crashes are more likely to occur and more severe following low sentiment, whereas joint euphoric gains are more prevalent following high

sentiment. Although diversification across the anomalies enhances the Sharpe ratio, it does not eliminate the crash risk.

Acknowledgements

I owe my sincere gratitude to Dr. Timothy Chue, for leading me along this intellectual journey. Particularly when the road got tough, he encouraged and guided me to find a path forward and help me grow professionally. All those enlightened counselling, inspiring discussions, and valuable suggestions from him throughout the course of my research have made this work possible.

Apart from my supervisor, I would like to extend my appreciation to members on my thesis committee - Prof. David Cook, Dr. Julan Du and Dr. Byoung Kang, for their insightful comments and suggestions on my work. I would also like to acknowledge Dr. Andy Chui and Dr. Te Feng Chen, for their inspiration and helpful advice on my confirmation paper.

I am profoundly grateful to my loving parents, whose affection, love, and encouragement make me able to accomplish this degree.

In addition, I would like to thank my family and friends for their company and support.

May end of this journey start a new chapter in my life.

Contents

Chapter 1 Carry, Momentum, and Anchoring on 52-Week Extremes in the Foreign Exchange Market

1.1 Introduction

In this chapter, we examine two trading strategies in the foreign exchange (FX) market: the carry trade and the momentum strategy. The carry trade borrows funds in low interest rate currencies, before lending them in currencies that offer higher interest rates. The momentum strategy takes short positions in currencies with low past returns (the “losers”) and goes long in currencies with high past returns (the “winners”).

These two self-financing strategies have been shown to generate large excess returns, yet risk-based explanations that can fully account for them remain elusive. Risk factors constructed from the long-short carry portfolios themselves are capable of explaining carry trade returns, but can hardly explain currency momentum. Since our understanding of these strategies is still incomplete, we examine the potential role played by investors’ anchoring bias in accounting for their returns.

In the absence of anchoring effects, investors would find high interest currencies more attractive - bidding up its value until its expected depreciation exactly offsets its interest rate advantage. But when investors are suffering from anchoring bias, they become reluctant to further bid up the value of high interest rate currencies that are already near their 52-week high. Likewise, investors are unwilling to further bid down the value of low interest rate currencies that are already near their 52-week low. This delay in the exchange rate adjustment process causes high interest rate currencies to continue to appreciate and low interest currencies to continue to depreciate, generating positive returns to the carry trade.

News (other than interest rate movements) can also cause currencies to appreciate (become “winners”) and depreciate (become “losers”). Yet, when investors are suffering from anchoring bias, they become reluctant to further bid up the value of winner currencies that are already near their 52-week high, or to further bid down the value of loser currencies that are already near their 52-week low. This delay in exchange rate adjustment to news causes recent winners that are near their 52-week high to continue to appreciate, and recent losers that are near their 52-week low to continue to depreciate.

Based on this reasoning, we construct “anchored” carry and momentum strategies. Anchored carry goes long high interest rate currencies that are closest to their 52-week highs and shorts low interest rate currencies that are closest to their 52-week lows. Anchored momentum goes long past winner currencies that are closest to their 52-week highs and shorts past loser currencies that are closest to their 52-week lows.

We find that these anchored strategies earn significantly higher returns than their corresponding “residual” strategies—where currencies that are near their 52-week extremes are excluded. This result suggests that a significant fraction of the “unconditional” carry and momentum returns—examined by previous studies—are attributable to currencies near their

52-week extremes. When spot rates are neither near nor far from their 52-week extremes, predictable returns associated with both carry and momentum become less pronounced.

To rule out the alternative explanation that these excess returns are compensation for risk exposure, we further control for various risk factors proposed in prior literature. We find that the excess returns associated with carry and momentum cannot be explained by their exposure to a number of macroeconomic risk proxies, stock market risks as captured by the Fama-French three factors and stock market momentum, and global FX volatility. While the carry trade factor HML_{FX} can account for the returns of unconditional carry, it can only partially explain the returns on anchored carry and cannot account for currency momentum at all.

Our study of anchoring on 52-week extreme exchange rates in the FX market is motivated by related behavioral research in the stock market. Individuals rely on heuristics to economize cognitive workload. The snapshot model suggests that people assess past experience based only on a few salient moments, rather than forming a cumulative impression of the entire experience (Daniel, Hirshleifer, and Subrahmanyam 1998, Barberis, Shleifer, and Vishny 1998, and Hong and Stein 1999). In George and Hwang (2004), they find that the 52-week high stock price dominates the forecast power of past returns. George, Hwang, and Li (2015) further show that anchoring on the 52-week high price leads to inadequate response to information and thus the post-earnings-announcement drift. Since the 52-week extreme exchange rates are just as salient in the FX market—as they are prominently displayed on virtually all financial newspapers, websites, and trading platforms—we postulate that they constitute likely candidates as investors' anchoring point when they evaluate the potential impact of news and interest rate movements.

A long literature examines the performance of various trading strategies in the FX market. Hansen and Hodrick (1980) and Fama (1984) document time-series violations of uncovered interest rate parity (UIP) and the presence of carry returns for individual currency pairs. Early studies on currency momentum focus on time-series momentum, also known as technical trading, which is to sell (buy) currencies that were profitable to sell (buy) in the past (Dooley and Shafer (1983), Levich and Thomas (1993), Neely, Weller, and Ulrich (2009), Moskowitz, Ooi, and Pedersen (2012)).

More recently, researchers begin to investigate cross-sectional carry and momentum strategies in the FX markets. Lustig and Verdelhan (2007) are the first to form high-minus-low carry portfolios based on cross-sectional interest rate differentials, regardless of the history of interest rate differences for individual currency pairs. This approach averages out idiosyncratic volatility in exchange rates. Okunev and White (2003) are the first to study cross-sectional momentum among eight currencies. Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) document cross-sectional currency momentum for 48 currencies and show that the phenomenon is distinct from time-series momentum and the carry trade.

Many studies attempt to rationalize currency excess returns from a risk-based perspective. Lustig and Verdelhan (2007) show that aggregate consumption growth risk accounts for a large portion of currency returns. High interest rate currencies earn positive excess returns as compensation for their depreciation in bad states; while low interest rate currencies earn negative excess returns as they provide a hedge against U.S. consumption risks. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) show that stock market risk factors such as the market, size, book-to-market, and momentum factors cannot explain either carry or momentum in the FX market. Using FX-based factors, such as the high-minus-low carry portfolio and the global FX volatility factor, Lustig, Roussanov, and Verdelhan (2011) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) achieve some success in pricing the returns from carry. But these risk factors still fail to explain currency momentum. Lustig, Roussanov, and Verdelhan (2014) further find that U.S. macroeconomic variables are powerful forecasters of currency returns at short horizons, and these returns are strongly countercyclical. Londono and Zhou (2017) show that currency and stock market variance risk premia have significant predictive power for carry returns.

Another strand of research justifies carry returns as a reflection of a Peso problem. Lewis (1995) proposes that the probability of extreme events is underestimated in sample. Burnside (2011) suggests that investors' concern with such rare events out of sample can justify the excess returns on currencies. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) use currency options to construct hedged carry trades and find that the payoff difference between hedged and unhedged carry is small in the peso state. This result suggests that the peso event is actually associated with a high value of the stochastic discount factor, rather than large negative payoffs.

Frankel and Froot (1989) and Evans and Lewis (1995) attribute currency excess returns to systematic expectation errors of economic agents. De Grauwe and Kaltwasser (2006) present a model in which agents incorporate only small bits of the total information set, leading to cyclical movements of exchange rates around their fundamentals. Bacchetta and Van Wincoop (2010) find that the high uncertainty and low welfare of frequent portfolio adjustment result in inactive management of currency positions, which contribute to the slow diffusion of information in the foreign exchange market. Burnside, Han, Hirshleifer, and Wang (2011) show that overconfident agents overreact to future inflation information, leading to exchange rate overshooting that can be reconciled with the returns on carry. Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) find that currency momentum returns increase for up to one year after portfolio formation and then start to decline. This pattern is similar to the momentum returns in the stock market—suggesting that currency momentum returns may also be driven by initial underreaction and subsequent overreaction (as first proposed by Jegadeesh and Titman (1993) for the stock market).

The remainder of this paper proceeds as follows. Section 2 describes our data. Section 3 presents the construction and documents the performance of various currency portfolios. Section 4 further examines the performance of currency portfolios in multivariate regressions. Section 5 examines the exposure of currency portfolios to various risk factors. Section 6 concludes.

1.2 Data and Sample Selection

We obtain daily foreign exchange rate data from DataStream, sourced from Barclay/Reuters. Data contain spot exchange rate S_t and one-month forward exchange rate F_t. Both S_t and F_t are mid quotes in units of foreign currency per U.S. dollar. We retain the exchange rates on the last trading day in each month as our monthly data series. To employ a longer time span back to 1976, we convert GBP quotes to USD quotes by multiplying the GBP/FCU by USD/GBP quotes for 16 developed countries. They are Austria, Belgium, Canada, Denmark, France, Germany, Ireland, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. Our sample period spans from January 1976 to January 2018.

Our total sample consists of the following 48 countries: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, Euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Iceland, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, United Kingdom. Our effective sample size varies overtime as new currencies coming in when data become available or when currencies cease to exist due to adoption of Euro. So our sample does not cover all 48 currencies at the same time. As illustrated in Fig. 1, at beginning we have 14 currencies and a maximum of 37 currencies in year 2004 and finally end up with 34 currencies. Following Lustig, Roussanov and Verdelhan (2011), we drop the following observations from our sample due to large failures of covered interest rate parity: Malaysia from the end of August 1998 to the end of June 2005; Indonesia from the end of December 2000 to the end of May 2007. The total number of currency-month observation is 13073.

[Table 1.1 about here]

[Figure 1.1 about here]

It is worth noting that, Hong Kong Dollar and Saudi Arabian Riyal have pegged their exchange rate partly to USD, and India has capital account restrictions. We still keep them in our sample for several reasons. First, forward contracts of these currencies are easily accessible so that we can have a larger cross-section for portfolio analyses. Second, though currencies with semi fixed exchange rates are less flexible, they are still managed in crawling bands and this leaves us some room to investigate the impact of anchoring in exchange rate variations for these currencies. Third, recent literature has emphasized currency excess returns are not driven by currency regimes or capital account controls (Menkhoff, Sarno, Schmeling and Schrimpf (2012a)). In addition, it is difficult to identify a declared free-floating exchange rate regime is actually just *de jure* or *de facto* (Frankel and Poonawala (2009)).

1.3 Currency portfolios

1.3.1 Currency excess returns. We take the perspective of U.S. investors and assume U.S. dollar (USD) as home currency in this paper. We denote the U.S. risk-free rate by i_t and foreign risk-free rate by i_t^*. s_t is the log of spot exchange rate and f_t is the log of forward exchange rate, both in units of foreign currency per USD. An increase in s_t means an appreciation of USD. To a U.S. investor, the log excess return on buying a foreign currency in forward market and then selling it in the spot market after one month is:

$$er_{t+1} = i_t^* - i_t - \Delta s_{t+1} \tag{1}$$

Under covered interest rate parity condition, we have:

$$i_t^* - i_t = f_t - s_t \tag{2}$$

Therefore, currency excess return is:

$$er_{t+1} = f_t - s_{t+1} \tag{3}$$

1.3.2 Unconditional trading strategies

High minus low carry portfolio:

At the end of each month t, currencies are allocated into three portfolios based upon forward discount f_t - s_t. Currencies with lowest forward discount are allocated to the first portfolio (low interest), and currencies with the highest forward discount are allocated to the third portfolio (high interest). The unconditional High-minus-Low carry strategy is to go long currencies in high interest rate portfolio and short currencies in low interest rate portfolio. We compute the portfolio return by taking the average of the log excess return of each currency in this portfolio. Portfolios are rebalanced monthly.

Table 2 Panel A to D present, for each currency portfolio, the average change in log spot exchange rates Δs_{t+1}, the average log forward discount f_t - s_t, the average log excess return er_{t+1}. Failure of UIP suggests that adjustment in spot rates fall short to wipe out interest rate margin. This leads to predictable excess returns from carry trade. For unconditional HML carry, currencies in the first portfolio trade at an average forward discount of -319 basis points, only appreciate by 40 basis points on average. Currencies in the third portfolio trade at an average discount of 760 basis points, but they depreciate on average by only 373 basis points. This adds up to an average monthly log excess return of 665 basis points for a high minus low carry portfolio.

The cross-section momentum portfolio:

At the end of each month t, currencies are ranked into three portfolios based on one-month lagged excess return of holding a foreign currency, i.e. er_t = f_{t-1} - s_t. Currencies with the lowest past returns are allocated to the first portfolio denoted as "loser", and currencies with the highest past returns are allocated to the third portfolio denoted as "winner". A cross-section momentum strategy is to long currencies in winner portfolio and short currencies in loser portfolio. We compute the portfolio return by taking the average of the log excess return of each currency in this portfolio. Portfolios are rebalanced monthly.

As shown in Table 2 Panel E to H, for unconditional WML momentum, currencies in the loser portfolio trade at an average forward discount of 24 basis points and depreciate by 276 basis points on average. Currencies in the third portfolio trade at an average discount of 356 basis points and depreciate on average by 51 basis points. This adds up to an average monthly log excess return of 558 basis points for a winner minus loser momentum portfolio. Comparing to large spread in forward discount which ranges from -319 to 760 basis points across three carry portfolios, forward discount of three momentum portfolio only varies from 24 to 356 basis points. This implies that different from carry returns, currency momentum returns do not primarily source from exploiting cross-sectional interest rate differentials.

[Table 1.2 about here]

1.3.3 Anchored and Residual trading strategies

Traditional carry and momentum strategies do not discriminate currencies that are close to or far from 52-week extreme exchange rate. We construct novel carry and momentum portfolios, conditioning on currencies' distance to 52-week extremes. 52-week high is the highest end-of-day spot rate in prior 260 trading days. 52-week low is the lowest end-of-day spot rate in prior 260 trading days. Distance to 52-week extreme exchange rates is defined as ($S_{k,t}$ - $MID_{k,t}$)/($52H_{k,t}$ - $52L_{k,t}$) where $MID_{k,t}$ = ($52H_{k,t}$ + $52L_{k,t}$)/2, i.e. the midpoint between 52-week high and 52-week low of currency k at time t. As exchange rates in our paper are paired up with USD and quoted in units of foreign currencies per USD, a 52-week high price of USD represents the counterpart foreign currency is at its 52-week low; while a 52-week low price of USD represents the counterpart foreign currency is at its 52-week high. For ease of interpretation, we use - ($S_{k,t}$ - $MID_{k,t}$)/($52H_{k,t}$ - $52L_{k,t}$) in portfolio sorting and regression analyses. A higher value indicates foreign currency closer to its 52-week high and lower value means foreign currency close to its 52-week low.

Anchored HML carry:

Currencies are allocated into 3*3 groups based upon their forward discount and distance to 52-week extreme spot rates for anchored carry trade. At the end of each month t, currencies are ranked into three portfolios based on their forward discount f_t - s_t. Currencies with lowest forward discount are allocated to the first portfolio, and currencies with the highest forward discount are allocated to the third portfolio. Next, within each of the three groups sorted on forward discount, currencies are allocated into 3 portfolios based upon their distance to 52-week extreme spot rates. Currencies with lowest distance value are allocated to the first portfolio, i.e. currencies closest to 52-week low; while currencies with the highest distance value are allocated to the third portfolio, i.e. currencies closest to 52-week high. An anchored carry portfolio is to go long currencies with highest forward discount and closest to their 52-week high and short currencies with lowest forward discount and closest to their 52-week low.

