Asset Returns, Risks, and Cash Flow Expectations

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Submitted in partial fulfillment of the
requirements for the degree
of Doctor of Philosophy
in the Graduate School of Arts and Sciences

COLUMBIA UNIVERSITY

2014

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ABSTRACT

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This dissertation delves into the relation between asset returns, risks, and cash flow expectations. The first chapter uses the model-implied patterns of cash flow expectations to differentiate among the three most prominent behavioral theories explaining stock return momentum and reversal. Using analyst earnings forecasts as a proxy for cash flow expectations, I trace the dynamics of the expectation errors for winner and loser stocks in a 24-month holding period, during which returns are characterized by a momentum phase followed by a reversal phase. The large positive cross-sectional difference in expectation errors between winner and loser stocks gradually shrinks to zero over the holding period. This pattern is most consistent with the underreaction hypothesis in Hong and Stein (1999), in which cash flow expectation errors can only explain momentum, and price extrapolation is needed to explain reversal.

The second chapter examines carry trade returns formed from the G10 currencies. Performance attributes depend on the base currency. Spread-weighting and risk-rebalancing positions over time improve performance. Hedging with options reduces profitability. Equity, bond, FX, and volatility risks cannot explain profitability. Time-varying dollar exposure produces abnormal excess returns. Dollar-neutral carry trades exhibit insignificant abnormal returns, while the dollar exposure part of the carry trade earns significant alphas and little skewness. Downside equity market betas of carry trades are not significantly different from unconditional betas. Distributions of drawdowns and maximum losses from daily data indicate the importance of autocorrelation in determining the negative skewness of longer horizon returns.

The third chapter investigates the question of whether sovereigns pay a premium on their own borrowing as a result of (implicitly or explicitly) guaranteeing sub-entities' debt has been explored only little. We use an event study approach with separate equations for two levels of government to test for a simultaneous increase in sovereign risk premia and decrease in sub-national risk premia—or a de facto transfer of risk from the latter to the former—on the day a sovereign bailout is announced. Using daily financial market data for Spain and its autonomous regions from January 2010 to June 2013, we find support for our risk transfer hypothesis. We estimate that the Spanish sovereign's spread may have increased by around 70 basis points as a result of the central government's support for fiscally distressed comunidades autónomas.

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Acknowledgements

First and foremost I would like to thank my advisor, Dr. Robert Hodrick, for his confidence in me and his enduring encouragement and guidance. His generous accessibility was the rock of stability over my PhD study: whenever I discovered something new or got stuck, I simply stopped by his office, talked to him, and walked out with a broader perspective and inspiration.

I express my profound gratitude to my other beloved committee members, Dr. Kent Daniel, Dr. Paul Tetlock, and Dr. Gil Sadka, as well as Dr. Tano Santos. They differ in style but not in their unreserved, penetrating insights and critiques that have tremendously impacted my work and my thinking about a wide variety of asset pricing issues. I would also like to thank Dr. Wei Jiang, Dr. Suresh Sundaresan, Dr. John Donaldson, and Dr. Emily Breza, whom I frequently turned to for guidance. I am indebted to these faculty members, and I can only hope to become as resourceful and inspiring to my future students as they have been to me.

I would also like to thank my wife and my parents. I would not have completed this dissertation without the vital moral support of my wife, Yi, who has been indispensable since we decided to pursue my graduate studies in the United States. My parents gave me my character and allowed me to pursue my dream, even though that meant they could not see me often.

Finally, I thank Dr. Yingzi Zhu, my senior honors thesis advisor, who introduced me to academic research. I would also like to thank Jed Shahrar, for teaching me how to write an academic paper, and my colleagues Mattia, Jun Kyung, An Li, Bronson, Bingxu, Guojun, Andrey, Andrea, and Andres for the good rapport. I am very grateful for the opportunity

to have studied at Columbia Business School, and I extend my gratitude to all the faculty, staff, and students who have taught and helped me over the past four years.

To my beloved—

Mom and Dad, who raised me,
Yi and Ryan, whose love and laugh sustain my life

Chapter 1

Can Cash Flow Expectations Explain Momentum and Reversal

Zhongjin Lu

1.1 Introduction

Momentum and reversal are two of the best-established return predictabilities in asset pricing. Momentum is a phenomenon in which stocks with relatively stronger/weaker recent performance—that is, winner/loser stocks—continue to outperform/underperform other stocks in the short to medium run (Jegadeesh and Titman (1993)). Reversal is a phenomenon in which winner/loser stocks begin underperforming/outperforming other stocks in the long run (e.g., DeBondt and Thaler (1985); Jegadeesh and Titman (2001)). According to recent research, momentum and reversal exist not only in the U.S. equity market but also in others, such as the U.K. and Continental Europe equity markets, as well as in other asset classes, such as commodities and currencies (e.g., Moskowitz, Ooi, and Pedersen (2012); Menkhoff, Sarno, Schmeling, and Schrimpf (2012b); Asness, Moskowitz, and Pedersen (2013)). Not surprisingly, a large body of literature has been devoted to explaining these two important regularities. However, since models have mostly been built to generate momentum and/or reversal, researchers have found it difficult to discriminate among the competing mechanisms by examining the moment conditions of returns. In this study, I adopt a different approach by examining the model-implied moment conditions of expected cash flows, and in doing so, I am able to sharpen the investigation of the mechanisms behind momentum and reversal.

I categorize the existing theories of momentum and reversal into two types. The first type resides within the rational expectations paradigm and argues that predictable returns are compensation for taking covariance risk.¹ The second type deviates from the rational expectations framework and attributes momentum and reversal to systematic biases in ex-

¹An incomplete list of risk-based explanations for momentum includes Johnson (2002); Sagi and Seasholes (2007); Bansal, Dittmar, and Lundblad (2005); Chordia and Shivakumar (2002); Liu and Zhang (2011). An incomplete list of risk-based explanations for reversal, which is closely related to value premium, includes Zhang (2005); Hansen, Heaton, and Li (2008); Lettau and Wachter (2007); Carlson, Fisher, and Giammarino (2004); and Bansal, Dittmar, and Lundblad (2005).

pectations. In this chapter, I focus primarily on three models of the second type—Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999), and Barberis, Shleifer, and Vishny (1998) (hereafter, DHS, HS, and BSV)—because they are able to offer coherent explanations for momentum *and* reversal in a unified framework,² while a unified explanation remains difficult to achieve in risk-based theories.³ Nevertheless, DHS, HS, and BSV emphasize distinctively different behavioral biases: DHS postulate that agents overreact to cash flow news, HS postulate that agents underreact to available cash flow news,⁴ and BSV postulate a combination of both. Existing literature has documented several characteristics associated with the strength of momentum and reversal (Hong, Lim, and Stein (2000); Avramov, Chordia, Jostova, and Philipov (2007); Cooper, Gutierrez, and Hameed (2004); ?), but these characteristics of returns are of little help in differentiating one model from another.

I propose to distinguish among the models by examining the model-implied pattern of cash flow expectations. Models under rational expectations do not rely on cash flow expectations to generate momentum or reversal. Nevertheless, they imply that the expectation errors are not predictable and thus should always be zero, on average. On the other hand, models under the behavioral view use cash flow expectations as the main mechanism to

²I emphasize both momentum and reversal because, as Fama (1998) states, “Any alternative model (to market efficiency)... must specify biases in information processing that cause the same investors to underreact to some types of events and overreact to others.” Moreover as Hong and Stein (1998) states, “There seems to be broad agreement that to be successful, any candidate theory should, at a minimum: ... (2) explain the existing evidence in a parsimonious and unified way.”

³The transition from momentum to reversal occurs approximately six months to one year after sorting (e.g., Jegadeesh and Titman (1993); Lewellen (2002)). To offer a joint explanation of momentum and reversal, risk-based theories need to generate a covariance structure that reverses the cross-sectional pattern at a frequency of six months to one year. Recently, Vayanos and Woolley (2013) use a time-varying agency cost to achieve this, and Li (2012) proposed an investment-based model in which the expiration of investment commitments helps to reverse the covariance structure.

⁴Other than the underreaction to cash flow news, HS also features price extrapolation.

generate momentum and reversal; therefore, they impose more structural restrictions of cash flow expectations. I show that these models imply diametrically opposed moment conditions of cash flow expectations, and I nest these moment conditions in one specification test.

To empirically study cash flow expectations, we need a proxy. Among a limited set of available candidates, earnings forecasts of financial analysts are the most appropriate proxy for three reasons.⁵ First, earnings forecasts are arguably the “benchmark” for expected earnings, since earnings surprises reported in financial outlets are calculated as actual earnings minus the average earnings forecasts. Second, earnings forecasts are practically public information as they are accessible through various brokerage accounts. Third, in accounting literature, earnings forecasts have been found to outperform a large class of time series models in terms of predicting annual earnings.⁶

Using earnings forecasts as a proxy for cash flow expectations, my research demonstrates that winner stocks have more positive cash flow expectation errors than loser stocks throughout a two-year holding period, during which returns are characterized by a momentum phase followed by a reversal phase. This systematic expectation bias lends support to the behavioral view. Furthermore, the pattern of expectation errors implies that the cash flow expectations of winner (loser) stocks do not incorporate the information in past good (bad) returns sufficiently, thereby pinpointing underreaction to information as the dominant bias in cash flow expectations underlying both momentum and reversal. Although the literature has generally appreciated underreaction in cash flow expectations as an important mechanism for momentum, what has been much less appreciated is that underreaction in cash flow expectations

⁵I pay special attention to some known issues regarding analyst forecast data when I conduct the empirical test. I discuss these in the data section.

⁶See Brown, Hagerman, Griffin, and Zmijewski (1987). Bradshaw, Drake, Myers, and Myers (2012) offer a re-examination and confirm that analyst forecasts are a superior predictor for the current fiscal year and the next fiscal year.

is also associated with reversal. This is because reversal is perceived to be associated with overreaction. In this regard, I highlight the distinction between overreaction in cash flow expectations and overreaction in price expectations. I find a large positive cross-sectional difference in cash flow expectation errors between winner and loser stocks, and I find that this difference gradually shrinks to zero over the holding period. This pattern is most consistent with HS's hypothesis that cash flow expectations exhibit underreaction, thereby suggesting that overreaction is more likely to exist in price expectations.

Finally, I test two novel predictions of the HS model centering around cash flow expectations. First, I decompose the past returns into a cash flow related component and the residual component. I find that both components predict return momentum but only the residual component predicts return reversal. Simulation of the HS model reveals that the model can generate similar patterns only under a specific set of parameters. Second, I sort stocks by their following analysts' underreaction intensity. I find that stock covered by analysts who more severely underreact to cash flow news exhibit stronger momentum, consistent with the underreaction mechanism.

In sum, this chapter documents new predictable patterns regarding momentum and reversal from the angle of cash flow expectations. These patterns offer informative restrictions on theories attempting to explain momentum and reversal via cash flow expectations.

1.2 Literature Review

This study belongs to the literature that confronts competing explanations of momentum and reversal with new empirical findings. Jegadeesh and Titman (2001) cite the reversal that follows the return momentum as support for behavioral models over Conrad and Kaul (1998). Nevertheless, their results cannot discriminate among the competing behavioral models be-

cause they only examine the dynamics of returns. Kothari, Lewellen, and Warner (2006) attempt to reject a broad class of behavioral theories—including DHS, HS, and BSV—by showing the theories to be inconsistent with the empirical relation between aggregate earnings and aggregate returns. However, this conclusion is disputed by Sadka and Sadka (2009). The disagreement stems from the fact that the seasonal change in aggregate earnings is strongly predictable, and Sadka and Sadka (2009) claim that the change is not an appropriate proxy for earnings surprises. These contradictory results indicate that the dynamics of expectations are at the heart of behavioral theories. Avramov, Chordia, Jostova, and Philipov (2007), Cooper, Gutierrez, and Hameed (2004), Chan (2003), and Vega (2006), among others, find various firm characteristics that are associated with the strength of momentum and reversal, but these patterns of returns cannot differentiate one behavioral theory from another. The current study contributes to this literature in two respects. Methodologically, it shows that the three most prominent behavioral theories are distinct in their predictions of cash flow expectation errors and that the predictions can be tested under one nesting specification. Empirically, it documents the full dynamics of cash flow expectation errors for stocks undergoing the momentum and reversal phases.⁷

This chapter also complements an influential strand of literature such as Chopra, Lakonishok, and Ritter (1992) and Porta, Lakonishok, Shleifer, and Vishny (1997), in which researchers try to use earnings announcement returns as a proxy for expectation errors to differentiate risk-based explanations of return predictabilities from the behavioral explanations. Earnings announcement returns, as with other returns, conflate surprises in cash flow expectations and surprises in discount rate expectations. This study focuses on cash flow expectation errors and therefore is able to further differentiate between behavioral explana-

⁷To be clear, the main objective of this study is to identify the most powerful test of the existing behavioral theories of momentum and reversal. It is possible that the empirical results documented here are consistent with alternative theories.

tions.

Two earlier studies—Chui, Titman, and Wei (2003) and Hwang (2010)—explicitly attempt to differentiate Daniel, Hirshleifer, and Subrahmanyam (1998) from Hong and Stein (1999). Chui, Titman, and Wei (2003) examine the strength of momentum within real estate investment trusts (REITs) before and after 1990. To differentiate the hypotheses, they have to assume that REITs in the post-1990 period experienced more severe overconfidence but faster information diffusion. This additional assumption is hard to verify. Hwang (2010) finds that momentum strength is positively correlated with the cross-sectional average correlation of earnings forecast errors. This is inconsistent with the information diffusion in Hong and Stein (2007). However, an alternative information diffusion process, under which most analysts underreact to similar information, can conform to Hwang’s empirical finding while keeping the main predictions of the theory.

This study differs from Chui, Titman, and Wei (2003) and Hwang (2010) mainly in two ways. First, tests in this study are direct and robust to possible model modifications because they target the dynamics of cash flow expectations, which are the main mechanisms of the theories. Second, this study not only tests the theory predictions in the momentum phase, as done in the two abovementioned papers, but it also simultaneously tests the predictions in the reversal phase.

1.3 Cash Flow Expectations in the Three Theories

In this section, I formally lay out the moment conditions of cash flow expectations imposed by DHS, HS, and BSV. I find that moment conditions predicted by BSV are indistinguishable from those predicted by DHS, while moment conditions predicted by HS are very different from those of the former two.

1.3.1 Daniel, Hirshleifer, and Subrahmanyam (1998)

In the DHS model, a risk-neutral representative investor receives news about future cash flows and prices stocks according to discounted cash flow model:

$$P_t = \sum_{j \geq 1} \frac{E_t(CF_{t+j})}{(1+r)^j}.$$

Because discount rates are assumed to be constant, the cash flow expectations determine the stock prices in this model. The investor initially receives a noisy private signal about future cash flows, followed by noisy public signals in subsequent periods. Public signals will eventually reveal the true cash flows. In this model, due to overconfidence and self-attribution biases, the investor's cash flow expectations show increasing overreaction initially and then revert to the rational level, thereby resulting in momentum and reversal.

Consider a loser stock as an example. Initially, the investor receives a private signal about a permanent decrease in future cash flows. Under rational expectations, the investor's cash flow expectations will fall once and for all upon receiving the signal. However, due to the overconfidence bias, the investor in this model overestimates the precision of this negative private signal. Then, this signal has a disproportionately large influence in dragging down the investor's expectation to a level below the rational one, that is, there is overreaction.⁸ Due to the self-attribution bias, when subsequent public signals confirm the private signal, the investor believes that his private signal is truly superior and further raises his confidence in the private signal; when subsequent public signals disapprove the private signal, the investor believes it is due to bad luck and maintains his confidence in the private signal. On average,

⁸Daniel, Hirshleifer, and Subrahmanyam (1998) assume that the representative investor is overly confident in the first period. However, overconfidence at the beginning of the momentum phase is not indispensable to the model's main results. Hence, I avoid testing the sign of forecast errors in the initial momentum phase.

the arrival of public signals increases the investor's confidence in the negative private signal. For a while, the private signal acquires greater influence and thus pushes the cash flow expectations progressively lower, i.e., a continuing overreaction. Eventually, despite the fact that the private signal carries a disproportionate weight, the amassed public news will lift the expectation back to the rational level. Note that the cash flow expectations determine the price in this model. Hence, after the initial price drop, the model predicts a continuous decline in the price due to the continuing overreaction in cash flow expectations, that is, a momentum phase. This is followed by price recovery due to the correction of cash flow expectations, that is, a reversal phase.

The upper panel of Figure 3.1 features the prediction regarding expected earnings in the DHS model. The dashed line represents rational expectations, an unbiased estimate of future cash flows. The investor's expectation, which experiences continuing overreaction and subsequent correction, is represented by the black line with an arrow.

[Insert Figure 3.1 here]

Defining expectation errors as actual cash flows minus expectations, I test the following two key hypotheses of the DHS model, presented in the lower panel of Figure 3.1:

1. The cross-sectional difference between winner and loser stocks in expectation errors is negative: it is most negative around the turning point from the momentum phase to the reversal phase.
2. The cross-sectional difference between winner and loser stocks in expectation errors will decline progressively to a negative value in the momentum phase but increase toward zero in the reversal phase.

1.3.2 Hong and Stein (1999)

The HS model features two heterogeneous groups of investors: news watchers and momentum traders. Momentum traders only observe past prices, and their trading positions are positively related to past returns. News watchers observe information on future cash flows and their trading positions are positively related to expected cash flows. Together, demands from momentum traders and news watchers determine the price. In this model, news watchers' cash flow expectations incorporate the available information with a delay. This delay causes underreaction in cash flow expectations, which initiates the momentum and thus attracts momentum trading. Momentum trading then fuels further momentum and results in eventual reversal.

Take a loser stock as an example. Initially, news about a permanent drop in future cash flows arrives in the market. The model assumes that each news watcher is able to obtain only a portion of the news, and although others' portions can be deduced from the price, news watchers fail to do so. Consequently, the average cash flow expectations of news watchers do not drop sufficiently, thereby resulting in an overly optimistic expectation. In subsequent periods, each news watcher will obtain additional pieces of the original bad news, correcting his/her initial underreaction, thereby lowering the expectation gradually toward the rational level. Thus, a momentum of price decline is formed. Then, the negative momentum attracts momentum traders to take short positions, thereby exacerbating the fall in price. Since momentum traders blindly trade on serial correlations, eventually they cause an excessive drop in the price. As more information on future cash flows is revealed, the demand of news watchers increases the price, momentum traders close their short positions, and the price increases back to the rational level.

The upper panel of Figure 3.2 presents the prediction of expected earnings under the HS model. The dashed line represents rational expectations, an unbiased estimate of future

cash flows. News watchers' cash flow expectations, which manifest the gradually corrected underreaction, are represented by the black line with an arrow.

[Insert Figure 3.2 here]

Comparing the lower panel of Figure 3.2 to that of Figure 3.1, it is evident that the HS model predicts different dynamics of expectation errors:

1. The cross-sectional difference between winner and loser stocks in expectation errors is positive (rather than negative in the DHS model).
2. The cross-sectional difference between winner and loser stocks in expectation errors shrinks from a positive number toward zero (rather than a U-shaped pattern in the DHS model).

1.3.3 Barberis, Shleifer, and Vishny (1998)

The BSV model was not originally designed to generate momentum and reversal in sequence, but it can do so under certain parameter configurations. Similar to DHS, BSV assume a risk-neutral representative investor who sets prices by discounting expected cash flows. BSV assume that the true cash flow dynamics are a random walk, but the representative investor nevertheless believes that cash flows follow a regime-switching model with two Markov regimes: a trending regime, in which positive shocks are followed by positive shocks; and a mean-reverting regime, in which positive shocks are followed by negative shocks. The investor first believes in the mean-reverting regime and then Bayesian updates the probability of each regime upon new shocks.

Consider a loser stock whose the price falls because of a negative cash flow shock initially. Under rational expectations, the negative shock will cause a permanent fall in the expectations of all future cash flows because the true dynamics are assumed to be a random walk

in this model. However, believing in mean-reversion, the investor expects a positive shock in the next period. Thus, the investor's cash flow expectations are too optimistic relative to what the random walk process implies in the first period. In the second period, the average shock is zero under the random walk process, thereby leading to a negative surprise for the investor because the investor expects a positive shock. In addition, the investor will also lower his expectation of future cash flows. To understand this, consider that negative and positive shocks have equal probability of occurrence under the random walk process. If the investor observes negative shocks again in the second period, he switches his belief from mean-reverting to trending under certain model configurations. Consequently, the investor expects negative shocks to occur in the third period. For the other half of the chance, the investor observes positive shocks in the second period and then believes that he is still in the mean-reverting regime (note that this stock has a negative shock in the first period). Consequently, the investor again expects negative shocks for the third period. Thus, in the second period, the investor will experience a negative earnings surprise and lower the expectation for future earnings. Consequently, the price will continue its fall from the first period, thereby resulting in a momentum phase. Finally, since the second period's expectations of negative shocks are overly pessimistic compared to the random walk process, the subsequent returns will be positive, thereby resulting in a reversal phase.

The upper panel of Figure 3.3 presents the prediction regarding expected earnings under the BSV model, and the lower panel of Figure 3.3 summarizes the two key predictions of BSV. Although BSV are motivated by different behavioral biases from those in DHS, comparing Figures 3.2 and 3.3, it is evident that BSV actually have predictions on cash flow expectations that are indistinguishable from the predictions in DHS.

Finally, I summarize the different patterns of cash flow expectation errors implied by the three models in Figure 3.4. In a nutshell, the three behavioral theories disagree on whether

there should be an overreaction in cash flow expectations (DHS/BSV) or not (HS) when the return pattern shifts from momentum to reversal. In addition, models under rational expectations predict that both winner and loser stocks should have zero cash flow expectation errors throughout the holding period.

[Insert Figure 3.4 here]

1.4 Data

1.4.1 Data Description

My data encompass the period from 1985 to 2012 and include all nonfinancial common stocks traded on NYSE, AMEX, and NASDAQ from the CRSP database.

Stock prices, total shares outstanding, and market values are taken from CRSP. Book values are taken from COMPUSTAT. Monthly returns are adjusted by delisting returns when applicable. Annual earnings forecasts and actual earnings are taken from I/B/E/S unadjusted detail files. I use actual earnings reported in I/B/E/S rather than those in COMPUSTAT because I/B/E/S actual earnings use an earnings definition that is closer to what is used by analysts.⁹ I use forecasts for the current fiscal year end and the next fiscal year end, because these are the two most frequently issued annual forecasts. Then, I merge CRSP data with I/B/E/S earnings forecasts by matching CUSIPs. I follow Payne and Thomas (2003) by adjusting the effect of changes in shares on EPS (earnings per share) that occurred between the portfolio formation date and the dates of interest.

To minimize the attrition effect over a holding horizon of two years, I only include firms that satisfy the following characteristics when I form the portfolios: positive book equity,

⁹See Bradshaw and Sloan (2002) and Livnat and Mendenhall (2006) for a discussion on the difference between the COMPUSTAT earnings definition and the I/B/E/S earnings definition.

price per share higher than \$5, market value larger than NYSE bottom size decile, more than two analysts providing coverage, and no missing returns in the past 18 months. Table 3.1 provides a step-by-step description of the data cleaning process.

[Insert Table 3.1 here]

Table 3.2 presents the distribution of firm size, number of analysts, and book-to-market ratios averaging over portfolio formation dates for each of the momentum quintile portfolios.¹⁰ In my sample, stocks in the loser portfolio (the lowest momentum quintile) have the smallest average market capitalization. The mean is \$3.1 billion and the median is \$611 million. Stocks in the winner portfolio (the highest momentum quintile) have the second-smallest average market capitalization. The mean is \$4.8 billion and the median is \$1 billion. Loser stocks have the highest average book-to-market ratio. The mean is 0.64 and the median is 0.49, which are approximately twice as large as the mean and the median of the book-to-market ratio of winner stocks, respectively. With regard to the number of analysts providing coverage for one particular stock, the distribution appears rather even across momentum portfolios. For stocks in the loser or winner portfolios, the mean number of analysts providing coverage is approximately 7.5 and the median is approximately 6.

[Insert Table 3.2 here]

1.4.2 Proxy for Cash Flow Expectations

Although earnings forecasts of financial analysts are the best available proxy for cash flow expectations, there are several known issues related to earnings forecasts. I pay special attention to avoiding them when I construct the proxy for cash flow expectations. First,

¹⁰At the end of each month t , I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Then, stocks are sorted into momentum quintile portfolios based on these breakpoints.

the analyst forecasts database I/B/E/S does not specify the time frame for its consensus forecasts, so the consensus forecasts can include stale forecasts. Stale forecasts are found to reduce the accuracy of forecasts (O'Brien (1988)) and may complicate the use of predictive regressions. Second, the distribution of earnings forecast errors is left skewed, and the distribution may have a discrete jump from small negative errors to small positive errors (Abarbanell and Lehavy (2003)). Third, the literature disagrees on whether an average optimism bias exists in earnings forecasts (Chen and Jiang (2006)) or not (Gu and Wu (2003)). To avoid these issues, I work with individual forecasts and construct my own consensus forecasts to ensure that forecasts used in the left-hand side of predictive regressions are newly issued after the portfolio formation date. Thus, under rational expectations, the momentum rankings should not predict future forecast errors. Second, aware of the skewness effect in the data, I show that the main results are robust to the choice of median or mean errors, as well as to the different choices of winsorization. Third, I focus on cross-sectional differences in forecast errors to avoid statistical issues surrounding the estimate of the average forecast bias. As long as the potential optimism is symmetric across portfolios, the results of cross-sectional differences are robust to average biases.

In the robustness section, I also address the concern that earnings forecasts may systematically differ from the cash flow expectations of the market.

1.5 Main Analysis

In this section, I first show how I construct the proxy for cash flow expectations. Then, I identify the momentum and reversal phases in my sample. Finally, I check whether the empirical pattern of cash flow expectation errors in the momentum and reversal phases is consistent with model predictions.

1.5.1 Construction of the Proxy for Cash Flow Expectations

Figure 3.5 illustrates how I construct the portfolios and the associated cash flow expectations.

[Insert Table 3.5 here]

At the end of each month t , I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Then, stocks are sorted into momentum quintile portfolios based on these breakpoints and held for 24 months. I use mom_t^i to denote the resultant quintile rankings. To calculate the consensus forecast for stock i in the $k+1$ month after the portfolio formation month t , in a quarter-long window from month $t+k+1$ to $t+k+3$, I collect all newly issued earnings forecasts made for the fiscal year end that is closest to month $t+k+1$ but still at least six months away from month $t+k+1$. Thus, the forecast horizon ranges from 6 months to 18 months. If one analyst issues more than one such forecast in the quarter long window, I choose the latest one. I calculate the median of these forecasts for stock i and call it the consensus forecast $AF_{t,t+k+1 \rightarrow t+k+3,T_k}^i$. Note that t signifies that stocks are sorted on momentum at time t , $t+k+1 \rightarrow t+k+3$ signifies that the forecasts are issued between month $t+k+1$ and month $t+k+3$, and T_k signifies the fiscal year forecasted. I use $AF_{t,t+k+1 \rightarrow t+k+3,T_k}^i$ as the proxy for cash flow expectations in this study. While the window of a quarter ensures that there are sufficient forecasts to compute the consensus forecasts, it nevertheless leads to some overlapping. I take account of the serial correlation in the calculation of standard errors throughout the paper by using Newey-West heteroskedasticity and autocorrelation consistent standard errors (Newey and West (1987)). I use $Act_{T_k}^i$ to denote the actual realized earnings for $AF_{t,t+k+1 \rightarrow t+k+3,T_k}^i$, which is usually announced within three to six months after the fiscal year end. The forecast errors are defined as actual earnings minus the consensus forecasts. Then, I normalize the forecast errors by the absolute value of forecasts to convert them into percentage errors, thereby conforming closer to a normal distribution. The percentage errors are denoted as

$FE_{t+k+1 \rightarrow t+k+3}^i = \frac{Act_{T_k}^i - AF_{t,t+k+1 \rightarrow t+k+3,T_k}^i}{|AF_{t,t+k+1 \rightarrow t+k+3,T_k}^i|}.$ ¹¹ For each stock i and portfolio-formation month t , I calculate 24 $FE_{t+k+1 \rightarrow t+k+3}^i$'s for the holding period, $k = 0, 1, \dots, 23$.

Finally, I repeat the calculations for each portfolio formation month t from 1988/1 to 2008/6,¹² thereby generating a time series of monthly observations for $FE_{t+k \rightarrow t+k+2}^i$, $k = 1, 1, \dots, 24$.

1.5.2 Momentum and Reversal in the Sample

[Insert Figure 3.6 here]

Figure 3.6 depicts the differences in the cumulative returns over the holding period between stocks in the lowest momentum quintile (loser stocks) and stocks in the highest quintile (winner stocks). The dots are the time series average across portfolio formation dates and the t statistics are reported below the figure. The k^{th} dot represents the average winner-minus-loser cumulative return over the first k months after sorting. Figure 3.6 shows that the winner-minus-loser portfolio generates a gain of approximately 3.5% per dollar in the first six months and then a loss of approximately 4.8% in the following 18 months. Thus, I categorize months 1 to 6 as the momentum phase and the remainder as the reversal phase. Momentum is significant in months 1 to 6, and reversal is significant in months 9 to 13, as shown in the table within Figure 3.6. The return pattern of a momentum phase followed by a reversal phase is well documented in the literature, such as Lewellen (2002) and Jegadeesh

¹¹Earnings per share are much less correlated with the size of the firm than the total earnings. Similar results are attained with forecast errors without normalization and with forecast errors normalized by price or standard deviations of changes in quarterly earnings.

¹²The sample could be pushed to 1985. But in later tests, past information is needed. Starting from 1988 ensure we have consistent sample throughout the paper. The portfolio formation stops in 2008/6 because the holding period is 24 months. This implies that the last forecasts for stocks sorted into portfolios in 2008/6 are made in 2010/6 for the fiscal year ending in 2011. The 2011 earnings are announced in 2012, which is the end of my data sample.

and Titman (2001).¹³ As discussed in Section 3, the dynamics of forecast errors in the two phases will convey critical information to distinguish among the different explanations of momentum and reversal.

1.5.3 Main Tests

Once I identify the momentum and reversal phases, I go directly to the main test. DHS and BSV predict the difference in forecast errors between winner and loser portfolios to be *negative* at the end of the momentum phase, whereas HS predicts this difference to be *positive*. Furthermore, DHS and BSV predict the difference to decrease in the momentum and increase in the reversal phase, whereas HS predicts the difference to decrease monotonically throughout both phases. See Figure 3.4 for an illustration.

Dynamics of Forecast Errors

[Insert Figure 3.7 here]

Figure 3.7 depicts the pattern of forecast errors for winner and loser portfolios in the holding period. The line with dots (triangles) is the time series average pattern for the winner portfolio (loser portfolio). The asterisks indicate the 95% confidence interval. The winner portfolio has positive forecast errors initially at an approximate level of 0.7% in the first month, which then gradually decline to -3.2% at the end of the holding period.¹⁴

¹³As Jegadeesh and Titman (2001) note, hereafter JT, the switch of momentum and reversal at a frequency of less than one year is very challenging for a risk-based model to explain. My results are more similar to Lewellen (2002), which sorts stocks by the past 12-month returns. JT sort stocks by the past six-month returns, so readers should compare the holding period in this chapter with the holding period from the sixth month onwards in JT. The magnitude of momentum is 0.6% per month in my sample, which is similar to Lewellen's results but a little lower than JT's results. The magnitude of reversal is -0.25% per month in my sample, which is between Lewellen's results and JT's results.

¹⁴Forecast errors are defined as actual earnings minus forecasts. Recall that I use a quarter-long window to calculate the consensus forecasts, so the first month is really the quarter-long window starting from the

The forecast errors for the loser portfolio gradually shrink from -17.4% at the beginning of the holding period to -5.1% at the end of the holding period. With regard to the key moment conditions that differentiate the HS model from the DHS and BSV models: around the transition period from the momentum phase to the reversal phase, i.e., months 6 to 9 in the holding period, the cross-sectional differences in forecast errors between winner and loser portfolios are all significantly positive; in addition, these differences decrease gradually from approximately 18% to 2% through the momentum and reversal phases. These results indicate that the cash flow expectations for winner stocks are less optimistic relative to those for loser stocks, and the cross-sectional difference in expectation errors diminishes over the holding period. Comparing Figure 3.7 with Figure 3.4, it is evident that the dynamics of forecast errors fit the prediction of the underreaction mechanism postulated in Hong and Stein (1999) very well. Table 3.4 confirms that the winner-minus-loser differences in forecast errors remain significantly positive for approximately 13 to 15 months. Thus the pattern of forecast errors is consistent with the underreaction hypothesis, which helps to explain the return momentum, but runs counter to the subsequent return reversal. This finding highlights the important role of momentum traders in the HS model: without momentum traders, cash flow expectation errors can only cause return momentum. Because momentum traders exploit the return momentum by extrapolating prices blindly,¹⁵ they inevitably push the prices too far from the fundamental value, thereby causing return reversal.

[Insert Figure 3.7 Here]

The economic magnitude of the cross-sectional differences in forecast errors between winner and loser portfolios should be interpreted with additional assumptions. I use the

first month.

¹⁵HS show that it is not a suboptimal strategy because momentum traders actually front-run traders who are slowly incorporating cash flow news.

forecasts for the current fiscal year and the next fiscal year to construct consensus forecasts. Thus, if the cross-sectional differences in forecast errors are similar for these forecasts and the forecasts concerning earnings beyond the next fiscal year, the correction of forecast errors will generate a 16% to 18% difference in cumulative returns between winner and loser stocks over the two-year holding period. In contrast, if the cross-sectional differences in forecast errors for forecasts beyond the next fiscal year are smaller, e.g., zero, then the correction of forecast errors will only generate a 1.6% to 1.8% difference in cumulative returns, assuming a P/E ratio of 10.¹⁶ Therefore, gauging the exact impact of forecast errors on returns can be difficult.

Previous studies have examined the relation between forecast errors and past returns (e.g., ?Easterwood and Nutt (1999); Doukas, Kim, and Pantzalis (2002); Piotroski and So (2012));¹⁷ however, to my knowledge, this study is the first to examine the full dynamics of the forecast errors simultaneously in the momentum and reversal phases and to connect these dynamics to a test of three prominent behavioral theories. Taking advantage of sharp predictions from the theories also grants my tests extra robustness and power in distinguishing between the underreaction and overreaction mechanisms. First, all three theories can predict more positive forecast errors for winner stocks at the beginning of the momentum phase. Thus, the evidence that winner stocks have positive forecasts errors at the beginning of the momentum phase may not be sufficient to support the underreaction mechanism. My tests avoid this problem by explicitly utilizing the information from returns to identify the

¹⁶Under the discounted cash flow model, assuming discount rates are the same between earnings forecast days and earnings announcement days, I obtain $P_{realized} = \frac{CF_1}{1+r_1} + \frac{CF_2}{1+r_2} + \dots + \frac{CF_\infty}{1+r_\infty}$ and $P_{expected} = \frac{AF_1}{1+r_1} + \frac{AF_2}{1+r_2} + \dots + \frac{AF_\infty}{1+r_\infty}$. If percentage forecast errors for winner stocks are 16% higher for all earnings CF_1 to CF_∞ , i.e., $\frac{CF_n - AF_n}{|AF_n|} = 16\%$ for all n , then $\frac{P_{realized} - P_{expected}}{P_{expected}} = 16\%$. In contrast, if $\frac{CF_n - AF_n}{|AF_n|} = 0\%$ for all $n > 1$, assuming $\frac{P_{expected}}{AF_1} = 10$, then $\frac{P_{realized} - P_{expected}}{P_{expected}} = \frac{CF_1 - AF_1}{AF_1} / \frac{P_{expected}}{AF_1} = 1.6\%$.

¹⁷Please see Ramnath, Rock, and Shane (2008) for a more comprehensive review.

transition period from the momentum phase to the reversal phase when different mechanisms generate diametrically opposite predictions. I show that the cross-sectional difference in cash flow expectation errors remains positive in and beyond the transition period. Second, researchers disagree on the magnitude of the average optimistic bias in analysts earnings forecasts. My tests focus on the predicted pattern of cross-sectional differences in forecast errors and thereby do not need to adjust forecasts errors for the average biases.

Panel Regression

To formally test the implied moment conditions of cash flow expectation errors from the theories, I run the following panel regression:

$$FE_{t+k \rightarrow t+k+2}^i = c_1^k + \lambda_k mom_t^i + Yearmon_t + \epsilon_{t+k}^i. \quad (1.1)$$

The models under rational expectations predict that all λ_k s are equal to zero, i.e., momentum rankings in month t cannot predict the errors for forecasts made between months $t+k$ and $t+k+2$. The main difference between the three behavioral models is that DHS and BSV predict that λ_k s are *negative* in the transition period from momentum to reversal as well as in the reversal phase. DHS and BSV also predict that λ_k s grow more negative in the momentum phase and then gradually return to zero in the reversal phase, a U-shaped trend. In contrast, HS predict that λ_k s are *positive* throughout the momentum phase and reversal phases and the λ_k s will decrease from a positive number to zero. Put it simply, underreaction (overreaction) is associated with positive (negative) λ_k s. In the DHS and BSV models, overreaction in cash flow expectations peaks at the end of the momentum phase and its subsequent abatement generates return reversal. In the HS model, underreaction in cash

flow expectations subsides monotonically over time.

[Insert Table 3.5 here]

Table 3.5 presents the regression results. The 24 λ'_k s are all significantly positive, and the magnitude of λ'_k s declines throughout the momentum and reversal phases. The t-statistics of λ'_k s clearly reject the hypothesis that λ'_k s are zero, thereby suggesting that the consensus earnings forecasts systematically deviate from rational expectations. The t-statistics also reject the hypothesis that λ'_k s are negative around the turning point from the momentum phase to the reversal phase. I can also easily reject the hypothesis that λ'_k s are jointly negatively for months 9 to 13, the return reversal is significant. Therefore, I conclude that the pattern of the forecast errors is most consistent with Hong and Stein (1999).

Control for Analyst-Specific Sluggishness

In the main results, I use earnings forecasts as a proxy for cash flow expectations in the tested models. I now discuss how the proxy error may affect the regression results.

I formally denote the cash flow expectations in the model as MF , i.e., marginal investors' expectations, earnings forecasts as AF , and the actual earnings as CF . This yields

$$AF_{t+k} = MF_{t+k} + \eta_{t+k}^A, \quad (1.2)$$

where η_{t+k}^A is the difference between the cash flow expectations in the model and the consensus forecasts. Under the null hypotheses derived from the three theories, cash flow expectation errors can be forecasted by past returns. Thus, the following relation between the errors for forecasts made in months k to $k+2$ after portfolio formation and momentum ranking upon the portfolio formation is obtained for each firm i and each portfolio formation

month t :

$$CF_{i,t+k} - MF_{i,t+k} = c_k + \lambda_k mom_{i,t} + \epsilon_{i,t+k}. \quad (1.3)$$

$CF_{i,t+k} - MF_{i,t+k}$ is the cash flow expectation error in the model. λ_k is the parameter of interest to distinguish among models. However, since I do not observe MF_{t+k} , I replace it with AF_{t+k} . Combining equations 1.2 and 1.3, I obtain

$$CF_{i,t+k} - AF_{i,t+k} = c_k + \lambda_k mom_{i,t} + \epsilon_{i,t+k} - \eta_{i,t+k}^A, \quad (1.4)$$

where $CF_{i,t+k} - AF_{i,t+k}$ is the forecast errors. I do not need zero proxy error $\eta_{i,t+k}^A$ to obtain a consistent estimate of the key coefficient λ_k . For consistency, I only need the proxy error $\eta_{i,t+k}^A$ to be orthogonal to the momentum ranking $mom_{i,t}$. Nevertheless, there is a concern that $\eta_{i,t+k}^A$ is correlated with $mom_{i,t}$. For example, consider a loser stock that has had several disappointing quarterly earnings. It is possible that, while the marginal investor has already incorporated the firm's deteriorating business prospects into its price, the analysts are reluctant to lower their forecasts fully, thereby generating a positive proxy error $\eta_{i,t+k}^A$. As a result, this loser stock will have zero market expectation errors, but negative forecast errors. In this case, the momentum ranking can predict forecast errors but not market expectation errors. Consequently, the estimate of λ_k in regression equation 1.4 will be biased upward in favor of the underreaction mechanism.¹⁸ Because market expectations cannot be observed, one cannot eliminate the possible correlation between $\eta_{i,t+k}^A$ and $mom_{i,t}$

¹⁸The correlation between $\eta_{i,t+k}^A$ and $mom_{i,t}$ could be positive, and in that case, the estimate of λ_{t+k} will be biased downward.

completely. However, given a concrete conjecture of the *analyst-specific* forecast bias, I can control $\eta_{i,t+k}^A$. Below I posit that $\eta_{i,t+h}^A$ is a linear function of past forecast revisions, past earnings announcement returns, and past standardized earnings surprises. This conjecture imposes strong restrictions against ascertaining the predictive power of past returns because it assumes that the marginal investor efficiently uses the information contained in these control variables, even though under the null hypotheses of the three theories the marginal investor does not use information efficiently. Though this additional conjecture is probably not realistic, it serves as a stress test for the main results.

I therefore run the following regression:

$$FE_{i,t+k} = \hat{\lambda}_k mom_{i,t} + \rho_{1,k} SUE_{i,t} + \rho_{2,k} SUE_{i,t,L1} + \rho_{3,k} EAR_{i,t} + \rho_{4,k} EAR_{i,t,L1} + \rho_{5,k} REV_{i,t} + \rho_{6,k} REV_{i,t,L1} + \rho_{7,k} REV_{i,t,L2} + \eta_{i,t+h}, \quad (1.5)$$

where $SUE_{i,t}$ is the last quarterly earnings surprise before month t , defined as IBES actual earnings minus analyst consensus forecasts divided by prices at the fiscal quarter-end;¹⁹ $EAR_{i,t}$ is the three-day return centered around the last quarterly earnings announcement; and $REV_{i,t}$ is the percentage forecast change in the last calendar quarter, defined as the difference between the median annual forecast over months $t-2$ to t and the median annual forecast over months $t-5$ to $t-3$ scaled by the absolute value of the latter. $L1$ denotes the same variable with one lag. $L2$ denotes the same variable with two lags.

These variables are correlated with the past 11-month returns for obvious reasons; e.g., past earnings announcement returns EAR_t and lagged EAR_t are a mechanical part of the past 11-month return. Thus, I expect that including these correlated variables in the con-

¹⁹I follow the approach outlined in Livnat and Mendenhall (2006).

trol variables will reduce the significance of the momentum ranking mom_t , generating a conservative estimate of the coefficient $\hat{\lambda}_{t+k}$.

Tables 3.6 and 3.7 present the regression results for equation 1.5. Comparing the coefficients of momentum rankings in this regression to those in regression 1.4, it is evident that the magnitude of the coefficients is reduced by approximately 50% when using control variables. Nevertheless, the important pattern of the loadings on momentum rankings does not change. The coefficients λ_k 's remain significantly positive well into the reversal phase, and the magnitude of these coefficients declines consistently after the portfolio formation. Both are consistent with the pattern found in regression 1.4. Most control variables emerge as statistically significant. Variables such as past forecast revisions predict the forecast errors as strongly as the momentum rankings do. As discussed before, it is difficult to gauge whether the forecast errors predicted by control variables only pertain to analysts or if they are part of market expectation errors. Nevertheless, even assuming the former, I reach the same conclusion.

[Insert Table 3.6 here]

1.6 Testing New Predictions

In this section, I probe the validity of the HS model and the appropriateness of using analyst forecasts as a proxy for cash flow expectations in an alternative manner. The main results of this chapter highlight that the HS model features different dynamics for cash flow expectations and prices. With the proxy of cash flow expectations in hand, I can divide past returns into a component related to cash flow expectations and a residual component. The latter component captures the momentum trading demand in the HS model. I will show that the latter but not the former predicts return reversal in the data. As shown below, this novel

empirical pattern poses informative restrictions on the parameters of the HS model.

1.6.1 Return Decomposition

I divide past returns into two parts by regressing returns on revisions of cash flow expectations in a cross section:

$$r_t^i = \beta_t \times Rev_t^i + \epsilon_t^i, \forall i$$

. Revisions of cash flow expectations are proxied by forecast revisions of annual earnings. The linear projection captures returns associated with cash flow expectation changes. The residuals are returns unrelated to current changes in cash flow expectations, and can be linked to the momentum trading demand in the HS model.²⁰ In the HS model the cash flow expectations suffer from underreaction, so current changes of cash flow expectations predict future changes. Consequently, the cash flow component of past returns predicts the return momentum; on the other hand, in the model momentum traders extrapolate past returns, therefore the residual component is likely to predict the return reversal.²¹ Therefore, investigating the predictive power of these two components is a straightforward joint test of the validity of the model and the empirical proxy.

The implementation of the return decomposition merits further explanations because forecasts are not issued regularly. For each three-month window, I use the median of newly

²⁰The estimated residuals are a noisy measure of the momentum trading demand because our proxy for cash flow expectations is not perfect and the HS model might be mis-specified.

²¹I derive this prediction formally in the appendix.

issued forecasts as the consensus forecasts.²² When I have two consecutive non-overlapping consensus forecasts $EF_{t-3,t}$ and $EF_{t,t+3}$ for the same firm fiscal-year pair, I calculate the forecast revisions $Rev_{t \rightarrow t+3} = \frac{EF_{t,t+3} - EF_{t-3,t}}{P_t}$. Ideally, I could just regress $r_{t \rightarrow t+3}$ onto $Rev_{t \rightarrow t+3}$. However, because forecasts are not issued regularly, the revisions are not in perfect synchronization with the quarterly returns. For example, if forecasts used to calculate $EF_{t,t+3}$ ($EF_{t-3,t}$) are mostly issued near the end of month $t+3$ (month t), then $EF_{t,t+3} - EF_{t-3,t}$ is roughly in synchronization with the quarterly return $r_{t \rightarrow t+3}$. On the other hand, if forecasts used to calculate $EF_{t,t+3}$ ($EF_{t-3,t}$) are mostly issued near the beginning of month $t+1$ (month $t-2$), then $EF_{t,t+3} - EF_{t-3,t}$ is more aligned with the return $r_{t-3 \rightarrow t}$. Consequently, forecast revisions $Rev_{t \rightarrow t+3}$ can be correlated with any returns between $r_{t-3 \rightarrow t}$ and $r_{t \rightarrow t+3}$. To minimize the estimation error due to this synchronization issue, I regress the average of four consecutive, non-overlapping quarterly returns onto the corresponding average of four forecast revisions to estimate the slope coefficient:²³

$$\overline{r_{t-12 \rightarrow t}^i} = c + \beta_t \overline{REV_{t-12 \rightarrow t}^i} + \epsilon_t^i \quad (1.6)$$

,

where $\overline{REV_{t-12 \rightarrow t}^i} = \frac{1}{4} \sum_{k=1}^4 REV_{t-3 \times k \rightarrow t-3 \times (k-1)}$ and $\overline{r_{t-12 \rightarrow t}^i} = \frac{1}{4} \sum_{k=1}^4 r_{t-3 \times k \rightarrow t-3 \times (k-1)}$.

Because the sensitivity of return to forecast revisions is likely to vary across value and growth stocks, I allow the cross-sectional regression coefficients to be a function of lagged book-to-market ratios.²⁴ Table 3.8 reports the time series statistics of the rolling cross-

²²If one analyst issues more than one forecasts, I choose the latest one.

²³If past revisions are missing, I set the corresponding three-month return missing too.

²⁴Book value for fiscal year the ending in calendar year t is scaled by the market value to get the corresponding book-to-market value between June of calendar year t and May of year $t+1$. The book-to-market

sectional regressions. As Panel A of Table 3.8 shows, revisions of earnings forecasts are the most significant factor in explaining past returns. The average coefficient of forecast revisions is 4.34, indicating that a 1% positive revision in earnings forecasts, relative to prices, explains a 4.3% increase in price. The coefficient is highly significant with an average t statistic of 10.3. Other coefficients are also consistent with economic intuitions: returns are positively correlated with lagged book-to-market ratios; growth firms command a higher sensitivity of return to forecast revisions, a 0.1 increase in log book-to-market ratio results in a decrease of 0.11 in the coefficient on forecast revisions. Panel B of Table 3.8 shows that the regressions carry considerable explanatory power, the average R^2 is 16%.²⁵

1.6.2 Predictive Power of Two Components of Past Returns

Finally, I use the time series average coefficients in Table 3.8 to calculate the cash flow component and the residual component of past six-month returns.²⁶ Decomposing past returns over even longer period can further mitigate the aforementioned synchronization issues, but it risks using stale information; six-month is a choice that balances these two considerations. Table 3.9 reports the results of regressing future monthly returns on these two components.

$$r_t^i = c + \gamma_1 CF_{t-n,-6}^i + \gamma_2 \widetilde{r_{t-n,-6}^i} + \epsilon_t^i \quad (1.7)$$

ratio is then lagged 12 months in the regression.

²⁵Un-tabulated results show that much of the explanatory power comes from the forecast revisions. Regressions of quarterly returns on contemporaneous revisions without taking the average generate a low R^2 of approximately 5% due to the synchronization issue.

²⁶I use the whole sample average coefficients. Results using the coefficients of the rolling cross-sectional regressions at each point yield qualitatively similar results.

, where $CF_{t-n,-6}^i = (\beta_{REV} + \beta_{\log BM \times REV} \log BM_{t-n-12}^i) \frac{REV_{t-n-6,t-n-3}^i + REV_{t-n-3,t-n}^i}{2}$, β_{REV} and $\beta_{\log BM \times REV}$ are the time series average coefficients from Regression (1.6), and $\widetilde{r_{t-n,-6}^i} = \frac{r_{t-n-6,t-n-3}^i + r_{t-n-3,t-n}^i}{2} - CF_{t-n,-6}^i$.

Both components contribute to the predictability of momentum: the cash flow component predicts future returns significantly and positively in month 1 ($t=3.7$), month 2 ($t=2.5$), and month 5 ($t=2.2$); the residual component predicts returns significantly and positively between months 4 and 8, with t statistics of 1.9, 1.9, 2.3, 3.2, and 2.2. On the other hand, only the residual part predicts the reversal significantly. Between months 13 and 17, the t statistics are -2.7, -2.9, -3.4, -2.5, and -2.4.

Figure 3.8 illustrates the cumulative sum of the regression coefficients. The Fama Macbeth coefficient on one regressor has the interpretation of the average return to a portfolio that has one unit of exposure to that regressor and zero exposure to the other regressors. Therefore, take the coefficients on cash flow component as an example, the cumulative sum can be interpreted as cumulative returns to a long/short portfolio that is long (short) stocks with high (low) value of cash flow component while maintaining zero exposure to the residual component. The stronger predictability of the residual component for return reversal is easily seen from the graph. After 18 months, more than 80% of momentum profit reverses for the residual sorted portfolios while less than 40% reverses for cash flow sorted portfolios.

1.6.3 Simulation of the HS Model

The key question to be answered in this section is whether the HS model can generate the distinctive predictive power of the two return components under reasonable parameters. The empirical patterns in Figure 3.8 impose very restrictive conditions on the model parameters. The information diffusion speed z is chosen to match the timing of the transition from momentum to reversal. The intensity of momentum trading ϕ is chosen to match the magnitude

of reversal. Lastly, the holding horizon j is left to generate the stronger predictive power of the residual component for the long term reversal. I simulate 500 cross-sections, each with 1,000 observations under the following parameters: momentum holding horizon $j = 12$, information diffusion horizon is $z = 15$ months, and the equilibrium momentum trading intensity $\phi = 0.1955$.²⁷ I then repeat the same analysis on the simulated data. Figure 3.9 shows that the HS model simulated under these parameters largely reproduces the empirical pattern in the data: both the cash flow component and the residual component predict return momentum, but the residual component predicts return reversal more strongly than the cash flow component.

The intuition is as follows. Returns reverse in the long run because momentum trading over-extrapolates past returns; meanwhile in the near term, returns continue with the past trend because positive returns are associated positive cash flow news, which predicts positive changes in future cash flow expectations due to the underreaction mechanism. The cash flow component of returns contains most recent cash flow news while the residual component, which is associated with momentum trading, contains lagged cash flow news.²⁸ So both the cash flow component and the residual component predict returns positively in the near term; as we move further into the holding period, cash flow news contained in the residual component loses predictive power for the changes in cash flow expectations, and the residual component starts predicting the long-term reversal.

The parameters are not unreasonable. The cycle of information diffusion being 15 months is consistent with the main results that past returns predict forecast errors up to two years;

²⁷ $\phi = 0.1955$ is solved under $j = 12$, $z = 15$, absolute risk tolerance γ of momentum traders is three times that of news watchers. Volatility of innovations σ is chosen so that the volatility of stock price is 5% per month.

²⁸As derived in the appendix, the residual from the first stage regression is positively related to past innovations that predict near term cash flow news.

momentum holding horizon being 12 months suggests traders re-balance once a year, which is reasonable for the whole universe of stock holders. The momentum trading intensity of 0.1955 requires the risk tolerance of momentum traders to be three times as large as that of news watchers, which is also possible.

To sum up, the cash flow component and the residual component of past returns have distinct predictive power of future returns. These empirical patterns are consistent with the HS model and help us identify the model parameters.

1.7 A Measure of Underreaction

In the HS model, return momentum originates from news watchers' underreaction to cash flow news. The more severe the underreaction is, the stronger the momentum is. Therefore, I create a bottom-up measure of underreaction for each firm using only earnings forecasts. Then, I check whether sorting on this underreaction measure can generate the predicted variation in the pattern of earnings forecast errors. Finally, I check whether the same sorting can generate the predicted variation in the pattern of returns. If the HS model does not conform to the data or the analyst forecasts are a bad proxy for cash flow expectations in the model, one will not observe the predicted variation in forecast errors or returns across the portfolios sorted on the underreaction measure.

Construction of the Underreaction Measure

To capture the tendency of analysts' underreaction, I construct the following measure. I trace each analyst's forecast revision history for a particular firm-fiscal year. For concreteness, consider a situation in which one analyst n makes three forecasts for a particular firm-fiscal year i : $AF_{i,t}^n$, $AF_{i,t-1}^n$, and $AF_{i,t-2}^n$. The corresponding revisions are $Rev_{i,t}^n = AF_{i,t}^n - AF_{i,t-1}^n$

and $Rev_{i,t-1}^n = AF_{i,t-1}^n - AF_{i,t-2}^n$. If one analyst uses information efficiently, no information before time $t - 1$ can predict $Rev_{i,t}^n$, including $Rev_{i,t-1}^n$. However, if one analyst underreacted to information at time $t - 1$, which affected the previous revision $Rev_{i,t-1}^n$, then as the analyst incorporates more of the information subsequently, his/her next revision $Rev_{i,t}^n$ will be forecastable by $Rev_{i,t-1}^n$. Therefore, at the end of each month t , for each analyst n , I run a simple pooled regression of $Rev_{i,t-h}^n$ on $Rev_{i,t-h-1}^n$ for all the forecast revisions that one analyst made in the past 24 months,

$$Rev_{i,t-h}^n = c + \beta_t^n Rev_{i,t-h-1}^n + \epsilon_{i,t-h}^n, \quad 0 \leq h \leq 24, \quad i = 1, 2, \dots, I. \quad (1.8)$$

A positive β_t^n indicates that analyst n is sluggish in revising his/her forecasts. To see why, consider a stock that is hit with bad news. If one analyst underreacts to this bad news, the forecast is revised downward insufficiently. Subsequently, the analyst incorporates more of this bad news when he/she issues the next forecast, thereby resulting in another negative revision. A negative previous revision $Rev_{i,t-h-1}^n$ followed by a negative revision $Rev_{i,t-h}^n$ will result in a positive regression coefficient β_t^n . A more positive β_t^n implies that lesser information was incorporated initially and thus indicates more severe underreaction.

With the measure of underreaction at the analyst level, the HS model predicts that, if a stock is covered by analysts who underreact more severely, the momentum phase for this stock will be stronger. Thus, for each firm i , at the end of month t , I calculate the median β_t^n of all analysts who cover firm i , and this is the underreaction measure for firm i at the portfolio formation month t . Based on the underreaction measure, the median β_t^n , I assign firms into quintile groups and term the quintile rankings “the underreaction rankings.” A high underreaction ranking implies that a firm is covered by analysts who underreact severely. For

firms within each quintile underreaction ranking, I further sort them into tertile portfolios based on returns of the past 11 months independently and again hold them for 24 months.²⁹ Then, I trace out the dynamics of the forecast errors and the dynamics of the returns in the holding period, similar to what I did in the main analysis. Under the HS model, I expect the winner-minus-loser momentum portfolio within the highest underreaction ranking to exhibit the most severe underreaction in cash flow expectations and the strongest momentum phase.

Dynamics of Forecast Errors for Firms Covered by Sluggish Analysts

Figure 3.10 depicts the pattern of the forecast errors for the winner and loser portfolios in the holding period across different underreaction quintiles. First, I observe that sorting on underreaction rankings indeed induces a variation in the dynamics of earnings forecast errors. In the upper-left panel, stocks with the lowest underreaction ranking have an initial difference of approximately 13%, and the gap shrinks to 1% after one year. In contrast, in the lower-left panel, stocks with the highest underreaction ranking exhibit a larger difference, from 17% at the beginning to 5% after one year.

[Insert Figure 3.10 here]

To formally test whether underreaction in cash flow expectations is more severe in firms with the highest underreaction ranking, I run the following regression:

$$\begin{aligned}
 FE_{t+k \rightarrow t+k+2}^i &= c_1^k + c_2^k I(Under_{t+k}^i = 5) + \lambda_k mom_{i,t} + \\
 &\dots \beta^k I(Under_{t+k}^i = 5) \times mom_{i,t} + \epsilon_{t+k}^i.
 \end{aligned} \tag{1.9}$$

²⁹I sort stocks into tertile momentum portfolios to ensure I have sufficient stocks within each of the 5-by-3 portfolios.

The results in Table 3.10 indicate that the coefficient of the product term β^k is positive for approximately 22 months, with the first 18 months being statistically significant. These results confirm that our empirical underreaction measures capture the tendency of underreaction in earnings forecasts with of firms.³⁰

Return Momentum and Reversal for Firms Covered by Sluggish Analysts

If analyst forecasts were a poor proxy for the cash flow expectations in the HS model, then the variation in the dynamics of forecast errors would not cause a variation in the pattern of momentum and reversal. Figure 3.11 shows the opposite. In the upper-left panel, for stocks with the least underreaction, momentum lasts approximately six months. Thereafter, reversal kicks in. This is consistent with the pattern of the full sample. In contrast, in the lower-left panel, for stocks with the most severe underreaction, momentum is stronger and lasts three months longer, and reversal is weaker.

[Insert Figure 3.11 here]

To formally test whether the momentum phase is stronger in the firms with the highest underreaction ranking, I compare the average returns in the momentum and reversal phases across the underreaction rankings. As Table 3.11 shows, in months 1 to 6, the winner-minus-loser portfolio in the highest underreaction ranking achieves stronger momentum than the winner-minus-loser portfolios in the other underreaction quintiles. The difference is approximately 0.24% per month and significant at the 5% level, which is a noticeable amount given that the average winner-minus-loser profit of the momentum tertile portfolios

³⁰The results of a version with control variables is also available upon request.

$$\begin{aligned} FE_{t+k \rightarrow t+k+2}^i &= c_1^k + c_2^k I(Under_{t+k}^i = 5) + \lambda_k mom_{i,t} + \\ &\dots \beta^k I(Under_{t+k}^i = 5) \times mom_{i,t} + X_t^i + \epsilon_{t+k}^i \end{aligned}$$

The results do not change much in the regression with control variables.

is approximately 0.44% per month among stocks in the underreaction quintiles 1-4. The winner-minus-loser portfolio with the highest underreaction ranking also has a more persistent momentum phase. For months 7 to 9, while this portfolio still exhibits some momentum, the winner-minus-loser portfolios in other underreaction quintiles have begun reversal. The difference is 0.41% per month and is significant at the 5% level. Finally, from month 7 to month 24, the general reversal phase for the momentum portfolios in the full sample, the winner-minus-loser portfolio in the highest underreaction ranking exhibits little reversal, -0.1% per month, while the winner-minus-loser portfolios in other underreaction quintiles exhibit a reversal -0.28% per month. The difference is 0.17% and is marginally significant at the 10% level. Similar to the pattern of forecast errors, in un-tabulated results, I find that most of return variations come from the loser portfolio.

In summary, I find that the stocks exhibit stronger return momentum if they are covered by analysts who underreact severely to past information. This evidence supports the underreaction mechanism postulated by HS and validates the use of analyst forecasts as a proxy for the cash flow expectations.

1.8 Robustness

In this section, I report results under methodological variations. First, I report the results using earnings forecasts with longer/shorter forecasting horizons. Second, I discuss test results using forecast revisions. Then, I discuss the relation between earnings forecast errors and earnings announcement returns. Finally, I discuss the applicability of the methodology.

1.8.1 Cash Flow Expectations: Long-Term vs. Short-Term

Due to the limitations of the data, I have good proxies for the earnings expectation up to two years at a point of time.³¹ Still, in DHS, BSV, and HS, long-term cash flow expectations should have similar expectation errors as those of the short-term cash flow expectations because all three models do not distinguish long-term expectations from short-term expectations. Under this embedded auxiliary assumption, my findings regarding the dynamics of annual forecast errors suggest that cash flow expectations cannot explain momentum and reversal simultaneously. Nevertheless, there is a possibility that in the data long-term and short-term cash flow expectations suffer opposite errors: more specifically, long-term expectations exhibit the overreaction bias, while short-term expectations exhibit the underreaction bias. In this case, models beyond DHS, BSV, and HS are needed.³² To investigate this possibilities, I repeat the main analysis on forecasts with the shortest and longest forecasting horizons in the data, i.e., the nearest quarterly forecasts and two-year-ahead forecasts. If the positive difference in forecast errors between winner and loser stocks is smaller for the two-year-ahead forecasts than that for the nearest quarterly forecasts, then the difference

³¹One may propose using analysts' forecasts of long-term growth, but I caution against it for several reasons. First, analysts actually do not specify the exact forecasting horizons for long-term growth forecasts. Therefore, it is almost impossible to evaluate the accuracy of these forecasts precisely. Second, because the median analyst tenure is approximately three to five years, it is not practical to evaluate an analyst based on the accuracy of his/her long-term forecasts. Third, analysts update their long-term forecasts much less frequently. Consequently, analysts' long-term growth forecasts are a poor predictor for the actual long-term growth rate (Chan, Karceski, and Lakonishok (2003)) and not a good proxy for corresponding market expectations.

³²This is not completely unforeseen by previous researchers; e.g., BSV (1998) page 332 says, "One possible way to extend the model *is to allow investors to estimate the level and the growth rate of earnings separately*"(italic emphasis added). I can interpret the "level" as near-term earnings and the "growth" as long-term earnings.

The results using analysts' long-term forecasts are consistent with the overreaction mechanism. However, the statistical significance is marred by the infrequent updates and the long-run characteristic. In addition, as discussed in the previous footnote, analysts' long-term forecasts are not widely taken as a good proxy for market expectations of long-term earnings.

may turn negative for forecasts concerning earnings beyond two years, i.e., the underreaction bias may turn to the overreaction bias for long-term forecasts. However, in results shown in the Figure 3.12 and 3.13, I fail to find such a tendency—the two-year-ahead forecasts have larger forecast errors between winner and loser portfolios than the one-quarter-ahead forecasts, 22% vs. 10% at the beginning of the holding period and 5% vs. 1% at the end of the twelfth month. Overall, if there is a trend in forecast errors, forecast errors are larger but not smaller for longer-term forecasts.

1.8.2 Forecast Errors vs. Forecast Revisions

The focus in the main test is on forecast errors but not on forecast revisions because the predicted dynamics of forecast revisions in the momentum phase under the three tested models are indistinguishable: winner stocks have positive forecast revisions and loser stocks have negative forecast revisions. The key difference among the theories, that is, whether the cash flow expectations underreact or overreact to past information, manifests in the level of cash flow expectations relative to the level of rational expectations. Therefore, taking the actual earnings as the benchmark of rational expectations and examining the forecast errors, i.e., actual minus forecasts, yields sharper tests of the models.

Nevertheless, the three models still have distinctively different predictions of forecast revisions in the reversal phase. The HS model predicts that winner stocks will have more positive revisions in the reversal phase, while the DHS and BSV models predict the opposite. Empirically, taking the first difference in the forecasts to calculate revisions offers the unique advantage of eliminating the analyst-specific fixed effect. Besides, McNichols and O'Brien (1997) find that analysts tend to self-censor negative views. This is not a problem for forecast revisions, because revisions can only be calculated for analysts who are still issuing forecasts. Thus, checking whether the dynamics of revisions also support the underreaction mechanism

postulated by the HS model can offer corroborating evidence.