[Table 1.3 about here]

If investors do anchor on 52-week extreme exchange rates, high interest rate currencies trade at 52-week highs would bring subsequent positive returns and low interest rate currencies trade at 52-week lows would bring subsequent negative returns. This is exactly what we observe in our empirical results. High interest rate currencies that closest to 52-week highs generate 6.15% p.a. and low interest rate currencies that closest to 52-week lows generate -7.23% p.a., which contributes to an annual return of 13.39% for anchored carry. Further decompose anchored carry returns into interest rate margin and change in spot rate in Table 4 Panel A to D, we find currencies on long leg of anchored carry trade at an average forward discount of 630 basis points, only depreciate by 15 basis points on average (recall that currencies in long portfolio of unconditional carry trade at an average forward discount of 760 basis points but depreciate by 373 basis points). Currencies on short leg of anchored carry trade at an average discount of -595 basis points, but they depreciate on average by 128 basis points (recall that currencies in short portfolio of unconditional carry trade at an average forward discount of -319 basis points but appreciate by 40 basis points). Anchored carry strategy enables investors to exploit more extreme positions from failure of UIP, i.e. on long side, we have high interest rate currencies that appreciate more (or depreciate less) and on short side, we have low interest currencies that depreciate more.

Residual HML carry:

To carry out residual carry trade, we exclude currencies selected by anchored carry portfolios on long and short sides. For currencies remaining in the pool, we go long those ones left in the third portfolio sorted on forward discount and short those ones left in the first portfolio sorted on forward discount.

Table 4 Panel E to H present average change in log spot exchange rates and average log forward discount for residual carry portfolios. Currencies on long leg of residual carry trade at an average forward discount of 769 basis points, depreciate by 472 basis points on average, which largely reduce the return by holding high interest rate currencies. Currencies on short leg of residual carry trade at an average forward discount of -225 basis points, but they appreciate on average by 103 basis points, leaving only a return of 122 basis points by shorting low interest currencies. Excluding high interest rate currencies closest to 52-week high and low interest rate currencies closest to 52-week low, residual carry brings 4.19% per annum, which is almost only 60% of unconditional carry return and 30% of anchored carry return. This further confirms that a large portion of carry profits stem from the subsequent returns of currencies near 52-week extremes.

[Table 1.4 about here]

Anchored WML momentum:

Currencies are allocated into 3*3 groups based upon their one-month lagged excess return and distance to 52-week extreme spot rates for anchored momentum trade. At the end of each month t, currencies are ranked into three portfolios based on one-month lagged excess return $er_t = f_{t-1} - s_t$. Currencies with lowest past returns (losers) are allocated to the first portfolio, and currencies with the highest past returns (winners) are allocated to the third portfolio. Next, within each of the three portfolios sorted on past return, currencies are allocated into 3 portfolios based upon their distance to 52-week extreme spot rates. Currencies with lowest distance value are allocated to the first portfolio, i.e. currencies closest to 52-week low; while currencies with the highest distance value are allocated to the third portfolio, i.e. currencies closest to 52-week high. An anchored momentum portfolio is to go long currencies with highest past return and closest to their 52-week high and short currencies with lowest past return and closest to their 52-week low.

[Table 1.5 about here]

If anchoring on 52-week extreme exchange rates holds, we expect that past winner currencies coincide with spot rates that are near 52-week high would bring more positive return and past loser currencies coincide with spot rates near 52-week low would bring more negative return. The long side of anchored momentum generates 4.37 % p.a. and short side generates -4.23% p.a., constituting to an annual return of 8.60% for anchored momentum. Further decompose these returns into interest rate margin and spot rate movement in Table 6 Panel A to D we find currencies on long side of anchored momentum strategy trade at an average forward discount of 211 basis points, and spot rate moves by -111 basis points on average (recall that currencies in long portfolio of unconditional momentum trade at an average forward discount of 356 basis points but spot rate moves only by 51 basis points). Currencies on short side of anchored momentum trade at an average discount of 19 basis points, and spot rate move on average by 442 basis points (recall that currencies in short portfolio of unconditional momentum trade at an average forward discount of 24 basis points but spot rate moves only 276 basis points on average). Anchored momentum strategy enables investors to exploit more favorable movement in spot rate, i.e. on long side, we have past winner currencies that appreciate more and on short side, we have past loser currencies that depreciate more.

Residual WML momentum:

To implement residual momentum strategy, we exclude currencies selected by anchored momentum portfolios on long and short sides. For currencies remaining in the pool, we go long those ones left in the third portfolio sorted on one month-lagged excess return and short those ones left in the first portfolio sorted on one month-lagged excess return.

Table 6 Panel E to H present average change in log spot exchange rates and average log forward discount for residual momentum portfolios. Currencies on long side of residual momentum trade at an average forward discount of 403 basis points, depreciate by 177 basis points on average, which produce a return of 226 basis points by holding past winner currencies. Currencies on short side of residual momentum trade at an average forward discount of -2 basis points, but spot rate goes up by 157 basis points, which gives a negative return of 159 basis points by shorting past loser currencies. Excluding past winner currencies closest to 52-week high and past loser currencies closest to 52-week low, residual momentum brings 3.85% per annum, which is lower than unconditional momentum return (5.58 %) and anchored momentum return (8.60%). This supports that future returns of currencies near 52-week extremes attribute to a considerable part of momentum profits.

[Table 1.6 about here]

1.4 Regression analyses

1.4.1 Summary statistics and correlation of variables in regressions

Independent variable $\Delta FWD_{i,t}$ is defined as the difference between forward discount for the long and short sides of a strategy at time t, i.e. average forward discount of currencies in long portfolio of strategy i - average forward discount of currencies in short portfolio of strategy i in month t; $\Delta MM_{i,t}$ is defined as the difference between past return for the long and short sides of a strategy at time t, i.e. average past return of currencies in long portfolio of strategy i - average past return of currencies in short portfolio of strategy i in month t; $\Delta DIS_{i,t}$ is defined as the difference between distance measure for the long and short sides of a strategy at time t, i.e. average distance to 52-week extremes of currencies in long portfolio of strategy i - average distance to 52-week extremes of currencies in short portfolio of strategy i in month t. Table 7 Panel A presents monthly mean and Panel B presents standard deviation of independent variables $\Delta FWD_{i,t}$, $\Delta MM_{i,t}$ and $\Delta DIS_{i,t}$ and dependent variable monthly long-short portfolio return $ret_{i,t+1}$ for anchored carry, residual carry, anchored momentum and residual momentum. The variation in average of independent variables $\Delta FWD_{i,t}$, $\Delta MM_{i,t}$ and $\Delta DIS_{i,t}$ is large across the four strategies, among which averages of $\Delta MM_{i,t}$ and $\Delta DIS_{i,t}$ even turn negative for residual carry. Standard deviations of these variables are always higher for anchored strategies than residual strategies.

[Table 1.7 about here]

Table 8 presents Pearson correlation coefficients of pairwise variables in regressions for four strategies, i.e. anchored carry, residual carry, anchored momentum, and residual momentum.

The correlation coefficient between forward discount spread $\Delta FWD_{i,t}$ and one-month lagged return spread $\Delta MM_{i,t}$ for anchored carry strategy is 0.48 and is 0.09 for residual carry strategy. The correlation coefficient between forward discount spread $\Delta FWD_{i,t}$ and one-month lagged return spread $\Delta MM_{i,t}$ for anchored momentum strategy is 0.29 and is 0.11 for residual carry strategy. The higher correlation coefficients between $\Delta FWD_{i,t}$ and $\Delta MM_{i,t}$ for anchored carry and anchored momentum explains the variation in coefficient estimate on $\Delta MM_{i,t}$ in Spec (3) and Spec (5), i.e. positive predictability of $\Delta MM_{i,t}$ in Spec (3) dissipates when controlling $\Delta FWD_{i,t}$ in Spec (5). Across the four strategies, one-month lagged return spread $\Delta MM_{i,t}$ and distance spread $\Delta DIS_{i,t}$ are moderately positively correlated, but neither one of them drives out each other in terms of their predictive power as shown by the significantly positive coefficient estimates on both $\Delta MM_{i,t}$ and $\Delta DIS_{i,t}$ in Spec (7). The negative correlation between forward discount spread $\Delta FWD_{i,t}$ and distance spread $\Delta DIS_{i,t}$ as shown in Table 11 and the negative average distance spread for residual carry in Table 10 is consistent with $\Delta DIS_{i,t}$ having a negative contribution of -55.72% to the returns to residual carry as in decomposition analyses in Table 13.

[Table 1.8 about here]

1.4.2 Regression specifications

To prove anchored strategies significantly outperform residual strategies in regression analyses, we use returns of anchored and residual strategies at time t+1 as test portfolios and run multivariate panel regressions with following independent variables: $\Delta FWD_{i,t}$, $\Delta MM_{i,t}$, $\Delta DIS_{i,t}$ and strategy dummy variables; Carry, ACarry, Mom and AMom are binary dummy variables; we define carry dummy Carry = 1 if portfolio i is anchored or residual carry portfolio; anchored carry dummy ACarry = 1 if portfolio i is anchored carry portfolio; momentum dummy Mom = 1 if portfolio i is anchored or residual momentum portfolio; anchored momentum dummy AMom = 1 if portfolio i is anchored momentum portfolio. Total number of monthly portfolios in each regression is 1972.

In specification (1) with four dummy variables only, coefficient of dummy Carry is the average of monthly portfolio returns of residual carry; coefficient of dummy ACarry indicates anchored carry earn a significantly higher monthly return of 0.0077 more than residual carry; coefficient of dummy Mom is the average of monthly portfolio returns of residual momentum; coefficient of dummy AMom shows anchored momentum earn a significantly higher monthly return of 0.0040 more than residual momentum. For other specifications with dummy variables, estimations of regression coefficients of interest are that of ACarry and AMom, which represent return spread between anchored carry and residual carry, and anchored momentum and residual momentum, respectively.

In Spec (2) controlling for $\Delta FWD_{i,t}$, Spec (3) controlling for $\Delta MM_{i,t}$ and Spec (5) controlling for both $\Delta FWD_{i,t}$ and $\Delta MM_{i,t}$, coefficient estimates of dummy ACarry and/or dummy AMom remain significantly positive, which indicate difference in forward discount and past return could not fully explain the higher return of anchored strategies over residual strategies. In specifications controlling for $\Delta DIS_{i,t}$, i.e. Spec (4), (6), (7) and (8), coefficient estimates of dummy ACarry and dummy AMom become insignificant, which prove difference in distance measure could account for the return spreads between anchored and residual strategies.

Specifically in Spec (8), with simultaneously controlling for $\Delta FWD_{i,t}$, $\Delta MM_{i,t}$, and $\Delta DIS_{i,t}$, coefficient estimates of all four dummy variables become insignificant, which suggest difference in forward discount, past return and distance not only explain return spreads between anchored and residual strategies, but also account for the returns of residual strategies. In Spec (8) and Spec (9), $\Delta FWD_{i,t}$ and $\Delta DIS_{i,t}$ together drive out the positive predictive power of $\Delta MM_{i,t}$ as it shows in Spec (3) and Spec (7). This is also supported by the results in Spec (6) that without $\Delta MM_{i,t}$, $\Delta FWD_{i,t}$ and $\Delta DIS_{i,t}$ could explain the return of residual strategies and the return spreads between anchored and residual strategies, as coefficient estimates of four dummy variables are insignificant. It is also worth noting that coefficient estimates of $\Delta DIS_{i,t}$ across different regression specifications are always positive at 5% significance level and above, which confirms our findings that anchoring on 52-week extremes augments the excess returns associated with carry and momentum hence anchored strategies earn predictable higher returns than unconditional and residual strategies. The size and significance level of coefficient estimates on $\Delta FWD_{i,t}$ show interest rate differential plays a critical role in contributing to the profitability of carry and momentum strategies in FX market, which is consistent with prior studies on currency excess return.

[Table 1.9 about here]

1.4.3 Economic significance and decomposition of strategy returns

Using the coefficient estimates on $\Delta FWD_{i,t}$ and $\Delta DIS_{i,t}$ from regression Spec (6) in Table 9 and standard deviation of independent variables in Table 7, ceteris paribus, 1 standard deviation increase in forward discount spread would translate into 129bps (i.e. 0.8613*0.0150) increase in monthly anchored carry return, 41bps increase in monthly residual carry return, 102bps increase in monthly anchored momentum return and 56 increase in monthly residual momentum return. 1 standard deviation increase in distance spread would result in 20bps (i.e. 0.0071*0.2771) increase in monthly anchored carry return, 14bps increase in monthly residual carry return, 17bps increase in monthly anchored momentum return and 14bps increase in monthly residual momentum return.

Decompose strategy mean return $ret_{i,t+1}$ into $\Delta FWD_{i,t}$ and $\Delta DIS_{i,t}$, we could see about 78.44% (0.0102*0.8613/0.0112) of the anchored carry mean return is explained by forward discount spread $\Delta FWD_{i,t}$ and 24.93% (0.3932*0.0071/0.0112) by distance spread $\Delta DIS_{i,t}$. By contrast, about 19.14% (0.0016*0.8613/0.0072) of anchored momentum is explained by forward discount spread and 60.15% (0.61*0.0071/0.0072) by distance spread. This decomposition demonstrates that carry spread is still the primary driver of anchored carry return. However, distance spread becomes the dominant source of anchored momentum return - it not only drives out the positive predictability of momentum spread, but also weigh far more over carry spread in contributing to anchored momentum return. After excluding currencies closest to 52-week extremes, distance spread contributes negatively to residual carry return, which is -55.72% (0.0071*(-0.2747)/0.0035) of monthly mean return of residual carry and it makes for 0.08% (0.0071*0.0036/0.0032) of monthly mean return of residual momentum. Carry spread contributes significantly to both residual carry and momentum return, being the leading factor to profitability of residual strategies. We further decompose the return spread between the anchored and residual carry and the return spread between the anchored and residual momentum. Difference in $\Delta FWD_{i,t}$ accounts for 21.69% of return spread between anchored carry and residual carry, which is calculated from (0.0102-0.0083)/(0.0112-0.0035)*0.8613. Difference in $\Delta DIS_{i,t}$ accounts for 61.87% of return spread between anchored carry and residual carry, which is calculated from (0.61-0.0036)/(0.0112-0.0035)*0.0071. Difference in $\Delta FWD_{i,t}$ accounts for -38.53% of return spread between anchored momentum and residual momentum, which is obtained from (0.0016-0.0034)/(0.0072-0.0032)*0.8613. Difference in $\Delta DIS_{i,t}$ accounts for 108.79% of return spread between anchored momentum and residual momentum, which is obtained from (0.61-0.0036)/(0.0072-0.0032)*0.0071. The decomposition of return spreads between anchored and residual strategies substantiate our finding than distance to 52-week extremes play an essential role accounting for superior returns of anchored strategies.