I provide the results of forecast revisions in the appendix. The dynamics of forecast revisions are consistent with conclusions drawn from examining the dynamics of forecast errors. Winner stocks have significantly more positive forecast revisions than loser stocks more than 13 months into the holding period, which is consistent with the underreaction hypothesis in Hong and Stein (1999). I also experiment with different normalization schemes, such as normalizing by past prices or standard deviations of past changes in quarterly earnings. Overall, I find that the dynamics of the forecast revisions are consistent with the underreaction hypothesis across all variations.

1.8.3 Earnings Forecast Errors vs. Earnings Announcement Returns

Examining the earnings announcement returns is not optimal for this study because earnings announcement returns are not a direct measure of cash flow news. As with any other returns, earnings announcement returns have three components: expected returns, cash flow news, and discount rate news (Campbell and Shiller (1988)). Firms release all kinds of information around earnings announcement days, and research shows that the expected returns and discount rate news are important around these days (Kishore, Brandt, Santa-Clara, and Venkatachalam (2008); Dubinsky and Johannes (2006)).³³ Because earnings announcement returns conflate cash flow news with the other two components, it is not well suited for the purpose of this study, which is to discriminate among models that predict similar return

³³Kishore, Brandt, Santa-Clara, and Venkatachalam (2008) show that the earnings announcement returns include more information than cash flow news. One interpretation of their results is that earnings announcements release a great deal of information regarding the riskiness of the business prospects, which affects the discount rate. Dubinsky and Johannes (2006) find that market participants expect a large amount of uncertainty to be resolved around scheduled announcement windows using option data. Thus, expected returns are also likely to play a non-negligible role in announcement returns.

dynamics but different dynamics of cash flow expectations.

1.8.4 Applicability of the Methodology

The test design proposed in this study is a general one. For any asset pricing model that relies on the dynamics of cash flow expectations to generate specific return regularities, I can test the implied moment conditions of cash flow expectations. These moment conditions are particularly informative when models are designed to fit return patterns and thus are difficult to test by examining the moment conditions of returns.

1.9 Conclusion

Despite voluminous research on momentum and reversal, discriminating among competing explanations of momentum and reversal has remained an unresolved challenge. In this study, I propose to distinguish among the three most prominent behavioral models by examining their predicted pattern of cash flow expectation errors. I carefully construct the proxy for cash flow expectations from earnings forecasts and trace the dynamics of expectation errors over a two-year holding period, during which returns are characterized by a momentum phase followed by a reversal phase. I find that winner stocks have significantly more positive cash flow expectation errors than loser stocks over both the momentum phase and the beginning of the reversal phase. The large positive cross-sectional difference in cash flow expectation errors between winner and loser stocks gradually shrinks to zero over the holding period. I obtain similar results either by examining the portfolio median expectation errors or by examining the expectation errors at the individual stock level in a regression setting. The results are robust to whether I use nearest quarterly forecasts or two-year-ahead forecasts. The results are also robust to a regression setting that controls for analyst-specific sluggishness. When

I rank stocks by the underreaction severity of the following analysts, I find momentum is stronger among stocks with the highest underreaction ranking. Taken together, the results are most consistent with the prediction of Hong and Stein (1999), in which underreaction in cash flow expectations drive return momentum, but price extrapolation is needed to generate reversal. I also examine the dynamics of forecast revisions in the holding period. Results corroborate the main conclusion.

While the results are most consistent with Hong and Stein (1999), direct evidence on the price extrapolation behavior of momentum traders is needed to further validate the model. Greenwood and Shleifer (2013) find direct evidence for price extrapolation at the aggregate market level, but evidence at the stock level is scant. Future research on this front will complement this study in providing the empirical basis for behavioral theories that use extrapolative expectations to generate reversal-like return predictability.

The methodology used in this chapter can be directly applied to study the patterns of cash flow expectation errors underlying other return regularities in the equity market. The identified patterns could shed light on the plausible unified mechanism involving cash flow expectations behind these phenomena, and could provide informative moment conditions to pin down the parameters of behavioral biases in structural estimations.

Chapter 2

The Carry Trade: Risks and Drawdowns

Kent Daniel, Robert Hodrick, and Zhongjin Lu

2.1 Introduction

This paper examines some empirical properties of the carry trade in international currency markets. The carry trade is defined to be an investment in a high interest rate currency that is funded by borrowing a low interest rate currency. The 'carry' is the positive interest differential. The return to the carry trade is uncertain because the exchange rate between the two currencies may change. The carry trade is profitable when the high interest rate currency depreciates relative to the low interest rate currency by less than the interest differential. By interest rate parity, the interest differential is linked to the forward premium or discount. Absence of covered interest arbitrage implies that high interest rate currencies trade at forward discounts relative to low interest rate currencies, and low interest rate currencies trade at forward premiums. Thus, the carry trade can also be implemented in forward markets by going long in currencies trading at forward discounts and going short in currencies trading at forward premiums. Such forward market trades are profitable as long as the currency trading at the forward discount depreciates less than the forward discount or as long as the currency trading at a forward premium appreciates less than the forward premium.

Carry trades are known to have a high Sharpe ratios, as emphasized by Burnside, Eichenbaum, Kleschelski, and Rebelo (2011). They are also known to do poorly in highly volatile environments, as emphasized by Bhansali (2007), Clarida, Davis, and Pedersen (2009), and Menkhoff, Sarno, Schmeling, and Schrimpf (2012). Brunnermeier, Nagel and Pedersen (2009) document that returns to carry trades have negative skewness. There is a substantive debate about whether carry trades are exposed to risk factors. Burnside, et al. (2011) argue that carry trade returns are not exposed to standard risk factors, in sample. Many others, cited below, find exposures to a variety of risk factors. Burnside (2012) provides

a review of the literature. We contribute to this debate by demonstrating that non-dollar carry trades are exposed to risks, but carry trades versus only the dollar are not, at least not unconditionally in our sample.

What is less well known about carry trades is the nature of their drawdowns. We define a drawdown to be the loss that a trader experiences from the peak (or high-water mark) to the trough in the cumulative return to a trading strategy. Sornette (2003) defines drawdowns to be a persistent decrease in an asset price over consecutive days. We refer to such price movements as pure drawdowns. We will document that carry-trade drawdowns are large and occur over substantial time intervals. By examining daily data, we can assess whether the distribution of drawdowns is more or less severe than would be expected if the innovations to the rate of appreciation were normally distributed or followed a GARCH process. As Sornette (2003, p. 55) notes, “drawdowns will keep precisely the information relevant to identifying the possible burst of local dependence leading to possibly extraordinarily large cumulative losses.” We also examine the time it takes for the carry trade to recover to the previous high-water mark. We contrast these drawdowns with the characterizations of carry trade returns by *The Economist* (2007) as “picking up nickels in front of a steam roller,” and by Breedon (2001) who noted that traders view carry-trade returns as arising by going up the stairs and coming down the elevator.” Both of these characterizations suggest that negative skewness in the trades is substantially due to sharp drops. We do not find that the data support this view. Analysis of the drawdowns indicates that they are not jumps or large crashes which implies that models focusing on large crash risk are not correct.

2.2 Background Ideas and Essential Theory

Because the carry trade can be implemented in the forward market, it is intimately connected to the forward premium anomaly – that is the empirical finding that the forward premium on the foreign currency, the difference between the forward rate and the current spot rate expressed as a percentage of the spot, is not an unbiased forecast of the rate of appreciation of the foreign currency. In fact, expected profits on the carry trade would be zero if the forward premium were an unbiased predictor of the rate of appreciation of the foreign currency. Thus, the finding of apparent non-zero profits on the carry trade can be related to the classic interpretations of the apparent rejection of the unbiasedness hypothesis. The profession has recognized that there are four ways to interpret the rejection of unbiasedness forward rates:

1. First, the forecastability of the difference between forward rates and future spot rates could result from an equilibrium risk premium. Hansen and Hodrick (1983) provide an early econometric analysis of the restrictions that arise from a model of a rational, risk averse, representative investor. Fama (1984) demonstrates that if one interprets the econometric analysis from this efficient markets point of view, the data imply that risk premiums are more variable than expected rates of depreciation.
2. The second interpretation of the data, first offered by Bilson (1981), is that the nature of the predictability of future spot rates implies a market inefficiency. The profitability of trading strategies appears to be too good to be consistent with rational risk premiums. Froot and Thaler (1990) support this view by arguing that the data are consistent with ideas from behavioral finance.
3. The third interpretation of the findings involves relaxation of the assumption that investors have rational expectations. Lewis (1989) proposes that learning by investors could reconcile the econometric findings with equilibrium theory.

4. Finally, Krasker (1980) argues that the interpretation of the econometrics could be flawed because so-called 'peso problems' might be present.¹

Surveys of the literature by Hodrick (1987) and Engel (1996) provide extensive reviews of the research on these issues as they relate to the forward premium anomaly.

Each of these themes also plays out in the more recent literature on the carry trade. Nielsen and Saá-Requejo (1993) and Frachot (1996) develop the first continuous time models designed to explain the forward premium anomaly as resulting from risk-based equilibrium. Backus, Foresi, and Telmer (2001) develop the first discrete time affine model capable of explaining the forward premium anomaly. Bansal and Shaliastovich (2013) argue that an equilibrium long-run risks model is capable of explaining the predictability of returns in bond and currency markets.

Several papers find support for the hypothesis that returns to the carry trade are exposed to risk factors. For example, Lustig, Roussanov, and Verdelhan (2011) argue that common movements in the carry trade across portfolios of currencies indicate rational risk premiums. Rafferty (2012) relates carry trade returns to a skewness risk factor in currency markets. Dobrynskaya (2014) and Lettau, Maggiori, and Weber (2014) argue that large average returns to high interest rate currencies are explained by their high conditional exposures to the market return, and Christiansen, Rinaldo, and Soderlind (2011) note that carry trade returns are more positively related to equity returns and more negatively related to bond risks the more volatile is the foreign exchange market. Rinaldo and Soderlind (2010) argue that the funding currencies have 'safe haven' attributes, which implies that they tend to appreciate during times of crisis. Menkhoff, et al. (2012) argue that carry trades are exposed to a global

¹While peso problems were originally interpreted as large events on which agents placed prior probability and that didn't occur in the sample, Evans (1996) reviews the literature that broadened the definition to be situations in which the ex post realizations of returns do not match the ex ante frequencies from investors' subjective probability distributions.

FX volatility risk. Beber, Breedon, and Buraschi (2010) note that the yen-dollar carry trade performs poorly when differences of opinion are high. Mancini, Ranaldo, and Wrampelmeyer (2013) find that systematic variation in liquidity in the foreign exchange market contributes to the returns to the carry trade. Bakshi and Panayotov (2013) include commodity returns as well as foreign exchange volatility and liquidity in their risk factors. Sarno, Schneider and Wagner (2012) estimate multi-currency affine models with four dimensional latent variables. They find that such variables can explain the predictability of currency returns, but there is a tradeoff between the ability of the models to price the term structure of interest rates and the currency returns. Bakshi, Carr, and Wu (2008) use option prices to infer the dynamics of risk premiums for the dollar, pound and yen pricing kernels.

In contrast to these studies that find substantive financial risks in currency markets, Burnside, et al. (2011) explore whether the carry trade has exposure to a variety of standard sources of risk. Finding none, they conclude that peso problems explain the average returns. By hedging the carry trade with the appropriate option transaction to mitigate downside risk, they determine that the peso state involves a very high value for the stochastic discount factor. Jurek (2009), on the other hand, examines the hedged carry trade and finds little evidence of excess returns after paying for the options that hedge the downside risk.

Farhi and Gabaix (2011) and Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2013) and argue that the carry trade is exposed to rare crash states in which the high interest rate currency depreciates.

Jordà and Taylor (2012) dismiss the profitability of the naive carry trade based only on interest differentials as poor given its performance in the financial crisis of 2008, but they advocate simple modifications of the positions based on long-run fundamentals that enhance its profitability and protect it from downside moves indicating a market inefficiency.

2.2.1 Terminology

This section develops notation and provides background theory that is useful in interpreting the empirical analysis. Let the level of the exchange rate of dollars per unit of a foreign currency be S_t , and let the forward exchange rate that is known today for exchange of currencies in one period be F_t . Let the one-period dollar interest rate be $i_t^{\$}$, and let the one-period foreign currency interest rate be i_t^* .² An investment of one dollar in the dollar money market pays off $(1+i_t^{\$})$ dollars in one period. Investing a dollar in the foreign currency money market requires converting the dollar into $\frac{1}{S_t}$ units of the foreign currency, getting the per unit foreign currency money market return of $(1+i_t^*)$, and selling the total amount of the foreign currency proceeds for dollars. If the sale of the foreign currency proceeds is done in the forward market, the return is

$$F_t \frac{(1+i_t^*)}{S_t}$$

Because this dollar return is known when the investment is made, ignoring transaction costs, the foreign return must be equal to the dollar money market return. Equating the two returns gives

$$F_t \frac{(1+i_t^*)}{S_t} = (1+i_t^{\$}) \quad (2.1)$$

Equation (2.1) is a statement of interest rate parity.³ Dividing equation (2.1) by $(1+i_t^{\$})$

²When it is necessary to distinguish between the dollar exchange rate versus various currencies or the various interest rates, we will superscript them with numbers.

³In normal times, interest rate parity works very well, as Taylor (1987) and Akram, Rime, and Sarno (2008) document. While evidence against covered interest rate parity is rare prior to the financial crisis that began in the summer of 2007, Baba and Parker (2009) document severe deviations from covered interest rate parity during the crisis especially after the failure of Lehman Brothers in September 2008.

and subtracting one from both sides gives

$$\frac{(F_t - S_t)}{S_t} = \frac{(i_t^{\$} - i_t^*)}{(1 + i_t^*)} \quad (2.2)$$

Equation (2.2) relates the forward premium or discount on the foreign currency to the interest differential between the two currencies. When investing in the foreign money market, if the sale of the foreign currency interest plus principal is done in the future spot market, the dollar return from investing one dollar in the foreign currency money market is

$$S_{t+1} \frac{(1 + i_t^*)}{S_t}$$

which is uncertain because the foreign currency may strengthen or weaken relative to the dollar. The interesting issue is what is the expected return on these unhedged investments in the foreign currency money market. One possibility is uncovered interest rate parity, which is equality between the expected uncovered dollar return in the foreign money market and the known return in the dollar money market:

$$E_t(S_{t+1}) \frac{(1 + i_t^*)}{S_t} = (1 + i_t^{\$}) \quad (2.3)$$

Dividing by $(1 + i_t^*)$ and subtracting one produces equality between the expected rate of appreciation of the foreign currency and the interest differential:

$$E_t\left(\frac{S_{t+1} - S_t}{S_t}\right) = \frac{(i_t^{\$} - i_t^*)}{(1 + i_t^*)} \quad (2.4)$$

If uncovered interest rate parity holds, high interest rate currencies would tend to depreciate relative to low interest rate currencies. This depreciation is needed to offset the fact

that the interest earned from investing in the high interest rate currency would be greater than the cost of borrowing the low interest rate currency. Substituting from equation (2.2), we find that the expected rate of appreciation of the foreign currency would also equal the forward premium:

$$E_t \left(\frac{S_{t+1} - S_t}{S_t} \right) = \frac{(F_t - S_t)}{S_t} \quad (2.5)$$

Equation (2.5) indicates that uncovered interest rate parity implies that currencies that are at a forward premium should appreciate by the percentage forward premium, and currencies that are at a forward discount should depreciate by the percentage discount.

2.2.2 The Forward Premium Anomaly

If uncovered interest rate parity holds and the econometrician assumes investors have rational expectations, then in the following regression,

$$\frac{S_{t+1} - S_t}{S_t} = \alpha + \beta \frac{F_t - S_t}{S_t} + \epsilon_{t+1} \quad (2.6)$$

the constant should be zero and the slope coefficient should be one. Beginning with Tryon (1979), Bilson (1981) and especially Fama (1984), econometricians have found that the point estimates of the slope coefficient are negative and reliably less than one. While many authors interpret this finding to mean that currencies trading at a forward premium are actually expected to depreciate, Bekaert and Hodrick (2012) caution that the constant term may be sufficiently large that this interpretation is incorrect. What is correct to say is that higher interest rate currencies depreciate less than is predicted by uncovered interest rate parity. Bekaert and Hodrick (2012) also note that there is a great deal of instability in the slope coefficient estimates. Depending on what five-year interval is considered, the

estimated slope coefficients in equation (2.6) can be quite negative or quite positive.

Because uncovered interest rate parity appears to be severely at variance with the data, the possibility exists that a trading strategy can take advantage of this situation. This is what the carry trade seeks to do.

2.2.3 Implementing the Carry Trade

If the carry trade is done by borrowing and lending in the money markets, the dollar payoff to the carry trade without transaction costs can be written as

$$[(1 + i_t^*) \frac{S_{t+1}}{S_t} - (1 + i_t^{\$})] y_t \quad (2.7)$$

where

$$y_t = \begin{cases} +1 & \text{if } i_t^* > i_t^{\$} \\ -1 & \text{if } i_t^{\$} > i_t^* \end{cases}$$

Equation (2.7) scales the carry trade either by borrowing one dollar and investing in the foreign currency money market, or by borrowing the appropriate amount of foreign currency to invest one dollar in the dollar money market.⁴ When interest rate parity holds, from equation (2.2), if $i_t^* > i_t^{\$}$, $F_t < S_t$, the foreign currency is at a discount in the forward market. Conversely, if $i_t^* < i_t^{\$}$, $F_t > S_t$, and the foreign currency is at a premium in the forward market. Thus, the carry-trade can also be implemented by going long in the foreign currency in the forward market when the foreign currency is at a discount, and conversely, going short in the foreign currency in the forward market when the foreign currency is at a premium in terms of the dollar. Let w_t be the amount of foreign currency bought in the

⁴Transaction costs are quite small in the money markets and foreign exchange markets, and we will consequently ignore them as we work with averages of bid and ask rates.

forward market. The dollar payoff to this strategy is

$$z_{t+1} = w_t(S_{t+1} - F_t) \quad (2.8)$$

To scale the forward positions to be either long or short in the forward market an amount of dollars equal to one dollar in the spot market as in equation (2.7), let

$$w_t = \left\{ \begin{array}{ll} \frac{1}{F_t}(1 + i_t^{\$}) & \text{if } F_t < S_t \\ -\frac{1}{F_t}(1 + i_t^{\$}) & \text{if } F_t > S_t \end{array} \right\} \quad (2.9)$$

When covered interest rate parity holds, and in the absence of transaction costs, the forward market strategy for implementing the carry trade in equation (2.8) is exactly equivalent to the carry trade strategy in equation (2.7).

Uncovered interest rate parity ignores the possibility that changes in the values of currencies are exposed to risk factors, in which case risk premiums can arise. To incorporate risk aversion, we need to examine pricing kernels.

2.2.4 Pricing Kernels

One of the fundamentals of no-arbitrage pricing is that there is a dollar pricing kernel or stochastic discount factor, M_{t+1} , that prices all dollar returns, R_{t+1} , from the investment of one dollar:

$$E_t [M_{t+1}R_{t+1}] = 1 \quad (2.10)$$

Because implementing the carry trade in the forward market does not require an invest-

ment at time t , the no-arbitrage condition is

$$E_t(M_{t+1}z_{t+1}) = 0 \quad (2.11)$$

Taking the unconditional expectation of equation (2.11) and rearranging gives

$$E(z_{t+1}) = \frac{-Cov(M_{t+1}, z_{t+1})}{E(M_{t+1})} \quad (2.12)$$

The expected value of the unconditional return on the carry trade could be non-zero if the return on the carry trade covaries negatively with the innovation to the dollar pricing kernel. Equation (2.12) provides the essence of a risk based explanation of the average returns to the carry trade.

There is also a foreign currency pricing kernel, M_{t+1}^* , that prices all foreign currency denominated returns, R_{t+1}^* :

$$E_t [M_{t+1}^* R_{t+1}^*] = 1 \quad (2.13)$$

Because all foreign currency returns can be converted into dollar returns by multiplying by $\frac{S_{t+1}}{S_t}$, if asset markets are complete, it is well known that

$$M_{t+1} \frac{S_{t+1}}{S_t} = M_{t+1}^* \quad (2.14)$$

Taking the natural logarithm of equation (2.14) gives

$$s_{t+1} - s_t = m_{t+1}^* - m_{t+1} \quad (2.15)$$

Equation (2.15) states that the continuously compounded rate of appreciation of the foreign currency equals the difference in the natural logarithms of the foreign currency and

dollar pricing kernels. If the pricing kernels are also conditionally log-normally distributed, they may be written as

$$m_{t+1}^j = -i_t^j - 0.5\lambda_t^{j'}\lambda_t^j - \lambda_t^{j'}\varepsilon_{t+1}^j \quad (2.16)$$

where ε_{t+1}^j is a vector of $N(0, I)$ sources of risks in the j -th economy, λ_t^j is a vector of the prices of risks that arise from the covariance of returns with these sources of risks, and with slight abuse of notation, the interest rates are now interpreted as continuously compounded rates. Substituting from equation (2.16) into equation (2.15) gives

$$s_{t+1} - s_t = i_t^\$ - i_t^* + 0.5(\lambda_t'\lambda_t - \lambda_t^{*'}\lambda_t^*) + \lambda_t'\varepsilon_{t+1} - \lambda_t^{*'}\varepsilon_{t+1}^* \quad (2.17)$$

Equation (2.17) conveys an important message because it indicates that the rate of appreciation of the foreign currency is driven by **all** of the sources of risks in the two countries.

In contrast to the prediction of uncovered interest rate parity, equation (2.17) implies that the expected continuously compounded rate of appreciation of the foreign currency is

$$E_t(s_{t+1} - s_t) = i_t^\$ - i_t^* + 0.5(\lambda_t'\lambda_t - \lambda_t^{*'}\lambda_t^*) \quad (2.18)$$

Equation (2.18) provides a logical way to view the risks of the carry trade. In continuously compounded excess rates of return, the carry trade works if

$$E_t(s_{t+1} - s_t) + i_t^* - i_t^\$ > 0, \text{ when } i_t^* > i_t^\$$$

and

$$E_t(s_{t+1} - s_t) + i_t^* - i_t^\$ < 0, \text{ when } i_t^* < i_t^\$$$

From equation (2.18), we see that the first condition is satisfied if $\lambda_t'\lambda_t > \lambda_t^{*'}\lambda_t^*$, and the

second condition is satisfied if $\lambda'_t \lambda_t < \lambda_t^* \lambda_t^*$. The terms $\lambda'_t \lambda_t$ and $\lambda_t^* \lambda_t^*$ are the conditional variances of the natural logarithms of the dollar pricing kernel and the foreign currency pricing kernel, respectively. For the carry trade to be consistent with a risk-based explanation, the conditional variance of the dollar pricing kernel has to be greater than the conditional variance of the foreign pricing kernel when the foreign interest rate is greater than the dollar interest rate, and conversely, the conditional variance of the dollar pricing kernel has to be less than the conditional variance of the foreign pricing kernel when the foreign interest rate is less than the dollar interest rate. It is definitely possible to construct models in which pricing kernels have these properties. For example, Backus, Gavazzoni, Telmer and Zin (2010) offer an explanation in terms of monetary policy conducted through Taylor Rules that provides the necessary asymmetric responses to be consistent with the forward premium anomaly regression and hence the carry trade. Also, Lustig, Roussanov, and Verdelhan (2014) calibrate a no-arbitrage model that has the necessary properties.

2.2.5 The Hedged Carry Trade

Jurek (2009), Farhi, et al. (2013), and Burnside, et al. (2011) examine hedging the downside risks of the carry trade by purchasing insurance in the foreign currency option markets. To examine this analysis, let C_t and P_t be the dollar prices of one-period foreign currency call and put options with strike price K on one unit of foreign currency. Buying one unit of foreign currency in the forward market costs F_t dollars in one period, which is an unconditional future cost. One can also unconditionally buy the foreign currency forward by buying a call option with strike price K and selling a put option with the same strike price in which case the future cost is $K + C_t(1 + i_t^{\$}) - P_t(1 + i_t^{\$})$. To prevent arbitrage, these two unconditional

future costs of purchasing the foreign currency in one period must be the same. Hence,

$$F_t = K + C_t(1 + i_t^{\$}) - P_t(1 + i_t^{\$}) \quad (2.19)$$

which is put-call parity for foreign currency options.

Now, suppose a dollar-based speculator wants to be long $w_t = (1 + i_t^{\$})/F_t$ units of foreign currency in the forward market, which, as above, is the foreign currency equivalent of one dollar spot. The payoff is negative if the realized future spot rate of dollars per foreign currency is less than the forward rate. To place a floor on losses from a depreciation of the foreign currency, the speculator can hedge by purchasing out-of-the-money put options on the foreign currency. If the speculator borrows the funds to buy put options on w_t units of foreign currency, the option payoff is $[\max(0, K - S_{t+1}) - P_t(1 + i_t^{\$})]w_t$. The dollar return from the hedged long position in the forward market is therefore the sum of the two positions:

$$z_{t+1}^H = [S_{t+1} - F_t + \max(0, K - S_{t+1}) - P_t(1 + i_t^{\$})]w_t$$

Substituting from put-call parity gives

$$z_{t+1}^H = [S_{t+1} - K + \max(0, K - S_{t+1}) - C_t(1 + i_t^{\$})]w_t \quad (2.20)$$

When $S_{t+1} < K$, $[S_{t+1} - K + \max(0, K - S_{t+1})] = 0$; and if $S_{t+1} > K$, $\max(0, K - S_{t+1}) = 0$. Hence, we can write equation (2.20) as

$$z_{t+1}^H = [\max(0, S_{t+1} - K) - C_t(1 + i_t^{\$})]w_t$$

which is the return to borrowing enough dollars to buy call options on w_t units of foreign

currency. Thus, hedging a long forward position by buying out-of-the-money put options with borrowed dollars is equivalent to implementing the trade by directly borrowing dollars to buy the same foreign currency amount of in-the-money call options with the same strike price.

Now, suppose the dollar-based speculator wants to sell w_t units of the foreign currency in the forward market. The payoff is negative if the realized spot rate of dollars per foreign currency is greater than the forward rate. To place a floor on losses from an appreciation of the foreign currency, the speculator can hedge the position by purchasing out-of-the-money call options. The dollar return from the hedged short position in the forward market is

$$z_{t+1}^H = [F_t - S_{t+1} + \max(0, S_{t+1} - K) - C_t(1 + i_t^\$)]w_t$$

Substituting from put-call parity gives

$$z_{t+1}^H = [K - S_{t+1} + \max(0, S_{t+1} - K) - P_t(1 + i_t^\$)]w_t \quad (2.21)$$

When $S_{t+1} > K$, $[K - S_{t+1} + \max(0, S_{t+1} - K)] = 0$; and if $S_{t+1} < K$, $\max(0, S_{t+1} - K) = 0$. Hence, we can write equation (2.21) as

$$z_{t+1}^H = [\max(0, K - S_{t+1}) - P_t(1 + i_t^\$)]w_t$$

which is the return to purchasing put options on w_t units of foreign currency with borrowed dollars. Thus, hedging a short forward position by buying out-of-the-money call options is equivalent to implementing the trade by directly buying in-the-money foreign currency put options with the same strike price.

When implementing the hedged carry trade, we examine two choices of strike prices

corresponding to 10δ and 25δ options, where δ measures the sensitivity of the option price to movements in the underlying exchange rate.⁵ Because the hedged carry trades are also zero net investment strategies, they must also satisfy equation (2.11).

2.3 Data for the Carry Trades

In constructing our carry trade returns, we only use data on the G-10 currencies: the Australian dollar, AUD; the British pound, GBP; the Canadian dollar, CAD; the euro, EUR, spliced with historical data from the Deutsche mark; the Japanese yen, JPY; the New Zealand dollar, NZD; the Norwegian krone, NOK; the Swedish krona, SEK; the Swiss franc, CHF; and the U.S. dollar, USD. All spot and forward exchange rates are dollar denominated and are from Datastream and IHS Global Insight. For most currencies, the beginning of the sample is January 1976, and the end of the sample is August 2013, which provides a total of 451 observations on the carry trade. Data for the AUD and the NZD start in October 1986. Interest rate data are eurocurrency interest rates from Datastream.

We explicitly exclude the European currencies other than the euro (and its precursor, the Deutsche mark), because we know that several of these currencies, such as the Italian lira, the Portuguese escudo, and the Spanish peseta, were relatively high interest rate currencies prior to the creation of the euro. At that time traders engaged in the “convergence trade,” which was a form of carry trade predicated on a bet that the euro would be created in which case the interest rates in the high interest rate countries would come down and those currencies would strengthen relative to the Deutsche mark. An obvious peso problem exists in these data because there was uncertainty about whether the euro would indeed be created. If the

⁵The δ of an option is the derivative of the value of the option with a change in the underlying spot rate. A 10δ (25δ) call option increases in price by 0.10 (0.25) times the small increase in the spot rate. The δ of a put option is negative.

euro had not succeeded, the lira, escudo, and peseta would have suffered large devaluations relative to Deutsche mark.

We also avoid emerging market currencies as nominal interest rates in these currencies also incorporate substantive sovereign risk premiums. The essence of the pure carry trade is that the investor bears pure foreign exchange risk, not sovereign risk. Furthermore, Longstaff, Pan, Pedersen, and Singleton (2011) demonstrate that sovereign risk premiums, as measured by credit default swaps, are not idiosyncratic because they covary with the U.S. stock and high-yield credit markets. Thus, including emerging market currencies could bias the analysis toward finding that the average returns to the broadly defined carry trade are due to exposure to risks.

Our foreign currency options data are from JP Morgan.⁶ After evaluating the quality of the data, we decided that high quality data were only available from September 2000 to August 2013.

We describe the data on various risk factors as they are introduced below.

2.4 Unconditional Results on the Carry Trade

Table 3.12 reports basic unconditional sample statistics for five dollar-based carry trades from the G10 currencies. All of the statistics refer to annualized returns, and all the strategies invest in every currency in each period, if data are available. For the basic carry trade, labeled EQ, if the interest rate in currency j is higher (lower) than the dollar interest rate, the dollar-based investor goes long (short) 1/9-th of a dollar in the forward market of currency j . This equal-weight approach is the way most academic articles implement the carry trade.

Our second strategy is ‘spread-weighted’ and is denoted SPD. The long or short position

⁶We thank Tracy Johnson at JP Morgan for her assistance in obtaining the data.

is again determined by the interest differential versus the dollar, but the fraction of a dollar invested in a particular currency is determined by the interest differential divided by the sum of the absolute values of the interest differentials:

$$w_{j,t}^{SPD} = \frac{i_t^j - i_t^{\$}}{\sum_{j=1}^9 |i_t^j - i_t^{\$}|}$$

The SPD strategy thus invests more in currencies that have larger interest differentials while retaining the idea that the investment is scaled to have a total of one dollar spread across the absolute values of the long and short positions.

Although it is often said that only one dollar is at risk in such a situation, this is not true when the trader shorts a foreign currency. When a trader borrows a dollar to invest in the foreign currency, the most the trader can lose is the one dollar if the foreign currency becomes worthless, but when a trader borrows the foreign currency equivalent of one dollar to invest in the U.S. money market, the amount of dollars that must be repaid could theoretically go to infinity if the foreign currency strengthens massively versus the dollar, as inspection of equation (2.7) indicates. Traders would consequently be unlikely to follow the EQ and SPD strategies because they take more risk when the volatility of the foreign exchange market is high than when it is low. In actual markets, traders typically face value-at-risk limits in which the possible loss of a particular amount on their portfolio of positions is calibrated to be a certain probability. For example, a typical value-at-risk model would constrain a trader to take positions such that the probability of losing more than \$1 million on any given day is no larger than 1%. Implementing such a strategy requires a conditional covariance matrix of the returns on the nine currencies versus the dollar.

To calculate this conditional covariance matrix, we construct simple IGARCH models from daily data. Let H_t denote the conditional covariance matrix of returns at time t with

typical element, h_t^{ij} , which denotes the conditional covariance between the i -th and j -th currency returns realized at time $t + 1$. Then, the IGARCH model is

$$h_t^{ij} = \alpha(r_t^i r_t^j) + (1 - \alpha)h_{t-1}^{ij} \quad (2.22)$$

where we treat the product to the returns as equivalent to the product of the innovations in the returns. We set $\alpha = 0.06$, as suggested in RiskMetrics (1996). We multiply the daily IGARCH model by 22 to get the monthly covariance matrix.