[Table 1.10 about here]

1.5 Controlling for risks

To further investigate the possibility that the expected excess returns associated with carry and momentum are due to risk exposure, we run time-series regression tests of anchored, residual, and unconditional returns on various risk factors. First, we consider a number of proxies for macroeconomic risks, including Durable Consumption (the growth rate of real durable goods consumption), Non-durable Consumption (the growth rate of real non-durable goods consumption), Real Consumption (the growth rate of real consumption growth), Employment (U.S. total nonfarm employment growth), ISM (the ISM manufacturing index), IP (the growth rate in real industrial production), CPI (the inflation rate), M2 (the growth in real money balances), Disp Inc (the growth in real disposable personal income), TED (the TED spread), and

TERM (the 10-year minus 3-month yield spread). Next, we consider two FX risk factors: HML_{FX}, the return to the carry trade long-short portfolio (Lustig, Roussanov, Verdelhan, 2011), and VOL_{FX}, a proxy for global FX volatility (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012b). Finally, we include U.S. stock market factors: the Fama-French factors (MKTRF, HML, and SMB), and the momentum factor (UMD).

Panel A shows results for univariate regressions (intercepts α, slope coefficients β, and the adjusted R^2) of carry returns and Panel B shows results for univariate regressions of momentum returns. Panel C shows results from a multivariate regression of carry returns on the three Fama-French factors and UMD and Panel D shows results from a multivariate regression of momentum returns on the three Fama-French factors and UMD factor.

Looking across results in Table 11, in both univariate regressions on macroeconomic or currency-specific risk factors and multivariate regressions on Fama-French three factors plus UMD, the key results to note are the slope coefficients are insignificantly different from zero and the adjusted R^2's are small—suggesting that there is little evidence that exposure to these factors can account for the strategies' returns. The one exception is the HML_{FX} factor, which is built from currency portfolios by going long high interest rate currencies and short low interest rate currencies, can indeed account for the excess return of unconditional carry (but not momentum). After controlling for HML_{FX}, the alpha of unconditional carry turns insignificant, with a highly significant beta estimate and an adjusted R^2 of 76%. However, even the exposure to HML_{FX} cannot fully account for anchored carry—as its alpha remains significantly positive and with an adjusted R^2 of 29% only.

[Table 1.11 about here]

1.6 Conclusion

Both the carry and momentum strategies have been shown to generate large excess returns in the foreign exchange market, and these returns cannot be fully accounted for by risk-based explanations. In this paper, we examine the potential role played by investors' anchoring bias in explaining these returns. We find that the distance of current exchange rates to their 52-week extremes explains a significant portion of both carry and momentum returns. Anchored carry/momentum strategies that go long high interest rate/past winner currencies that are closest to their 52-week highs and short low interest rate/past loser currencies that are closest to their 52-week lows earn significantly higher returns than their corresponding "residual" strategies—where currencies that are near their 52-week extremes are excluded. These results are robust to simultaneously controlling for the carry spread (i.e. difference between interest rate for long and short portfolio) and the momentum spread (i.e. difference between one-month lagged excess returns for long and short portfolio) in multivariate regression analyses, and are not due to the exposure of the anchored strategies to various macroeconomic and stock market factors.

Chapter 2 Investor Sentiment and the Crash Risk of Anomalies

2.1 Introduction

Many studies try to find anomalous investment strategies that generate superior returns. However, few of them look at the crash risk of such strategies, especially under different market states. In this chapter, we study the left-tail risk of 11 anomalies in Stambaugh, Yu and Yuan (2012; hereafter SYY) as well as market, size and value strategies in the Fama-French three-factor model. We confirm SYY's finding that the mean returns of these strategies are always higher following high sentiment than following low sentiment, except for *Accruals*, *Market* and *Size*. Following low sentiment, the majority of the 14 strategies exhibit significantly negative skewness, whereas most of them exhibit significantly positive skewness following high sentiment. Moreover, the standardized CVaR levels of these strategies are more negative following low sentiment. This evidence suggests that crash risk is greater following low sentiment than following high sentiment. Thus, if crash risk demands a premium, it may not serve as a plausible explanation for the higher abnormal returns following high sentiment. In the test of co-exceedances of extreme returns, we find that a co-crash is more likely and more severe following low sentiment and that joint euphoric gains are more likely and greater following high sentiment. To the best of our knowledge, our study is the first to focus on the crash and co-crash risk of a basket of anomalies following high and low market sentiment.

In the area of foreign exchange research, Rafferty (2012) introduces a global currency skewness risk factor that successfully prices cross sections of currency portfolios sorted on currency carry, currency momentum and currency value simultaneously, which is better than the HMLfx carry and global volatility factors. It captures the notion that in particularly bad times for currency investors, investment currencies tend to crash (depreciate sharply) as a group relative to funding currencies. Kelly and Jiang (2014) extract tail risk measures from S&P 500 option data to predict aggregate market returns, and they find that common fluctuations in tail risk across firms can lead to simultaneous disinvestment, which potentially translates firm-level tail risk into aggregate asset-price oscillations. Lempérière, Deremble, Nguyen, Seager, Potters and Bouchaud (2016) demonstrate that skewness demands a risk premium, so negatively skewed strategies should be compensated with higher returns to remain attractive to investors. Kadan and Liu (2014) present that momentum exhibits significant left-tail risks such that it is much less attractive when accounting for high moments and rare events. Chue, Wang and Xu (2015) find that momentum strategy does not benefit from international diversification due to heavily correlated left-tail risk across the G-7 countries. Daniel and Moskovitz (2016) also document momentum experiences of infrequent but strong and persistent strings of negative returns. More specifically, they find that momentum crashes arise from panic states. Yang and Zhang (2019) find that excluding stocks with extreme absolute strength helps alleviate momentum crashes. In the sentiment literature, Barberis, Shleifer and Vishny (1998) propose a sentiment model to illustrate how investors' shifting beliefs sway stock prices. Daniel, Hirshleifer and Subrahmanyam (1998) show that investors' under- and overreactions to news drive different waves of sentiment. Baker and Wurgler (2006 & 2007) find that sentiment has the greatest effect if a stock is difficult to arbitrage or value and that a market crash is more likely following high sentiment. Stambaugh, Yu and Yuan (2012) show that mispricing is stronger following high sentiment, and thus anomalies are more profitable in such periods. Chue, Gul and Mian (2019) also document that return synchronicity is more pronounced for small, young, volatile, non-dividend-paying and low-priced stocks following high sentiment. Cui and Zhang (2019) confirm that firms with higher leverage ratios, a greater default risk and larger analyst forecast dispersion have a higher crash risk in high-sentiment periods. They also find that firms are more likely to hoard bad news during a high investor sentiment period, leading to a price crash when piled-up negative information is released all at once.

Inspired by the distinct performance of these strategies under different market states, we investigate how market conditions potentially shape their left-tail risk. The first contribution of our study is that we examine the crash risk of 14 investment strategies in a batch. Second, we look at both the crash risk of each strategy and the co-crash risk of all of the strategies. Third, we investigate how the crash risks of the 14 strategies vary under different market states by classifying the months in the sample into high-and low-sentiment periods. The remainder of this paper is organized as follows. Section II describes the data and strategies. Section III provides empirical analyses of the 14 strategies. Section IV concludes this paper.

2.2 Data

We use investor sentiment index data provided by Baker and Wurgler (BW). The BW sentiment index is from July 1965 to December 2016. We define high-sentiment periods as months in which the value of the BW sentiment index is greater than the median value for the sample period, and we define low-sentiment periods as months in which the BW sentiment index is lower than the median value. We classify anomaly returns into two groups according to market sentiment indicators, i.e., the return following either a high- or low-sentiment month, and we report the empirical analysis results separately for the high and low groups.

The 14 strategies we examine include market, size and value from the Fama-French three-factor model and the 11 well-documented anomalies in SYY 2012. The monthly return data are obtained from French's data library and Stambaugh, Yu and Yuan's 'Mispricing Factors' data. To match it to the BW sentiment data, we use each strategy's return series from August 1965 to December 2016, except for *Return on Assets* from November 1971 and *Failure Probability* from October 1973 due to data availability. The Appendix gives a description of each anomaly.

2.3 Empirical analysis

2.3.1 Summary statistics and left-tail risk

Table 2.1 presents the unconditional correlation coefficients of the 14 strategies. Basically, they are not highly correlated. The market and size strategies exhibit the lowest correlations with the other strategies as their correlation coefficients are mostly negative.

[Table 2.1 about here]

In Table 2.2, Panel A, we provide a comparison between our results and Stambaugh, Yu and Yuan's (2012) results. The unconditional mean returns column shows that 13 of the 14 strategies produce significant positive returns with the *Failure Probability*, *Gross Profitability* and *Size* factors being marginally significant. Comparing to SYY's unconditional mean returns, anomaly O-score shows insignificant excess returns in our sample. When classifying returns following a high- or a low-sentiment month, we find that 11 of the 14 strategies exhibit higher returns following high sentiment and 8 of those 11 are significantly higher. Our results show that the return spreads between high and low sentiment for the *Accruals*, *Gross Profitability*, *Investment to Assets*, *Momentum*, *Market* and *Size* factors are insignificant. SYY (2012) reports similar results except for *Accruals*. An equal-weighted portfolio of the 14 strategies earns 38 bps more following high sentiment, with a t-statistic of 3.33. Overall, most of the 14 strategies produce higher mean returns following high sentiment than following low sentiment, which is consistent with the results documented in SYY (2012). Our longer sample period may contribute to the slight difference between our results and those reported by SYY.

Table 2.2, Panel B, gives more information on the mean returns, standard deviations, Sharpe ratios, skewness levels and 5% expected shortfalls of the 14 strategies and an equal-weighted portfolio. *Momentum* produces a monthly mean return of 127 bps, which is the highest among the 14 strategies. Ohlson's O-score generates the lowest mean return of 4 bps per month. *Momentum* and *Failure Probability* have the largest standard deviation, whereas *Net Stock Issues* has the smallest standard deviation. Both *Momentum* and *Net Stock Issues* have a Sharpe ratio of 0.20, which is the highest among the 14 strategies, as a result of having the highest mean return and lowest standard deviation, respectively. Holding an equal-weighted portfolio brings 48 bps per month with an enhanced Sharpe ratio of 0.33, which suggests we could obtain a more efficient portfolio by lowering the strategy-specific variance from diversification. We use skewness and 5% expected shortfalls to measure crash risk. For each anomaly, we calculate the mean of the observations that fall in the bottom 5% of the return distribution as 5% expected shortfall (CVaR). To make it comparable across the 14 strategies, we also calculate the standardized 5% expected shortfall (STDCVaR). Table 2.2, Panel B, shows that only *Momentum* and *Market* exhibit negative skewness. Although *Momentum* has the highest mean return, it also has the most negative skewness. This is in line with the literature showing that stock momentum increases the crash risk. The 5% expected shortfall of the 14 strategies spans a wide spectrum, from -1504 bps to -546 bps. The expected shortfall of *Failure Probability* and *Momentum* is about three times higher than that of *Investment to Assets*. *Market Portfolio* exhibits a high crash risk in terms of both highly negative skewness and CVaR. With standardized units, variation in the 5% expected shortfall across the 14 strategies drops, ranging from -253 bps to -204 bps. Although a diversified equal-weighted portfolio may smooth return volatility, it does not seem to drive away the crash risk. The equal-weighted portfolio returns show negative skewness, and the magnitude of its reduced CVaR shrinks when using standardized units; at -2.37, it is still significantly more negative than the 5% expected shortfall of the standard normal distribution.

[Table 2.2 about here]

To investigate how the crash risk may emerge differently following high- and low-sentiment periods, we further look into skewness and 5% expected shortfalls following high- and low-sentiment periods. Table 2.3 shows that following low sentiment, 9 of the 14 strategies exhibit negative skewness. Following high sentiment, 11 of the 14 strategies show positive skewness. With respect to another crash risk measurement, 5% expected shortfall, we document more negative CVaR and standardized CVaR for most of the strategies following low sentiment. This is evidence that the crash risk is greater following low sentiment than following high sentiment. *Market Portfolio* is the only exception, showing more negative skewness, CVaR and standardized CVaR following high sentiment, which suggests that the market is more likely to crash following high sentiment. Our results echo studies showing that market crashes tend to occur in high-sentiment periods. An increase in sentiment by optimistic speculators boosts the relative prices of stocks that are difficult to value and arbitrage, leaving those stocks vulnerable to a subsequent crash risk.

[Table 2.3 about here]

2.3.2 Statistical tests: Monte Carlo simulations

Although the summary statistics show different mean returns, skewness and CVaR following high- and low-sentiment periods, we conduct Monte Carlo simulations to examine a strategy with left-tail risks that are significantly different from those of a standard normal distribution. Null distributions of return skewness and 5% expected shortfall are generated from 5,000 random samples, each with 309 observations (the number of months in the high/low-sentiment sample). We calculate the skewness and standardized CVaR of each sample to get a skewness/CVaR distribution. We compare the skewness and standardized CVaR of each strategy with the null distributions. The 5% expected shortfall of a standard normal distribution is -2.06. The p-values of the two-sided tests report the relative standing of the observed skewness/CVaR of each strategy in this distribution. Table 2.4, Panel A, presents the skewness and standardized CVaR following low-sentiment months. The figures with asterisks show the negative skewness and standardized CVaR levels that are statistically lower than that of a standard normal distribution, which is the case for *Accruals*, *Composite Equity Issues*, *Failure Probability*, *Momentum*, *Net Stock Issues, HML* and *Market*. Table 2.4, Panel B, presents the skewness and standardized CVaR levels following high-sentiment months. *Accruals, Asset*

Growth, Composite Equity Issues, *Failure Probability*, *Gross Profitability, Net Stock Issues, Return on Assets and SMB* exhibit positive skewness that is statistically higher than that of a standard normal distribution. Comparing the CVaR levels in Panels A and B, we can see that more strategies exhibit significantly lower standardized CVaR levels following low sentiment than following high sentiment, which proves that there is a greater crash risk following low sentiment than following high sentiment. The equal-weighted portfolio shows significantly negative standardized CVaR levels following both high and low sentiment, which again suggests crash risk could not be diversified away. Another point to note is the different messages that skewness and standardized CVaR give for crash risk—there are multiple cases in which the standardized CVaR is significantly more negative than the standard normal distribution and yet they have positive skewness, i.e., *Accruals, Failure Probability and Return on Assets*. This may illustrate the limitations of using skewness alone as a measure of crash risk.

[Table 2.4 about here]

2.3.3 Sentiment and co-crash risk

Following Bae et al. (2003), we use another crash risk measurement, positive/negative return exceedances. Negative return exceedances occur when returns lie below the 5th percentile of the portfolio return distribution. Positive return exceedances occur when returns lie above the 95th percentile of the portfolio return distribution. Co-exceedances is defined as the joint occurrence of extreme return exceedances that measure the incidence of joint favorable returns and co-crash risk across 14 anomalies in a given month. We split the months in our sample into high- and low-sentiment periods. A Co-exceedances count of *i* is a joint occurrence of positive/negative return exceedances across *i* different strategies following high- and low-sentiment periods.