We use the conditional covariance matrixes in two strategies. In the first strategy, to maintain the monthly horizon common in the academic literature, we target a fixed monthly standard deviation of $5\%/\sqrt{12}$, which corresponds to an approximate annualized standard deviation of 5%, and we adjust the dollar scale of the EQ and SPD carry trades accordingly. These strategies are labeled EQ-RR and SPD-RR to indicate risk rebalancing. We also use the conditional covariance matrixes in successive one-period mean-variance maximization. Beginning with the analysis of Meese and Rogoff (1983), it is often argued that expected rates of currency appreciation are essentially unforecastable. Hence, we take the vector of interest differentials, μ_t , to be the conditional means of the currency returns, and we take positions proportional to $H_t^{-1}\mu_t$, where H_t is the conditional covariance matrix. We label this strategy OPT. As with the risk-rebalanced strategies, we target a common annualized standard deviation of 5%. Thus, our portfolio of positions is

$$w_t^{OPT} = \frac{(0.05/\sqrt{12})}{(\mu_t' H_t^{-1} \mu_t)^{0.5}} H_t^{-1} \mu_t \quad (2.23)$$

and the conditional mean of the portfolio is $(0.05/\sqrt{12}) (\mu_t' H_t^{-1} \mu_t)^{0.5}$. In contrast, Ackermann, Pohl, and Schmedders (2012) also use conditional mean variance modeling so their

positions are proportional to $H_t^{-1}\mu_t$, but they target a constant mean return of 5% per annum. Hence, their positions satisfy

$$w_t^{APS} = \frac{(0.05/12)}{\mu_t' H_t^{-1} \mu_t} H_t^{-1} \mu_t \quad (2.24)$$

and the standard deviation of their portfolio is $(0.05/12) / (\mu_t' H_t^{-1} \mu_t)^{0.5}$. In both cases, if the conditional moments were correct, the conditional Sharpe ratio would be the same and would equal $(\mu_t' H_t^{-1} \mu_t)^{0.5}$. Hence, the Ackermann, Pohl, and Schmedders (2012) approach actually scales up the standard deviation of the portfolio when the reward to risk ratio is low and scales it down when the Sharpe ratio is high.

Table 3.12 reports the first four moments of the various carry trade strategies as well as their Sharpe ratios and first order autocorrelations. Standard errors are in parenthesis and are based on Hansen's (1982) Generalized Method of Moments, as explained in the Appendix B.1. For the full sample, the carry trades for the USD-based investor have statistically significant average annual returns ranging from 2.10% (0.47) for the *OPT* strategy, to 3.96% (0.91) for the EQ strategy, and to 6.60% (1.31) for the SPD strategy. The strategies also have impressive Sharpe ratios, which range from 0.78 (0.19) for the EQ strategy to 1.02 (0.19) for the SPD-RR strategy. As Brunnermeier, Nagel and Pedersen (2009) note, each of these strategies is significantly negatively skewed, with the OPT strategy having the worst skewness of -0.89 (0.34). Table 3.12 also reports positive excess kurtosis that is statistically significant for all strategies. The first order autocorrelations of the strategies are low, as would be expected in currency markets, and only for the EQ-RR strategy can we reject that the first order autocorrelation is zero. Of course, this test has very low power. The minimum monthly returns for the strategies are all quite large, ranging from -4.01% for the OPT strategy to -7.26% for the SPD. The maximum monthly returns range from 3.21% for

the OPT to 8.07% for the SPD. Finally, Table 3.12 indicates that the carry trade strategies are profitable on between 288 months for the EQ strategy and 303 months for the OPT strategy out of the total of 451 months.

Table 3.13 presents results for the equal-weighted carry trade in which each currency is considered to be the base currency. For each strategy, if the interest rate in currency j is higher (lower) than the interest rate of the base currency, the investor goes long (short) in the forward market of currency j . The average annualized profitabilities of these carry trades range from 2.33% (1.02) for the SEK to 3.92% (1.50) for the NZD. These mean returns are all less than the 3.96% (0.88) for the USD although given their standard errors it is unlikely that we would be able to reject equivalence of the means. For all base currencies, the average profitability is statistically significance at the .06 marginal level of significance or smaller. The Sharpe ratios of the alternative-currency-based carry trades are also smaller than the USD-based Sharpe ratio of 0.78 (0.19). The lowest Sharpe ratio of the alternative-currency-based carry trades is 0.36 (0.19) for the JPY, and the highest is 0.71 (0.18) for the CAD. The point estimates of skewness for the alternative-currency-based carry trades are all negative, except for the EUR, and the statistical significance of skewness is high for the JPY, NOK, SEK, NZD, and AUD. All of these alternative-currency-based carry trades have positive, statistically significant, excess kurtosis. Only the GBP-base carry trade shows any sign of first-order autocorrelation. The maximum gains and losses on these strategies generally exceed those of the USD-based strategy. Only the CAD and EUR have smaller maximum monthly losses than the USD-based strategy, and the maximum monthly losses for the JPY, SEK, NZD, and AUD carry trades exceed 10%. The alternative-currency-based carry trades are also profitable on slightly fewer days than the USD-based EQ trade, and the percentage of profitable days for the NZD and AUD is slightly smaller than for the USD.

Table 3.14 reports the results for the hedged carry trade for the much shorter sample,

September 2000 to August 2013, for which we have high quality options data. We only consider the equal weighted hedged carry trade and the spread weighted hedged carry trade. For comparison, the statistics for the corresponding unhedged carry trades over the same sample are also reported. The first thing to notice is that the profitability of the unhedged carry trades is not as large in the shorter sample. The average returns are only 3.11% (1.52) for the EQ and 5.49% (2.51) for the SPD strategies. The Sharpe ratios are also slightly lower at 0.59 (0.39) and 0.65 (0.31), respectively, and they are less precisely estimated. While the point estimates of unconditional skewness of the unhedged strategies remain negative, they are insignificantly different from zero. The average returns for the hedged carry trades are reported for 10δ and 25δ option contracts. In each case, the average hedged returns are lower than the corresponding unhedged returns. For the 10δ strategies, the hedged EQ trade is 105 basis points less than its unhedged counterpart, and the hedged SPD trade is 28 basis points less than its unhedged counterpart. For the 25δ strategies, the hedged EQ trade is 166 basis points less than its unhedged counterpart, and the hedged SPD trade is 123 basis points less than its unhedged counterpart. Although the average returns of the hedged EQ strategies are positive, the p -values of the 10δ and 25δ hedged EQ strategies indicate loss of statistical significance as they are .111 and .171, respectively. On the other hand, the p -values of the 10δ and 25δ hedged SPD strategies are .017 and .020, respectively. Comparing the maximum losses across the unhedged and hedged strategies, one sees that purchasing the protection from large losses can be a substantial cost as the maximum unhedged loss for the EQ strategy is 3.94% and the maximum losses for the EQ hedged 10δ and 25δ strategies are 2.95% and 3.52%, respectively. Similarly, the maximum unhedged loss for the SPD strategy is 7.36% and the maximum losses for the SPD hedged 10δ and 25δ strategies are 6.30% and 4.75%, respectively. As might be expected, large unhedged losses tend to occur during volatile times, and the hedged losses discussed above tend to occur immediately after

the largest unhedged losses. It is difficult to assess whether purchasing protection from even larger losses at high option prices was rationally priced or not, as additional larger losses did not occur in the sample.

2.5 Carry-Trade Exposures to Risk Factors

This section examines whether the average returns to the carry trades described above can be explained by exposures to a variety of risk factors. We include equity market, foreign exchange market, bond market, and volatility factors. In each case we run a regression of a carry-trade return, R_t , on a vector of returns on portfolios, F_t , that represent the sources of risks as in

$$R_t = \alpha + \beta' F_t + \varepsilon_t \quad (2.25)$$

Because we use returns as risk factors, the constant term in the regression, α , measures the average performance of the carry trade that is not explained by unconditional exposure of the trades to the market traded risks included in the regression.

2.5.1 Equity Market Risks

Table 3.15 presents the results of regressions of our carry-trade portfolio returns on the three Fama-French (1993) equity market risk factors: the market return, denoted $R_{m,t}$, and proxied by the return on the NYSE and AMEX markets; the return on a portfolio of small market capitalization stocks minus the return on a portfolio of big stocks, denoted $R_{SMB,t}$; and the return on a portfolio of high book-to-market stocks minus the return on a portfolio of low book-to-market stocks, denoted $R_{HML,t}$.⁷ Although the Fama-French factors exhibit some

⁷The Fama-French risk factors were obtained from Kenneth French's web site which also describes the construction of these portfolios.

modest explanatory power with nine of the 15 coefficients having t -statistics that are greater than 1.88, the overall impression is that these equity market factors essentially leave most of the averages of the carry trade returns unexplained, as the constants in the regressions range from 1.83% with a t -statistic of 3.72 for the OPT strategy, to 5.55% with a t -statistic of 4.84 for the SPD-RR strategy. These equity market risk factors clearly do not explain the average carry trade returns.

2.5.2 Pure FX Risks

Table 3.16 presents the results of regressions of our carry-trade portfolio returns on the two pure foreign exchange market risk factors proposed by Lustig, Roussanov, and Verdelhan (2011) who sort 35 currencies into six portfolios based on their interest rates relative to the dollar interest rate, with the lowest interest rate currencies in portfolio one and the highest interest rate currencies in portfolio six. Their two risk factors are the average return on all six currency portfolios, denoted RX , which has a correlation of 0.99 with the first principal component of the six returns, and $R_{HML-FX,t}$, which is the difference in the returns on portfolio 6 and portfolio 1 and has a correlation of 0.94 with the second principal component of the returns. The data are from Adrien Verdelhan's web site, and the sample period is 1983:11-2013:08 for 358 observations. Unsurprisingly, given its construction as the difference in returns on high and low interest rate portfolios, the $R_{HML-FX,t}$ return has significant explanatory power for our carry-trade returns with robust t -statistics between 6.22 for the OPT portfolio to 8.85 for the EQ-RR portfolio. The R^2 's are also higher than with the equity risk factors, ranging between 0.13 and 0.34. Nevertheless, this pure FX risk model does not explain the average returns to our strategies as the constant terms in the regressions remain highly significant and range from a low of 1.29% for the OPT portfolio to 3.60% for the SPD-RR portfolio.

2.5.3 Bond Market Risks

Because exchange rates are the relative prices of currencies and relative rates of currency depreciation are in theory driven by all sources of aggregate risks, as in equation (2.17), it is logical that bond market risk factors should have explanatory power for the carry trade as the bond markets must price the important risks of changes in the stochastic discount factor. Table 3.17 presents the results of regressions of the carry trade returns on the 10-year bond return, used to represent the risk arising from changes in the level of interest rates, and the difference in returns between the 10-year bond and the 2-year note, used to represent the risk arising from changes in the slope of the term structure of interest rates. The bond market returns are from CRSP. We also include the equity market return in the regressions. Both of the bond market factors are highly significant. Positive returns on the 10-year bond, which are matched by the return on the 2-year note, which would be caused by unanticipated decreases in the USD bond yields, are bad for the USD-based carry trades. Also, when the 10-year bond under-performs the two-year bond, the carry trades do poorly. Notice, though, that the R^2 's of the regressions remain between .02 and .05, as in the equity market regressions, and that the constants in the regressions indicate that the means of the carry trade strategies remain statistically significant after these risk adjustment, earning between 2.15% for the OPT strategy to 6.71% for the SPD strategy.

2.5.4 Volatility Risk

To capture possible exposure of the carry trade to equity market volatility, we introduce the return on a variance swap as a risk factor. This return is calculated as

$$R_{VS,t+1} = \sum_{d=1}^{Ndays} \left(\ln \frac{P_{t+1,d}}{P_{t+1,d-1}} \right)^2 \left(\frac{30}{Ndays} \right) - VIX_t^2$$

where $Ndays$ represents the number of trading days in a month and $P_{t+1,d}$ is the value of the *S&P 500* index on day d of month $t+1$. Data for *VIX* are obtained from the web site of the CBOE. The availability of data on the *VIX* limits the sample to 283 observations. The regression results are presented in Tables ?? and 3.19. Because $R_{VS,t+1}$ is a return, we can continue to examine the constant terms in the regressions to assess whether exposure of the carry trade to risks explains the average returns. When we add $R_{VS,t+1}$ to the regressions in Tables 3.15 to 3.17, very little changes as the largest t -statistic in absolute value is 1.40 for the equity market risks and 1.76 for the bond market risks, and the constant terms remain highly significant. The coefficients on $R_{VS,t+1}$ are negative in the specifications with the equity and bond market risks indicating that the carry trades do tend to do badly when equity volatility increases, but this exposure is not enough to explain the profitability of the trades.

2.6 Dollar Neutral and Pure Dollar Carry Trades

In the basic EQ carry trade analysis discussed above, we take equal sized positions in nine currencies versus the dollar, either long or short, depending on whether a currency's interest rate is greater than the dollar interest rate or less than the dollar interest rate. Because there are nine currencies, the EQ portfolio is always either long or short the dollar versus some set of currencies. To develop a dollar-neutral carry trade, we exclude the dollar interest rate and calculate the median interest rate of the remaining nine currencies. We then take equal long (short) positions versus the dollar in the four currencies whose interest rates are greater (less) than the median interest rate, and we scale the size of the equal-weighted positions to be the same magnitude as that of EQ. We use *EQ0* to denote this portfolio which has zero direct dollar exposure. When the value of the dollar experiences a common movement

relative to all currencies, the *EQ0* portfolio earns the average interest differential between the above median interest rates and the below median interest rates times one plus the common rate of appreciation of the foreign currencies versus the dollar. The sign of the profit or loss consequently does not depend on the common movements in the value of the dollar relative to all currencies.

The second columns of Panels A and B of Table 3.20 report the first four moments of the *EQ0* carry trade as well as the Sharpe ratio and the first order autocorrelation. Panel A reports the full sample results, and Panel B reports the results over the later half of the sample when *VIX* data become available (1990:02-2013:08). Heteroskedasticity consistent standard errors are in parenthesis. For ease of comparison, we list the same set of statistics for EQ in Column 1. The *EQ0* portfolio has statistically significant average annual returns in both samples, 1.61% (0.58) for the full sample and 1.72% (0.72) for the later sample. While these returns are lower than the EQ strategy, the volatility of the *EQ0* strategy is lower, and its Sharpe ratio is 0.49 (0.19) in the full sample and 0.52 (0.23) in the later sample. These point estimates are about 30% lower than the respective Sharpe ratios of the EQ strategy. The skewness of the *EQ0* strategy is -0.47(0.19) and -0.47 (0.28) for the full sample and the later sample, respectively. The autocorrelation of the *EQ0* strategy is negligible, and the maximum losses are smaller than those of the EQ strategy. The next question is whether the *EQ0* strategy is exposed to risks.

Column 2 of Table 3.21 presents the results of regressions of the *EQ0* returns on the three Fama-French (1993) equity market risk factors. Notice that *EQ0* loads significantly on the market return and the HML factor, with *t*-statistics of 5.29 and 2.83, respectively. The loading on the market return explains approximately 30% of the average return, and the loading on the HML factor explains another 15% of the average return. The resulting constant in the regression has a *t*-statistic of 1.54, and the R^2 is .10. In comparison, the

regression of EQ returns on the same equity risk factors has a constant term with t -statistic of 3.76 and an R^2 of only .04. The Fama-French three factor model clearly does a better job of explaining the average return of *EQ0* strategy.

These results are surprising for two reasons. First, the *EQ0* strategy follows the same “carry” strategy using the G10 currencies as in the commonly studied EQ portfolio. The only difference is the dollar exposure, which makes a huge difference in abnormal returns and risk factor loadings. Second, the literature currently leans toward the belief that FX carry trades cannot be explained by equity risk factors. We have just demonstrated that the average returns to a typical FX carry trade can be explained by commonly used equity risk factors, with the caveat that the portfolio has zero direct exposure to the dollar.

2.6.1 Decomposition of Carry Trade

To understand the difference between *EQ* and *EQ0*, we subtract the *EQ0* positions from the EQ positions to get another portfolio, which we label *EQ-minus*. Recall that the positions in the EQ portfolio for currencies $j = 1, \dots, N$ in the sample at time t are

$$y_t^j = \begin{cases} +\frac{1}{N} & \text{if } i_t^j > i_t^{\$} \\ -\frac{1}{N} & \text{if } i_t^j < i_t^{\$} \end{cases}$$

The currency positions in the *EQ0* portfolio are

$$y_t^j = \begin{cases} +\frac{1}{N} & \text{if } i_t^j > \text{med}\{i_t^k\} \\ -\frac{1}{N} & \text{if } i_t^j < \text{med}\{i_t^k\} \end{cases}$$

where $\text{med}\{i_t^k\}$ indicates the median of the interest rates excluding the dollar.

Subtracting the currency positions in the *EQ0* strategy from those in EQ strategy gives

the positions in *EQ-minus*, which goes long (short) the dollar when the dollar interest rate is higher (lower) than the median interest rate but only against currencies with interest rates between the median and dollar interest rates. The exact positions of the portfolio are as follows:

If $i_t^{\$} < med \{i_t^k\}$ then

$$y_t^j = \begin{cases} 0 & \text{if } i_t^j > med \{i_t^k\} \\ \frac{1}{N} & \text{if } i_t^j = med \{i_t^k\} \\ \frac{2}{N} & \text{if } i_t^{\$} < i_t^j < med \{i_t^k\} \\ 0 & \text{if } i_t^j \leq i_t^{\$} \end{cases}$$

If $i_t^{\$} > median \{i_t^k\}$ then

$$y_t^j = \begin{cases} 0 & \text{if } i_t^j > i_t^{\$} \\ -\frac{1}{N} & \text{if } i_t^j = med \{i_t^k\} \\ \frac{-2}{N} & \text{if } med \{i_t^k\} < i_t^j \leq i_t^{\$} \\ 0 & \text{if } i_t^j \leq med \{i_t^k\} \end{cases}$$

The *EQ0* and *EQ-minus* portfolios decompose the EQ carry trade into two components: a dollar neutral component and a dollar component.

Column 3 of Panels A and B in Table 3.20 reports the first four moments of the *EQ-minus* strategy, which has statistically significant average annual returns in both samples, 2.35 (0.66) for the full sample and 2.11 (0.92) for the later sample. The Sharpe ratio of the *EQ-minus* strategy is slightly higher than that of the *EQ0* strategy in the full sample, 0.61 versus 0.49; but in later half of the sample, the *EQ-minus* strategy has a lower Sharpe ratio, 0.49 versus 0.52, than the *EQ0* strategy..

Skewness of *EQ-minus* is quite negative -0.65 (0.44) and -0.76 (0.45) for the full sample

and the later sample, respectively, although we note that the estimates of skewness are actually statistically insignificant due to the large standard error in both samples, a point to which we return later. In terms of the Sharpe ratio and skewness, the *EQ-minus* strategy appears no better than the *EQ0* strategy. Nevertheless, the *EQ-minus* strategy has a correlation of -.11 with the *EQ0* strategy, and the following results illustrate that the *EQ-minus* strategy also differs significantly from the *EQ0* strategy in its risk exposures..

Column 3 of Table 3.21 presents the results of regressions of the *EQ-minus* returns on the three Fama-French (1993) equity market risk factors. Unlike *EQ0*, none of the Fama-French factors shows any explanatory power for the *EQ-minus* returns. The constant in the regression is 2.36% with a *t*-statistic of 3.60. The R^2 is .04. The equity market risk factors clearly do not explain the average returns to the *EQ-minus* strategy.

Columns 1 to 3 of Table 3.22 present regressions of the returns of the *EQ* strategy and its two components, *EQ0* and *EQ-minus*, on the equity market excess return and two bond market risk factors. Similar to our previous findings, the market excess return and the bond market risk factors have significant explanatory power for the returns of *EQ0* and a relatively high R^2 of .12. By comparison, none of the risk factors has any significant explanatory power for the returns on the *EQ-minus* strategy, and the resulting R^2 is only .02.

Finally, Columns 1 to 3 of Table ?? present regressions of the returns of *EQ* and its two components, *EQ0* and *EQ-minus*, on the two FX risk factors. The two factor FX model completely explains the average returns of the *EQ0* strategy while explaining only 25% of the average returns of *EQ-minus*. The constant term in the *EQ-minus* regression also is significant with a value of 1.49% and a *t*-statistic of 1.86 in the FX two factor model.

In summary, these results suggest that for the G10 currencies, the conditional dollar exposure contributes to the carry trade “puzzle” more than does the non-dollar component.

2.6.2 Pure Dollar Factor

As noted above, the *EQ-minus* strategy goes long (short) the dollar when the dollar interest rate is above (below) the G10 median interest rate. It has the nice property of complementing the *EQ0* strategy to become the commonly studied equally weighted carry trade strategy. However, the other leg of the *EQ-minus* portfolio goes short (long) the currencies with interest rates between the G10 median rate and the dollar interest rate. It takes positions in relatively few currencies and thus seems under-diversified, a potential explanation for the large standard errors of its estimated skewness. Since the results just presented indicate that the abnormal returns of *EQ* hinge on the conditional dollar exposure, which is distinct from “carry”, we now expand the other leg of *EQ-minus* to all foreign currencies. We thus create the following strategy *EQ-USD*:

$$y_t^j = \begin{cases} +\frac{1}{N} & \text{if } \text{med}\{i_t^k\} > i_t^{\$} \\ -\frac{1}{N} & \text{if } \text{med}\{i_t^k\} \leq i_t^{\$} \end{cases}$$

The *EQ-USD* strategy focuses on the conditional exposure of dollar. It goes long (short) the dollar against all nine foreign currencies when the dollar interest rate is higher (lower) than the global median interest rate. Panels A and B of Table 3.20 Column 4 report the first four moments of the returns to the *EQ-USD* strategy for the full sample and the sample for which equity volatility is available. We find that *EQ-USD* has statistically significant average annual returns in both samples, 5.54% (1.37) for the full sample and 5.21% (1.60) for the later sample. Although its volatility is also higher than the *EQ* strategy, its Sharpe ratio of 0.68 (0.18) in the full sample and 0.66 (0.21) in the later sample are larger although not significantly different from those of the *EQ* strategy. Skewness of the *EQ-USD* strategy is insignificant as we find estimates of -0.11(0.17) for the full sample and -0.05 (0.22) for

the later sample. Thus, the *EQ-USD* strategy does not suffer from the extreme negative skewness often mentioned as the hallmark of carry trade. Column 4 of Tables 3.21 to ?? reports regressions of the returns of *EQ-USD* on the Fama-French three factors, the bond factors, and the FX risk factors. The only significant loading is on *RX*, which goes long all foreign currencies. The constants in these regressions range from 5.18% with a *t*-statistic of 3.40 in the FX market risks regression to 5.82% with a *t*-statistic of 4.01 for the bond market risks regression. When we use all of the risk factors simultaneously in Table 3.24 for the shorter sample period, the foreign exchange risk factors and the volatility factor have significant loadings, but the constant in the regression is 4.52% with a *t*-statistic of 2.79.

In summary, the commonly used equity market risk factors cannot explain the *EQ* carry strategy because of the conditional dollar exposure of *EQ*. What is more, the *EQ-USD* portfolio built on the conditional dollar exposure has insignificant negative skewness, indicating that skewness is not an explanation for the abnormal excess return of the carry trade.

2.6.3 The Downside Market Risk Explanation

Our last investigation of the potential risks of the carry trade involves the approach taken by Lettau, Maggiori, and Weber (2014) who find that although portfolios of high interest rate currencies have higher market betas than portfolios of low interest rate currencies, this market-beta differential is insufficiently large to explain the magnitude of carry trade returns. To develop a market-return risk based explanation of the average carry trade returns, Lettau, Maggiori, and Weber (2014) modify the downside market risk model of Ang, Chen, and Xing (2006) and argue that the exposure of the carry trade to the return on the market is larger conditional on the market return being down. Lettau, Maggiori, and Weber (2014) find that the down-market-beta differential between the high and low interest rate sorted portfolios combined with a high price of down market risk is sufficient to explain the average

returns to the carry trade. In their empirical analysis, Lettau, Maggiori, and Weber (2014) define the downside market return, which we denote $R_{m,t}^-$, as equal to the market return when the market return is one standard deviation below the average market return and zero otherwise. To examine whether the $R_{m,t}^-$ risk factor explains our G10 carry trade strategies, we investigate whether our six currency portfolios have significant betas with respect to $R_{m,t}^-$. We show that our portfolios as well as other currency portfolios more generally, have statistically insignificant beta differentials which invalidates the Lettau, Maggiori, Weber (2014) explanation

In their econometric analysis, Lettau, Maggiori, and Weber (2014) run separate univariate regressions of returns on $R_{m,t}$ and $R_{m,t}^-$ to define the risk exposures, β and β^- . Then, they impose that the price of $R_{m,t}$ risk is the average return on the market, $E(r_{M,t})$, and they estimate a separate price of risk for $R_{m,t}^-$, denoted λ^- , in a cross-sectional regression. The unconditional expected return on an asset is therefore predicted to be

$$E(r_t) = \beta E(r_{M,t}) + (\beta^- - \beta)\lambda^-$$

To test this explanation of our carry trades we first run a bivariate regression of a carry trade return on a constant; an indicator dummy variable, I^- , that is one when $R_{m,t}^-$ is non-zero and zero otherwise; and the two risk factors, $R_{m,t}$ and $R_{m,t}^-$. Thus, we estimate

$$r_t = \alpha_1 + \alpha_2 I^- + \beta_1 R_{m,t} + \beta_2 R_{m,t}^- + \varepsilon_t$$

In this specification, β_1 measures the asset's exposure to the market excess return when the market is not in the downstate, which is β^+ ; and β_2 measures the asset's additional exposure to the market excess return when the market is in the downstate, $\beta_2 = (\beta^- - \beta^+)$. We then test the significance of β_2 using heteroskedasticity and autocorrelation consistent

standard errors because β_2 must be non-zero for $(\beta^- - \beta)$, the additional source of risk in the Lettau, Maggiori, and Weber (2014) model, to be non-zero. Table 3.25 presents the results of these regressions for our six carry trade portfolios. We first present the estimates of β to establish the unconditional exposures when $R_{m,t}$ is the only risk factor. We find that the five basic carry trade portfolios have small positive β 's, but only the SPD portfolio has a statistically significant β . The EQ-USD strategy, on the other hand, has a slightly negative β . Because the risk factor in these regressions is a return, the constant terms can be interpreted as abnormal returns, and all the constants are highly significant. When we add $R_{m,t}^-$ and the downside indicator dummy to the regressions, we find that the β_2 's for the five basic carry trade portfolios are indeed positive, indicating that the point estimates of β^- are indeed slightly larger than those of β^+ , but we cannot reject the hypothesis that $\beta_2 = (\beta^- - \beta^+) = 0$. Moreover, the estimated β_2 in the EQ-USD regression is actually negative indicating that this carry trade strategy is less exposed to the market's downside risk than to the upside of market returns. Because $R_{m,t}^-$ is not a return, one cannot interpret the intercepts in these regressions as abnormal returns, which is why Lettau, Maggiori, and Weber (2014) performed the cross-sectional analysis that is required to estimate the price of downside market risk. To determine how much our estimated exposures to downside risk could possibly explain the average return to the carry trade, we use the estimates from Lettau, Maggiori, and Weber (2014) rather than our own cross-sectional analysis.

Lettau, Maggiori, and Weber (2014) include assets other than currencies in their cross-sectional analysis and find a large positive price of downside market risk. When they include currencies and equities with returns measured in percentage points per month, they find an estimate of λ^- equal to 1.41%, or 16.92% per annum. When they include only currencies, they find an estimate of λ^- equal to 2.18%, or 26.2% per annum. To determine the explanatory power of $(\beta^- - \beta)\lambda^-$ for our carry trade portfolios, we first add β_1 and β_2 to get an estimate

of β^- from which we subtract the unconditional estimate of β from the first regressions. The last two rows of Panel C in Table 3.25 multiply the results by 16.92% or 26.2% to provide the explained part of the average carry trade returns that is due to downside risk exposure. Compared to the constant terms in Panel A, the extra return explained by downside risk exposure is minimal for the EQ and EQ-RR strategies. The downside risk premium explains between 0% and 5% of the CAPM alphas of these two strategies, respectively. For the SPD and SPD-RR strategies, the downside risk premium explains between 20% and 40% of the CAPM alphas. Notice also that the negative β_2 for the EQ-USD strategy implies that the downside market risk theory cannot explain the excess return of the EQ-USD strategy as the additional expected return from downside risk exposure is actually -2.12% or -3.28%, depending on the value of λ^- .

As a check on the sensitivity of our conclusions about the inability of downside risk to explain the carry trade, we run the same regressions using the six interest rate sorted portfolios of Lustig, Roussanov, and Verdelhan (2011) who place the lowest interest rate currencies in portfolio P1 and the highest interest rate currencies in portfolio P6. The average returns on these portfolios increase monotonically from P1 to P6. Panel A of Table 3.27 shows the CAPM regression results. The β' s on $R_{m,t}$ for portfolios P1 to P6 are small but monotonically increasing, and the excess return, P6-P1, is significantly explained by $R_{m,t}$ with a t -statistic of 5.62. Nevertheless, consistent with our results, the market β of the P6-P1 return is only 0.18, which is too small to explain the average return. The CAPM α' s on these portfolios increase monotonically from P1 to P6, and the α of P6-P1 portfolio is 6.46% with a t -statistic of 3.67. Panel B of Table 3.27 shows the regression results in presence of downside risk. The slope coefficients on $R_{m,t}$ are close to monotonically increasing; but the slope coefficients on $R_{m,t}^-$ do not increase monotonically. The β'_2 s of portfolios P4 and P5 are smaller than those of portfolios P1 to P3. The β'_2 s are also all insignificantly different from

zero as the largest t -statistic is 0.56 indicating that all the coefficients are smaller than their standard errors. While the statistical insignificance of the beta differential could be taken at face value as to indicate that downside risk cannot be the explanation, we also perform the necessary calculations as above to derive the explanatory power of the downside risk premium taking the coefficients at their point estimates. We find that the downside risk effect is not monotonic as portfolios P2, P4 and P5 are predicted to have more negative downside risk premiums than portfolio P1 even though the CAPM α 's of P2, P4, and P5 are larger than P1. At the extreme end, the P6-P1 portfolio has a positive though insignificant β_2 . With an annualized downside risk premium of 26.2%, the difference between the downside beta and the unconditional beta helps to explain about a quarter of the CAPM α of the P6-P1 portfolio.

The fact that the six portfolios of Lustig, Roussanov, and Verdelhan (2011) have β_2 slope coefficients that are insignificantly different from zero and not monotonic is surprising because Lettau, Maggiori, and Weber (2014) use six similarly constructed currency portfolios from a comparably large number of countries and show that these portfolios have monotonically increasing directly estimated loadings on $R_{m,t}^-$. Two things are important to note. First, Lettau, Maggiori, and Weber (2014) estimate the β 's directly in separate univariate regressions, while we sum our two slope coefficients, β_1 and β_2 to find the β 's. Second, Lettau, Maggiori, and Weber (2014) use different currencies in their analysis than Lustig, Roussanov, and Verdelhan (2012) and a different but overlapping time period. For the time period over which the two data sets coincide, the correlation of the returns to the two P6 - P1 portfolios is actually only .4. For the smaller developed currencies sample, both studies sort currencies into five portfolios, and the correlation of the returns to the two P5 - P1 portfolios rises to .8. We therefore further explore our approach with the Lettau, Maggiori, and Weber (2014) developed country portfolios for a sample which starts in 1983:11, when

the Lustig, Roussanov, and Verdelhan (2011) sample starts, and ends in 2010:03.

Panel A of Table 3.28 demonstrates that the CAPM α 's are monotonically increasing from P1 to P5 and the P5-P1 portfolio has a CAPM α of 4.52% with a t -statistic of 2.68. Similar to the previous results, Panel B of Table 3.28 shows that the point estimates of the β'_2 s of all the portfolios are insignificantly different from zero indicating that the downside beta is not significantly different from the upside beta. Panel C of Table 3.28 shows that the predicted downside risk premium is not monotonically increasing from P1 to P5. The P1 portfolio has a larger downside risk premium than the P2 and P3 portfolios, even though the CAPM α of the P1 portfolio is 0.8% and 3.99% smaller than CAPM α of the P2 and P3 portfolios, respectively. Nevertheless, we note that 60% of the CAPM α of the P5-P1 portfolio can be explained by the difference between the downside beta and the unconditional beta with an annualized downside risk premium of 26.2%. Overall, the regression results of these currency portfolios highlight the concern that the downside betas are not precisely estimated. The relation of the betas across the interest rate sorted portfolios is not monotone in most of testing results, which implies that downside market risk cannot explain the average returns to the portfolios, which are monotonically increasing.