Panels A1 and A2 of Table 2.5 show negative co-exceedances following low sentiment and negative co-exceedances following high sentiment. Table 2.5, Panel A1, shows that following a low-sentiment period, the maximum joint occurrence of extreme negative returns is that 8 of 14 anomalies crash at the same time. The total column shows this happens once across 308 low-sentiment months. Cases that observed months of negative co-exceedance significantly higher than the expected number under null are count *i* = 3, 4, 5, 6, 8. The total number of negative co-exceedance events in these cases adds up to 33 following low-sentiment indicators. In Panel A2, following high-sentiment indicators, the observed months of negative co-exceedance that are significantly higher than the expected number under null is *i* = 4, 6, 7. Such events happen 12 times. Hence, the incidence of negative return co-exceedance is higher following low sentiment than following high sentiment. In Table 2.5, Panel B1 shows multiple cases where the observed months of positive co-exceedance following low sentiment that are significantly higher than the expected number under null when count *i* = 4, 5, 6, 7. The total number of positive co-exceedance events in these cases is 10. In Panel B2, the observed months of positive co-exceedance following high-sentiment indicators that are significantly higher than the expected number under null is *i* = 3, 4, 5, 6, 7, 8. Such events happen 32 times. Excluding the marginally significant case when i = 3 with p-value being 0.06, such events total to 20, which is still twice the number of positive co-exceedance following low sentiment. We see positive return co-exceedance occur much more often following high sentiment than following low sentiment.

Panels A3 and B3 of Table 2.5 report the means of strategy returns involved in given co-exceedance counts. The total column displays the average of the strategy-month returns involved. Panel A3 illustrates that on the negative co-exceedance side, these strategies suffer more loss following low sentiment than following high sentiment by documenting the total standardized returns as being -0.71 versus -0.64 and -1.35 versus -1.12 below the mean with respect to $i > 3$ (6). Panel B3 shows that on the positive co-exceedance side, these strategies earn higher returns following high-sentiment periods than following low sentiment with total standardized returns being 0.5 versus 0.83 and 0.89 versus 1.57 above the mean with respect to $i > 3$ (6). This evidence substantiates that co-crash risk is not only more likely but also more severe following low sentiment and that joint euphoric gains are more likely and greater following high sentiment.

[Table 2.5 about here]

The binomial distribution is used to test whether the co-exceedance numbers we observe are statistically different from a situation in which extreme returns occur independently across the 14 strategies. The null hypothesis is that the negative/positive exceedances of individual strategy are independent of each other. As extreme returns are defined as returns falling in the top/bottom 5% of the return distribution, the probability of success in each Bernoulli experiment is 0.05, and the co-exceedance count is the number of successes in a string of 14 Bernoulli experiments. For example, $i = 0$ means there is no negative/positive exceedance occurring in any of the 14 strategies. If the extreme returns of the 14 strategies arise independently, we expect the probability of event $i = 0$ is $C_{14}^{0} * 0.05^{0} * 0.95^{14} = 0.488$. We examine 309 months, if the null (all exceedances are independent) is true, the observed number of co-exceedances should not be significantly different from the expected number, which is given by 0.488*309 = 150. For i = 0, … 14, the expected number of observations is 150, 111, 37, 7, 1, 0, 0, 0, 0, 0, 0, 0, 0 and 0, respectively. We conduct a right-tailed test; thus the alternative hypothesis is that the extreme return exceedances are correlated, and then the observed co-exceedance is significantly higher than the expected number. A p-value <= 0.05 suggests that the observed number is significantly larger than expected under the null at 5% level. The binomial distribution tests support that the extreme returns are correlated rather than occurring independently. There are more months than expected in which no extreme returns arise and extreme returns jointly occur. There are more months with negative co-exceedance following low sentiment than following high sentiment, whereas there are more months with positive co-exceedance following high sentiment than following low sentiment.

2.4 Conclusion

Consistent with SYY's finding that anomaly returns are always higher following high sentiment than following low sentiment, our paper further documents that the majority of anomalies exhibit significant negative skewness following low sentiment, whereas most of them show significant positive skewness following high sentiment. Moreover, the standardized CVaR levels of these strategies are more negative following low sentiment. This evidence suggests that the crash risk is greater following periods of low sentiment than following periods of high sentiment. Thus, left-tail risk does not seem to be a plausible explanation for these strategies' higher returns following high sentiment. In the test of co-exceedances of extreme returns, we find that a co-crash risk is higher and more severe following low sentiment and that the joint euphoric gains are more likely and greater following high sentiment. A diversified equal-weighted portfolio enhances the Sharpe ratio but does not eliminate crash risk.

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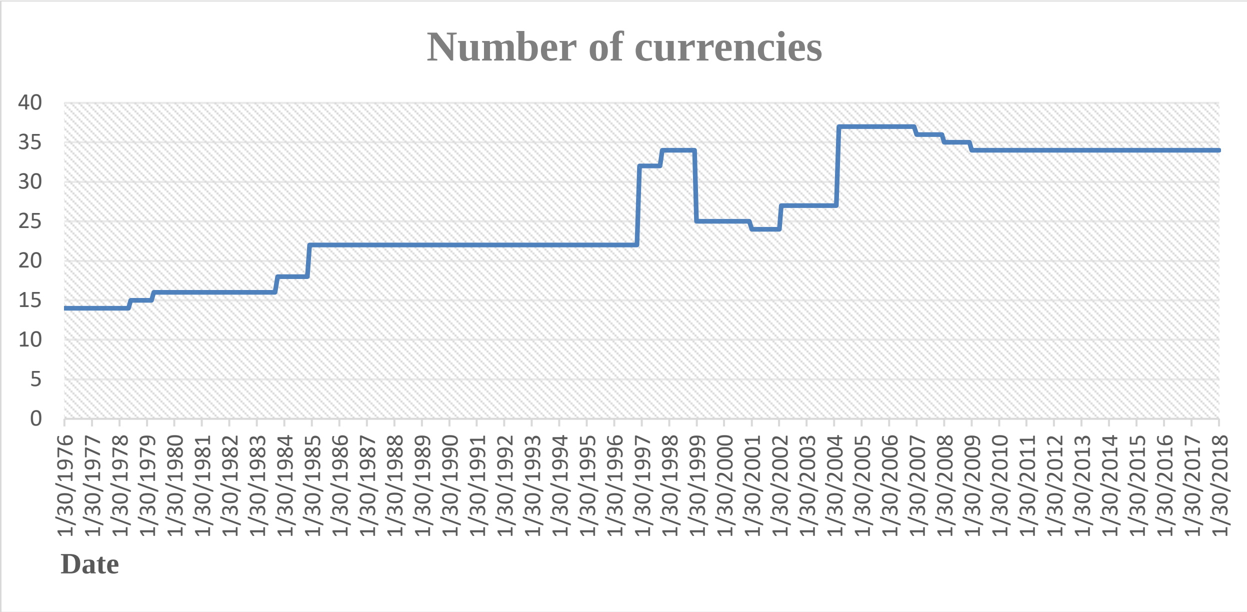
Figure 1.1 Number of available currencies

This figure presents number of available currencies across our sample period, i.e. currencies with available data for both forward and spot exchange rates. Our effective sample size varies overtime as new currencies coming in when data become available or when currencies cease to exist due to launch of Euro. The sample period runs from January 1976 to January 2018.


Number of currencies
40
35
30
25
20
15
10
5
0
1/30/1976
1/30/1977
1/30/1978
1/30/1979
1/30/1980
1/30/1981
1/30/1982
1/30/1983
1/30/1984
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1/30/2011
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1/30/2014
1/30/2015
1/30/2016
1/30/2017
1/30/2018
Date

Table 1.1 Currencies in the sample

This table shows the start and end dates of 48 currencies in our sample. The sample period runs from January 1976 to January 2018. The total number of currency-month observations is 13073.

Country	Start Date	End Date	Country	Start Date	End Date
Australia	12/31/1984	1/31/2018	S. Korea	2/28/2002	1/31/2018
Austria	1/30/1976	12/31/1998	Kuwait	12/31/1996	1/31/2018
Belgium	1/30/1976	12/31/1998	Malaysia	12/31/1984	1/31/2018
Brazil	3/31/2004	1/31/2018	Mexico	12/31/1996	1/31/2018
Bulgaria	3/31/2004	1/31/2018	Netherlands	1/30/1976	12/31/1998
Canada	1/30/1976	1/31/2018	Norway	1/30/1976	1/31/2018
Croatia	3/31/2004	1/31/2018	New Z.	12/31/1984	1/31/2018
Cyprus	3/31/2004	12/31/2007	Indonesia	12/31/1996	1/31/2018
Czech Rep.	12/31/1996	1/31/2018	Philippines	12/31/1996	1/31/2018
Denmark	1/30/1976	1/31/2018	Poland	2/28/2002	1/31/2018
Egypt	3/31/2004	1/31/2018	Portugal	1/30/1976	12/31/1998
EU	1/29/1999	1/31/2018	Russia	3/31/2004	1/31/2018
Finland	12/31/1996	12/31/1998	Saudi A.	12/31/1996	1/31/2018
France	1/30/1976	12/31/1998	S. Africa	10/31/1983	1/31/2018
Germany	1/30/1976	12/31/1998	Singapore	12/31/1984	1/31/2018
Greece	12/31/1996	12/29/2000	Slovakia	2/28/2002	12/31/2008
Hong Kong	10/31/1983	1/31/2018	Slovenia	3/31/2004	12/29/2006
Hungary	10/31/1997	1/31/2018	Spain	1/30/1976	12/31/1998
Iceland	3/31/2004	1/31/2018	Sweden	1/30/1976	1/31/2018
India	10/31/1997	1/31/2018	Switzerland	1/30/1976	1/31/2018
Ireland	4/30/1979	12/31/1998	Thai	12/31/1996	1/31/2018
Israel	3/31/2004	1/31/2018	Taiwan	12/31/1996	1/31/2018
Italy	1/30/1976	12/31/1998	UK	1/30/1976	1/31/2018
Japan	6/30/1978	1/31/2018	Ukraine	3/31/2004	1/31/2018

Table 1.2 Unconditional carry portfolios sort on one-month lagged forward discount and unconditional cross-section momentum portfolios sort on one-month lagged excess return

s_t (in units of foreign currency per USD) is log of the spot exchange rate at time t, and f_t (in units of foreign currency per USD) is log of the forward exchange rate with one-month maturity at time t. Log currency excess returns are computed as er_{t+1} = f_t - s_t - Δs_{t+1}.

For unconditional carry strategy, currency portfolios are constructed by sorting currencies into three groups based upon forward discount at the end of each month t. The first portfolio contains currencies with the lowest interest rates and the third portfolio contains currencies with the highest interest rates. Panel A to D present, for each currency portfolio, the average change in log spot exchange rates Δs_{t+1}, the average log forward discount f_t-s_t, the average log excess return er_{t+1} *and* the average return of unconditional High-minus-Low carry strategy, er^3_{t+1} - er^1_{t+1}, by going long in high interest currencies and short low interest currencies.

For unconditional momentum strategy, at the end of each month t, currency portfolios are constructed by sorting currencies into three groups based upon one month-lagged excess return of holding a foreign currency, i.e. er_t = f_{t-1} - s_t. The first portfolio contains currencies with the lowest past returns and the third portfolio contains currencies with the highest past returns. Panel E to H present, for each currency portfolio, the average change in log spot exchange rates Δs_{t+1}, the average log forward discount f_t-s_t, the average log excess return er_{t+1} *and* the average return of unconditional Winner-minus-Loser momentum strategy, er^3_{t+1} - er^1_{t+1}, by going long in past winner currencies and short past loser currencies.

First and second moments are annualized and reported in percentage points. Sharpe ratios (SR) are computed as ratios of annualized means to annualized standard deviations. White's heteroscedasticity-consistent standard errors (in %) are reported between parentheses for long-short portfolio returns. Data is at monthly frequency, retrieved from DataStream (collected by Barclays and Reuters). The sample period is 01/1976 – 01/2018.

Portfolio	1(Low i currency)	2	3(High i currency)	1(Losers)	2	3(Winners)
Panel A. Spot change: Δs_{t+1} *(%)*				Panel E. Spot change: Δs_{t+1} *(%)*		
Mean	-0.40	0.17	3.73	2.76	0.42	0.51
Std	7.71	7.98	8.83	8.67	8.20	8.12
Panel B. Forward discount: f_t-s_t *(%)*				Panel F. Forward discount: f_t-s_t *(%)*		
Mean	-3.19	1.28	7.60	0.24	1.94	3.56
Std	1.57	0.53	1.16	1.73	0.70	1.04
Panel C. Excess return: er_{t+1} *(%)*				Panel G. Excess return: er_{t+1} *(%)*		
Mean	-2.79	1.11	3.87	-2.53	1.53	3.06
Std	7.86	8.03	8.82	8.72	8.30	8.13
SR	-0.35	0.14	0.44	-0.29	0.18	0.38
Panel D. High-minus-Low: er_{t+1}^3 - er_{t+1}^1 *(%)*				Panel H. Winner-minus-Loser: er_{t+1}^3 - er_{t+1}^1 *(%)*		
Mean			6.65			5.58
			(0.96)			(1.10)
Std			6.19			7.12
SR			1.08			0.78

Table 1.3 Anchored carry portfolios – Double sort on forward discount and distance to 52-week extremes

52-week high is the highest end-of-day spot rate in prior 260 trading days. 52-week low is the lowest end-of-day spot rate in prior 260 trading days. Distance to 52-week extreme exchange rates is defined as ($S_{k,t}$ - $MID_{k,t}$)/($52H_{k,t}$ - $52L_{k,t}$) where $MID_{k,t}$ = ($52H_{k,t}$ + $52L_{k,t}$)/2, i.e. the midpoint between 52-week high and 52-week low of currency k at time t. As exchange rates in this paper are quoted in units of foreign currencies per USD, a 52-week high price of USD represents the counterpart foreign currency is at its 52-week low; while a 52-week low price of USD represents the counterpart foreign currency is at its 52-week high. For ease of interpretation, we use - ($S_{k,t}$ - $MID_{k,t}$)/($52H_{k,t}$ - $52L_{k,t}$) in portfolio sorting. A higher value indicates foreign currency closer to its 52-week high and lower value means foreign currency close to its 52-week low. Currencies are allocated into 3*3 groups based upon their forward discount and distance to 52-week extreme spot rates for anchored carry trade. At the end of each month t, currencies are ranked into three portfolios based on their forward discount f_t - s_t. Currencies with lowest forward discount are allocated to the first portfolio, and currencies with the highest forward discount are allocated to the third portfolio. Next, within each of the three groups sorted on forward discount, currencies are allocated into 3 portfolios based upon their distance to 52-week extreme spot rates. Currencies with lowest distance value are allocated to the first portfolio, i.e. currencies closest to 52-week low; while currencies with the highest distance value are allocated to the third portfolio, i.e. currencies closest to 52-week high. An anchored carry portfolio is to go long currencies with highest forward discount and closest to their 52-week high (marked with underscore) and short currencies with lowest forward discount and closest to their 52-week low (marked with underscore). White's heteroscedasticity-consistent standard errors (in %) are reported between parentheses. The sample period is 01/1976 – 01/2018.