2.7 Downside Risk—An Analysis at the Daily Frequency

Carry trades are generally found to have negative skewness. The literature has associated this negative skewness with crash risk. However, negative skewness at the monthly level can stem from extreme negatively skewed daily returns or from a sequence of persistent, negative daily returns that are not negatively skewed. These two cases have very different implications for risk management. In the latter case, the detection of increased serial dependence could potentially be used to limit losses. While the literature has almost exclusively focused on

the characteristics of carry trade returns at the monthly frequency, we now characterize the downside risks of carry trade returns at the daily frequency while retaining the monthly decision interval.

While traders in foreign exchange markets easily adjust their carry trade or other FX strategies at the daily frequency if not intraday with minimal transaction costs, we choose to examine the daily returns to carry trades that are rebalanced monthly. We do so to maintain consistency with the academic literature and because we do not have quotes on forward rates for arbitrary maturities.

To calculate daily returns for a carry trade strategy, we consider that a trader has one dollar of capital that is deposited in the bank at the end of month $t - 1$. The trader earns the one-month dollar interest rate, $i_t^{\$}$, prorated per day. We use the one month euro-currency dollar deposit rate as the interest rate at which traders borrow and lend, and we infer the one month foreign interest rate from covered interest rate parity. At time $t - 1$, the trader also enters one of the four carry trade strategies, EQ, EQ-RR, SPD, SPD-RR, which he re-balances at the end of a month t . Let $P_{t,\tau}$ be the cumulative carry trade profit on day τ during month t . The committed capital of one dollar plus the profit on the carry trade at the end of month t will grow to $P_{t,\tau} + (1 + i_t^{\$})^{\frac{\tau}{D_t}}$ by the τ^{th} trading day of month t with D_t being the number of trading days within the month. The excess daily return can then be calculated as:

$$rx_{t,\tau} = \frac{\left(P_{t,\tau} + (1 + i_t^{\$})^{\frac{\tau}{D_t}}\right) - \left(P_{t,\tau-1} + (1 + i_t^{\$})^{\frac{\tau-1}{D_t}}\right)}{P_{t,\tau-1} + (1 + i_t^{\$})^{\frac{\tau-1}{D_t}}} - (1 + i_t^{\$})^{\frac{1}{D_t}}$$

Panel A of Table 3.29 shows the summary statistics of the daily returns of four carry trade strategies. For ease of comparison, we list the same set of summary statistics of the monthly returns in Panel B. If the daily returns of a portfolio are independently and

identically distributed, the moments at the daily and monthly levels should have the following relationship (all annualized, assuming 21 trading days within a month): $\mu^d = \mu^m$, $\sigma^d = \sigma^m$, $skew^d = \sqrt{21} \times skew^m$, $Kurt^d = 21 \times Kurt^m$, where $skew^d = \gamma_3^d / (\gamma_2^d)^{\frac{3}{2}}$, $Kurt^d = \gamma_4^d / (\gamma_2^d)^2$, and γ_h^d represents the h -th sample moment around the mean. Derivations are shown in the Appendix.

Table 3.29 shows that the annualized average returns for the daily carry trades and their corresponding monthly counterparts are almost identical. The annualized standard deviations of the four daily strategies are all slightly below the annualized monthly standard deviations, consistent with small positive autocorrelations at the daily frequency. Ratios of standardized daily skewness relative to monthly skewness vary considerably across the portfolios. For the EQ and SPD portfolios, the ratios are 0.64 and 1.90, well below the value implied by the i.i.d. assumption, which is approximately $4.6 = \sqrt{21}$. On the other hand, the same ratios for the risk rebalancing portfolios are markedly higher, 2.7 for EQ-RR and 3.6 for SPD-RR. This is not surprising because risk rebalancing targets a constant IGARCH predicted variance over time, thereby reducing the serial dependence in the conditional variances. As a result, the data generating process of the risk rebalancing portfolios conform better to the i.i.d. assumption. Similarly, ratios between daily and monthly kurtosis are closer to the value implied by the i.i.d. assumption for the risk rebalancing portfolios. Risk rebalancing tilts the data generating process towards the i.i.d. distribution, and it reveals substantial negative skewness at the daily level. The daily skewness of the EQ-RR and SPD-RR strategies is -1.01 and -1.62, respectively. Lastly, the minimum annualized daily returns are of similar size to the minimum monthly returns for all four strategies.

We use three measures to capture the downside risks of carry trade portfolios. The first is its drawdown, which is defined as the percentage return from the previous high-water mark to the following lowest point. The second is its pure drawdown, which is defined as the

percentage return from consecutive negative returns. The third is its maximum loss, which is defined as the minimum cumulative return over a given period of time. We calculate the distributions of drawdowns and pure drawdowns, which are defined as the number of drawdowns (pure drawdowns) more severe than a certain value. For maximum losses, we calculate the distribution as the maximum loss versus a particular time horizon.

To draw statistical inference under the assumption that the returns are independent across time, we simulate the daily excess returns of the four strategies under a normal distribution with the corresponding unconditional mean and standard deviation of the data. To capture non-normalities while retaining the i.i.d. assumption, we also simulate the daily excess returns using independent bootstrapping with replacement. We simulate 10,000 trials of the same size as the data. We can then calculate the probability of observing the observed empirical patterns under these two simulation methods, which we report as p -values.

Drawdowns

Table 3.30 reports the p -values for drawdowns under simulations from the normal distribution (labeled as “p_n”) and from the bootstrap (labeled as “p_b”). The worst EQ strategy drawdown is 12.0%, which corresponds to a p -value of .13 under either the normal or the bootstrap distribution. Because these values exceed the .05 threshold, the probability of observing one drawdown worse than 12.0% is not inconsistent with the i.i.d. models. But, as we move towards less severe drawdowns, we observe two drawdowns worse than 10.8% for the EQ strategy. The probability of observing two drawdowns worse than 10.8% is .016 under the normal distribution and .018 under the bootstrap. Therefore, while a single worst drawdown of 12.0% is not uncommon under the assumption of the i.i.d. normal distribution, for less extreme but still severe drawdowns, the EQ portfolio suffers them more frequently than the i.i.d. distributions suggest. For the SPD strategy, the worst drawdown

for the SPD strategy is 21.5%, which has p -values of .017 for the normal and .023 for the bootstrap. Drawdowns with magnitudes between 8.2% and 8.9% happen more frequently in the data than both simulation methods would suggest with p -values of .05. The effect of risk-rebalancing on the EQ strategy is minimal, while the rebalancing the SPD strategy cuts the largest drawdown in half. The distributions of drawdowns for the risk rebalanced strategies, EQ-RR and SPD-RR, often reach p -values below .05 under both simulation methods.

Maximum Losses

Table 3.31 reports the p -values for maximum losses under the two simulations. Take the maximum loss for the EQ strategy as an example. It has a maximum daily loss of -2.7%, which is the minimum daily return in the sample. This one-day loss clearly rejects the assumption of a normal distribution. This is not surprising because the portfolio has a significantly negative skewness and other higher moments. Bootstrapping captures these higher moment, and using this simulation method, the maximum daily loss of -2.7% has a p -value as high as 59.4%. This means the probability of observing a maximum loss over one day that is worse than -2.7% is 59.4%. As we move towards longer horizons, the maximum loss in the data increases steadily until 180 days. After that, the maximum loss decreases because even though longer horizons mean the losing streak could be longer, it seems to be offset by the positive average returns.

Simulations under a normal distribution fail to match the empirical distribution of maximum loss over all holding horizons for all four strategies, indicating the limitations of using the normal distribution when studying the most extreme tail events. Thus, we focus on the bootstrapping results. For the EQ portfolio, the maximum losses within periods shorter than one, two, and three days obtain p -values larger than 5%. For longer horizons, the maximum losses usually are much more severe than what the bootstrapping 5% bound suggests.

Maximum losses for SPD over periods short than 35 days are well within the 5% bound. But for periods longer than 40 days, the maximum losses for SPD start to exceed the 5% bound. This suggests that even taking account of the daily skewness and higher moments, distribution of maximum losses for EQ and SPD at longer horizons rejects the i.i.d. assumption underlying the bootstrapping. The rejection can come from serial dependence of different moments. Volatility of returns is usually quite persistent, and thus controlling for serial dependency in the second moment seems to be a natural, first step to examine why bootstrapping fails to match the empirical maximum loss. EQ-RR and SPD-RR affords us such a chance because EQ-RR and SPD-RR are rebalanced to achieve a constant IGARCH predicted volatility. These two return series have less serial dependency in the second moments. As we can see from the Table 3.31, once we take account of the stochastic volatility, the maximum loss we observe in the data largely lies within the 5% bound. Therefore, even though the drawdown analysis shows that risk rebalancing is not effective at regulating the distribution of drawdowns to what would be implied by i.i.d., risk-rebalancing certainly helps to align the distribution of the maximum loss with what implied by an i.i.d. distribution.

Pure Drawdown

Table 3.32 reports simulations of the pure drawdowns under the two simulations. The i.i.d. normal distribution fails to match the empirical distributions of pure drawdowns for virtually all magnitudes and frequencies. We thus focus on the p -value under bootstrapping. For the EQ strategy, the worst pure drawdown is 5.2% with a p -value of .014 under the bootstrap. For less severe pure drawdowns, we see that the bootstrap simulations also fail to match the frequencies at these thresholds. Similar observations can be made for the SPD strategy. In results available in the online appendix, we observe that the durations of pure drawdown, that is, the number of days with consecutive negative returns, are well within

the .05 bounds implied by two simulations. These results suggest that the low p -values of the empirical distributions of the magnitudes of pure drawdowns stem mainly from the fact that the consecutive negative returns tend to have larger variances than the typical returns.⁸ When we apply the risk-rebalancing strategies in EQ-RR and SPD-RR which scales down the magnitudes of the positions in the volatile times, we find that the worst five pure drawdowns lie well within the .05 bounds, while less extreme pure drawdowns happen more frequently than is implied by the bootstrap's .05 bound. Recall that the distribution of maximum losses of EQ-RR and SPD-RR lie within the bootstrap's .05 bound also, while the distributions of drawdowns of the two EQ and SPD strategies do not. These results together suggest that controlling for serial dependence in volatility greatly improves the accuracy of an i.i.d. approximation for studying the extreme downside risks. But to fully match the frequencies of less extreme, but still severe downside events, we need a richer model to capture the serial dependence in the data.

To sum up, studying the four carry trade strategies at the daily level conveys rich information regarding the downside risks. The minimum daily returns are of similar size of the minimum monthly returns, suggesting that extreme negative returns happen within days and are hard to avoid even when traders can re-balance daily. Simulations using a normal distribution fail to match the empirical frequencies of downside events in most cases. This is consistent with the significant, negative skewness at the daily frequency. Bootstrapping captures the negative skewness and other higher moments of the distributions, and bootstrapping with a volatility forecasting model helps to match the frequencies of the most extreme tail events in the data, but it fails to match the frequencies of less extreme but still severe tail events.

⁸Similarly, we find larger values of pure run-ups than is implied by the simulations.

2.8 Conclusions

This paper provides some perspectives on the risks of carry trade that differ from the conventional wisdom in the literature. First, it is generally argued that exposure to the three Fama-French (1993) equity market risk factors cannot explain the returns to the carry trade. We find that these equity market risks do significantly explain the returns to an equally weighted carry trade that has no direct exposure to the dollar. Our second finding is also surprising. We find that our carry trade strategies with alternative weighting schemes cannot be fully priced by the HML_{FX} factor proposed by Lustig, Roussanov, and Verdelhan (2011), which is basically a carry trade return across a broader set of currencies. Third, we argue that the time varying dollar exposure of the carry trade is at the core of carry trade puzzle. A dollar carry factor earns a significant abnormal return in the presence of equity market risks, bond market risks, FX risk, as well as a volatility risk factor. The dollar carry factor also has insignificant skewness, indicating crash risk cannot explain its abnormal return. Our fourth finding that is inconsistent with the literature is that the exposure of our carry trades to downside market risk is not statistically significantly different from the unconditional exposure. Thus, the downside risk explanation of Dobrynskaya (2014) and Lettau, Maggiori, and Weber (2014) does not explain the average returns to our strategies.

We also show that spread-weighting and risk-rebalancing the currency positions improve the Sharpe ratios of the carry trades, and the returns to these strategies earn significant abnormal returns in presence of the “carry” factor proposed by Lustig, Roussanov, and Verdelhan (2011). The choice of benchmark currency also matters. We show that equally weighted carry trades can have a Sharpe Ratio as low as 0.36 when JPY is chosen as the benchmark currency and as high as 0.78 when USD is chosen as the benchmark currency. Currency exposure explains the difference between these carry trade strategies. We thus

decompose the equally weighted USD based carry trade into two components: one has zero direct exposure to the dollar and the other that contains the strategy's dollar exposure. We find that the dollar-neutral part of carry trade exhibits an insignificant alpha in the Fama-French three-factor model. On the other hand, a dollar carry factor based on the carry trade's time varying exposure to the dollar cannot be priced by a combination of equity, bond, volatility, and FX "carry" risk factors, commanding insignificant loadings on either of these risk factors and a significant alpha.

We also initiate a discussion of the attributes of the distributions of the drawdowns of different strategies using daily data while maintaining a monthly rebalancing strategy. We do so in an intuitive way using simulations, as the statistical properties of drawdowns are less developed than other measures of risk, such as standard deviation and skewness. Although we correct for time varying heteroskedasticity with our risk rebalancing model, we still find that most of the time the empirical distributions of the drawdowns of our carry trade strategies lie outside of the 95% confidence band based on a normal distribution that matches the unconditional mean and standard deviation of the strategy. Simulating from an i.i.d. bootstrap does a much better job of predicting the distributions of carry trade drawdowns, but it cannot fully capture the severity of the drawdowns. Adding conditional autocorrelation, especially in down states, seems necessary to fully characterize the distributions of drawdowns and the negative skewness that characterizes the monthly data.

Chapter 3

Sub-national Credit Risk and Sovereign Bailouts—Who Pays the Premium

Eva Jenkner and Zhongjin Lu

3.1 Introduction

As fiscal pressures at all levels of government heightened during the global financial crisis, the issues of risk pooling and intergovernmental fiscal support have come under renewed focus (Bordo et al., 2011). The question whether to bail out a fiscally profligate sub-national government (SNG) is mostly approached from two angles: the need to reduce systemic spillovers, and the potential for creating or exacerbating moral hazard. More often than not decisions are taken in light of the former, imminent pressures, and moral hazard concerns are addressed through conditionality and a tightening of fiscal constraints; although there has been a growing preference for some bailing in of private sector creditors to deter irresponsible lending.

Despite often extensive public debate on the merits and cost of providing financial assistance along the lines described above, one additional aspect has received only scant attention thus far: the question whether bailouts may impair the creditworthiness of the entity *providing* financial support, leading to higher borrowing costs over the short to medium-run. This additional risk could add substantially to the total cost of the bailout, and undermine already precarious debt sustainability. Our paper aims to fill the analytical gap on this little-understood phenomenon and contribute to the policy debate on sub-national bailouts.

Part II introduces the issues of sub-national borrowing and potential implications of explicit or implicit sovereign support for sub-national borrowing, including our central hypothesis on the transfer of risk. Part III presents our empirical analysis of the case of Spain and its autonomous regions as they underwent significant fiscal stress during the first half of 2012. We find support in favor of a risk transfer from the region of Valencia to the Spanish sovereign. Part IV concludes.

3.2 A new Take on Sovereign Guarantees for Sub-national Borrowing

3.2.1 Overview

Over the last decades, borrowing on capital markets became a significant source of financing for state and local governments around the globe.¹ At the same time, many central governments have sought to regulate such borrowing, on the basic premise that market discipline alone is not deemed sufficient to ensure sound fiscal performance.² Rules and restrictions imposed (or self-imposed) on SNGs have ranged from cooperative controls to outright prohibition (Ter Minassian, 1997; Eyraud and Gomez-Sirera, 2013).

A broad literature has explored the reasons behind markets' failure to ensure sufficient fiscal discipline at SNG levels. These include the difficulty to obtain and process information for small entities, as well as potential incentives for local governments to borrow beyond their means on the basis of the expectation that they will be bailed out by higher-level governments, so-called moral hazard concerns (Rodden, 2006). Creditors underpricing sub-sovereign risk on the very same bailout expectation also contribute to unsustainable borrowing, exacerbating the problematic incentives.

Credit ratings of sub-national governments tend to follow sovereign ratings closely and generally do not exceed the sovereign's creditworthiness. Figure 3.16 shows the commonly observed sovereign "cap" on sub-national ratings, to which there have been only few excep-

¹While the United States still have by far the largest market for sub-national bonds with an approximate annual capitalization of 400 billion dollars, issuances in Germany, Japan, China, Canada, and Spain have gained in importance, reaching approximately 260 billion dollars in 2009 (Canuto and Liu, 2010).

²Evidence varies across countries, likely according to the history of bailouts (Von Hagen et al. 2000; Bordo et al. 2011). For example, Bayoumi et al. (1995) find support for the market discipline hypothesis in the case of US States; and the US federal government has a long-established, credible no bailout policy.

tions, including the Spanish regions of Navarre and the Basque country seen in this example (Canuto and Liu, 2010). This particular disconnect has its roots in the fiscal autonomy of those traditional “fueros” regions. More generally, the fiscal intergovernmental regime (including transfers, fiscal rules etc.) plays an important role in determining borrowing premia for sub-national entities (Liu and Tan, 2009; Palomba et al., 2013). Presumably—from the markets’ point of view—a close financial relationship ties the fiscal fates of the different levels of government closer together, and increases the probability of a bailout.

A few studies have examined the impact of intergovernmental fiscal links on SNGs’ borrowing costs empirically. Schuknecht et. al (2008) and Schulz and Wolff (2009) find that in the case of Germany, which implements large-scale intergovernmental transfers, interest rate premia paid by SNGs have been unduly suppressed and de-linked from underlying fiscal performance, including debt levels (the most important predictors of default risk). Heppke-Falk and Wolff (2008) confirm the presence of moral hazard in the German sub-national bond market by examining the relationship between financing costs and the interest-to-revenue ratio—the ratio seen as crucial to determine the probability of a court bailout. Although they find states’ debt ratios to matter in determining risk premia, this is more than offset by downward pressure on premia as the critical interest-to-revenue ratio (and probability of default) rises.

Even in the case of Canadian provinces that enjoy greater fiscal independence in general, Joffe (2012) finds evidence of an implicit interest rate subsidy on the basis of bailout expectations—while the last actual bailouts date back to the 1930s. On the flip side, Landon and Smith (2000) analyze debt spillovers within the Canadian federation and conclude that high federal debt negatively affects the creditworthiness of indebted provinces, which they interpret to be the result of reduced central government fiscal space for provincial bailouts. Finally, borrowing costs least depend on fiscal fundamentals in German or Cana-

dian provinces that receive the most in transfers (Schuknecht et al., 2008). On the contrary, the same study finds credit risk premia in Spanish regions to be in line with their fiscal fundamentals.³

3.2.2 The risk transfer hypothesis

While some research indicates that bailout expectations may lead markets to underprice sub-national risk, the question whether sovereigns at the same time pay a premium on their borrowing as a result of (implicitly or explicitly) assuming sub-entities' risk has been explored only little. To fill this gap, we try to determine if an observed, sudden drop in sub-national risk in reaction to a sovereign intervention coincides with an increase in the sovereign risk premium—or, in other words, whether there is a transfer of risk from the sub-national entity to the sovereign. Specifically, we use daily financial market data to test for a simultaneous *increase* in sovereign risk premia and *decrease* in sub-national risk premia on the very same day that new information on sovereign support for sub-national entities becomes available.

To the best of our knowledge, practically no studies have tried to establish the existence of such a risk transfer between the sovereign and sub-sovereign government levels. In the only similar study, albeit at lower levels of government, Feld et al. (2013) examine the case of the Swiss community Leukerbad which experienced financial difficulty in 2003. After a court decision in July 2003 *not* to hold the canton Valais responsible for its sub-entity's debt, they observe a drop in cantonal risk premia of around 25 basis points—ostensibly as a credible non-bailout regime has been established. However, several studies established the existence of a transfer of risk from financial sector entities to sovereign entities during the financial

³Dell'Ariccia et al. (2006) find evidence that emerging market countries' risk spreads became more dispersed as Russia was *not* bailed out in 1998—presumably on the basis of more country-specific risk assessments and reduced expectations of bailouts.

sector turmoil in 2008-09 (Ejsing and Lemke, 2011; Attinasi, Checherita and Nickel, 2010; IMF, 2009). Specifically, they found empirical evidence that in the event of financial sector bailouts financial sector risk premia declined and sovereign risk premia climbed beyond levels that can be explained by other fundamental determinants. This is interpreted as markets transferring risk from the financial sector to the sovereign.

3.3 The Empirical Analysis: Spain and its *comunidades autónomas* in 2012

3.3.1 General approach and methodology

In our empirical analysis, we examine daily financial sector data to find evidence of simultaneous decreases in regional credit risk and increases in sovereign credit risk coincidental with the announcement of sovereign guarantees or financial support of sub-national entities. Our research faces a number of major challenges.

First, we can only expect guarantees or bailouts to affect regional or sovereign risk premia if they are indeed a surprise to the market and have not already been factored into current risk assessments. This is a critical prerequisite. Second, risk premia are driven by a number of factors—some observed and some unobserved—and it is hard to control for the universe of these potential determinants while trying to identify the impact of a single event. Consequently, even if an unexplained increase in sovereign borrowing costs is observed upon a bailout, this does not automatically confirm a risk transfer to be the underlying explanation. Third, the initial fiscal position of the sovereign and the relative size of the financial obligations taken on can potentially make a significant difference. Markets may not react to a financial transfer or new contingent liabilities that do not fundamentally affect the central

government's fiscal soundness.

In order to address these challenges, we use an event study approach with a very short time window. Specifically, we set the window to be one day. One day is long enough for the information to be incorporated by markets, and it is the shortest interval for which we do not need to worry about the synchronization of trades in different over-the-counter markets. The identification assumption is that—even if some kind of intervention had been expected and incorporated by markets—the exact date and magnitude were unknown, and the unexpected part of the intervention will still be reflected as a discontinuous short-term jump in prices. Using a very short time horizon also helps us control for other underlying determinants of credit risk premia, especially slower-moving structural and economic factors. We note, however, that high-frequency estimations in relatively shallow markets, such as SNG debt markets at a time of distress, carry challenges of themselves, and will need to be interpreted with caution.

Finally, we estimate two separate equations for credit risk at the sovereign and sub-national levels. As discussed above, sovereign and sub-sovereign risk assessments tend to be closely linked and can be influenced by a number of unobserved factors in the short run. Simultaneous *decreases* in sub-sovereign risk and *increases* in sovereign risk are therefore a good indication that shared determinants of risk (such as general risk aversion) can be ruled out and that a risk transfer has occurred.

The Spanish autonomous regions' fiscal crisis in the first half of 2012 is a good case to examine our risk transfer hypothesis. First, Spain enshrined a formal no-bailout clause in its Constitution in 2011, after amending its budget systems law to the same effect in 2006. Moreover, as discussed above, the findings of Schuknecht et al. (2008) imply that Spanish regional risk premia did not reflect any bailout expectations even before 2005—which is reassuring for our analysis. Second, if sovereign debt had been at its low pre-

crisis levels, markets could have easily ignored the unexpected additional burden from the autonomous regions. However, the sovereign's perceived financial vulnerability at the time made a discernible impact on sovereign risk more likely, all the more so as regional debt and deficit levels had grown significantly in the run-up to the crisis episode, posing a realistic threat to fiscal consolidation efforts at the central level.⁴

3.3.2 The events to study: Spain and its *comunidades autónomas* in 2012

After the onset of the 2008 global financial crisis, Spain entered into a double-dip recession, and its budget surplus turned into deficits of around 10 percent of GDP from 2009-11. Spain's total debt to GDP ratio increased substantially, from 36 percent in 2007 to 86 percent in 2012 (Banco de España, 2013). Apart from the recession, fiscal stimulus measures contributed to elevated fiscal deficits (IMF, 2012). In addition, financial sector weaknesses kept surfacing, raising uncertainties about the need for further capital injections from the government. As a result, Spain's sovereign yields and CDS spreads increased through 2010-11. In the course of 2012, Spain's sovereign CDS spread was propelled well above average European market risk, and the country's financing cost rose towards unsustainable levels (Figure 3.17).^{5 6} In response, the central government stuck to its ambitious fiscal consolidation and economic re-

⁴Other episodes of sub-national fiscal distress that could be studied include Argentina, Brazil, Mexico, or the UAE (See Jaramillo et al (2013) for a survey). However, regional credit ratings and some daily sub-national financial sector data are more easily available for Spain, facilitating our analysis.

⁵As will be discussed later, a number of studies have suggested that CDS and bond spreads may rise well above reasonable default risk expectations; potentially due to market overreactions, proxy hedging or speculation (see De Grauwe and Ji, 2012 and 2013; or Becker, 2009).

⁶We use the iTraxx index Europe as a proxy for general risk aversion. See Part C and Appendix 1 for a more detailed description.

form plan, and ultimately tapped European partners for financial sector support.⁷ However, pressures on Spanish public debt only subsided after ECB President Draghi sent a strong signal to markets by announcing his “unlimited support” for euro area countries on July 26, 2012. This policy was formally enshrined as Outright Monetary Transactions (OMT) in August, and later institutionalized through the creation of the European Stability Mechanism (ESM).⁸

The central governments’ long-standing difficulty to control spending by the autonomous regions was a major contributing factor to Spain’s fiscal troubles. Debt of the *comunidades autónomas* increased from 6 percent of GDP in 2007 to 18 percent of GDP at end-2012, with more than half concentrated in the three most indebted regions: Catalonia, Andalucía, and Valencia. Even scaled by regional GDP—Catalonia being a major contributor to national GDP—liabilities exceeded 25 percent in Catalonia and Valencia. The regions’ deficit surged from 0.2 percent of GDP in 2007 to 5.2 percent of GDP in 2011. The central government’s lack of control over regional spending became particularly clear in May 2012, when the 2011 general government public deficit had to be revised up to 8.9 percent of GDP—compared to an original target of 6 percent of GDP—on account of upward revisions in three regions (MHAP, 2012). At last, the 2011 deficit was estimated at 9.6 percent of GDP, with the regions’ contribution at 5.2 percent of GDP—seriously undermining consolidation efforts that had taken place at the central level (Banco de España, 2013).⁹

As fiscal pressures and the weak economy made it harder and harder for many regions to

⁷An EC support loan of 100 billion euros for Spanish banks was approved in June; see IMF (2012) and (2013) for a more comprehensive description of the government’s reform efforts.

⁸See De Grauwe and Ji (2012) and (2013) for an analysis of sovereign risk pricing in selected euro area countries and a justification of ECB liquidity support.

⁹Between 2009 and 2011, the central government deficit decreased from 9.3 percent of GDP to 3.5 percent of GDP.

pay their suppliers and roll over their debt, the government was forced to gradually increase its support for the embattled regions. Initially, towards the end of 2011, the government advanced regular transfers to regions as needed, provided verbal support, and extended repayment periods of past revenue overpayments with a view to calm markets (IMF, 2012). However, as market pressures continued to build, arrears to suppliers further dampened the weak economy, and some regions (notably Valencia) were teetering on the brink of default, it became evident that more substantial interventions would be required. In response, the central government set up three main financing mechanisms (subsequently) to help the autonomous regions pay suppliers and meet their debt obligations:

- In early February 2012, the government provided cash-strapped regions with a 10 billion euros credit line (extendable to 15 billion euros) through the state-owned bank ICO.
- In early March 2012, the FFPP (Fund for the Financing of Payments to Suppliers) was set up to provide up to 35 billion euros in 10-year loans to help regions pay their mounting debt to suppliers.
- In July 2102, additional liquidity support was made available to regions through a Regional Liquidity Mechanism (FLA), with 18 billion euros allocated in 2012 and 23 billion euros projected to be needed in 2013.

Well aware of the need to strengthen control over sub-national finances, the government linked all financial support to strict monitoring and conditionality (such as sharp deficit reductions) in line with the budget stability law (BSL) enacted in April 2012. In particular, the BSL (also referred to as Organic Budget Law) provided the central government with additional control mechanisms over regional finances, that were deemed critical in order to meet fiscal obligations under the European Stability and Growth Pact going forward (IMF, 2012;

IMF, 2013b). Importantly, the BSL enhances timely monitoring of SNG finances (including through an early-warning system), and establishes enforcement and sanction mechanisms.¹⁰ Not least as a result of these efforts to improve fiscal responsibility at the regional level, regional deficits decreased sharply in 2012, to 1.8 percent of GDP. However, full implementation of all the tools in the BSL remains pending (IMF, 2013).

In our empirical estimation, we focus on the period between end-2011, as the central government started supporting regions, and end-July 2012, as the ECB President Draghi announced unlimited ECB support—easing pressures on the Spanish sovereign—and regions started to tap the regional liquidity fund (FLA). In order to determine whether a risk transfer may have occurred as the rescue of the regions unfolded in the course of 2012, we apply the event study approach to Spain’s sovereign CDS (credit default swap), a proxy for credit risk at the sovereign level; and regional bond yields, a proxy for the credit risk premium at the regional level (since there are no CDSs for regional bonds).¹¹ In our analysis we concentrate on the potential impact of the following three groups of events: central government verbal pledges of support for regions; announcements of concrete guarantees and financial support for regions (including the three mechanisms described above); and so-called “credit negative” events for regions, including rating downgrades or the May 2012 upward revision of three

¹⁰The Organic Law of Budgetary Stability and Financial Sustainability (Ley 2/2012) establishes a set of fiscal discipline principles at all levels of government in Spain in line with the limits set out in the European Growth and Stability Pact (EGSP). Its focuses on prevention, transparency and compliance: the law includes a new early-warning system, aimed at detecting imbalances and issuing the relevant recommendations to achieve the budget targets; it requires monthly and quarterly reporting on budget execution, and the central government-issued guidelines prior to the approval of regional government budgets; and the law establishes sanctions and forced compliance for SNGs (Source: <http://www.spanishreforms.com/-/organic-law-on-budget-stability-and-financial-sustainability>).

¹¹As bond yields include information beyond credit risk (notably interest rate risk and liquidity risk), we are likely to see more estimation noise even after we control for the short-term risk free rate and a proxy for liquidity, raising the bar of finding significant results. Also, liquidity risk is generally found to be higher for bond yields than CDS, and sub national bond markets are particularly shallow (Kiff et al. 2009; Canuto and Liu, 2010).

regions' 2011 deficit levels.¹²

For our risk transfer hypothesis to be confirmed, we would expect the first two groups of events (sovereign support for regions) to *decrease* the regional risk premia and simultaneously *increase* the sovereign risk premium. Furthermore, we would also expect the (completed) risk transfer to manifest itself in two additional effects: First, we would expect to see stronger co-movements in Spanish sovereign and regional credit risks. Second, we would expect *regional* credit negative events to increase the *sovereign* risk premium as markets factor in the de-facto sovereign guarantee for regional debt.

3.3.3 Specifications and data

The basic model

The estimated model has separate equations for the sovereign and the regional governments, respectively. At the sovereign level, the model is:

$$SCR_{i,t} = \beta_0 + \beta_1 liq_{i,t} + \beta_2 RA_t + \sum_{k=1}^4 \gamma_k D_k + \epsilon_{i,t} \quad (3.1)$$

where $SCR_{i,t}$ is sovereign credit risk; $liq_{i,t}$ is market liquidity; RA_t is general risk aversion; and D_k are dummies for events of interest. Subscript i denotes country i; subscript t denotes trading day t; subscript k denotes dummy.

The dependent variable is $SCR_{i,t}$, or sovereign credit risk. We use the spread of 5-year sovereign CDSs as a proxy for sovereign credit risk, as CDS is the price assigned to the sovereign credit exposure by the market. Since CDS spreads are influenced by factors other

¹²For more detail please see Appendix 1, Table A.10.

than credit risk—most importantly, market liquidity conditions and general risk aversion—we try to control for them to reduce any potential estimation errors.¹³ We control for the liquidity factor $liq_{i,t}$ in the CDS market by using the bid/ask spread of the CDS; and we control for the general market risk in Europe RA_t by using the Markit iTraxx Europe index, which is an equally weighted index of 125 investment grade corporate CDSs in Europe.¹⁴

At the regional level, we use a slightly different set-up:

$$RCR_{i,t} = \beta_0 + \beta_1 SCR_t + \beta_2 liq_{i,t} + \beta_3 RA_t + \beta_4 RF_t + \sum_{k=1}^4 \gamma_k D_k + \epsilon_{i,t} \quad (3.2)$$

where $RCR_{i,t}$ is regional credit risk; SCR_t is Spain's sovereign credit risk; $liq_{i,t}$ is market liquidity; RA_t is general risk aversion; RF_t is the short-term interest rate; D_k are dummies for events of interest. Subscript i denotes region i ; subscript t denotes trading day t ; subscript k denotes dummy.

The regional credit risk equation is slightly different from the sovereign credit risk equation (1) for two main reasons. First, we expect that sovereign risk represents an important factor in market assessments of sub-entities' risk, so we include SCR_t on the right-hand side.¹⁵ Also, in absence of CDSs, we have to use regional bond yields as a proxy for credit risk of each of the autonomous regions, $RCR_{i,t}$.¹⁶ This requires us to additionally include

¹³The question whether CDS spreads reflect liquidity risk has been subject to debate, yet a lot of research has shown the existence and importance of liquidity in determining CDS spreads (see for example Tang and Yan (2007), Arakelyan et al. (2012) or Bongaerts et al. (2011)). CDS spreads also reflect counterparty risk; we assume that counterparty risk is slow-moving (or relatively constant) throughout our estimation period, which seems defensible for the time period under consideration.

¹⁴We choose the iTraxx Europe index because it tracks the European risk more closely than other commonly used measures of general risk, such as VIX (CBOE volatility index) and the Bank of America BBB spread. Substituting them in our estimation still produces similar results, however.

¹⁵Please see Ianchovichina et al. (2006), or Liu and Tan (2009) or Von Mueller (2012) for empirical evidence and a detailed explanation of the underlying reasons.

¹⁶We use the yield of the most liquid bond issued by the respective region; data remains patchy.

the Euribor 3-month rate to control for the short-term interest rate, RF_t . Finally, as in equation (1), we compute the bid/ask spread of the regional bond to control for liquidity, $liq_{i,t}$, and use the Markit iTraxx Europe index to control for general risk aversion in Europe, RA_t .¹⁷

For both equations, our main variables of interest are the event dummies D_1 - D_4 which capture a number of related events each. These dummies are equal to 1 only on the specific event days that pertain to each group, and are aimed to capture any changes in market risk assessments that might have taken place shortly after the events in question.¹⁸ Essentially,

- D_1 captures “news” on central government verbal pledges of support for regions;
- D_2 captures “news” on concrete central government guarantees and financial support for regions (the key variable for testing our hypothesis);
- D_3 captures “news” on so-called “credit negative” events for regions; and
- D_4 marks ECB President Draghi’s July 26th speech about the ECB’s commitment to preserving the euro.

3.3.4 Further tweaks

Moving to the empirical estimation, we take a few additional steps to adjust our basic model. First, our daily series of CDSs and regional bond yields are highly persistent.¹⁹

¹⁷Market risk is a major explanatory factor of sovereign CDS spreads (and we find this confirmed in our results below). Hence, in our robustness check, we drop the iTraxx index from our regional equation, which already contains sovereign credit risk as a control variable. Our results remain virtually unchanged (Table 3.34, column 7).

¹⁸See Appendix 1, Table A.10i for a more detailed description of the individual events.

¹⁹We run the Phillips-Perron unit root test with 5 lags, which uses Newey-West standard errors to account for serial correlation (Phillips and Perron, 1988). Both the Phillips-Perron τ test and ρ test cannot reject

Therefore, a dynamic specification estimated in first difference seems appropriate, and we include the lagged dependent variables $\Delta SCR_{i,t-1}$ and $\Delta RCR_{i,t-1}$ on the right-hand side. Using first differences also helps us to minimize the potential influence of omitted slow-moving macroeconomic state variables, which are commonly included in similar estimations with lower frequencies.

Second, as we are expecting the relationship between regional credit risk and sovereign credit risk to be time-variant with respect to market expectations of sovereign support, we include an interaction term. Specifically, to test for a structural break we create a period dummy, $I_{pre-bailout}$, which is equal to one prior to the “bailout period” (January 1, 2010 to December 19, 2011), and interact it with the sovereign credit risk variable included in the regional credit risk equation.²⁰

Third, we include a period dummy for the period after ECB President Draghi’s speech (July 26, 2012), $I_{post-bailout}$, which had a specifically calming effect on debt markets in Spain and Italy that had come under heavy pressure. By inserting the two period dummies into the sovereign credit risk equation, we allow the constant term to be different in the pre-bailout era and the post-Draghi’s speech era to capture potential regime shifts.

Fourth, we estimate the regional credit risk equation for Valencia, as only Valencia’s bonds have tradable quotes on the event days we are interested in. As a result, our event dummies for regional credit negative events, group D_3 , are equal to one only on the days of the first, second, fourth, and sixth events, since the other events are not credit negative for Valencia. Nevertheless, in the robustness section, we present panel regression results using

the hypothesis that Spanish CDS have a unit root at all common significance levels, regardless of whether we use a trend specification or not. Similarly, none of the tests can reject that the Valencia’s bond yield has a unit root. See Appendix 1, Table A.11 for our results.

²⁰To assess our risk hypothesis we test for a structural break with the onset of the bailouts (associated with the pre-bailout dummy); we do not expect a reversal of greater co-movements after July 2012 (the post-Draghi dummy) and hence only test for it for robustness purposes.

data for Catalonia and Andalucía whenever they are available.

The final equations we estimate are therefore:

$$\begin{aligned} \Delta SCR_{i,t} = & \beta_0 + \beta_1 \Delta SCR_{i,t-1} + \beta_2 \Delta liq_{i,t} + \beta_3 \Delta RA_t + \sum_{k=1}^4 \gamma_k D_k \\ & + \beta'_0 I_{pre-bailout} + \beta''_0 I_{post-Draghi} + \epsilon_{i,t} \end{aligned} \quad (3.3)$$

$$\begin{aligned} \Delta RCR_{i,t} = & \beta_0 + \beta_1 \Delta RCR_{i,t-1} + \beta_2 \Delta SCR_t + \beta_3 \Delta liq_{i,t} + \beta_4 \Delta RA_t \\ & + \beta_5 \Delta RF_t + \sum_{k=1}^4 \gamma_k D_k + \beta'_2 \Delta SCR_t \times I_{pre-bailout} + \epsilon_{i,t} \end{aligned} \quad (3.4)$$

where $I_{pre-bailout}$ is a period dummy for the period up to December 19, 2011; and $I_{post-Draghi}$ is a period dummy for the period after July 26, 2012.²¹

Given the very limited number of events under each category, we find OLS standard errors to be appropriate. We explore a number of different approaches in the robustness section below.²²

3.4 Main results

The estimation results for sovereign credit risk are presented in Table 3.33, column 1. Overall, results are consistent with our risk transfer hypothesis: the coefficients of the events where

²¹In Tables 3.33 and 3.34 we refer to these period dummies as PD1 and PD2, respectively.

²²In the robustness section, we also show standard errors adjusted for serial correlation and heteroskedasticity (Newey and West, 1987). However, these adjustments are based on asymptotic theory and should be viewed with caution (Wooldridge, 2002). We also estimate both equations jointly using seemingly unrelated regressions.

the government pledges support (D_1) and concrete bailout measures are implemented (D_2) are both positive, implying that on those days sovereign credit risk—as assessed by the market—increased. Specifically, during the two events in which the central government provides verbal support, the Spanish sovereign CDS spread on average went up by 8 basis points. The coefficient is not statistically significant, however; as such pledges may not be taken as seriously by the market. In contrast, the coefficient on D_2 , the group of concrete bailout measures is significant and suggests that the government's steps raised the Spanish sovereign CDS spread by $10\frac{1}{2}$ basis points, on average.

To put these findings in context, during the seven event days represented by D_1 and D_2 the sovereign CDS spread increased by about 70 basis points in total. This represents a significant amount, given that the CDS spread in our sample ranges from 93 to 641 basis points, with an average of 310.²³ In terms of interest payments, a 70 basis points increase could translate into an extra cost of 600 million euros per year for short-term debt, and almost 2 billion euros once medium-term bonds are also rolled over and serviced at higher rates.²⁴

The coefficient of D_3 is positive but not significant, suggesting that regional credit negative events are associated with some upward pressure on sovereign risk assessments at the margin, but the effect is not large enough to be significant. Finally, the coefficient of D_4 is large and negative, confirming that the ECB President Draghi's announcement of OMT

²³As could be expected, we also find the first single events to have the largest coefficients and to be the most significant. The total size of the financial assistance pledged at each point in time does not seem to be relevant. This result is in line with Attinasi et al. (2010), who find the size of financial rescue packages in Europe during the global financial crisis not to have a significant impact on government bond yields.

²⁴These figures are approximate and calculated on the basis of Q2-2013 central government debt figures from the Bank of Spain (2013): roughly 85 billion euros in short-term debt, and 173 billion in medium-term fixed-rate bonds. At end-June 2013, the bulk of Spanish central government debt was in long-term fixed-rate bonds (over 10-30 years). Using all marketable debt as a basis (730 billion euros) would imply an additional interest cost of about 5 billion euros per year.

coincided with a large reduction in markets' perceived sovereign credit risk in Spain, perhaps reflecting "exaggerated fears" (De Grauwe and Ji, 2013) or an unraveling of speculative positions betting on higher spreads.²⁵ The coefficient is not significant, which is not surprising given the limited power of a single event day. Likewise, both period dummies for the periods before the bailouts (PD1) and after President Draghi's speech (PD2) have a negative sign, implying that the Spanish sovereign CDS market was generally more distressed in 2012 (beyond what is captured by the explanatory variables), but the difference is relatively small and not significant.

The signs of the control variables are mostly in line with expectations. Changes in general risk aversion in Europe are associated with significant and positive changes in the Spanish CDS spread, consistent with findings in the literature. Changes in the bid/ask spread, our measure of liquidity, are associated with significant and negative changes in the Spanish CDS spread. Intuitively, one may expect a positive relationship, or higher spreads being associated with lower liquidity. The negative sign is reasonable in this particular context, however, if we assume that during this period the market for Spanish sovereign CDS was dominated by protection buyers motivated by proxy hedges or speculation that spreads would increase further. Specifically, our results indicate that those protection buyers would only be willing to pay a lower spread as the market becomes less liquid and the CDS instruments become harder to trade, reflected in the negative association between the bid/ask spread and CDS prices. Applying the same logic to the bond market, bond yields would be expected to rise (and bond prices to fall) in a less liquid market *ceteris paribus*, as issuers would need

²⁵In line with De Grauwe and Yin (2012)'s analysis of bond spreads, Becker (2009) finds that default probabilities contained in European sovereign CDS spreads during the 2008-09 financial crisis were excessive, even compared to bond yields' predictions, indicating the likely presence of speculation or cross-hedging (hedging financial sector risk with insurance for sovereign risk). Such factors may have been at play in Spain in 2012 as well.

to compensate investors for holding less liquid instruments.²⁶ This relationship is confirmed below in the case of our regional credit risk equation (4) with changes in regional bond yields on the left-hand side.

Our regression results on changes in bond yields issued by Valencia are shown in Table 3.34, column 1. The coefficients for both D_1 and D_2 are negative, confirming that both government pledges of support and concrete steps to provide financing to distressed regions are associated with lower bond yields. Specifically, pledges are associated with reductions of about 2 basis points, and concrete financial support measures with a statistically significant drop in yields by 16 basis points. Again, to put these findings in context, during the five event days represented by D_2 , Valencia's yield fell by about 80 basis points in total. While one may question the relevance of this finding, taking into account that Valencia—and other regions—remained shut of debt markets, it nonetheless constitutes a significant step towards regions ultimately being able to issue their own debt at sustainable rates.

The coefficient on D_3 is positive—credit negative events are associated with higher bond yields—but it is not significant. The coefficient on D_4 is again negative, suggesting that the ECB's announcement was associated with an immediate (albeit small) drop in the financing cost for Valencia. The fact that we find our period dummies (PD1 and PD2) to be significantly more negative for the pre-bailout and post-Draghi's speech era confirms the presence of significant upward pressure on Valencia's financing costs during the first half of 2012.

²⁶While the positive liquidity premium contained in bond yields is relatively uncontroversial, the existence, size and sign of any liquidity premium in CDS spreads remain the subject of debate. Empirical studies examining the size and the sign of the liquidity premium in the CDS market have produced a number of different results, especially across credit quality categories (higher or lower-rated instruments), maturities, and times of more or less market distress (Tang and Yan (2007); Bongaerts et al. (2011); Arakelyan et al. (2012)). Theoretically, if we assume that the bid/ask spread in bond prices and the bid/ask spread in CDS are positively correlated, investors demanding higher bond yields to compensate for illiquidity in the bond market could also produce higher CDS spreads via the non-arbitrage condition, thus inducing a positive relationship between CDS spreads and illiquidity. However, our results seem to indicate the dominance of protection buyers at the time.

The signs of the control variables in the regional credit risk equation are also generally in line with expectations. Increases in the bid/ask spread of bond yields (proxying for a reduction in liquidity); increases in sovereign credit risk; increases in general risk aversion; and increases in short-term interest rates are all positively associated with Valencia having to borrow at higher yields. As discussed before, these signs are all in line with our priors.

In sum, combining our estimation results for the Spanish sovereign's and Valencia's credit risks, we find evidence in support of a risk transfer having taken place. Specifically, the significantly positive coefficient on D_2 in the sovereign credit risk equation coinciding with a significantly negative coefficient on D_2 in the regional credit risk equation implies that concrete bailout measures in Spain in 2012 coincided with higher sovereign credit risk and lower bond yields in Valencia. Alternative explanations, while plausible ex-ante, are therefore not supported by the data.²⁷ However, as discussed above, obvious caveats apply given the difficulty of estimating high-frequency event studies in relatively shallow markets.

In order to find further support for our hypothesis, we also examine co-movements of our sovereign and regional credit risk measures across time. Should sovereign support for regions indeed lead to a closer link between market assessments of sovereign and regional risks, we would expect to see a greater co-movement between the sovereign and the regional financing costs after such interventions occurred. In order to test for this, we interact the period dummy for the pre-crisis period (PD1) with the sovereign credit risk variable in the regional credit risk equation for Valencia. If no shift had taken place, this interaction term should not be significantly negative, implying that regional credit risk did not become more sensitive to movements in sovereign credit risk as the bailouts unfolded. However, we find that the

²⁷For example, a (perfectly plausible) story that bailout announcements are viewed upon positively by markets as they reduce uncertainty would imply a negative coefficient on D_2 in both regressions. In contrast, the hypothesis that the bailout might reveal new regional risks to the market should lead to positive coefficients on D_2 in both estimations.

coefficient on the interaction term is significant and negative, almost exactly canceling out the significant and positive coefficient on the unconstrained sovereign credit risk variable (Table 3.34, column 1). In other words, we find the correlation between Valencia's bond yields and Spanish sovereign CDSs to become significant and positive in early 2012, after having been close to zero in the pre-bailout era up to end-2011, lending additional support to our hypothesis.²⁸ The only prior we cannot confirm is that regional credit negative events also started putting upward pressure on sovereign borrowing cost: the coefficient on D_3 in equation (3) is still positive, but not significant.²⁹

3.5 Robustness checks

We undertake a number of checks to determine the robustness of our results to changes in estimation methodology; to a pooling of events; to changes in the time window; and to inclusion of additional European sovereigns and Spanish regions.

In Tables 3.33 and 3.34, columns 2, we estimate the same coefficients using Newey-West standard errors, which adjust for heteroskedasticity and serial correlation (Newey and West, 1988). The results for both equations show only very small changes in coefficients and significance.³⁰ As common unobserved factors may lead to errors in both equations being

²⁸Including a separate interaction term of sovereign credit risk with the post-Draghi dummy (PD2) confirms even more pronounced co-movements after July 2012, as the FLA has started operating. Results are available upon request.

²⁹It is worth noting that the same is true for equation (4), meaning that also Valencia's yields were not significantly affected by those regional credit negative events, hence suggesting that overall the credit negative events chosen may not have been deemed significant from the markets' perspective.

³⁰In the sovereign equation, the significance of the key dummy variables D_1 was boosted to the 10% level, while the significance of D_2 decreases a bit to the 10% level. D_4 becomes highly significant under the Newey-West adjustment, but this result has to be interpreted with caution as asymptotic standard errors are not suitable to assess a single event's significance. Similarly, estimation results for the regional equation with Newey-West standard errors remain largely the same.

correlated, we also estimate both equations jointly, using seemingly unrelated regressions (SUR) (Tables 3.33 and 3.34, columns 3). Our results remain robust. In order to test for the robustness of our various event assumptions, we pool the dummies D_1 and D_2 together: they remain significant with our three estimation techniques (Tables 3.33 and 3.34, columns 5).³¹ We also test for significance of our event dummies up until 5 days before and after each event. The results need to be interpreted with caution, as we may be capturing a number of additional, unrelated events. However, they re-confirm the appropriateness of the event days chosen.³²

In Table 3.33 columns 4 and 6, we estimate the equation for sovereign risk under a fixed effect pooling panel specification with 11 other European countries.³³ The event dummies remain exclusive to Spain and are equal to zero for all other countries. If these European countries have the same coefficients of the control variables, pooling them together should help us estimate the coefficients more accurately. On the other hand, if they have different coefficients, estimating them separately would be more appropriate. Since we do not have a strong prior, we estimate the panel to see whether our main results are robust to modest variations in specification. Overall, there are some appreciable changes in coefficients. The estimated signs remain mostly the same, however, except that the coefficient on our liquidity proxy, the bid/ask spread of CDS, becomes positive—possibly because the general prior on the liquidity premium holds after all in our broader data set.³⁴ Importantly, the coefficient of the key variable D_2 remains stable, and its significance is boosted.

We also re-estimate the regional bond yield equation by adding two more regions: An-

³¹Newey-West adjusted and SUR estimations available on request.

³²Results available upon request.

³³See the Appendix 1 for a list of the countries included.

³⁴See discussion above.

dalucía and Catalonia (Table 3.34, columns 4 and 6).³⁵ As in the panel regression for sovereigns, both our main results still hold under this alternative specification: the coefficient on D_2 increases by 24 basis points and remains significant, and the coefficient on the interaction term of the pre-bailout period dummy and the sovereign credit risk variable remains negative and highly significant. As a final check, we drop the general risk aversion measure from the regional equation (Table 3.34, column 7). Since the iTraxx index is a significant determinant of changes in sovereign credit risk (Table 3.33), it might be preferable to drop it as a control variable in equation (4) to avoid multicollinearity. As Table 3.34 column 7 shows, our results for Valencia remain robust to this change in specification.

3.6 Conclusions and Policy Implications

As our findings for the Spanish 2012 sub-national credit crisis illustrate, fiscal risks emanating from SNGs can have significant implications for the sovereign's own creditworthiness. Similar to what was found in the case of financial sector bailouts in Europe in 2008-09, our analysis lends support to the hypothesis that sub-national bailouts might also have the capacity to influence markets' risk assessments of the entity bailing out a troubled debtor—specifically if the entity in question is under pressure itself. This could lead to potentially higher borrowing costs for already vulnerable central governments—in addition to the (commonly repayable) bailout amount committed up-front.³⁶

In light of these additional risks, central governments—apart from keeping their own fiscal house in order— may consider two policy options to guard against any potential negative

³⁵Unfortunately the bond yield data for these two regions are quite patchy, however, and data are missing on most event days.

³⁶The persistence of higher yields should be subject to further research.

spillovers: to establish a credible no bailout regime (as illustrated in Feld et al. 2013); or to try to ensure fiscal discipline at local government levels through means such as fiscal rules and regulations. In practice, few no-bailout regimes are fully credible due to the considerable spillover risks and social and political consequences of letting states or communities default: Spain—which boasted a no-bailout clause in its Constitution—is a key example. This makes tight fiscal controls on SNG finances inevitable, and, as the example of Spain its Organic Budget Law shows, many countries are moving in this direction.³⁷

Notably, even countries with relatively credible no-bailout regimes and high fiscal autonomy of SNGs (such as Switzerland or the US) boast almost universal, self-imposed borrowing restrictions at local government levels (Eyraud and Gomez-Sirera, 2013)—which are shown to reduce financing costs (Poterba and Rueben, 1999; Feld et al., 2013). Joint borrowing, another alternative to support sub-entities that was also considered in Spain, could lower financing costs of weaker entities, but would likely accomplish little to improve markets' risk perceptions and those entities' implicit risk premia. The main result would also be a financial transfer from the stronger to the weaker participants (as seen with the German Bund-Länder Anleihen, Appendix 2) and the creation of moral hazard that could exacerbate fiscal weaknesses even further.³⁸

³⁷The German Schuldenbremse that requires states to balance their books by 2020 is another example.

³⁸Whether the subsidy will be limited to the joint debt issue or the joint issue will affect the universe of sovereign borrowing should be the subject of further research. As in the case we study, the result is likely driven by initial fiscal conditions and the significance of the potential liability for central government debt.

Tables

Table 3.1: Data Filters (1985-2012)

Sample	Cleaning Criteria (Additive)	Ave. Firms per Month	Ave. % of CRSP Mkt Cap
CRSP	All CRSP common stocks in NYSE, AMEX, and NASDAQ	5,702	100%
	Nonmissing returns for the past 18 months	5,275	98%
Merge w/Comp	Book equity > 0 and COMPUSTAT history ≥ 3 years	4,453	94%
	Price per share > \$5 and Market value > NYSE bottom size decile	2,298	93%
CRSP/COMP	Exclude financial firms (SIC between 6000 and 6999)	1,880	77%
Sample	Cleaning Criteria (Additive)	Ave. Firms per Month	Ave. % of CRSP/COMP Mkt Cap
CRSP/COMP	See above	1,880	100%
Merge w/ IBES	Within the past quarter, No. of analysts FY1(FY2) forecasts ≥ 2	1,215	92%

Table 3.2: Characteristics for Momentum Quintile Portfolios

Stocks in the sample are non-financial common stocks in NYSE, AMEX, and NASDAQ with nonmissing returns for the past 18 months, price per share greater than \$5, market value larger than the NYSE bottom size decile, positive book equity, more than three year COMPUSTAT records, and at least two analysts' forecasts for the current fiscal year and two analysts' forecasts for the next fiscal year within the past quarter. Every month, stocks are sorted into momentum quintile portfolios by the past 11-month returns. Quintile breakpoints are calculated based on NYSE stocks only. Sorting is done monthly from 1988/1-2008/6. P1-P99 are variable values at corresponding percentiles. Market capitalization is measured at the end of the portfolio-formation month. Book-to-market ratios for July year t to June year $t + 1$ are the ratio of book equity of fiscal year $t - 1$ over the market value at December year $t - 1$. The number of following analysts are the number of analysts who issue annual forecasts in the last quarter for the nearest fiscal year that is at least six months away.

Market Capitalization (\$Millions)						
Mom_ Quintile	Mean	P1	P25	P50	P75	P99
1	3,104	69	282	611	1,658	51,286
2	5,385	75	441	1,111	3,222	78,893
3	6,333	90	579	1,448	4,162	87,930
4	6,314	94	590	1,491	4,377	84,842
5	4,867	84	434	1,029	2,904	72,328
All	5,129	79	429	1,067	3,122	74,586
Book-to-market Ratio						
Mom_ Quintile	Mean	P1	P25	P50	P75	P99
1	0.64	0.04	0.29	0.49	0.80	2.96
2	0.58	0.05	0.28	0.46	0.75	2.29
3	0.53	0.04	0.26	0.43	0.69	2.04
4	0.46	0.03	0.22	0.36	0.59	1.76
5	0.31	0.01	0.12	0.23	0.39	1.40
All	0.49	0.02	0.21	0.38	0.64	2.19
Number of Following Analysts						
Mom_ Quintile	Mean	P1	P25	P50	P75	P99
1	7.83	2	4	6	10	26
2	7.82	2	4	6	10	26
3	7.72	2	4	6	10	25
4	7.58	2	4	6	10	25
5	7.36	2	4	6	9	26
All	7.65	2	4	6	10	25

Table 3.3: *Momentum and Reversal*

I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Stocks are then sorted into momentum quintile portfolios based on these breakpoints and held for 24 months. The winner-minus-loser portfolio is formed by taking a long position in the highest quintile portfolio and a short position in the lowest quintile portfolio. Sorting is done monthly from 1988/1-2008/6. Returns are equally weighted returns. Average monthly returns in the months after sorting are shown in the following table.

		EW Portfolio Average Monthly Return (Percent)											
n^{th}	Month after Sorting	1	2	3	4	5	6	7	8	9	10	11	12
	Ave. Monthly Return	0.67	0.86	0.71	0.55	0.49	0.32	0.05	-0.04	-0.32	-0.48	-0.39	-0.49
	T-stat	1.9	2.6	2.3	1.9	1.7	1.1	0.2	-0.1	-1.2	-1.7	-1.5	-1.9
n^{th}	Month after Sorting	13	14	15	16	17	18	19	20	21	22	23	24
	Ave. Monthly Return	-0.59	-0.24	-0.20	-0.10	-0.08	-0.19	-0.17	-0.20	-0.24	-0.45	-0.38	-0.40
	T-stat	-2.2	-0.9	-0.8	-0.4	-0.3	-0.8	-0.7	-0.9	-1.1	-2.1	-1.8	-1.9

Table 3.4: *Dynamics of Forecast Errors*

I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Stocks are then sorted into momentum quintile portfolios based on these breakpoints and held for 24 months. The cross sectional differences in forecast errors between winner and loser portfolios between month k and month $k + 2$ in the holding period are calculated. This table reports the averages and the t statistics. For details regarding calculations of forecast errors, please refer to Section 1.5.1 or Figure 3.7. T -statistics are calculated based on Newey-West standard errors with 18 lags.

Portfolio Median Forecast Errors													
Months in the Holding Period		1-3	2-4	3-5	4-6	5-7	6-8	7-9	8-10	9-11	10-12	11-13	12-14
Ave. Winner-Loser Diff.		18.1%	16.0%	14.0%	12.2%	10.6%	9.0%	7.5%	6.5%	5.4%	4.5%	3.9%	3.3%
T-stat		8.1	8.1	7.7	7.3	7.0	6.7	6.1	5.4	4.6	3.8	3.2	2.6
Months in the Holding Period		13-15	14-16	15-17	16-18	17-19	18-20	19-21	20-22	21-23	22-24	23-25	24-26
Ave. Winner-Loser Diff.		3.1%	2.7%	2.4%	2.2%	1.9%	1.7%	1.6%	1.7%	1.8%	2.0%	1.9%	2.0%
T-stat		2.3	2.1	2.0	1.9	1.7	1.6	1.6	1.7	1.7	1.9	2.0	2.0

Table 3.5: Regression of Forecast Errors

I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Stocks are then sorted into momentum quintile portfolios based on these breakpoints and held for 24 months. $mom_{i,t}$ is the quintile momentum ranking for firm i . $FE_{t+k \rightarrow t+k+2}^i$ is the forecast error for the median forecast made for firm i between month k and month $k+2$ in the holding period, and t signifies the portfolio-formation month. $Yearmon_t$ is the year-month dummy to control for the time fixed effect. Standard errors are clustered at the firm level to account for the serial correlation. Forecast errors are winsorized at the 2.5% level at both tails. Regressions are in the following form:

$$FE_{i,t+k \rightarrow t+k+2} = c_k + \lambda_k mom_{i,t} + Yearmon_t + \epsilon_{i,t+k \rightarrow t+k+2}$$

k	1	2	3	4	5	6	7	8	9	10	11	12
λ_k	0.073*** (32.82)	0.068*** (29.13)	0.061*** (25.89)	0.056*** (22.82)	0.050*** (20.13)	0.045*** (17.93)	0.041*** (16.21)	0.038*** (14.64)	0.034*** (13.07)	0.031*** (11.94)	0.029*** (11.10)	0.027*** (10.35)
N	246164	244829	243289	241752	240322	238976	237737	236465	235063	233865	231458	229630
R^2	0.061	0.056	0.052	0.049	0.047	0.046	0.045	0.044	0.042	0.041	0.041	0.041
N_clust	4465	4440	4399	4355	4323	4265	4207	4190	4159	4128	4094	4064
k	13	14	15	16	17	18	19	20	21	22	23	24
λ_k	0.025*** (9.67)	0.024*** (9.15)	0.023*** (8.52)	0.022*** (7.99)	0.021*** (7.63)	0.020*** (7.28)	0.019*** (7.02)	0.019*** (6.78)	0.018*** (6.55)	0.018*** (6.34)	0.017*** (6.03)	0.017*** (5.97)
N	227989	226516	225011	223578	222313	221235	220143	218933	217635	216478	214436	212980
R^2	0.041	0.041	0.04	0.04	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041
N_clust	4024	3993	3964	3928	3878	3820	3761	3740	3730	3707	3690	3661

* p < 0.1, ** p < 0.05, *** p < 0.01

Table 3.6: Regressions of Forecast Errors (w /controls)

$$FE_{t+k \rightarrow t+k+2}^i = \hat{\lambda}_{i+k} mom_{i,t} + \rho_{1,k} SUE_{i,t} + \rho_{2,k} SUE_{i,t,L1} + \rho_{3,k} EAR_{i,t} + \rho_{4,k} EAR_{i,t,L1} + \rho_{5,k} REV_{i,t} + \rho_{6,k} REV_{i,t,L1} + \rho_{7,k} REV_{i,t,L2} + Y_{earmon_t} + \eta_{i,t+h}$$

I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Stocks are then sorted into momentum quintile portfolios based on these breakpoints and held for 24 months. $mom_{i,t}$ is the quintile momentum ranking for firm i . $FE_{t+k \rightarrow t+k+2}^i$ is the forecast error for the median forecast made for firm i between month k and month $k+2$ in the holding period, and t signifies the portfolio-formation month.