Portfolio return			
	Forward discount tertile		
Distance to 52-week extremes tertile	1(low i currency)	2	3(high i currency)
1 (close to 52-week low)	-7.23	0.50	1.57
	(1.56)	(1.34)	(1.68)
2	-1.94	0.51	3.94
	(1.47)	(1.44)	(1.61)
3 (close 52-week high)	-0.27	2.03	6.15
	(1.32)	(1.35)	(1.50)

Table 1.4 Summary statistics of anchored carry and residual carry portfolios

Panel A to D present, for the anchored carry portfolio, the average change in log spot exchange rates Δs_{t+1}, the average log forward discount f_t - s_t, the average log excess return er_{t+1} and the average return of anchored carry strategy, er_{t+1}^{LONG} - er_{t+1}^{SHORT}. Currencies are allocated into 3*3 groups based upon their forward discount and distance to 52-week extreme spot rates for anchored carry trade. At the end of each month t, currencies are ranked into three portfolios based on their forward discount f_t - s_t. Currencies with lowest forward discount are allocated to the first portfolio, and currencies with the highest forward discount are allocated to the third portfolio. Next, within each of the three groups sorted on forward discount, currencies are allocated into 3 portfolios based upon their distance to 52-week extreme spot rates. Currencies with lowest distance value are allocated to the first portfolio, i.e. currencies closest to 52-week low; while currencies with the highest distance value are allocated to the third portfolio, i.e. currencies closest to 52-week high. The long side of anchored carry portfolio contains currencies with highest forward discount and closest to 52-week high and the short side contains currencies with lowest forward discount and closest to 52-week low.

To carry out residual carry trade, we exclude currencies selected by anchored carry portfolios on long and short sides. For currencies remaining in the pool, we go long those ones left in the third portfolio sorted on forward discount and short those ones left in the first portfolio sorted on forward discount. Panel E to H present, for each currency portfolio, the average change in log spot exchange rates Δs_{t+1}, the average log forward discount f_t - s_t, the average log excess return er_{t+1} *and* the average return of residual High-minus-Low carry strategy, er_{t+1}^{3} - er_{t+1}^{1}, by going long in high forward discount currencies and short low forward discount currencies. Log currency excess returns are computed as er_{t+1} = f_t - s_t - Δs_{t+1}.

First and second moments are annualized and reported in percentage. Sharpe ratios (SR) are computed as ratios of annualized means to annualized standard deviations. White's heteroscedasticity-consistent standard errors (in %) are reported between parentheses. The sample period is 01/1977 – 01/2018.

Portfolio	SHORT	LONG	SHORT	LONG
Panel A. Spot change: Δs_{t+1} *(%)*			Panel E. Spot change: Δs_{t+1} *(%)*	
Mean	1.28	0.15	-1.03	4.72
Std	8.61	9.57	8.35	9.51
Panel B. Forward discount: f_t-s_t *(%)*			Panel F. Forward discount: f_t-s_t *(%)*	
Mean	-5.95	6.30	-2.25	7.69
Std	5.15	0.96	0.95	1.42
Panel C. Excess return: er_{t+1} *(%)*			Panel G. Excess return: er_{t+1} *(%)*	
Mean	-7.23	6.15	-1.22	2.97
Std	9.98	9.64	8.48	9.42
SR	-0.72	0.64	-0.14	0.32
Panel D. High-minus-Low: er_{t+1}^{LONG} - er_{t+1}^{SHORT} *(%)*			Panel H. High-minus-Low: er_{t+1}^{LONG} - er_{t+1}^{SHORT} *(%)*	
Mean		13.39		4.19
		(1.62)		(1.10)
Std		10.37		7.06
SR		1.29		0.59

Table 1.5 Anchored momentum portfolios – Double sort on past return and distance to 52-week extremes

52-week high is the highest end-of-day spot rate in prior 260 trading days. 52-week low is the lowest end-of-day spot rate in prior 260 trading days. Distance to 52-week extreme exchange rates is defined as ($S_{k,t}$ - $MID_{k,t}$)/($52H_{k,t}$ - $52L_{k,t}$) where $MID_{k,t}$ = ($52H_{k,t}$ + $52L_{k,t}$)/2, i.e. the midpoint between 52-week high and 52-week low of currency k at time t. As exchange rates in this paper are quoted in units of foreign currencies per USD, a 52-week high price of USD represents the counterpart foreign currency is at its 52-week low; while a 52-week low price of USD represents the counterpart foreign currency is at its 52-week high. For ease of interpretation, we use - ($S_{k,t}$ - $MID_{k,t}$)/($52H_{k,t}$ - $52L_{k,t}$) in portfolio sorting. A higher value indicates foreign currency closer to its 52-week high and lower value means foreign currency close to its 52-week low. Currencies are allocated into 3*3 groups based upon their past return and distance to 52-week extreme spot rates for anchored momentum strategy. At the end of each month t, currencies are ranked into three portfolios based on one month-lagged excess return of holding a foreign currency, i.e. er_t = f_{t-1} - s_t. Currencies with lowest past return (loser) are allocated to the first portfolio, and currencies with the highest past return (winner) are allocated to the third portfolio. Next, within each of the three groups sorted on past return, currencies are allocated into 3 portfolios based upon their distance to 52-week extreme spot rates. Currencies with lowest distance value are allocated to the first portfolio, i.e. currencies closest to 52-week low; while currencies with the highest distance value are allocated to the third portfolio, i.e. currencies closest to 52-week high. An anchored momentum portfolio is to go long currencies with highest past return and closest to their 52-week high (marked with underscore) and short currencies with lowest past return and closest to their 52-week low (marked with underscore). White's heteroscedasticity-consistent standard errors (in %) are reported between parentheses. The sample period is 01/1976 – 01/2018.

Portfolio return

	One-month lagged excess return tertile		
Distance to 52-week extremes tertile	1(loser)	2	3(winner)
1 (close to 52-week low)	-4.23	1.35	2.37
	(1.54)	(1.31)	(1.65)
2	-2.03	0.55	2.21
	(1.53)	(1.50)	(1.44)
3 (close 52-week high)	-0.90	2.05	4.37
	(1.67)	(1.38)	(1.32)

Table 1.6 Summary statistics of anchored momentum and residual momentum portfolios

Panel A to D present, for the anchored momentum portfolio, the average change in log spot exchange rates Δs_{t+1}, the average log forward discount f_t - s_t, the average log excess return er_{t+1} and the average return of anchored carry strategy, er_{t+1}^{LONG} - er_{t+1}^{SHORT}. Currencies are allocated into 3*3 groups based upon their past return and distance to 52-week extreme spot rates for anchored momentum strategy. At the end of each month t, currencies are ranked into three portfolios based on their return er_t. Currencies with lowest past return are allocated to the first portfolio, and currencies with the highest past return are allocated to the third portfolio. Next, within each of the three groups sorted on past return, currencies are allocated into 3 portfolios based upon their distance to 52-week extreme spot rates. Currencies with lowest distance value are allocated to the first portfolio, i.e. currencies closest to 52-week low; while currencies with the highest distance value are allocated to the third portfolio, i.e. currencies closest to 52-week high. The long side of anchored momentum portfolio contains currencies with highest past return and closest to 52-week high and the short side contains currencies with lowest past return and closest to 52-week low.

To carry out residual momentum strategy, we exclude currencies selected by anchored momentum portfolios on long and short sides. For currencies remaining in the pool, we go long those ones left in the third portfolio sorted on one month-lagged excess return and short those ones left in the first portfolio sorted on one month-lagged excess return. Panel E to H present, for each currency portfolio, the average change in log spot exchange rates Δs_{t+1}, the average log forward discount f_t - s_t, the average log excess return er_{t+1} *and* the average return of residual Winner-minus-Loser momentum strategy, er_{t+1}^{3} - er_{t+1}^{1}, by going long in past winner currencies and short past loser currencies. Log currency excess returns are computed as er_{t+1} = f_t - s_t - Δs_{t+1}.

First and second moments are annualized and reported in percentage. Sharpe ratios (SR) are computed as ratios of annualized means to annualized standard deviations. White's heteroscedasticity-consistent standard errors (in %) are reported between parentheses. The sample period is 01/1977 – 01/2018.

Portfolio	SHORT	LONG	SHORT	LONG
Panel A. Spot change: Δs_{t+1} *(%)*			Panel E. Spot change: Δs_{t+1} *(%)*	
Mean	4.42	-2.26	1.57	1.77
Std	9.20	8.37	9.34	8.95
Panel B. Forward discount: f_t-s_t *(%)*			Panel F. Forward discount: f_t-s_t *(%)*	
Mean	0.19	2.11	-0.02	4.03
Std	4.04	0.89	1.75	1.41
Panel C. Excess return: er_{t+1} *(%)*			Panel G. Excess return: er_{t+1} *(%)*	
Mean	-4.23	4.37	-1.59	2.26
Std	9.88	8.47	9.43	8.86
SR	-0.43	0.52	-0.17	0.26
Panel D. Winner-minus-Loser: er_{t+1}^{LONG} - er_{t+1}^{SHORT} *(%)*			Panel H. Winner-minus-Loser: er_{t+1}^{LONG} - er_{t+1}^{SHORT} *(%)*	
Mean		8.60		3.85
		(1.64)		(1.19)
Std		10.50		7.66
SR		0.82		0.50

Table 1.7 Summary statistics of regression variables

Panel A presents monthly mean and Panel B presents standard deviation of independent variables $\Delta FWD_{i,t}$, $\Delta MM_{i,t}$ and $\Delta DIS_{i,t}$ and dependent variable monthly long-short portfolio return $ret_{i,t+1}$ for four strategies, i.e. anchored carry, residual carry, anchored momentum and residual momentum. The sample period is 01/1977 – 01/2018.

Panel A - Mean of dependent and independent variables

Variable	Anchored Carry	Residual Carry	Anchored Momentum	Residual Momentum
$ret_{i,t+1}$	0.0112	0.0035	0.0072	0.0032
$\Delta FWD_{i,t}$	0.0102	0.0083	0.0016	0.0034
$\Delta MM_{i,t}$	0.0254	-0.0027	0.0505	0.0382
$\Delta DIS_{i,t}$	0.3932	-0.2747	0.6100	0.0036

Panel B - Standard deviation of dependent and independent variables

Variable	Anchored Carry	Residual Carry	Anchored Momentum	Residual Momentum
$ret_{i,t+1}$	0.0299	0.0204	0.0303	0.0221
$\Delta FWD_{i,t}$	0.0150	0.0048	0.0118	0.0065
$\Delta MM_{i,t}$	0.0310	0.0193	0.0278	0.0192
$\Delta DIS_{i,t}$	0.2771	0.1996	0.2372	0.2037

Table 1.8 Correlation of regression variables

This table presents Pearson correlation coefficients of pairwise variables in regressions for each strategy, i.e. anchored carry, residual carry, anchored momentum and residual momentum. Standard errors are reported between parentheses. The sample period is 01/1977 – 01/2018.

Strategy	Variable	$ret_{i,t+1}$	$\Delta FWD_{i,t}$	$\Delta MM_{i,t}$	$\Delta DIS_{i,t}$
Anchored Carry	$ret_{i,t+1}$	.			
	$\Delta FWD_{i,t}$	0.4724	.		
		(0.0398)			
	$\Delta MM_{i,t}$	0.1712	0.4819	.	
		(0.0445)	(0.0395)		
	$\Delta DIS_{i,t}$	0.1265	0.0460	0.2935	.
		(0.0448)	(0.0451)	(0.0431)	
Residual Carry	$ret_{i,t+1}$	.			
	$\Delta FWD_{i,t}$	0.0500	.		
		(0.0451)			
	$\Delta MM_{i,t}$	0.0690	0.0896	.	
		(0.0450)	(0.0449)		
	$\Delta DIS_{i,t}$	-0.0021	-0.1994	0.2354	.
		(0.0451)	(0.0442)	(0.0439)	
Anchored Momentum	$ret_{i,t+1}$	.			
	$\Delta FWD_{i,t}$	0.3531	.		
		(0.0422)			
	$\Delta MM_{i,t}$	0.0418	0.2948	.	
		(0.0451)	(0.0431)		
	$\Delta DIS_{i,t}$	0.0266	0.0701	0.1255	.
		(0.0451)	(0.0450)	(0.0448)	
Residual Momentum	$ret_{i,t+1}$	.			
	$\Delta FWD_{i,t}$	0.1837	.		
		(0.0444)			
	$\Delta MM_{i,t}$	0.0223	0.1108	.	
		(0.0451)	(0.0449)		
	$\Delta DIS_{i,t}$	0.0595	-0.1611	0.1630	.
		(0.0450)	(0.0445)	(0. 0445)	

Table 1.9 Regression analyses

Test portfolio return $ret_{i,t+1}$ is return of anchored and residual strategies at time t+1. Independent variables $\Delta FWD_{i,t}$ is defined as the difference between forward discount for the long and short sides of a strategy at time t, i.e. average forward discount of currencies in long portfolio of strategy i - average forward discount of currencies in short portfolio of strategy i in month t; $\Delta MM_{i,t}$ is defined as the difference between past return for the long and short sides of a strategy at time t, i.e. average past return of currencies in long portfolio of strategy i - average past return of currencies in short portfolio of strategy i in month t; $\Delta DIS_{i,t}$ is defined as the difference between distance measure for the long and short sides of a strategy at time t, i.e. average distance to 52-week extremes of currencies in long portfolio of strategy i - average distance to 52-week extremes of currencies in short portfolio of strategy i in month t; Carry, ACarry, Mom and AMom are binary dummy variables: carry dummy Carry = 1 if portfolio i is anchored or residual carry portfolio; anchored carry dummy ACarry = 1 if portfolio i is anchored carry portfolio; momentum dummy Mom = 1 if portfolio i is anchored or residual momentum portfolio; anchored momentum dummy AMom = 1 if portfolio i is anchored momentum portfolio. White's heteroscedasticity-consistent standard error are reported between parentheses. *, ** and *** indicate coefficient estimates significant at 10%, 5% and 1% level, respectively. Total number of monthly portfolios in each regression is 1972.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta FWD_{i,t}$		0.8610***			0.8845***	0.8613***		0.8992***	0.8488***	0.8480***
		(0.0461)			(0.0575)	(0.0456)		(0.0572)	(0.0512)	(0.0482)
$\Delta MM_{i,t}$			0.0932**		-0.0294		0.0831**	-0.0475	-0.0180	-0.0185
			(0.0409)		(0.0377)		(0.0415)	(0.0388)	(0.0261)	(0.0313)
$\Delta DIS_{i,t}$				0.0070***		0.0071***	0.0051**	0.0081***	0.0096***	0.0096***
				(0.0026)		(0.0025)	(0.0026)	(0.0025)	(0.0018)	(0.0018)
Carry	0.0035***	-0.0036***	0.0037***	0.0054***	-0.0039***	-0.0017	0.0051***	-0.0018		
	(0.0009)	(0.0010)	(0.0009)	(0.0011)	(0.0010)	(0.0012)	(0.0011)	(0.0012)		
ACarry	0.0077***	0.0060***	0.0051***	0.0030	0.0068***	0.0013	0.0019	0.0018		
	(0.0016)	(0.0015)	(0.0019)	(0.0022)	(0.0018)	(0.0022)	(0.0023)	(0.0022)		
Mom	0.0032***	0.0003	-0.0003	0.0032***	0.0013	0.0003	0.0000	0.0020		
	(0.0010)	(0.0010)	(0.0017)	(0.0010)	(0.0015)	(0.0010)	(0.0017)	(0.0015)		
AMom	0.0040**	0.0055***	0.0028	-0.0003	0.0059***	0.0012	-0.0002	0.0012		
	(0.0017)	(0.0016)	(0.0017)	(0.0022)	(0.0017)	(0.0021)	(0.0022)	(0.0021)		
Cons.										0.0000
										(0.0008)
N	1972	1972	1972	1972	1972	1972	1972	1972	1972	1972
Adj R^2	0.0662	0.1752	0.0731	0.0694	0.1754	0.1784	0.0745	0.1796	0.1791	0.1324

Table 1.10 Decomposition of strategy mean return $\boldsymbol{ret_{i,t+1}}$ and spread in spread mean return of anchored and residual strategies into $\boldsymbol{\Delta FWD_{i,t}}$ and $\boldsymbol{\Delta DIS_{i,t}}$

This table presents the percentages of mean return explained by $\Delta FWD_{i,t}$ and $\Delta DIS_{i,t}$, obtained from using the coefficient estimate in Spec (6) in Table 9. About 78.44% (0.0102*.08613/0.0112) of the anchored carry mean return is explained by forward discount spread $\Delta FWD_{i,t}$ and 24.93% (0.3932*0.0071/0.0112) by distance spread $\Delta DIS_{i,t}$. About 19.14% (0.0016*0.8613/0.0072) of anchored momentum is explained by forward discount spread and 60.15% (0.61*0.0071/0.0072) by distance spread. Difference in $\Delta FWD_{i,t}$ accounts for 21.69% of return spread between anchored carry and residual carry, calculated from (0.0102-0.0083)/(0.0112-0.0035)*0.8613. Difference in $\Delta DIS_{i,t}$ accounts for 61.87% of return spread between anchored carry and residual carry, calculated from (0.61-0.0036)/(0.0112-0.0035)*0.0071. Difference in $\Delta FWD_{i,t}$ accounts for -38.53% of return spread between anchored momentum and residual momentum, calculated from (0.0016-0.0034)/(0.0072-0.0032)*0.8613. Difference in $\Delta DIS_{i,t}$ accounts for 108.79% of return spread between anchored momentum and residual momentum, calculated from (0.61-0.0036)/(0.0072-0.0032)*0.0071. Standard errors in % are reported between parentheses. The sample period is 01/1977 – 01/2018.

	Anchored Carry	Residual Carry	Anchored Momentum	Residual Momentum	Anchored Carry – Residual Carry	Anchored Momentum – Residual Momentum
Mean	0.0112	0.0035	0.0072	0.0032	0.0077	0.0040
% explained	78.44	204.25	19.14	91.51	21.69	-38.53
by $\Delta FWD_{i,t}$	(4.17)	(10.81)	(1.02)	(4.79)	(1.15)	(2.04)
% explained	24.93	-55.72	60.15	0.80	61.87	108.79
by $\Delta DIS_{i,t}$	(8.81)	(19.66)	(21.28)	(0.28)	(21.78)	(38.31)

Table 1.11 Controlling for risks

This table presents regressions estimates of returns from anchored, residual, and unconditional strategies on various risk factors. Durable Consumption is real consumption growth on durable goods, Non-durable Consumption is real consumption growth on non-durable goods, Real Consumption is real consumption growth, Employment is U.S. total nonfarm employment growth, ISM denotes the ISM manufacturing index, IP denotes growth in real industrial production, CPI is the inflation rate, M2 is the growth in real money balances, Disp Inc is growth in real disposable personal income, TED is the TED spread, TERM is the TERM spread (10 years minus 3 months), HML_{FX} is the return to the carry trade long-short portfolio (Lustig, Roussanov, Verdelhan, 2011), and VOL_{FX} is a proxy for global FX volatility (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012b). MKTRF, HML and SMB are the Fama-French factors and UMD is the momentum return to a long-short portfolio in U.S. stock market. Panel A shows results for univariate regressions (intercepts α, slope coefficients β, and the adjusted R^2, Newey-West standard errors of coefficient estimates in parentheses) of carry returns and Panel B shows results for univariate regressions of momentum returns. Panel C shows results from a multivariate regression of carry returns on the three Fama-French factors and UMD and Panel D shows results from a multivariate regression of momentum returns on the three Fama-French factors and UMD. The sample period is 01/1976 – 01/2018.

Panel A: Univariate regressions of carry returns

	Anchored carry			Residual carry			Unconditional carry		
	α	β	R^2	α	β	R^2	α	β	R^2
Durable	0.0110	0.0457	0.0015	0.0036	-0.0165	0.0004	0.0055	0.0160	0.0005
Consumption	(0.0020)	(0.0434)		(0.0010)	(0.0400)		(0.0010)	(0.0333)	
Non-durable	0.0109	0.1515	0.0011	0.0035	0.0225	0.0001	0.0054	0.0580	0.0004
Consumption	(0.0020)	(0.1901)		(0.0010)	(0.1268)		(0.0010)	(0.1066)	
Real	0.0101	0.4486	0.0051	0.0035	-0.0181	0.0000	0.0051	0.1714	0.0021
Consumption	(0.0021)	(0.2327)		(0.0011)	(0.1936)		(0.0011)	(0.1724)	
Employment	0.0083	2.3197	0.0224	0.0033	0.1556	0.0002	0.0047	0.6977	0.0056
	(0.0024)	(0.9883)		(0.0013)	(0.5880)		(0.0012)	(0.5038)	
ISM	0.0104	0.4199	0.0117	0.0034	0.0545	0.0004	0.0053	0.1473	0.0040
	(0.0021)	(0.2419)		(0.0010)	(0.1158)		(0.0010)	(0.1224)	
IP	0.0104	0.4565	0.0107	0.0036	-0.0522	0.0003	0.0054	0.0808	0.0009
	(0.0021)	(0.2682)		(0.0010)	(0.1179)		(0.0010)	(0.1189)	
CPI	0.0103	0.2817	0.0009	0.0023	0.4149	0.0043	0.0040	0.5147	0.0085
	(0.0027)	(0.4792)		(0.0018)	(0.4431)		(0.0017)	(0.3705)	
M2	0.0120	-0.4070	0.0042	0.0042	-0.3131	0.0054	0.0064	-0.3807	0.0104
	(0.0020)	(0.3318)		(0.0010)	(0.2913)		(0.0010)	(0.2615)	
Disp Inc	0.0110	0.0821	0.0004	0.0037	-0.0872	0.0010	0.0057	-0.0605	0.0006
	(0.0020)	(0.1244)		(0.0010)	(0.1054)		(0.0010)	(0.0755)	
TED	0.0147	-0.4953	0.0048	0.0066	-0.5243	0.0117	0.0088	-0.5383	0.0159
	(0.0038)	(0.4665)		(0.0023)	(0.3787)		(0.0023)	(0.3545)	
Term	0.0167	-0.2704	0.0099	0.0034	0.0078	0.0000	0.0066	-0.0565	0.0012
	(0.0036)	(0.1352)		(0.0020)	(0.0980)		(0.0019)	(0.0874)	
HML_{FX}	0.0060	0.5646	0.2874	-0.0013	0.5235	0.5326	0.0005	0.5507	0.7644
	(0.0015)	(0.0654)		(0.0007)	(0.0344)		(0.0004)	(0.0164)	
VOL_{FX}	0.0112	2.6144	0.0094	0.0035	-2.4473	0.0177	0.0055	-1.3276	0.0070
	(0.0019)	(1.5531)		(0.0009)	(1.4427)		(0.0010)	(1.2167)	

Panel B: Univariate regressions of momentum returns

	Anchored MM			Residual MM			Unconditional MM		
	α	β	R^2	α	β	R^2	α	β	R^2
Durable	0.0073	-0.0241	0.0004	0.0033	-0.0301	0.0012	0.0048	-0.0246	0.0009
Consumption	(0.0014)	(0.0496)		(0.0010)	(0.0365)		(0.0009)	(0.0332)	
Non-durable	0.0070	0.0651	0.0002	0.0032	-0.0065	0.0000	0.0047	-0.0139	0.0000
Consumption	(0.0014)	(0.2013)		(0.0010)	(0.1367)		(0.0009)	(0.1343)	
Real	0.0070	0.0494	0.0001	0.0033	-0.0428	0.0001	0.0047	-0.0281	0.0000
Consumption	(0.0016)	(0.2593)		(0.0011)	(0.1920)		(0.0010)	(0.1766)	
Employment	0.0068	0.2598	0.0003	0.0036	-0.3371	0.0009	0.0047	-0.0099	0.0000
	(0.0018)	(0.7565)		(0.0013)	(0.6070)		(0.0013)	(0.5712)	
ISM	0.0070	0.0735	0.0003	0.0035	-0.1440	0.0025	0.0048	-0.0653	0.0006
	(0.0014)	(0.2001)		(0.0011)	(0.1641)		(0.0010)	(0.1531)	
IP	0.0069	0.1671	0.0014	0.0035	-0.1842	0.0032	0.0048	-0.0565	0.0003
	(0.0014)	(0.1913)		(0.0010)	(0.1478)		(0.0010)	(0.1342)	
CPI	0.0091	-0.6710	0.0051	0.0060	-0.9510	0.0192	0.0069	-0.7560	0.0139
	(0.0023)	(0.6390)		(0.0017)	(0.4385)		(0.0017)	(0.4654)	
M2	0.0066	0.2713	0.0018	0.0021	0.5424	0.0138	0.0037	0.4469	0.0108
	(0.0017)	(0.4601)		(0.0010)	(0.3084)		(0.0010)	(0.3229)	
Disp Inc	0.0073	-0.0634	0.0002	0.0034	-0.0907	0.0009	0.0048	-0.0741	0.0007
	(0.0014)	(0.1874)		(0.0009)	(0.1038)		(0.0009)	(0.1123)	
TED	0.0073	0.0195	0.0000	0.0036	0.1273	0.0006	0.0044	0.1067	0.0005
	(0.0037)	(0.5852)		(0.0027)	(0.4573)		(0.0027)	(0.4754)	
Term	0.0051	0.1176	0.0018	0.0029	0.0483	0.0006	0.0034	0.0823	0.0018
	(0.0028)	(0.1319)		(0.0019)	(0.0915)		(0.0017)	(0.0868)	
HML_{FX}	0.0077	-0.0556	0.0027	0.0024	0.0886	0.0130	0.0043	0.0413	0.0032
	(0.0014)	(0.0738)		(0.0011)	(0.0603)		(0.0010)	(0.0499)	
VOL_{FX}	0.0072	3.4253	0.0156	0.0032	2.7378	0.0188	0.0047	3.1491	0.0297
	(0.0013)	(1.4030)		(0.0009)	(1.3664)		(0.0008)	(1.0952)	

Panel C: Multivariate regressions of carry returns

	Anchored carry			Residual carry			Unconditional carry		
	α	β	R^2	α	β	R^2	α	β	R^2
MKTRF	0.0101	0.1144	0.0261	0.0031	0.0884	0.0439	0.0050	0.0940	0.0533
	(0.0020)	(0.0340)		(0.0009)	(0.0236)		(0.0009)	(0.0202)	
SMB		-0.0581			0.0022			-0.0063	
		(0.0498)			(0.0356)			(0.0313)	
HML		0.0472			0.0028			0.0126	
		(0.0515)			(0.0369)			(0.0300)	
UMD		0.0434			-0.0329			-0.0164	
		(0.0329)			(0.0179)			(0.0147)	

Panel D: Multivariate regressions of momentum returns

	Anchored MM			Residual MM			Unconditional MM		
	α	β	R^2	α	β	R^2	α	β	R^2
MKTRF	0.0069	-0.0174	0.0053	0.0034	-0.0217	0.0031	0.0048	-0.0335	0.0052
	(0.0015)	(0.0497)		(0.0011)	(0.0344)		(0.0010)	(0.0350)	
SMB		0.0030			-0.0193			0.0115	
		(0.0530)			(0.0405)			(0.0342)	
HML		0.0211			-0.0014			-0.0029	
		(0.0452)			(0.0433)			(0.0358)	
UMD		0.0447			0.0035			0.0072	
		(0.0366)			(0.0277)			(0.0258)	

Table 2.1 Unconditional correlation matrix of 14 strategies

This table presents the unconditional correlation coefficients of the monthly returns of 14 strategies. The sample period is from 1965/07 to 2016/12 for all but Return on Assets, whose data starts from 1971/11, and Failure Probability, whose data begins from 1973/10. ACC is *Accruals*; AG is *Asset Growth*; CPI is *Composite Equity Issues*; FP is *Failure Probability*; GP is *Gross Profitability*; ITA is *Investment to Assets*; MM is *Momentum*; NI is *Net Stock Issues*; NOA is *Net Operating Assets*; OS is *O-score*; ROA is *Return on Assets*; SMB is *Size* factor; HML is *Value* factor; Mkt_Rf is return of market portfolio over one-month Treasury bill rate. Details of the constructions of 11 anomalies could be found in Appendix.

Strategy	ACC	AG	CPI	FP	GP	ITA	MM	NI	NOA	OS	ROA	SMB	HML	Mkt_RF
ACC	1.00													
AG	0.25	1.00												
CPI	0.30	0.53	1.00											
FP	0.06	0.12	0.28	1.00										
GP	-0.02	-0.13	0.01	0.54	1.00									
ITA	0.15	0.56	0.34	0.03	-0.18	1.00								
MM	0.08	-0.02	-0.06	0.57	0.31	0.07	1.00							
NI	0.23	0.41	0.71	0.46	0.21	0.30	0.09	1.00						
NOA	0.16	0.26	0.20	0.06	-0.20	0.32	0.03	0.27	1.00					
OS	0.25	-0.12	0.27	0.43	0.34	-0.08	0.05	0.37	0.23	1.00				
ROA	-0.11	-0.07	0.16	0.67	0.51	-0.11	0.31	0.36	0.00	0.51	1.00			
SMB	-0.32	-0.06	-0.39	-0.34	-0.05	0.00	0.01	-0.42	-0.15	-0.64	-0.42	1.00		
HML	0.19	0.57	0.57	-0.08	-0.45	0.35	-0.17	0.31	0.18	-0.08	-0.09	-0.20	1.00	
Mkt_RF	-0.23	-0.32	-0.48	-0.50	-0.22	-0.21	-0.14	-0.42	-0.08	-0.34	-0.27	0.30	-0.26	1.00

Table 2.2 Unconditional summary statistics

Panel A presents a comparison of unconditional monthly mean returns, mean returns following high and low sentiment and return spreads following high and low sentiment. T statistics are reported in parentheses. Panel B reports the monthly mean returns as percentages, standard deviations, skewness levels, Sharpe ratios, 5% expected shortfalls (CVaR) and standardized 5% expected shortfalls (STDCVaR).