$SUE_{i,t}$ is the last quarterly earnings surprise before month t , defined as IBES actual earnings minus analyst forecasts divided by prices at the fiscal quarter-end; $EAR_{i,t}$ is the three-day returns at the last quarterly earnings announcement before month t ; and $REV_{i,t}$ is the percentage forecast changes in the last calendar quarter, defined as the difference between the median annual forecast over month $t-2$ to t and the median annual forecast over month $t-5$ to $t-3$, scaled by the absolute value of the latter. $L1$ signifies one lag. $L2$ signifies two lags. Forecast errors and other non-return variables are winsorized at the 2.5% level at both tails.

k	1	2	3	4	5	6	7	8	9	10	11	12
λ_k	0.035*** (14.9)	0.033*** (13.4)	0.030*** (12.1)	0.027*** (10.6)	0.024*** (9.1)	0.022*** (8.0)	0.020*** (7.3)	0.018*** (6.6)	0.016*** (5.7)	0.014*** (5.1)	0.013*** (4.6)	0.011*** (3.8)
EAR_t	0.149*** (4.0)	0.136*** (3.6)	0.114*** (2.9)	0.090** (2.1)	0.059 (1.4)	0.036 (0.9)	0.023 (0.6)	0.033 (0.8)	0.02 (0.5)	0.015 (0.3)	0.021 (0.5)	0.026 (0.6)
lag EAR_t	-0.047 (-1.29)	-0.063* (-1.73)	-0.085** (-2.26)	-0.093** (-2.33)	-0.079** (-2.01)	-0.082** (-2.03)	-0.089** (-2.12)	-0.085** (-2.08)	-0.067 (-1.62)	-0.052 (-1.22)	-0.051 (-1.26)	-0.043 (-1.04)
sue	8.631*** (9.7)	7.895*** (8.7)	7.346*** (7.8)	6.729*** (6.9)	5.546*** (5.9)	5.085*** (5.4)	5.122*** (5.3)	5.674*** (6.0)	6.464*** (6.6)	6.713*** (6.7)	6.170*** (6.2)	5.488*** (5.4)
lag sue	1.994** (2.5)	1.451* (1.8)	1.299 (1.6)	1.328 (1.6)	2.123** (2.5)	2.876*** (3.3)	3.490*** (3.8)	3.257*** (3.6)	2.867*** (3.1)	2.861*** (3.0)	3.009*** (3.3)	3.153*** (3.6)
rev1	0.466*** (21.1)	0.457*** (20.2)	0.438*** (18.9)	0.429*** (17.5)	0.427*** (17.5)	0.400*** (16.9)	0.365*** (15.5)	0.316*** (14.1)	0.264*** (12.0)	0.222*** (10.1)	0.199*** (9.4)	0.205*** (9.8)
rev2	0.258*** (12.9)	0.269*** (13.5)	0.262*** (13.1)	0.236*** (11.3)	0.188*** (9.8)	0.144*** (8.0)	0.112*** (6.1)	0.114*** (6.2)	0.131*** (7.0)	0.151*** (7.7)	0.150*** (7.8)	0.143*** (7.5)
rev3	0.176*** (8.9)	0.141*** (7.4)	0.123*** (6.5)	0.117*** (5.9)	0.122*** (6.2)	0.142*** (7.1)	0.162*** (7.8)	0.168*** (8.4)	0.168*** (8.5)	0.158*** (7.5)	0.147*** (6.9)	0.135*** (6.4)
R^2	0.125	0.112	0.1	0.089	0.08	0.071	0.065	0.061	0.057	0.055	0.053	0.053

* p < 0.1, ** p < 0.05, *** p < 0.01

Table 3.7: Regressions of Forecast Errors ($w/controls$) Continued

k	13	14	15	16	17	18	19	20	21	22	23	24
λ_k	0.010*** (3.5)	0.010*** (3.3)	0.009*** (3.1)	0.009*** (2.9)	0.008*** (2.6)	0.008*** (2.5)	0.009*** (2.9)	0.009*** (2.9)	0.009*** (2.8)	0.009*** (2.7)	0.008*** (2.5)	0.009*** (2.6)
EAR_t	0.014 (0.3)	-0.001 (-0.02)	-0.015 (-0.35)	-0.029 (-0.65)	0	0.024 (0.6)	0.032 (0.7)	0.02	0.009 (0.2)	0.005 (0.1)	0.023 (0.5)	0.028 (0.7)
lag EAR_t	-0.039 (-0.90)	-0.018 (-0.45)	0.003 (0.1)	0.017 (0.4)	0.01	-0.003 (-0.07)	-0.022 (-0.51)	0.004 (0.1)	0.011 (0.3)	0.017 (0.4)	-0.005 (-0.13)	-0.039 (-0.91)
sue	5.035*** (4.8)	4.478*** (4.5)	4.492*** (4.5)	4.567*** (4.7)	4.593*** (4.8)	4.552*** (4.8)	4.289*** (4.5)	3.699*** (4.0)	3.278*** (3.4)	2.729*** (2.8)	2.363*** (2.5)	2.311*** (2.4)
lag sue	3.454*** (3.9)	3.688*** (4.2)	3.754*** (4.0)	3.473*** (3.6)	3.298*** (3.4)	2.739*** (2.9)	2.492*** (2.5)	2.195*** (2.3)	2.147*** (2.1)	2.056*** (2.0)	2.241*** (2.2)	2.005*** (2.0)
rev1	0.207*** (9.7)	0.217*** (9.9)	0.218*** (9.8)	0.215*** (9.2)	0.216*** (9.1)	0.209*** (8.8)	0.194*** (8.1)	0.164*** (7.1)	0.135*** (5.9)	0.111*** (4.9)	0.098*** (4.4)	0.093*** (4.2)
rev2	0.129*** (6.4)	0.124*** (6.0)	0.122*** (5.8)	0.108*** (5.1)	0.080*** (4.1)	0.057*** (3.0)	0.037*** (1.9)	0.035* (1.9)	0.041** (2.1)	0.055*** (2.6)	0.078*** (3.7)	0.091*** (4.3)
rev3	0.116*** (5.6)	0.083*** (4.1)	0.056*** (2.8)	0.048** (2.3)	0.051** (2.5)	0.064*** (3.0)	0.073*** (3.2)	0.101*** (4.2)	0.118*** (4.9)	0.137*** (5.7)	0.133*** (5.8)	0.122*** (5.3)
R^2	0.052	0.05	0.05	0.048	0.047	0.047	0.046	0.045	0.045	0.045	0.046	0.046

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.8: *Return Decomposition*

This table reports results from cross-sectional regressions of stock returns on earnings forecast revisions. Forecast revisions are defined as $Rev_{t \rightarrow t+3} = \frac{EF_{t,t+3} - EF_{t-3,t}}{P_t}$, where $EF_{t,t+3}$ is the median of newly issued forecasts between months t and $t+3$. Due to the synchronization issues, we use the average of four consecutive, non-overlapping forecast revisions $\overline{REV_{t-12 \rightarrow t}^i} = \frac{1}{4} \sum_{i=1}^4 REV_{t-3 \times i \rightarrow t-3 \times (i-1)}$ as the regressor. Same treatment to stocks returns, $\overline{r_{t-12 \rightarrow t}} = \frac{1}{4} \sum_{i=1}^4 r_{t-3 \times i \rightarrow t-3 \times (i-1)}$. Cross-sectional regressions are run every month. Independent variables are winsorized at the 5% and 95% levels, more aggressive than other analysis in the paper to ensure that the coefficients reflect the characteristics of the main sample. The sample covers 1985-2011.

Panel A: T statistics of β_t from the regressions of the form $r_t^i = \beta_t' \mathbf{x}_t^i + \epsilon_t^i$						
Time Series Summary Statistics (1985-2011)						
$\mathbf{x}_t^i$	$\overline{\beta_t}$	Mean	P25	P50	P75	N
$\overline{REV_{t-12,t}^i}$	4.34	10.31	8.31	10.41	12.56	324
$\log BM_{t-12}^i$	0.01	3.54	0.06	2.93	5.66	324
$\log BM_{t-12}^i \times \overline{REV_{t-12,t}^i}$	-1.10	-2.73	-4.50	-2.93	-1.10	324

Panel B: R^2 from regressions of the form $r_t^i = \beta_t' \mathbf{x}_t^i + \epsilon_t^i$						
Time Series Summary Statistics (1985-2011)						
	Mean	P25	P50	P75		N
R^2	0.16	0.12	0.16	0.20		324

Table 3.9: *Fama-Macbeth Regression of Returns on Two Components of Past Returns*

This table reports results from Fama and Macbeth regressions of stock returns on two components of past six-month returns: the cash flow component and the residual component. The cash flow component is defined as $CF_{t-n,-6}^i = (\beta_{REV} + \beta_{\log BM \times REV} \log BM_{t-n-12}^i) \frac{REV_{t-n-6,t-n-3}^i + REV_{t-n-3,t-n}^i}{2}$, β_{REV} and $\beta_{\log BM \times REV}$ are coefficients from Regression (1.6). The residual component is defined as $\widetilde{r_{t-n,-6}^i} = \frac{r_{t-n-6,t-n-3}^i + r_{t-n-3,t-n}^i}{2} - CF_{t-n,-6}^i$. The sample is winsorized at the 1% and 99% levels and covers 1988 to 2011.

Independent Variables x_{t-n}^i	Lag n											
	1	2	3	4	5	6	7	8	9	10	11	12
$\widetilde{r_{t-n,-6}^i}^a$	-0.13	0.47	0.84	0.93	0.98	1.22	1.54	1.05	0.42	0.43	0.12	-0.60
	[-0.23]	[0.84]	[1.53]	[1.86]	[1.89]	[2.32]	[3.15]	[2.20]	[0.91]	[1.02]	[0.28]	[-1.49]
	4.25	2.87	1.99	1.80	2.36	1.34	0.95	0.83	0.24	-0.02	-0.76	-0.67
$CF_{t-n,-6}^i$	[3.73]	[2.45]	[1.71]	[1.65]	[2.21]	[1.24]	[0.91]	[0.85]	[0.25]	[-0.03]	[-0.81]	[-0.68]
	13	14	15	16	17	18	19	20	21	22	23	24
$\widetilde{r_{t-n,-6}^i}$	-1.05	-1.17	-1.44	-1.06	-1.04	-0.50	0.39	0.18	0.31	0.62	0.33	-0.27
	[-2.70]	[-2.86]	[-3.38]	[-2.47]	[-2.39]	[-1.21]	[0.96]	[0.44]	[0.78]	[1.52]	[0.83]	[-0.70]
	-0.75	-0.69	-0.38	-0.92	0.45	0.35	0.11	0.20	-0.14	-0.21	-1.41	-1.81
$CF_{t-n,-6}^i$	[-0.77]	[-0.68]	[-0.37]	[-0.97]	[0.47]	[0.38]	[0.11]	[0.22]	[-0.15]	[-0.21]	[-1.51]	[-1.96]

$$^a \gamma_t^i = \beta_{rev} + \beta_{BM} \times \log BM_{t-12}^i$$

Table 3.10: Forecast Errors for Momentum/Underreaction Ranking Portfolios

I form momentum tertile breakpoints from all NYSE firms based on their past 11-month returns. I form underreaction quintile breakpoints from stocks in my sample based on their underreaction betas (see equation 1.8 in the text). Stocks are then sorted into three momentum groups and five underreaction groups based on these breakpoints. $Under_{i,t+k}$ is the quintile underreaction ranking for firm i . $mom_{i,t}$ is the tertile momentum ranking for firm i . $FE_{i,t+k \rightarrow t+k+2}$ is the forecast error for the median forecast made between holding months $t+k$ and $t+k+3$ for firm i . The following regression tests whether the gap in the forecast errors across momentum rankings is significantly wider for stocks with the highest underreaction ranking. Standard errors are clustered at the firm level to account for the serial correlation. Forecast errors are winsorized at the 2.5% level at both tails. A year-month dummy is added to control for time fixed effect.

$$FE_{i,t+k \rightarrow t+k+2} = c_1^k + c_2^k I(Under_{i,t+k} = 5) + \lambda_k mom_{i,t} + \beta^k I(Under_{i,t+k} = 5) \times mom_{i,t} + Yearmon_t + \epsilon_{i,t+k}$$

k	1	2	3	4	5	6	7	8	9	10	11	12
λ_k	0.118***	0.109***	0.100***	0.092***	0.082***	0.073***	0.067***	0.061***	0.054***	0.049***	0.045***	0.042***
	29.06	26.10	23.30	20.79	18.17	16.03	14.46	12.88	11.23	10.00	9.24	8.47
β^k	0.057***	0.058***	0.054***	0.051***	0.049***	0.048***	0.045***	0.044***	0.043***	0.042***	0.039***	0.037***
	5.74	5.58	5.14	4.70	4.54	4.41	3.96	3.85	3.80	3.65	3.45	3.35
R^2	0.061	0.056	0.052	0.048	0.044	0.041	0.04	0.039	0.038	0.038	0.038	0.039
k	13	14	15	16	17	18	19	20	21	22	23	24
λ_k	0.039***	0.037***	0.036***	0.035***	0.035***	0.033***	0.033***	0.033***	0.034***	0.033***	0.034***	0.034***
	7.76	7.35	6.89	6.59	6.52	6.24	6.07	6.05	6.12	6.06	6.14	6.18
β^k	0.036***	0.035***	0.031***	0.027**	0.023**	0.021*	0.017	0.012	0.006	0.001	-0.007	-0.009
	3.29	3.28	2.84	2.45	2.14	1.93	1.54	1.09	0.52	0.05	-0.63	-0.91
R^2	0.039	0.039	0.039	0.039	0.039	0.039	0.04	0.04	0.04	0.04	0.04	0.041

* p < 0.1, ** p < 0.05, *** p < 0.01

Table 3.11: Monthly Returns of Momentum Portfolios across Underreaction Ranking Quintiles

I form momentum tertile breakpoints from all NYSE firms based on their past 11-month returns. I form underreaction quintile breakpoints from stocks in my sample based on their underreaction betas (see equation 1.8 in the text). Stocks are then sorted into three momentum groups and five underreaction groups based on these breakpoints. The average monthly returns (in percent) of winner-minus-loser momentum portfolios are calculated for months in the holding period. Standard errors are Newey-West standard errors with lags.

Underreaction Ranking Quintile	Months	1-6	7-9	7-24
5 (High)	Ave. Ret	0.68***	0.25	-0.11
	T stat	2.8	1.0	-0.6
1 to 4 (Low)	Ave. Ret	0.44**	-0.16	-0.28
	T stat	2.2	-0.8	-1.6
High-minus-Low	Ave. Ret	0.24**	0.41**	0.17*
	T stat	2.1	2.3	1.8

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.12: Summary Statistics of USD Carry Trade Returns

This table presents summary statistics on the monthly zero-investment portfolio returns for five carry-trade strategies. The strategies are the basic equal-weighted (*EQ*) and spread-weighted (*SPD*) strategies, and their risk-rebalanced versions (labeled “-*RR*”) as well as a mean-variance optimized strategy (*OPT*). The weights in the basic strategies are calibrated to have one dollar at risk each month. The risk-rebalanced strategies rescale the basic weights by IGARCH estimates of a covariance matrix to target a 5 The *OPT* strategy is a conditional mean-variance efficient strategy at the beginning of each month, based on the IGARCH conditional covariance matrix and the assumption that the expected future excess currency return equals the interest rate differential. The sample period is 1976:02-2013:08 except for the AUD and the NZD, which start in October 1986. The reported parameters, (mean, standard deviation, skewness, excess kurtosis, and autocorrelation coefficient) and their associated standard errors are simultaneous GMM estimates. The Sharpe ratio is the ratio of the annualized mean and standard deviation, and its standard error is calculated using the delta method (see Appendix B.1.)

	Carry Trade Weighting Method				
	EQ	EQ-RR	SPD	SPD-RR	OPT
Ave Ret (% p.a.)	3.96	5.44	6.60	6.18	2.10
(std. err.)	(0.91)	(1.13)	(1.31)	(1.09)	(0.47)
Standard Deviation	5.06	5.90	7.62	6.08	2.62
(std. err.)	(0.28)	(0.22)	(0.41)	(0.24)	(0.17)
Sharpe Ratio	0.78	0.92	0.87	1.02	0.80
(std. err.)	(0.19)	(0.20)	(0.19)	(0.19)	(0.20)
Skewness	-0.49	-0.37	-0.31	-0.44	-0.89
(std. err.)	(0.21)	(0.11)	(0.19)	(0.14)	(0.34)
Excess Kurtosis	2.01	0.40	1.78	0.90	3.91
(std. err.)	(0.53)	(0.21)	(0.35)	(0.29)	(1.22)
Autocorrelation	0.08	0.16	0.02	0.09	0.06
(std. err.)	(0.07)	(0.05)	(0.07)	(0.05)	(0.07)
Max (% per month)	4.78	5.71	8.07	5.96	3.21
Min (% per month)	-6.01	-4.90	-7.26	-5.88	-4.01
No. Positive	288	288	297	297	303
No. Negative	163	163	154	154	148

Table 3.13: Summary Statistics of the Carry Trade by Currency of Investor

This table presents summary statistics on the monthly zero-investment portfolio returns to the equal weight strategy with each currency as the base. The sample period is 1976:02-2013:08 except for the AUD and the NZD, which start in October 1986. The reported parameters, (mean, standard deviation, skewness, excess kurtosis, and autocorrelation coefficient) and their associated standard errors are simultaneous GMM estimates. The Sharpe ratio is the ratio of the annualized mean and standard deviation, and its standard error is calculated using the delta method (see Appendix B.1.)

	Carry Trade Base Currency									
	CAD	EUR	JPY	NOK	SEK	CHF	GBP	NZD	AUD	USD
Average Return	3.02	2.69	3.40	2.67	2.33	3.05	3.09	3.92	3.23	3.96
(std. err.)	(0.73)	(0.90)	(1.70)	(0.84)	(1.02)	(1.21)	(0.97)	(1.50)	(1.41)	(0.88)
Standard Deviation	4.26	5.33	9.58	5.09	5.97	7.20	5.60	8.47	7.61	5.06
(std. err.)	(0.21)	(0.26)	(0.61)	(0.31)	(0.80)	(0.40)	(0.37)	(0.80)	(0.63)	(0.27)
Sharpe Ratio	0.71	0.50	0.36	0.52	0.39	0.42	0.55	0.46	0.42	0.78
(std. err.)	(0.18)	(0.17)	(0.19)	(0.18)	(0.21)	(0.17)	(0.18)	(0.19)	(0.20)	(0.19)
Skewness	-0.11	0.14	-0.79	-0.64	-3.77	-0.34	-0.26	-0.90	-0.97	-0.49
(std. err.)	(0.20)	(0.19)	(0.38)	(0.38)	(0.92)	(0.31)	(0.45)	(0.36)	(0.32)	(0.21)
Excess Kurtosis	1.53	1.43	3.68	3.71	30.24	2.41	4.41	5.57	4.15	2.01
(std. err.)	(0.36)	(0.46)	(1.64)	(1.24)	(7.37)	(0.87)	(1.48)	(1.58)	(1.87)	(0.53)
Autocorrelation	0.03	0.02	0.07	0.01	0.07	-0.02	0.10	-0.11	-0.07	0.08
(std. err.)	(0.07)	(0.06)	(0.08)	(0.06)	(0.05)	(0.06)	(0.06)	(0.10)	(0.11)	(0.06)
Max % per month	4.71	6.61	9.09	6.95	5.04	9.85	8.53	9.28	7.55	4.78
Min % per month	-4.24	-4.87	-16.02	-7.74	-16.47	-9.69	-8.69	-13.55	-12.28	-6.01
No. Positive	283	274	268	274	285	258	276	192	194	288
No. Negative	168	177	183	177	166	193	175	130	128	163

Table 3.14: Hedged Carry Trade Performance

This table presents summary statistics for the currency-hedged carry trades. The currency return data are monthly from 2000:10-2013:08. All nine currencies are included over the full sample in calculating the equal-weighted (EQ) and spread-weighted (SPD) strategies in the text. The reported parameters (mean, standard deviation, skewness, excess kurtosis, and autocorrelation coefficient) and their associated standard errors are simultaneous GMM estimates. The Sharpe ratio is the ratio of the annualized mean and standard deviation, and its standard error is calculated using the delta method (see Appendix B.1.) The hedging strategy is described in Section 2.2.5.

	Unhedged		Hedged			
	EQ	SPD	EQ-10 δ	EQ-25 δ	SPD-10 δ	SPD-25 δ
Ave Ret (% p.a.)	3.11	5.49	1.96	1.45	5.21	4.26
(std. err.)	(1.52)	(2.51)	(1.23)	(1.06)	(2.19)	(1.87)
Standard Deviation	5.28	8.45	4.44	4.05	7.53	6.65
(std. err.)	(0.44)	(0.79)	(0.34)	(0.32)	(0.69)	(0.62)
Sharpe Ratio	0.59	0.65	0.44	0.36	0.69	0.64
(std. err.)	(0.30)	(0.31)	(0.28)	(0.26)	(0.29)	(0.27)
Skewness	-0.19	-0.21	-0.01	0.23	0.28	0.70
(std. err.)	(0.24)	(0.28)	(0.17)	(0.25)	(0.25)	(0.26)
Excess Kurtosis	1.02	1.83	0.41	0.70	1.40	1.54
(std. err.)	(0.40)	(0.57)	(0.30)	(0.37)	(0.57)	(0.60)
Autocorrelation	-0.04	0.02	-0.10	-0.15	-0.02	-0.07
(std. err.)	(0.11)	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)
Max (% per month)	4.60	8.03	3.75	3.48	7.67	7.01
Min (% per month)	-4.53	-7.26	-2.95	-3.52	-6.30	-4.75
No. Positive	95	100	93	87	97	91
No. Negative	60	55	62	68	58	64

Table 3.15: Carry Trade Exposures to Basic Equity Risks

This table regresses the carry trade returns of five different strategies on three equity market risk factors postulated by Fama and French (1993): the excess return on the market portfolio; the excess return on small market capitalization stocks over big capitalization stocks; and the excess return of high book-to-market stocks over low book-to-market stocks as in the following. The regression specification is

$$R_t = \alpha + \beta_{MKT} \cdot R_{m,t} + \beta_{HML} \cdot R_{HML,t} + \beta_{SMB} \cdot R_{SMB,t} + \varepsilon_t$$

The Fama-French factors are from Ken French's data library. The sample period is 1976:02-2013:08 except for the AUD and the NZD, which start in October 1986. The reported alphas are annualized percentage terms. Autocorrelation and heteroskedasticity consistent t-statistics from GMM are in parentheses.

	EQ	SPD	EQ-RR	SPD-RR	OPT
α	3.39	5.34	4.95	5.55	1.83
t-stat	(3.76)	(4.00)	(4.27)	(4.84)	(3.72)
β_{MKT}	0.05	0.10	0.05	0.06	0.02
t-stat	(2.46)	(2.88)	(2.25)	(2.33)	(1.88)
β_{SMB}	-0.03	0.00	-0.03	-0.01	0.01
t-stat	(-0.90)	(0.06)	(-0.89)	(-0.18)	(0.96)
β_{HML}	0.07	0.13	0.05	0.07	0.03
t-stat	(2.21)	(2.93)	(1.62)	(2.27)	(1.98)
R^2	0.04	0.05	0.02	0.02	0.02
NOBS	451	451	451	451	451

Table 3.16: Carry Trade Exposures to FX Risks

This table regresses the carry trade returns of five different strategies on the two pure foreign exchange risk factors constructed by Lustig, Roussanov, and Verdelhan (2011): the average return on six carry trade portfolios sorted by currency interest differential versus the dollar, RX; and the excess return of the highest interest differential portfolio over the lowest interest differential portfolio, HML-FX. The regression specification is

$$R_t = \alpha + \beta_{RX} \cdot R_{RX,t} + \beta_{HML-FX} \cdot R_{HML-FX,t} + \varepsilon_t$$

The RX and HML-FX factor return data are from Adrien Verdelhan's web site, and the sample period is 1983:11-2013:08. The reported alphas are in annualized percentage terms. Autocorrelation and heteroskedasticity consistent t-statistics from GMM are in parentheses.

Before Transaction Costs	EQ	SPD	EQ-RR	SPD-RR	OPT
α	1.47	2.86	2.86	3.60	1.29
t-stat	(1.73)	(2.34)	(2.81)	(3.44)	(2.87)
β_{RX}	0.14	0.31	0.01	0.11	0.01
t-stat	(2.27)	(3.33)	(0.24)	(1.56)	(0.45)
β_{HML-FX}	0.28	0.39	0.34	0.32	0.09
t-stat	(8.24)	(7.04)	(8.85)	(6.57)	(6.22)
R^2	0.31	0.34	0.29	0.28	0.13
NOBS	358	358	358	358	358

Table 3.17: Carry Trade Exposures to Bond Risks

This table regresses the carry trade returns of five different strategies on the excess return on the U.S. equity market and two USD bond market risk factors: the excess return on the 10-year Treasury bond, 10y; and the excess return of the 10-year bond over the two-year Treasury note, 10y-2y. The regression specification is

$$R_t = \alpha + \beta_{MKT} \cdot R_{m,t} + \beta_{10y} \cdot R_{10y,t} + \beta_{10y-2y} \cdot (R_{10y,t} - R_{2y,t}) + \varepsilon_t$$

The reported alphas are in annualized percentage terms. Autocorrelation and heteroskedasticity consistent t-statistics from GMM are in parentheses. The sample period is 1976:01-2013:08.

	EQ	SPD	EQ-RR	SPD-RR	OPT
α	4.19	6.71	5.74	6.43	2.15
t-stat	(4.51)	(4.97)	(5.03)	(5.74)	(4.65)
β_{MKT}	0.04	0.08	0.04	0.04	0.02
t-stat	(1.81)	(2.36)	(1.92)	(2.01)	(1.74)
β_{10y}	-0.39	-0.51	-0.44	-0.41	-0.12
t-stat	(-2.97)	(-2.72)	(-4.25)	(-3.74)	(-2.97)
β_{10y-2y}	0.46	0.59	0.50	0.47	0.14
t-stat	(2.46)	(2.21)	(3.26)	(2.93)	(2.30)
R^2	0.05	0.05	0.05	0.04	0.02
NOBS	451	451	451	451	451

Table 3.20: Summary Statistics of Dollar-Neutral and Pure-Dollar Trades

This table presents summary statistics on the monthly zero-investment portfolio returns for four carry-trade strategies. The strategies are the basic equal-weighted (EQ) and dollar-neutral ($EQ0$) strategies, as well as the strategy ($EQ-minus$) which is the difference between EQ and $EQ0$. The fourth portfolio is pure dollar carry ($EQ-USD$). The weights in the strategies are discussed in the main text. The sample period is 1976:02-2013:08 except for the AUD and the NZD, which start in October 1986. The reported parameters, (mean, standard deviation, skewness, excess kurtosis, and autocorrelation coefficient) and their associated standard errors are simultaneous GMM estimates. The Sharpe ratio is the ratio of the annualized mean and standard deviation, and its standard error is calculated using the delta method (see Appendix B.1.) Panel A reports the results for the full sample, while Panel B reports results for the later half of the sample 1990:02-2013:08 when variance swap data become available.

Panel A: 1976/02-2013/08					Panel B: 1990/2-2013/8				
	EQ	$EQ0$	$EQ-minus$	$EQ-USD$	EQ	$EQ0$	$EQ-minus$	$EQ-USD$	
Ave Ret (% p.a.)	3.96	1.61	2.35	5.54	3.83	1.72	2.11	5.21	
(std. err.)	(0.91)	(0.58)	(0.66)	(1.37)	(1.17)	(0.72)	(0.92)	(1.60)	
Standard Deviation	5.06	3.28	3.85	8.18	5.43	3.30	4.31	7.89	
(std. err.)	(0.28)	(0.16)	(0.28)	(0.38)	(0.36)	(0.21)	(0.35)	(0.47)	
Sharpe Ratio	0.78	0.49	0.61	0.68	0.70	0.52	0.49	0.66	
(std. err.)	(0.19)	(0.19)	(0.18)	(0.18)	(0.24)	(0.23)	(0.23)	(0.21)	
Skewness	-0.49	-0.47	-0.65	-0.11	-0.60	-0.47	-0.76	-0.05	
(std. err.)	(0.21)	(0.19)	(0.44)	(0.17)	(0.22)	(0.28)	(0.45)	(0.22)	
Excess Kurtosis	2.01	1.34	4.84	0.86	1.68	1.66	3.87	1.04	
(std. err.)	(0.53)	(0.51)	(2.00)	(0.31)	(0.57)	(0.71)	(1.86)	(0.38)	
Autocorrelation	0.08	0.05	0.05	0.00	0.05	0.05	0.05	-0.03	
(std. err.)	(0.07)	(0.06)	(0.06)	(0.06)	(0.08)	(0.07)	(0.06)	(0.07)	
Max (% per month)	4.78	3.28	3.83	9.03	4.60	3.28	3.80	9.03	
Min (% per month)	-6.01	-3.92	-6.69	-8.27	-6.01	-3.92	-6.69	-7.22	
No. Positive	288	275	264	273	182	179	164	168	
No. Negative	163	176	187	178	101	104	119	115	

Table 3.21: Dollar Neutral and Pure Dollar Carry Trades Exposures to Basic Equity Risks

This table regresses the carry trade returns of four different strategies on three equity market risk factors postulated by Fama and French (1993): the excess return on the market portfolio; the excess return on small market capitalization stocks over big capitalization stocks; and the excess return of high book-to-market stocks over low book-to-market stocks as in the following. The regression specification is

$$R_t = \alpha + \beta_{MKT} \cdot R_{m,t} + \beta_{HML} \cdot R_{HML,t} + \beta_{SMB} \cdot R_{SMB,t} + \varepsilon_t$$

The Fama-French factors are from Ken French's data library. The sample period is 1976:02-2013:08 except for the AUD and the NZD, which start in October 1986. The reported alphas are annualized percentage terms. Autocorrelation and heteroskedasticity consistent t-statistics from GMM are in parentheses.

	<i>EQ</i>	<i>EQ0</i>	<i>EQ-minus</i>	<i>EQ-USD</i>
α	3.39	1.03	2.36	5.41
t-stat	(3.76)	(1.54)	(3.60)	(3.70)
β_{MKT}	0.05	0.08	-0.02	0.01
t-stat	(2.46)	(5.29)	(-1.24)	(0.21)
β_{SMB}	-0.03	0.02	-0.05	-0.05
t-stat	(-0.90)	(1.00)	(-1.84)	(-1.04)
β_{HML}	0.07	0.05	0.02	0.06
t-stat	(2.21)	(2.83)	(0.84)	(1.08)
R^2	0.04	0.10	0.04	0.01
NOBS	451	451	451	451

Table 3.22: Dollar Neutral and Pure Dollar Carry Trades Exposures to Basic Bond Risks

This table regresses the carry trade returns of four different strategies on the excess return on the U.S. equity market and two USD bond market risk factors: the excess return on the 10-year Treasury bond, 10y; and the excess return of the 10-year bond over the two-year Treasury note, 10y-2y. The regression specification is

$$R_t = \alpha + \beta_{MKT} \cdot R_{m,t} + \beta_{10y} \cdot R_{10y,t} + \beta_{10y-2y} \cdot (R_{10y,t} - R_{2y,t}) + \varepsilon_t$$

The reported alphas are in annualized percentage terms. Autocorrelation and heteroskedasticity consistent t-statistics from GMM are in parentheses. The sample period is 1976:01-2013:08.

	<i>EQ</i>	<i>EQ0</i>	<i>EQ-minus</i>	<i>EQ-USD</i>
α	4.19	1.50	2.69	5.82
t-stat	(4.51)	(2.77)	(3.88)	(4.01)
β_{MKT}	0.04	0.06	-0.03	-0.01
t-stat	(1.81)	(5.48)	(-1.60)	(-0.35)
β_{10y}	-0.39	-0.25	-0.14	-0.22
t-stat	(-2.97)	(-4.42)	(-1.16)	(-0.92)
β_{10y-2y}	0.46	0.29	0.17	0.32
t-stat	(2.46)	(3.52)	(1.02)	(0.93)
R^2	0.05	0.12	0.02	0.01
NOBS	451	451	451	451

Table 3.23: Dollar Neutral and Pure Dollar Carry Trades Exposures to FX Risks

This table regresses the carry trade returns of five different strategies on the two pure foreign exchange risk factors constructed by Lustig, Roussanov, and Verdelhan (2011): the average return on six carry trade portfolios sorted by currency interest differential versus the dollar, RX; and the excess return of the highest interest differential portfolio over the lowest interest differential portfolio, HML-FX. The regression specification is

$$R_t = \alpha + \beta_{RX} \cdot R_{RX,t} + \beta_{HML-FX} \cdot R_{HML-FX,t} + \varepsilon_t$$

The RX and HML-FX factor return data are from Adrien Verdelhan's web site, and the sample period is 1983:11-2013:08. The reported alphas are in annualized percentage terms. Autocorrelation and heteroskedasticity consistent t-statistics from GMM are in parentheses.

	<i>EQ</i>	<i>EQ0</i>	<i>EQ-minus</i>	<i>EQ-USD</i>
α	1.47	-0.03	1.49	5.18
t-stat	(1.73)	(-0.06)	(1.86)	(3.40)
β_{RX}	0.14	-0.02	0.15	0.52
t-stat	(2.27)	(-0.50)	(2.80)	(4.31)
β_{HML-FX}	0.28	0.24	0.04	0.00
t-stat	(8.24)	(11.03)	(1.58)	(-0.01)
R^2	0.31	0.41	0.09	0.20
NOBS	358	358	358	358

Table 3.24: All Risk Factors

This table regresses the pure dollar factor returns on a combination of equity market risk factors, bond risk factors, foreign exchange risk factors, and volatility risk factor. Three equity market risk factors are postulated by Fama and French (1993): the excess return on the market portfolio; the excess return on small market capitalization stocks over big capitalization stocks; and the excess return of high book-to-market stocks over low book-to-market stocks. Two USD bond market risk factors are the excess return on the 10-year Treasury bond, 10y; and the excess return of the 10-year bond over the two-year Treasury note, 10y-2y. Two foreign exchange risk factors are proposed by Lustig, Roussanov, and Verdelhan (2011): the average return on six carry trade portfolios sorted by currency interest differential versus the dollar, RX; and the excess return of the highest interest differential portfolio over the lowest interest differential portfolio, HML-FX. Volatility risk factor is the return on a variance swap based on VIX. The regression specification is

$$R_t = \alpha + \beta' F_t + \varepsilon_t$$

The sample period is 1990:02-2013:08 (283 observations). The reported alphas are in annualized percentage terms. Autocorrelation and heteroskedasticity consistent t-statistics from GMM are in parentheses.