Panel A – Comparison of monthly mean returns with SYY's statistics					Results from SYY (2012)			
STRATEGY	Unconditional Mean	High	Low	High-Low	Unconditional Mean	High	Low	High-Low
ACC	0.41	0.31	0.52	-0.20	0.58	0.94	0.23	0.70
	(2.96)	(1.52)	(2.72)	(-0.73)	(3.11)	(3.11)	(1.04)	(1.88)
AG	0.45	0.71	0.19	0.52	0.96	1.39	0.54	0.85
	(3.36)	(3.38)	(1.15)	(1.92)	(5.34)	(5.04)	(2.34)	(2.37)
CPI	0.50	0.80	0.20	0.60	0.42	0.81	0.02	0.79
	(3.57)	(3.70)	(1.13)	(2.15)	(2.59)	(3.19)	(0.13)	(2.46)
FP	0.48	1.00	-0.11	1.11	0.95	1.86	-0.10	1.96
	(1.70)	(2.55)	(-0.27)	(1.99)	(2.55)	(3.25)	(-0.24)	(2.72)
GP	0.25	0.30	0.21	0.09	0.40	0.65	0.15	0.50
	(1.70)	(1.50)	(0.93)	(0.30)	(2.45)	(2.93)	(0.64)	(1.53)
ITA	0.53	0.67	0.38	0.29	0.75	0.91	0.60	0.30
	(4.47)	(3.97)	(2.32)	(1.23)	(5.22)	(4.48)	(2.93)	(1.06)
MM	1.27	1.42	1.11	0.31	1.56	2.03	1.09	0.93
	(4.85)	(3.75)	(3.09)	(0.59)	(5.45)	(4.49)	(3.12)	(1.64)
NI	0.56	0.82	0.29	0.54	0.63	1.14	0.12	1.02
	(4.97)	(4.79)	(2.02)	(2.40)	(5.11)	(5.71)	(0.88)	(4.20)
NOA	0.55	1.02	0.08	0.94	0.65	1.07	0.24	0.83
	(4.63)	(5.84)	(0.53)	(3.96)	(4.41)	(4.66)	(1.29)	(2.84)
OS	0.04	0.38	-0.31	0.69	0.70	1.40	-0.00	1.40
	(0.26)	(1.87)	(-1.43)	(2.33)	(2.83)	(3.81)	(-0.01)	(2.85)
ROA	0.54	0.88	0.19	0.69	0.98	1.72	0.22	1.50
	(3.02)	(3.42)	(0.78)	(1.94)	(3.53)	(4.01)	(0.65)	(2.74)
SMB	0.23	0.04	0.43	-0.39	/	/	/	/
	(1.86)	(0.20)	(2.61)	(-1.56)				
HML	0.36	0.59	0.14	0.45	/	/	/	/
	(3.15)	(3.37)	(0.91)	(1.96)				
Mkt_RF	0.50	0.48	0.52	-0.04	/	/	/	/
	(2.76)	(1.88)	(2.03)	(-0.12)				
Equal-weighted	0.48	0.67	0.29	0.38	0.77	1.23	0.31	0.93
Portfolio	(8.21)	(7.43)	(3.96)	(3.33)	(6.91)	(6.64)	(2.64)	(4.25)

Panel B – Summary statistics						
STRATEGY	MEAN	STD	SKEWNESS	SHARPE	CVaR	STDCVaR
ACC	0.41	3.45	0.25	0.12	-7.24	-2.22
AG	0.45	3.35	0.48	0.14	-6.47	-2.07
CPI	0.50	3.47	0.00	0.14	-7.02	-2.20
FP	0.48	6.38	0.08	0.07	-15.04	-2.43
GP	0.25	3.71	0.18	0.07	-7.56	-2.15
ITA	0.53	2.94	0.08	0.18	-5.46	-2.04
MM	1.27	6.49	-0.84	0.20	-14.80	-2.53
NI	0.56	2.78	0.07	0.20	-5.64	-2.25
NOA	0.55	2.97	0.06	0.19	-5.73	-2.10
OS	0.04	3.70	0.16	0.01	-7.66	-2.12
ROA	0.54	4.14	0.37	0.13	-8.52	-2.19
SMB	0.23	3.13	0.48	0.07	-6.09	-2.06
HML	0.36	2.86	0.07	0.13	-5.91	-2.24
Mkt_RF	0.50	4.49	-0.51	0.11	-10.07	-2.40
Equal-weighted Portfolio	0.48	1.45	-0.03	0.33	-2.95	-2.37

Table 2.3 Crash risk following high and low investor sentiment

Panel A reports the monthly mean returns as percentages, standard deviations, skewness levels, Sharpe ratios, 5% expected shortfalls (CVaR) and standardized 5% expected shortfalls (STDCVaR) following low sentiment. Panel B reports the monthly mean returns as percentages, standard deviations, skewness levels, Sharpe ratios, 5% expected shortfalls (CVaR) and standardized 5% expected shortfalls (STDCVaR) following high sentiment.

Panel A – Low sentiment						
STRATEGY	MEAN	STD	SKEWNESS	SHARPE	CVaR	STDCVaR
ACC	0.52	3.29	0.21	0.16	-7.78	-2.38
AG	0.19	2.95	-0.03	0.07	-6.46	-2.07
CPI	0.20	3.10	-0.61	0.06	-7.23	-2.26
FP	-0.11	6.20	-0.44	-0.02	-15.51	-2.51
GP	0.21	3.91	0.09	0.05	-7.97	-2.27
ITA	0.38	2.90	0.03	0.13	-5.64	-2.10
MM	1.11	6.33	-1.31	0.18	-16.40	-2.78
NI	0.29	2.49	-0.43	0.12	-5.92	-2.36
NOA	0.08	2.79	-0.13	0.03	-5.79	-2.12
OS	-0.31	3.77	0.41	-0.08	-7.57	-2.09
ROA	0.19	4.02	-0.11	0.05	-8.35	-2.15
SMB	0.43	2.90	0.05	0.15	-6.09	-2.06
HML	0.14	2.63	-0.25	0.05	-6.05	-2.29
Mkt_RF	0.52	4.51	-0.31	0.12	-9.99	-2.38
Equal-weighted Portfolio	0.29	1.26	-0.50	0.23	-2.88	-2.33
Panel B – High sentiment						
STRATEGY	MEAN	STD	SKEWNESS	SHARPE	CVaR	STDCVaR
ACC	0.31	3.59	0.29	0.09	-7.01	-2.15
AG	0.71	3.70	0.66	0.19	-6.48	-2.07
CPI	0.80	3.79	0.26	0.21	-6.86	-2.15
FP	1.00	6.49	0.46	0.15	-14.45	-2.34
GP	0.30	3.49	0.32	0.09	-6.65	-1.90
ITA	0.67	2.98	0.12	0.23	-5.24	-1.96
MM	1.42	6.66	-0.44	0.21	-13.56	-2.33
NI	0.82	3.02	0.26	0.27	-5.34	-2.14
NOA	1.02	3.07	0.13	0.33	-5.64	-2.07
OS	0.38	3.60	-0.10	0.11	-7.77	-2.15
ROA	0.88	4.24	0.76	0.21	-8.87	-2.27
SMB	0.04	3.33	0.81	0.01	-6.08	-2.06
HML	0.59	3.06	0.22	0.19	-5.78	-2.19
Mkt_RF	0.48	4.48	-0.73	0.11	-10.15	-2.42
Equal-weighted Portfolio	0.67	1.59	0.07	0.42	-3.02	-2.42

Table 2.4 Statistical tests: Monte Carlo simulations

This table reports skewness levels, standardized 5% expected shortfalls (STDCVaR) and p-values in parentheses. The null hypothesis is skewness and 5% expected shortfall of each strategy is not different from those of a standard normal return distribution. The p-values of the two-sided tests report the relative standing of the observed skewness/CVaR of each strategy in standard normal distribution. * indicates p-value ≤0.05 or ≥0.95; ** indicates p-value ≤0.01 or ≥0.99; *** indicates p-value ≤0.001 or ≥0.999.

Panel A – Low sentiment			Panel B – High sentiment		
STRATEGY	SKEWNESS	STDCVaR	STRATEGY	SKEWNESS	STDCVaR
ACC	0.21	-2.38*	ACC	0.29**	-2.15
	(0.94)	(0.02)		(0.99)	(0.25)
AG	-0.03	-2.07	AG	0.66***	-2.07
	(0.41)	(0.49)		(1.00)	(0.49)
CPI	-0.61***	-2.26	CPI	0.26*	-2.15
	(0.00)	(0.07)		(0.97)	(0.25)
FP	-0.44**	-2.51**	FP	0.46***	-2.34*
	(0.01)	(0.01)		(1.00)	(0.03)
GP	0.09	-2.27	GP	0.32**	-1.90
	(0.74)	(0.07)		(0.99)	(0.88)
ITA	0.03	-2.10	ITA	0.12	-1.96
	(0.61)	(0.38)		(0.82)	(0.77)
MM	-1.31***	-2.78***	MM	-0.44**	-2.33*
	(0.00)	(0.00)		(0.01)	(0.03)
NI	-0.43**	-2.36*	NI	0.26*	-2.14
	(0.01)	(0.02)		(0.97)	(0.27)
NOA	-0.13	-2.12	NOA	0.13	-2.07
	(0.17)	(0.32)		(0.83)	(0.49)
OS	0.41	-2.09	OS	-0.10	-2.15
	(1.00)	(0.39)		(0.24)	(0.26)
ROA	-0.11	-2.15	ROA	0.76***	-2.27
	(0.21)	(0.26)		(1.00)	(0.07)
SMB	0.05	-2.06	SMB	0.81***	-2.06
	(0.67)	(0.50)		(1.00)	(0.50)
HML	-0.25*	-2.29*	HML	0.22	-2.19
	(0.04)	(0.05)		(0.94)	(0.17)
Mkt_RF	-0.31*	-2.38*	Mkt_RF	-0.73***	-2.42**
	(0.02)	(0.02)		(0.00)	(0.01)
Equal-weighted Portfolio	-0.50**	-2.33*	Equal-weighted Portfolio	0.07	-2.42**
	(0.01)	(0.03)		(0.70)	(0.01)

Table 2.5 Co-exceedances of portfolio returns

In this table, count (i) is a joint occurrence of positive (>95th percentile) or negative (<5th percentile) return exceedances for the 14 strategies in a given month. The null hypothesis is the negative/positive exceedances of individual strategy are independent of each other. A p-value (in parentheses) <=0.05 suggests the observed number is significantly larger than expected under the null at 5% level.

Panel A1 - Negative co-exceedances following low sentiment

i	ACC	AG	CPI	FP	GP	ITA	MM	NI	NOA	OS	ROA	SMB	HML	Mkt_RF	Total
0	199	199	199	199	199	199	199	199	199	199	199	199	199	199	199 (0.000)
1	3	8	1	1	6	6	2	1	6	6	4	5	2	8	59 (1.000)
2	2	2	0	0	2	2	0	3	5	4	1	4	5	4	17 (1.000)
3	2	2	6	3	6	3	4	4	3	2	5	3	4	4	17 (0.001)
4	1	1	2	5	3	2	3	2	2	4	4	0	2	1	8 (0.000)
5	0	1	3	4	4	2	3	3	1	0	3	0	1	0	5 (0.000)
6	0	1	1	1	1	1	1	2	1	1	1	0	1	0	2 (0.000)
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
8	1	1	1	0	0	1	1	1	0	1	0	0	1	0	1 (0.000)
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)

Panel A2 - Negative co-exceedances following high sentiment

i	ACC	AG	CPI	FP	GP	ITA	MM	NI	NOA	OS	ROA	SMB	HML	Mkt_RF	Total
0	193	193	193	193	193	193	193	193	193	193	193	193	193	193	193 (0.000)
1	9	6	2	1	7	6	3	4	6	4	1	10	2	7	68 (1.000)
2	3	3	6	3	1	2	4	2	3	5	3	8	7	6	28 (0.957)
3	2	1	4	1	0	4	3	1	3	1	1	0	1	2	8 (0.407)
4	4	2	3	3	1	2	4	4	0	1	1	1	2	0	7 (0.000)
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
6	1	1	1	2	1	0	2	2	1	2	3	0	2	0	3 (0.000)
7	2	2	2	1	0	0	2	2	0	1	0	0	2	0	2 (0.000)
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)

Panel A3 - Mean of portfolio returns (RET) and mean of standardized portfolio returns (SRET) for negative return co-exceedance i >3/6 (in %) following low and high sentiment. Total column displays the average of strategy-month returns involved in given co-exceedance count.

i>3																
		ACC	AG	CPI	FP	GP	ITA	MM	NI	NOA	OS	ROA	SMB	HML	Mkt_RF	Total
Low	RET	-1.02	-1.27	-3.72	-9.88	-3.51	-2.28	-8.14	-3.50	-1.29	-5.28	-4.42	3.13	0.18	4.73	-2.48
Low	SRET	-0.42	-0.50	-1.23	-1.62	-1.04	-0.96	-1.48	-1.47	-0.61	-1.46	-1.20	0.95	-0.07	0.95	-0.71
High	RET	-4.14	-3.79	-4.04	-10.76	-0.42	-0.24	-5.33	-4.44	-0.29	-1.94	-2.75	4.24	-2.00	4.42	-2.08
High	SRET	-1.32	-1.26	-1.33	-1.76	-0.19	-0.27	-1.04	-1.81	-0.28	-0.55	-0.79	1.31	-0.85	0.88	-0.64
i>6																
		ACC	AG	CPI	FP	GP	ITA	MM	NI	NOA	OS	ROA	SMB	HML	Mkt_RF	Total
Low	RET	-12.21	-7.74	-7.10	NA	-2.71	-6.47	-18.57	-5.37	1.82	-6.68	-2.88	7.91	-5.31	5.05	-4.64
Low	SRET	-3.66	-2.45	-2.22	NA	-0.82	-2.38	-3.12	-2.15	0.43	-1.85	-0.83	2.51	-2.03	1.03	-1.35
High	RET	-9.13	-6.47	-9.44	-12.49	2.20	-1.40	-14.87	-6.74	-1.79	-1.11	-0.25	4.57	-5.14	6.06	-3.82
High	SRET	-2.77	-2.07	-2.91	-2.03	0.54	-0.66	-2.54	-2.66	-0.78	-0.32	-0.19	1.42	-1.97	1.25	-1.12

Panel B1 - Positive co-exceedances following low sentiment

i	ACC	AG	CPI	FP	GP	ITA	MM	NI	NOA	OS	ROA	SMB	HML	Mkt_RF	Total
0	214	214	214	214	214	214	214	214	214	214	214	214	214	214	214 (0.000)
1	5	5	2	2	5	5	3	3	3	2	1	9	1	8	54 (1.000)
2	5	3	1	1	5	2	5	1	4	3	3	3	3	5	22 (0.998)
3	2	1	1	2	2	1	1	1	1	2	1	2	4	3	8 (0.407)
4	2	1	3	2	1	3	2	1	0	1	1	1	1	1	5 (0.001)
5	0	0	1	2	3	0	0	3	0	3	3	0	0	0	3 (0.000)
6	0	1	0	1	1	1	0	0	0	1	1	0	0	0	1 (0.000)
7	0	0	0	1	1	1	1	1	0	1	1	0	0	0	1 (0.000)
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)

Panel B2 - Positive co-exceedances following high sentiment

i	ACC	AG	CPI	FP	GP	ITA	MM	NI	NOA	OS	ROA	SMB	HML	Mkt_RF	Total
0	182	182	182	182	182	182	182	182	182	182	182	182	182	182	182 (0.000)
1	4	2	4	1	6	10	4	1	7	5	1	10	4	11	70 (1.000)
2	4	4	5	2	2	2	6	4	2	5	4	4	5	1	25 (0.988)
3	2	4	2	3	1	2	5	2	3	3	3	1	3	2	12 (0.061)
4	1	3	3	1	0	1	1	5	3	2	1	1	2	0	6 (0.000)
5	3	2	4	3	3	3	2	4	4	3	4	1	3	1	8 (0.000)
6	0	2	2	1	0	0	1	2	2	0	0	0	2	0	2 (0.000)
7	2	3	3	2	1	0	0	3	1	1	2	0	3	0	3 (0.000)
8	0	1	1	1	1	0	1	1	0	0	1	0	1	0	1 (0.000)
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 (1.000)

Panel B3 - Mean of portfolio returns (RET) and mean of standardized portfolio returns (SRET) for positive return co-exceedance i >3/6 (in %) following low and high sentiment. Total column displays the average of strategy-month returns involved in given co-exceedance count.

i>3																
		ACC	AG	CPI	FP	GP	ITA	MM	NI	NOA	OS	ROA	SMB	HML	Mkt_RF	Total
Low	RET	2.95	1.47	3.64	9.00	4.14	4.19	6.02	3.77	-0.74	4.05	6.43	-1.97	-0.86	-5.39	2.55
Low	SRET	0.74	0.32	0.92	1.34	1.07	1.24	0.75	1.18	-0.43	1.10	1.42	-0.71	-0.44	-1.34	0.50
High	RET	1.88	6.62	6.81	10.84	2.41	2.44	3.60	5.46	5.26	1.91	5.54	-1.03	3.42	-4.96	3.45
High	SRET	0.43	1.87	1.85	1.63	0.59	0.64	0.37	1.80	1.58	0.51	1.21	-0.41	1.08	-1.24	0.83
i>6																
		ACC	AG	CPI	FP	GP	ITA	MM	NI	NOA	OS	ROA	SMB	HML	Mkt_RF	Total
Low	RET	1.10	-0.32	3.18	18.30	6.86	6.36	13.82	5.52	4.24	11.56	12.64	-2.34	-2.90	-17.23	4.34
Low	SRET	0.20	-0.22	0.79	2.80	1.82	1.98	1.98	1.82	1.24	3.16	2.92	-0.84	-1.17	-4.02	0.89
High	RET	4.24	12.49	12.19	25.32	5.13	2.17	3.24	10.09	3.71	3.31	14.80	-3.35	9.03	-8.63	6.20
High	SRET	1.11	3.64	3.43	3.90	1.34	0.55	0.31	3.49	1.06	0.90	3.44	-1.16	3.08	-2.07	1.57

Appendix

Chapter 1: Comparison of different trading strategies

Table 1.12 in this part provides summary statistics for all trading strategies we examine in this paper. Anchored carry produces an average excess return of 13.39% p.a., while residual carry brings 4.19%. The return spread between these two strategies is as high as 9.19%. Anchored carry brings a significantly higher return than unconditional carry, and way more efficient with a higher Sharpe ratio. Anchored momentum yields an average excess return of 8.60 % p.a., which is 4.75% more than the return of residual momentum (3.85%) and 3.02% more than return of unconditional momentum (5.58%).

We also provide the results of anchored and residual strategies based on independent double sort on forward discount/past return and distance to 52-week extremes. The anchored carry generates 11.45% p.a. while residual carry gives 3.94%. The anchored momentum produces 8.06% while residual momentum brings 2.62%. It is worth noting that anchored strategies with independent sort are not always feasible due to empty portfolio on either long or short side. Across the 493 months in our sample, we could only carry out 386 months for anchored carry and 471 months for anchored momentum and 486 months for residual momentum (there are 7 months where currencies are all selected by anchored momentum strategy thus no currencies left in the long or short side for residual momentum). When calculating the average returns of independent sorted strategies across our sample period, we treat returns in infeasible months as zero.

We also carry out a pure 52-week high-low strategy that is going long in currencies near their 52-week highs and short currencies near their 52-week lows. This pure anchoring strategy derives an average excess return of 3.73%. The results presented in Table 10 provide strong evidence that a large portion of carry and momentum profits are concentrated in currencies near their 52-week extremes.

Table 1.12 Summary statistics of different trading strategies

This table reports mean, standard deviation, skewness, and kurtosis for excess returns to all currency trading strategies examined in this paper, as well as the mean return difference of anchored and residual strategies. Mean returns and standard deviations are annualized and reported in percentage points. Sharpe ratios (SR) are computed as ratios of annualized means to annualized standard deviations. White's heteroscedasticity-consistent standard errors (in %) of mean returns and p-value of mean return differences are reported between parentheses. The sample period is 01/1976 – 01/2018 for unconditional strategies and 01/1977 – 01/2018 for anchored and residual strategies.

	Mean(%)	STD(%)	Skewness	Kurtosis	SR
Strategies					
Unconditional HML Carry	6.65	6.19	-0.44	1.16	1.08
	(0.96)				
Anchored HML Carry	13.39	10.37	0.23	1.08	1.29
	(1.62)				
Residual HML carry	4.19	7.06	-0.77	2.90	0.59
	(1.10)				
Anchored Carry - Residual Carry	9.19				
	(p=0.00)				
Anchored HML Carry (independent)	11.45	9.78	0.73	2.58	1.17
	(1.53)				
Residual HML carry (independent)	3.94	6.83	-0.75	2.78	0.58
	(1.07)				
Anchored Carry - Residual Carry (independent)	7.51				
	(p=0.00)				
Unconditional Cross-section Momentum (1,1)	5.58	7.12	0.20	1.64	0.78
	(1.10)				
Anchored Momentum	8.60	10.50	0.33	1.57	0.82
	(1.64)				
Residual Momentum	3.85	7.66	0.21	2.12	0.50
	(1.19)				
Anchored Momentum - Residual Momentum	4.75				
	(p=0.02)				
Anchored Momentum (independent)	8.06	8.89	0.37	2.04	0.91
	(1.39)				
Residual Momentum (independent)	2.62	9.24	0.90	9.78	0.28
	(1.44)				
Anchored Momentum - Residual Momentum	5.45				
(independent)	(p=0.01)				
Pure 52H/L	3.73	6.13	0.18	1.80	0.61
	(0.96)				

Chapter 2: Construction of 11 anomalies

This part cited from Stambaugh and Yuan (2017) details the construction of 11 anomalies. The anomaly measures are computed at the end of each month. Stocks with share prices less than $5 are excluded primarily to avoid micro-structure effects, and ordinary common shares (CRSP codes 10 and 11) are selected. The anomaly portfolios are constructed using NYSE deciles as breakpoints. The values computed at the end of month $t-1$ for each anomaly are constructed as follows:

1. *Net Stock Issues (NI):* The stock issuing market has long been viewed as producing an anomaly arising from sentiment-driven mispricing: smart managers issue shares when sentiment-driven traders push prices to overvalued levels. Ritter (1991) and Loughran and Ritter (1995) show that, in post-issue years, equity issuers underperform matching nonissuers with similar characteristics. Motivated by this evidence, Fama and French (2008) show that net stock issues and subsequent returns are negatively correlated. Following Fama and French (2008), we measure net issuance as the annual log change in split-adjusted shares outstanding. Split-adjusted shares equal shares outstanding (Compustat annual item CSHO) times the adjustment factor (Compustat annual item ADJEX_C). The most recent reporting year used is the one that ends (according to item DATADATE) at least four months before the end of month $t-1$
2. *Composite Equity Issues (CPI) :* Daniel and Titman (2006) find that issuers underperform nonissuers using a measure they denote as composite equity issuance, defined as the growth in the firm's total market value of equity minus (i.e., not attributable to) the stock's rate of return. We compute this measure by subtracting the 12-month

cumulative stock return from the 12-month growth in equity market capitalization. We lag the quantity four months, to make its timing more coincident with the above measure of net stock issues.

3. *Accruals (ACC):* Sloan (1996) shows that firms with high accruals earn abnormally lower average returns than firms with low accruals, and he suggests that investors overestimate the persistence of the accrual component of earnings when forming earnings expectations. Following Sloan (1996), we measure total accruals as the annual change in noncash working capital minus depreciation and amortization expense (Compustat annual item DP), divided by average total assets (item AT) for the previous two fiscal years. Noncash working capital is computed as the change in current assets (item ACT) minus the change in cash and short-term investment (item CHE), minus the change in current liabilities (item DLC), plus the change in debt included in current liabilities (item LCT), plus the change in income taxes payable (item TXP). The most recent reporting year used is the one that ends (according to item DATADATE) at least four months before the end of month $t-1$

4. *Net Operating Assets(NOA):* Hirshleifer et al. (2004) find that net operating assets, defined as the difference on the balance sheet between all operating assets and all operating liabilities, scaled by total assets, is a strong negative predictor of long-run stock returns. The authors suggest that investors with limited attention tend to focus on accounting profitability, neglecting information about cash profitability, in which case net operating assets (equivalently measured as the cumulative difference between operating income and free cash flow) captures such a bias. Following Equations (4), (5),

and (6) of that study, we measure net operation assets as operating assets minus operating liabilities, divided by lagged total assets (Compustat annual item AT). Operating assets equal total assets (item AT) minus cash and short-term investment (item CHE). Operating liabilities equal total assets minus debt included in current liabilities (item DLC), minus long-term debt (item DLTT), minus common equity (item CEQ), minus minority interests (item MIB), minus preferred stocks (item PSTK). (The last two items are zero if missing.) The most recent reporting year used is the one that ends (according to item DATADATE) at least four months before the end of month $t-1$

5. *Asset Growth (AG):* Cooper, Gulen, and Schill (2008) find that companies that grow their total assets more earn lower subsequent returns. They suggest that this phenomenon is due to investors' initial overreaction to changes in future business prospects implied by asset expansions. Asset growth is measured as the growth rate of total assets in the previous fiscal year. Following that study, we measure asset growth as the most recent year-over-year annual growth rate of total assets (Compustat annual item AT). The most recent reporting year used is the one that ends (according to item DATADATE) at least four months before the end of month $t-1$
6. *Investment to Assets (ITA):* Titman, Wei, and Xie (2004) and Xing (2008) show that higher past investment predicts abnormally lower future returns. Titman, Wei, and Xie (2004) attribute this anomaly to investors' initial underreaction to overinvestment caused by managers' empire-building behavior. Here, investment to assets is measured as the annual change in gross property, plant, and equipment, plus the annual change in inventories, scaled by lagged book value of assets. Following the above studies, we

compute investment-to-assets as the changes in gross property, plant, and equipment (Compustat annual item PPEGT) plus changes in inventory (item INVT), divided by lagged total assets (item AT). The most recent reporting year used is the one that ends (according to item DATADATE) at least four months before the end of month t−1

7. *Failure Probability (FP):* Financial distress is often invoked to explain otherwise anomalous patterns in the cross-section of stock returns. However, Campbell, Hilscher, and Szilagyi (2008) find that firms with high failure probability have lower rather than higher subsequent returns. The authors suggest that their finding is a challenge to standard models of rational asset pricing. Failure probability is estimated with a dynamic logit model that uses several equity market variables, such as stock price, book to market, stock volatility, size relative to the S&P 500, and cumulative excess return relative to the S&P 500. Specifically, using the above study's Equations (2) and (3) along with its Table IV (12-month column), we compute the distress anomaly measure—failure probability—as

$$\pi = -20.26 NIMTAAVG + 1.42 TLMTA - 7.13 EXRETAVG + 1.41 SIGMA - 0.045 RSIZE - 2.13 CASHMTA + 0.075 MB - 0.058 PRICE - 9.16$$

where

$$NIMTAAVG_{t-1,t-12} = \frac{1-\phi^3}{1-\phi^{12}} \left(NIMTA_{t-1,t-3} + \ldots + \phi^9 NIMTA_{t-10,t-12} \right)$$

$$EXRETAVG_{t-1,t-12} = \frac{1-\phi}{1-\phi^{12}} \left(EXRET_{t-1} + \ldots + \phi^9 EXRET_{t-12} \right),$$

and ϕ=$2^{-1/3}$. *NIMTA* is net income (Compustat quarterly item NIQ) divided by firm scale, where the latter is computed as the sum of total liabilities (item LTQ) and market equity capitalization (data from CRSP). *EXRETs* is the stock's monthly log return in month *s* minus the log return on the S&P500 index. Missing values for *NIMTA* and *EXRET* are replaced by those quantities' cross-sectional means. *TLMTA* equals total liabilities divided by firm scale. *SIGMA* is the stock's daily standard deviation for the most recent three months, expressed on an annualized basis. At least five nonzero daily returns are required. *RSIZE* is the log of the ratio of the stock's market capitalization to that of the S&P500 index. *CASHMTA* equals cash and short-term investment (item CHEQ) divided by firm scale. *MB* is the market-to-book ratio. Following Campbell, Hilscher, and Szilagyi (2008), we increase book equity by 10% of the difference between market equity and book equity. If the resulting value of book equity is negative, then book equity is set to $1.*PRICE* is the log of the share price, truncated above at $15. All explanatory variables except *PRICE* are winsorized above and below at the 5% level in the cross section. CRSP based variables, *EXRETAVG*, *SIGMA*, *RSIZE* and *PRICE* are for month t−1. *NIQ* is for the most recent quarter for which the reporting date provided by Compustat (item RDQ) precedes the end of month t−1, whereas the items requiring information from the balance sheet (*LTQ*, *CHEQ* and *MB*) are for the prior quarter.

8. *O-score (OS):* This distress measure, from Ohlson (1980), predicts returns in a manner similar to the measure above. It is the probability of bankruptcy estimated in a static model using accounting variables. Following Ohlson (1980), we construct it as:

$$O=-0.407SIZE+6.03TLTA-1.43WCTA+0.076CLCA-1.72OENEG$$

$$=-2.37NITA-1.83FUTL+0.285INTWO-0.521CHIN-1.32,$$

where *SIZE* is the log of total assets (Compustat annual item AT), *TLTA* is the book value of debt (item DLC plus item DLTT) divided by total assets, *WCTA* is working capital (item ACT minus item LCT) divided by total assets, *CLCA* is current liabilities (item LCT) divided by current assets (item ACT), *ONEEG* is 1 if total liabilities (item LT) exceed total assets and is zero otherwise, *NITA* is net income (item NI) divided by total assets, *FUTL* is funds provided by operations (item PI) divided by total liabilities, *INTWO* is equal to 1 if net income (item NI) is negative for the last 2 years and zero otherwise, *CHIN* is $(NIj-NIj-1)/(|NIj|+|NIj-1|)$, in which *NIj* is the income (item NI) for year *j*, which is the most recent reporting year that ends (according to item DATADATE) at least four months before the end of month $t-1$

9. *Momentum (MM):* The momentum effect, discovered by Jegadeesh and Titman (1993), is one of the most robust anomalies in asset pricing. It refers to the phenomenon whereby high (low) past recent returns forecast high (low) future returns. The momentum ranking at the end of month $t-1$ uses the cumulative returns from month. This is the choice of ranking variable used by Carhart (1997) to construct the widely used momentum factor.
10. *Gross Profitability Premium (GP):* Novy-Marx (2013) shows that sorting on the ratio of gross profit to assets creates abnormal benchmark-adjusted returns, with more profitable firms having higher returns than less profitable ones. He argues that gross profit is the cleanest accounting measure of true economic profitability. The farther

down the income statement one goes, the more polluted profitability measures become, and the less related they are to true economic profitability. Following that study, we measure gross profitability as total revenue (Compustat annual item REVT) minus the cost of goods sold (item COGS), divided by current total assets (item AT). The most recent reporting year used is the one that ends (according to item DATADATE) at least four months before the end of month $t-1$.

11. *Return on Assets (ROA):* Fama and French (2006) find that more profitable firms have higher expected returns than less profitable firms. Chen, Novy-Marx, and Zhang (2010) show that firms with higher past return on assets earn abnormally higher subsequent returns. Return on assets is measured as the ratio of quarterly earnings to last quarter's assets. Wang and Yu (2013) find that the anomaly exists primarily among firms with high arbitrage costs and high information uncertainty, suggesting that mispricing is a culprit. Following Chen, Novy-Marx, and Zhang (2010), we compute return on assets as income before extraordinary items (Compustat quarterly item IBQ) divided by the previous quarter's total assets (item ATQ). Income is for the most recent quarter for which the reporting date provided by Compustat (item RDQ) precedes the end of month $t-1$, and assets are for the prior quarter.