	EQ-USD
α	4.52
t-stat	(2.79)
β_{MKT}	0.02
t-stat	(0.62)
β_{SMB}	-0.02
t-stat	(-0.36)
β_{HML}	0.06
t-stat	(1.15)
$\beta_{10\text{y}}$	0.43
t-stat	(1.47)
$\beta_{10\text{y}-2\text{y}}$	-0.57
t-stat	(-1.53)
β_{RX}	0.44
t-stat	(3.14)
$\beta_{\text{HML-FX}}$	0.14
t-stat	(2.03)
β_{vs}	0.13
t-stat	(2.67)
R^2	0.19

Table 3.25: Carry Trade Exposures to Downside Market Risk

This table regresses the carry trade returns of six different strategies on the market return and the downside market return defined by Lettau, Maggiori, and Weber (2014). The market return $R_{m,t}$ is the excess return on the market, the value-weight excess return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ; the downside market return $R_{m,t}^- = R_{m,t} \times I^-$ where $I^- = I(R_{m,t} < \overline{R_{m,t}} - std(R_{m,t}))$ is the indicator function equal to 1 when the market return is one standard deviation below the average market return and zero elsewhere. The regression specification is

$$R_t = \alpha_1 + \alpha_2 I^- + \beta_1 \cdot R_{m,t} + \beta_2 \cdot R_{m,t}^- + \varepsilon_t$$

in which case $\beta_1 = \beta^+$ and $\beta_2 = \beta^+ - \beta^-$. We define $\beta = \frac{Cov(R_{m,t}, R_t)}{Var(R_{m,t})}$, $\beta^+ = \frac{Cov(R_{m,t}, R_t|I^-=0)}{Var(R_{m,t}|I^-=0)}$, and $\beta^- = \frac{Cov(R_{m,t}, R_t|I^-=1)}{Var(R_{m,t}|I^-=1)}$. The sample period is 1976:02-2013:08. Excess returns are annualized. Autocorrelation and heteroskedasticity consistent t-statistics from GMM are in parentheses.

Panel A:	EQ	SPD	EQ-RR	SPD-RR	OPT	EQ-USD
α	3.72	6.08	5.17	5.91	1.99	5.63
t-stat	(4.01)	(4.55)	(4.49)	(5.28)	(4.16)	(4.03)
β	0.03	0.07	0.04	0.04	0.02	-0.01
t-stat	(1.55)	(2.13)	(1.59)	(1.71)	(1.51)	(-0.36)
R^2	0.01	0.02	0.01	0.01	0.01	0.00
NOBS	451	451	451	451	451	451

Panel B:	EQ	SPD	EQ-RR	SPD-RR	OPT	EQ-USD
α	4.08	6.19	5.94	6.38	2.22	4.86
t-stat	(3.86)	(4.13)	(4.50)	(4.82)	(4.69)	(3.13)
α^-	-1.26	7.02	-1.74	7.67	-0.73	-9.36
t-stat	(-0.20)	(0.91)	(-0.19)	(1.12)	(-0.21)	(-0.89)
β_1	0.02	0.06	0.01	0.02	0.01	0.02
t-stat	(0.87)	(1.51)	(0.57)	(0.73)	(0.66)	(0.45)
β_2	0.01	0.09	0.03	0.12	0.01	-0.16
t-stat	(0.15)	(0.98)	(0.28)	(1.43)	(0.17)	(-1.31)
R^2	0.01	0.02	0.01	0.02	0.01	0.01
NOBS	451	451	451	451	451	451

Panel C:	EQ	SPD	EQ-RR	SPD-RR	OPT	EQ-USD
$\beta^- - \beta$	0.00	0.08	0.01	0.10	0.00	-0.13
Downside Risk Premium $(\beta^- - \beta) \times \lambda^-$						
$\lambda^- = 16.9$	0.00	1.31	0.16	1.63	0.01	-2.12
$\lambda^- = 26.2$	0.00	2.02	0.25	2.53	0.02	-3.28

Table 3.26: Carry Trade Exposures to Downside Market Risk (Alternative Cutoff Value for Downside)

This table regresses the carry trade returns of six different strategies on the market return and the downside market return defined by Lettau, Maggiori, and Weber (2014). The market return $R_{m,t}$ is the excess return on the market, the value-weight excess return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ; the downside market return $R_{m,t}^- = R_{m,t} \times I^-$ where I^- is the indicator function. The regression specification is

$$R_t = \alpha_1 + \alpha_2 I^- + \beta_1 \cdot R_{m,t} + \beta_2 \cdot R_{m,t}^- + \varepsilon_t$$

. The sample period is 1976:02-2013:08. Excess returns are annualized. Autocorrelation and heteroskedasticity consistent t-statistics from GMM are in parentheses.

Panel A: $I^- = I(R_{m,t} < \overline{R_{m,t}})$						
	EQ	SPD	EQ-RR	SPD-RR	OPT	EQ-USD
α	-1.83	-2.47	0.90	1.09	3.07	-9.03
t-stat	(-0.85)	(-0.81)	(0.39)	(0.47)	(2.89)	(-2.93)
α^-	8.36	13.23	7.98	9.91	-1.12	17.44
t-stat	(2.98)	(3.46)	(2.40)	(3.10)	(-0.83)	(4.24)
β_1	0.13	0.22	0.10	0.11	-0.01	0.26
t-stat	(2.79)	(3.01)	(2.40)	(2.44)	(-0.21)	(4.39)
β_2	-0.07	-0.09	-0.01	0.01	0.02	-0.28
t-stat	(-1.27)	(-1.13)	(-0.23)	(0.10)	(0.73)	(-3.56)
R^2	0.03	0.05	0.02	0.03	0.01	0.05
NOBS	451	451	451	451	451	451

Panel B: $I^- = I(R_{m,t} < 0)$						
	EQ	SPD	EQ-RR	SPD-RR	OPT	EQ-USD
α	-0.08	0.40	2.89	4.10	2.97	-5.87
t-stat	(-0.04)	(0.15)	(1.36)	(1.85)	(3.23)	(-2.12)
α^-	6.57	10.22	5.52	5.73	-1.20	14.79
t-stat	(2.58)	(2.82)	(1.67)	(1.74)	(-0.92)	(3.57)
β_1	0.10	0.17	0.07	0.06	0.00	0.21
t-stat	(2.39)	(2.59)	(1.84)	(1.44)	(-0.16)	(3.70)
β_2	-0.04	-0.05	0.01	0.04	0.02	-0.23
t-stat	(-0.77)	(-0.63)	(0.15)	(0.57)	(0.61)	(-2.72)
R^2	0.03	0.04	0.02	0.02	0.01	0.04
NOBS	451	451	451	451	451	451

Table 3.27: Carry Trade Exposures to Downside Market Risk- LRV Six Portfolios

This table regresses Lustig, Roussanov, and Verdelhan (2011) six interest rate sorted portfolios returns on the market return and the downside market return defined by Lettau, Maggiori, and Weber (2014). Please refer to Table 3.25 for detailed descriptions of the risk factors. The regression specification is

$$R_t = \alpha_1 + \alpha_2 I^- + \beta_1 \cdot R_{m,t} + \beta_2 \cdot R_{m,t}^- + \varepsilon_t$$

in which case $\beta_1 = \beta^+$ and $\beta_2 = \beta^+ - \beta^-$. We define $\beta = \frac{Cov(R_{m,t}, R_t)}{Var(R_{m,t})}$, $\beta^+ = \frac{Cov(R_{m,t}, R_t|I^-=0)}{Var(R_{m,t}|I^-=0)}$, and $\beta^- = \frac{Cov(R_{m,t}, R_t|I^-=1)}{Var(R_{m,t}|I^-=1)}$. The sample period is 1976:02-2013:08. Excess returns are annualized. Autocorrelation and heteroskedasticity consistent t-statistics from GMM are in parentheses.

Panel A:	P1	P2	P3	P4	P5	P6	P6-P1
α	-1.59	-0.32	0.99	2.97	3.25	4.88	6.46
t-stat	(-1.00)	(-0.22)	(0.66)	(1.79)	(1.75)	(2.39)	(3.67)
β	0.02	0.04	0.05	0.07	0.12	0.20	0.18
t-stat	(0.42)	(1.09)	(1.49)	(1.73)	(2.45)	(4.39)	(5.62)
R^2	0.00	0.01	0.01	0.02	0.04	0.10	0.10
NOBS	358	358	358	358	358	358	358
Panel B:	P1	P2	P3	P4	P5	P6	P6-P1
α	-2.83	-0.44	0.72	2.50	3.49	4.09	6.92
t-stat	(-1.55)	(-0.26)	(0.44)	(1.47)	(1.68)	(1.87)	(3.50)
α^-	6.16	-0.87	3.86	-4.52	-7.78	10.70	4.55
t-stat	(0.49)	(-0.06)	(0.28)	(-0.44)	(-0.55)	(0.73)	(0.38)
β_1	0.05	0.04	0.06	0.09	0.11	0.21	0.17
t-stat	(1.21)	(1.16)	(1.43)	(2.09)	(2.15)	(4.34)	(3.76)
β_2	-0.01	-0.02	0.02	-0.08	-0.07	0.06	0.08
t-stat	(-0.08)	(-0.09)	(0.14)	(-0.55)	(-0.35)	(0.34)	(0.56)
R^2	0.01	0.01	0.01	0.02	0.05	0.10	0.10
NOBS	358	358	358	358	358	358	358
Panel C:	P1	P2	P3	P4	P5	P6	P6-P1
$\beta^- - \beta$	0.02	-0.01	0.03	-0.06	-0.07	0.08	0.06
Downside Risk Premium $(\beta^- - \beta) \times \lambda^-$							
$\lambda^- = 16.9$	0.33	-0.21	0.50	-1.04	-1.19	1.37	1.04
$\lambda^- = 26.2$	0.51	-0.33	0.78	-1.61	-1.83	2.12	1.61

Table 3.28: Carry Trade Exposures to Downside Market Risk-LMW Five Portfolios

This table regresses Lettau, Maggiori, and Weber (2014) five interest rate sorted portfolios returns on the market return and the downside market return. Please refer to Table 3.25 for detailed descriptions of the risk factors. The regression specification is

$$R_t = \alpha_1 + \alpha_2 I^- + \beta_1 \cdot R_{m,t} + \beta_2 \cdot R_{m,t}^- + \varepsilon_t$$

in which case $\beta_1 = \beta^+$ and $\beta_2 = \beta^+ - \beta^-$. We define $\beta = \frac{Cov(R_{m,t}, R_t)}{Var(R_{m,t})}$, $\beta^+ = \frac{Cov(R_{m,t}, R_t|I^-=0)}{Var(R_{m,t}|I^-=0)}$, and $\beta^- = \frac{Cov(R_{m,t}, R_t|I^-=1)}{Var(R_{m,t}|I^-=1)}$. The sample period is 1983:11-2010:03. Excess returns are annualized. Autocorrelation and heteroskedasticity consistent t-statistics from GMM are in parentheses.

Panel A:	P1	P2	P3	P4	P5	P5-P1
α	-0.35	0.45	2.64	3.48	4.17	4.52
t-stat	(-0.21)	(0.22)	(1.29)	(1.80)	(1.75)	(2.68)
β	-0.03	0.02	0.03	0.06	0.12	0.15
t-stat	(-0.87)	(0.60)	(0.59)	(1.44)	(1.90)	(3.85)
R^2	0.00	0.00	0.00	0.01	0.04	0.10
NOBS	317	317	317	317	317	317

Panel B:	P1	P2	P3	P4	P5	P5-P1
α	-1.34	1.22	2.31	3.66	5.36	6.70
t-stat	(-0.72)	(0.54)	(1.03)	(1.71)	(2.36)	(4.19)
$\alpha -$	5.64	-4.62	1.39	10.12	8.07	2.44
t-stat	(0.44)	(-0.33)	(0.09)	(0.79)	(0.41)	(0.23)
β_1	0.00	0.00	0.04	0.05	0.08	0.08
t-stat	(-0.12)	(0.07)	(0.72)	(0.97)	(1.39)	(2.00)
β_2	-0.01	0.00	-0.01	0.12	0.16	0.17
t-stat	(-0.03)	(0.01)	(-0.03)	(0.81)	(0.58)	(1.14)
R^2	0.01	0.00	0.00	0.02	0.04	0.12
NOBS	317	317	317	317	317	317

Panel C:	P1	P2	P3	P4	P5	P5-P1
$\beta^- - \beta$	0.02	-0.02	0.00	0.11	0.12	0.10
Downside Risk Premium $(\beta^- - \beta) \times \lambda^-$						
$\lambda^- = 16.9$	0.36	-0.33	0.04	1.78	2.03	1.66
$\lambda^- = 26.2$	0.56	-0.50	0.06	2.75	3.13	2.57

Table 3.29: Summary Statistics of Daily Carry Trade Returns

This table presents summary statistics on the daily zero-investment portfolio returns for five carry-trade strategies. The sample period is 1976:02-2013:08 except for the AUD and the NZD, which start in October 1986. The reported parameters, (mean, standard deviation, skewness, excess kurtosis, and autocorrelation coefficient) and their associated standard errors are simultaneous GMM estimates. The Sharpe ratio is the ratio of the annualized mean and standard deviation, and its standard error is calculated using the delta method (see Appendix B.1.)

Panel A: Daily Carry Trade Returns					Panel B: Monthly Carry Trade Returns				
	EQ	EQ-RR	SPD	SPD-RR	EQ	EQ-RR	SPD	SPD-RR	
Ave Ret (% p.a.)	3.92	5.38	6.53	6.13	3.96	5.44	6.60	6.18	
(std. err.)	(0.82)	(0.91)	(1.18)	(0.93)	(0.91)	(1.13)	(1.31)	(1.09)	
Standard Dev.	5.06	5.54	7.25	5.65	5.06	5.90	7.62	6.08	
(std. err.)	(0.10)	(0.11)	(0.15)	(0.15)	(0.28)	(0.22)	(0.41)	(0.24)	
Sharpe Ratio	0.77	0.97	0.90	1.08	0.78	0.92	0.87	1.02	
(std. err.)	(0.17)	(0.17)	(0.17)	(0.18)	(0.19)	(0.20)	(0.19)	(0.19)	
Skewness	-0.32	-1.01	-0.59	-1.62	-0.49	-0.37	-0.31	-0.44	
(std. err.)	(0.17)	(0.43)	(0.33)	(0.71)	(0.21)	(0.11)	(0.19)	(0.14)	
Excess Kurt.	7.46	11.90	10.25	24.43	2.01	0.40	1.78	0.90	
(std. err.)	(1.16)	(6.61)	(4.05)	(12.02)	(0.53)	(0.21)	(0.35)	(0.29)	
Autocorr.	0.03	0.02	0.02	0.02	0.08	0.16	0.02	0.09	
(std. err.)	(0.02)	(0.01)	(0.01)	(0.01)	(0.07)	(0.05)	(0.07)	(0.05)	
Max (%)	3.12	2.13	4.52	2.58	4.78	5.71	8.07	5.96	
Min (%)	-2.78	-5.64	-6.57	-6.61	-6.01	-4.90	-7.26	-5.88	
No. Positive	5230	5230	5223	5223	288	288	297	297	
No. Negative	4342	4342	4349	4349	163	163	154	154	

Panel C: Ratios of Moments between Daily and Monthly Carry Trades

	Ratios Implied by I.I.D			
	EQ	EQ-RR	SPD	SPD-RR
Ave Ret (% p.a.)	1.0	1.0	1.0	1.0
Standard Deviation	1.0	0.9	1.0	0.9
Sharpe Ratio	1.0	1.1	1.0	1.1
Skewness	0.6	2.7	1.9	3.6
Kurtosis	2.1	4.4	2.8	7.0

Table 3.30: Drawdowns

This table presents p-value of the cumulative distribution of drawdowns of the monthly zero-investment portfolio returns for four carry-trade strategies under two simulation methods. The p-value under simulations of a normal distribution is labeled “p_n” and the p-value under simulations of bootstrapping method is labeled “p_b”. The strategies are the basic equal-weighted (*EQ*) and spread-weighted (*SPD*) strategies, and their risk-rebalanced versions (labeled “-RR”). The weights in the basic strategies are calibrated to have one dollar at risk each month. The risk-rebalanced strategies rescale the basic weights by IGARCH estimates of a covariance matrix to target a 5% volatility. The sample period is 1976:02-2013:08 except for the AUD and the NZD, which start in October 1986.

Worst 20 Drawdowns

Freq	EQ			SPD			EQ-RR			SPD-RR		
	Mag.	p-n	p-b	Mag.	p-n	p-b	Mag.	p-n	p-b	Mag.	p-n	p-b
1	12.0%	12.6%	13.0%	21.5%	1.7%	2.3%	14.1%	4.2%	6.4%	10.2%	25.8%	40.3%
2	10.8%	1.6%	1.8%	13.2%	7.4%	9.8%	10.5%	2.4%	4.9%	9.7%	5.2%	14.3%
3	9.6%	0.3%	0.5%	9.5%	39.4%	46.0%	9.0%	1.5%	3.6%	8.4%	3.4%	13.4%
4	7.8%	1.1%	1.4%	9.4%	16.4%	21.8%	8.6%	0.3%	0.9%	7.6%	2.8%	13.4%
5	5.8%	21.9%	24.0%	9.4%	6.1%	8.9%	7.8%	0.3%	1.1%	7.2%	1.5%	8.8%
6	5.2%	34.1%	36.0%	9.0%	3.4%	5.1%	6.6%	1.7%	5.3%	7.1%	0.3%	3.2%
7	5.2%	17.8%	19.6%	8.9%	1.2%	1.9%	6.5%	0.5%	2.6%	6.7%	0.2%	2.6%
8	4.9%	20.4%	22.3%	8.4%	1.0%	2.0%	5.6%	5.6%	13.5%	6.4%	0.2%	2.1%
9	4.8%	10.5%	12.0%	8.2%	0.5%	0.9%	5.5%	2.2%	6.9%	5.8%	0.6%	3.8%
10	4.7%	6.9%	8.1%	8.2%	0.1%	0.2%	5.5%	0.7%	2.9%	5.6%	0.3%	2.5%
11	4.7%	4.3%	4.9%	6.4%	17.5%	20.4%	5.5%	0.2%	1.1%	5.6%	0.1%	1.0%
12	4.5%	4.9%	5.4%	6.3%	15.3%	17.5%	5.5%	0.1%	0.4%	5.4%	0.1%	0.7%
13	4.4%	3.0%	3.3%	6.1%	12.8%	14.4%	5.1%	0.2%	0.8%	5.3%	0.1%	0.4%
14	3.8%	25.8%	25.9%	5.8%	17.5%	17.9%	4.6%	2.2%	4.6%	5.2%	0.0%	0.2%
15	3.8%	20.3%	20.6%	5.8%	11.0%	11.5%	4.6%	1.0%	2.2%	5.0%	0.0%	0.2%
16	3.8%	12.6%	12.8%	5.5%	15.5%	14.7%	4.0%	17.0%	21.8%	4.4%	1.4%	2.0%
17	3.7%	12.5%	12.9%	5.5%	8.9%	8.5%	3.8%	28.9%	33.0%	4.2%	2.8%	3.4%
18	3.5%	16.8%	16.3%	4.8%	63.7%	55.5%	3.7%	26.7%	29.8%	4.0%	4.6%	4.9%
19	3.2%	52.5%	49.9%	4.7%	56.7%	47.5%	3.6%	34.5%	35.2%	3.7%	27.2%	19.9%
20	3.1%	54.0%	50.2%	4.5%	70.9%	61.3%	3.5%	35.4%	35.1%	3.6%	28.7%	20.2%

Table 3.31: Maximum Losses

This table presents p-value of maximum losses over a certain number of days of the monthly zero-investment portfolio returns for four carry-trade strategies under two simulation methods. The p-value under simulations of a normal distribution is labeled “p_n” and the p-value under simulations of bootstrapping method is labeled “p_b”. The strategies are the basic equal-weighted (*EQ*) and spread-weighted (*SPD*) strategies, and their risk-rebalanced versions (labeled “-RR”). The weights in the basic strategies are calibrated to have one dollar at risk each month. The risk-rebalanced strategies rescale the basic weights by IGARCH estimates of a covariance matrix to target a 5% volatility. The sample period is 1976:02-2013:08 except for the AUD and the NZD, which start in October 1986.

Horizon (days)	EQ			SPD			EQ-RR			SPD-RR		
	Mag.	p-n	p-b	Mag.	p-n	p-b	Mag.	p-n	p-b	Mag.	p-n	p-b
1	-2.7%	0.0%	59.4%	-6.5%	0.0%	44.6%	-5.6%	0.0%	43.5%	-6.6%	0.0%	43.5%
2	-3.5%	0.0%	8.1%	-6.4%	0.0%	56.9%	-5.5%	0.0%	55.6%	-6.5%	0.0%	57.2%
3	-4.0%	0.0%	5.4%	-6.6%	0.0%	48.0%	-6.0%	0.0%	23.9%	-6.6%	0.0%	48.7%
4	-4.4%	0.0%	2.9%	-6.5%	0.0%	54.3%	-5.8%	0.0%	42.3%	-6.5%	0.0%	58.4%
5	-5.0%	0.0%	1.2%	-6.8%	0.0%	43.3%	-5.8%	0.0%	45.1%	-6.5%	0.0%	62.2%
6	-5.2%	0.0%	1.3%	-7.3%	0.0%	28.9%	-5.9%	0.0%	41.9%	-6.5%	0.0%	62.4%
7	-4.9%	0.0%	3.9%	-6.7%	0.0%	50.4%	-5.9%	0.0%	41.2%	-6.4%	0.0%	65.7%
8	-5.2%	0.0%	2.7%	-7.2%	0.0%	37.0%	-6.1%	0.0%	36.7%	-6.4%	0.0%	67.3%
9	-5.5%	0.0%	1.7%	-7.7%	0.0%	27.2%	-6.3%	0.0%	30.2%	-6.3%	0.0%	69.1%
10	-6.0%	0.0%	0.8%	-8.1%	0.0%	18.6%	-6.4%	0.0%	29.0%	-6.3%	0.0%	69.8%
11	-6.7%	0.0%	0.2%	-8.8%	0.0%	10.3%	-6.2%	0.0%	38.0%	-6.3%	0.0%	70.6%
12	-7.0%	0.0%	0.1%	-9.2%	0.0%	6.8%	-6.2%	0.0%	39.7%	-6.3%	0.0%	71.0%
13	-7.0%	0.0%	0.2%	-9.2%	0.0%	8.4%	-6.3%	0.0%	38.0%	-6.3%	0.1%	71.5%
14	-5.5%	0.1%	6.6%	-8.4%	0.0%	19.4%	-6.1%	0.1%	44.5%	-6.3%	0.1%	72.1%
15	-5.1%	0.9%	18.2%	-8.0%	0.1%	28.8%	-6.1%	0.2%	45.1%	-6.2%	0.1%	73.5%
20	-5.9%	0.5%	9.0%	-8.7%	0.3%	22.9%	-6.0%	2.1%	53.7%	-6.2%	1.3%	74.9%
25	-6.7%	0.4%	4.8%	-8.7%	1.7%	28.4%	-6.0%	8.2%	59.3%	-6.6%	2.1%	67.2%
30	-7.6%	0.1%	1.6%	-10.2%	0.3%	10.9%	-7.3%	1.0%	25.6%	-6.7%	4.6%	66.1%
35	-8.2%	0.0%	1.1%	-10.7%	0.4%	9.3%	-7.6%	1.3%	22.0%	-7.1%	4.4%	57.4%
40	-8.4%	0.0%	1.3%	-12.1%	0.1%	3.6%	-8.4%	0.5%	11.9%	-8.1%	1.1%	32.6%
45	-8.9%	0.0%	0.8%	-12.2%	0.3%	4.3%	-8.3%	1.2%	14.3%	-8.2%	1.8%	33.0%
50	-9.2%	0.1%	0.8%	-11.8%	0.8%	7.1%	-9.0%	0.8%	9.5%	-8.0%	4.7%	39.3%
60	-10.0%	0.0%	0.5%	-13.3%	0.3%	3.3%	-9.6%	0.6%	6.7%	-9.1%	1.8%	21.1%
120	-11.0%	1.0%	1.6%	-17.4%	0.1%	0.8%	-10.2%	4.3%	9.8%	-8.3%	23.7%	40.7%
180	-11.3%	2.8%	3.3%	-20.2%	0.1%	0.4%	-10.3%	8.1%	12.7%	-8.4%	24.8%	34.7%

Table 3.32: Pure Drawdowns

This table presents p-value of the cumulative distribution of pure drawdowns of the monthly zero-investment portfolio returns for four carry-trade strategies under two simulation methods. The p-value under simulations of a normal distribution is labeled “p_n” and the p-value under simulations of bootstrapping method is labeled “p_b”. The strategies are the basic equal-weighted (*EQ*) and spread-weighted (*SPD*) strategies, and their risk-rebalanced versions (labeled “-*RR*”). The weights in the basic strategies are calibrated to have one dollar at risk each month. The risk-rebalanced strategies rescale the basic weights by IGARCH estimates of a covariance matrix to target a 5% volatility. The sample period is 1976:02-2013:08 except for the AUD and the NZD, which start in October 1986.

Worst 20 Pure Drawdowns

Freq	EQ			SPD			EQ-RR			SPD-RR		
	Mag.	p-n	p-b	Mag.	p-n	p-b	Mag.	p-n	p-b	Mag.	p-n	p-b
1	5.2%	0.3%	1.4%	7.3%	0.2%	19.1%	5.6%	0.3%	57.9%	6.6%	0.0%	61.3%
2	4.4%	0.1%	0.5%	6.9%	0.0%	6.4%	5.5%	0.0%	28.3%	5.8%	0.0%	44.0%
3	3.8%	0.0%	0.5%	6.5%	0.0%	5.9%	4.6%	0.0%	14.4%	5.6%	0.0%	29.0%
4	3.8%	0.0%	0.1%	6.2%	0.0%	2.4%	4.1%	0.0%	13.1%	4.5%	0.0%	27.3%
5	3.5%	0.0%	0.1%	5.8%	0.0%	0.7%	3.7%	0.0%	14.3%	4.2%	0.0%	22.1%
6	3.5%	0.0%	0.0%	4.8%	0.0%	0.8%	3.7%	0.0%	6.6%	3.7%	0.0%	14.7%
7	3.3%	0.0%	0.0%	4.7%	0.0%	0.3%	3.3%	0.0%	9.3%	3.6%	0.0%	8.2%
8	3.2%	0.0%	0.0%	4.6%	0.0%	0.1%	3.3%	0.0%	4.6%	3.5%	0.0%	4.5%
9	3.2%	0.0%	0.0%	4.4%	0.0%	0.1%	3.1%	0.0%	4.9%	3.4%	0.0%	2.3%
10	3.1%	0.0%	0.0%	4.4%	0.0%	0.0%	3.0%	0.0%	4.3%	3.2%	0.0%	1.8%
11	3.0%	0.0%	0.0%	4.4%	0.0%	0.0%	2.8%	0.1%	8.1%	3.1%	0.0%	1.4%
12	3.0%	0.0%	0.0%	4.3%	0.0%	0.0%	2.8%	0.0%	4.4%	2.9%	0.0%	3.2%
13	2.9%	0.0%	0.0%	4.2%	0.0%	0.0%	2.8%	0.0%	2.3%	2.9%	0.0%	1.8%
14	2.9%	0.0%	0.0%	4.1%	0.0%	0.0%	2.7%	0.0%	1.3%	2.8%	0.0%	1.3%
15	2.8%	0.0%	0.0%	3.9%	0.0%	0.0%	2.7%	0.0%	1.4%	2.7%	0.0%	1.6%
16	2.8%	0.0%	0.0%	3.8%	0.0%	0.0%	2.7%	0.0%	0.7%	2.7%	0.0%	0.9%
17	2.8%	0.0%	0.0%	3.7%	0.0%	0.0%	2.6%	0.0%	0.5%	2.7%	0.0%	0.7%
18	2.8%	0.0%	0.0%	3.7%	0.0%	0.0%	2.5%	0.0%	1.1%	2.6%	0.0%	0.5%
19	2.8%	0.0%	0.0%	3.7%	0.0%	0.0%	2.5%	0.0%	0.8%	2.6%	0.0%	0.3%
20	2.7%	0.0%	0.0%	3.6%	0.0%	0.0%	2.5%	0.0%	0.6%	2.6%	0.0%	0.2%

Table 3.33: Sovereign Equation

The estimated model has separate equations for the sovereign and the regional governments, respectively. At the sovereign level, the model is:

$$\Delta SCR_{i,t} = \beta_0 + \beta_1 \Delta SCR_{i,t-1} + \beta_2 \Delta liq_{i,t} + \beta_3 \Delta RA_t + \sum_{k=1}^4 \gamma_k D_k + \beta'_0 I_{pre-bailout} + \beta''_0 I_{post-Draghi} + \epsilon_{i,t}$$

,where $SCR_{i,t}$ is sovereign credit risk; $liq_{i,t}$ is market liquidity; RA_t is general risk aversion; and D_k are dummies for events of interest. Subscript i denotes country i; subscript t denotes trading day t; subscript k denotes dummy. $I_{pre-bailout}$ is a period dummy for the period up to December 19, 2011; and $I_{post-Draghi}$ is a period dummy for the period after July 26, 2012. T statistics are below the estimated coefficients.

	Columns					
	1	2	3	4	5	6
	OLS	NW_L5	SUR ³⁹	OLS	OLS	OLS
	(Spain)	(Spain)	(Spain)	Panel (12 countries) ⁴⁰	(Spain)	Panel (12 countries)
$\Delta SCR_{i,t-1}$	0.051**	0.051*	0.051**	0.187***	0.051**	0.187***
	2.066	1.663	2.076	21.865	2.065	21.862
ΔRA_t	2.277***	2.277***	2.279***	0.960***	2.278***	0.960***
	27.85	20.854	28.024	50.013	27.911	50.033
$\Delta liq_{i,t}$	-0.798***	-0.798***	-0.801***	0.298***	-0.796***	0.298***
	-5.622	-3.492	-5.685	10.817	-5.619	10.827
$I_{pre-bailout}$	-0.688	-0.688	-0.759	-0.455	-0.688	-0.456
	-0.699	-0.797	-0.775	-0.559	-0.699	-0.559
$I_{post-Draghi}$	-1.606	-1.606*	-1.607	-1.567*	-1.605	-1.567*
	-1.451	-1.789	-1.462	-1.714	-1.452	-1.714
D_1	8.23	8.230*	8.231	3.307		
	1.128	1.96	1.135	0.548		
D_2	10.449**	10.449*	10.451**	10.206***		
	2.242	1.77	2.257	2.647		
D_3	3.368	3.368	3.335	0.66	3.369	0.661
	0.789	1.311	0.786	0.187	0.79	0.187
D_4	-14.997	-14.997***	-14.982	-24.361***	-14.989	-24.358***
	-1.459	-11.067	-1.467	-2.87	-1.459	-2.869
DD					9.815**	8.235**
					2.477	2.51
Constant	0.79	0.79	0.791	0.053	0.79	0.053
	0.906	1.086	0.914	0.535	0.907	0.535
Adj- R^2	0.484			0.241	0.485	0.241
N	874	874	871	10437	874	10437

*p<0.1, **p<0.05, ***p<0.01

Table 3.34: Regional Equation

The estimated model has separate equations for the sovereign and the regional governments, respectively. At the sovereign level, the model is:

$$\begin{aligned}\Delta RCR_{i,t} = & \beta_0 + \beta_1 \Delta RCR_{i,t-1} + \beta_2 \Delta SCR_t + \beta_3 \Delta liq_{i,t} + \beta_4 \Delta RA_t \\ & + \beta_5 \Delta RF_t + \sum_{k=1}^4 \gamma_k D_k + \beta_2' \Delta SCR_t \times I_{pre-bailout} + \epsilon_{i,t}\end{aligned}$$

,where $RCR_{i,t}$ is regional credit risk; SCR_t is Spain's sovereign credit risk; $liq_{i,t}$ is market liquidity; RA_t is general risk aversion; RF_t is the short-term interest rate; D_k are dummies for events of interest. Subscript i denotes region i; subscript t denotes trading day t; subscript k denotes dummy. $I_{pre-bailout}$ is a period dummy for the period up to December 19, 2011; and $I_{post-Draghi}$ is a period dummy for the period after July 26, 2012. T statistics are below the estimated coefficients.

	Columns					
	1	2	3	4	5	6
	OLS (Valencia)	NW_L5 (Valencia)	SUR ⁴¹ (Spain)	OLS Panel ⁴²	OLS (Valencia)	OLS Panel
$\Delta RCR_{i,t-1}$	-0.083** -2.445	-0.083* -1.81	-0.083** -2.462	-0.009 -0.456	-0.084** -2.487	-0.009 -0.477
$\Delta liq_{i,t}$	0.073*** 2.787	0.073 0.953	0.073*** 2.81	0.005 0.24	0.074*** 2.828	0.005 0.266
ΔRA_t	0.001 0.426	0.001 0.32	0.036 0.208	-0.001 -0.746	0.001 0.387	-0.001 -0.771
ΔSCR_t	0.232*** 3.18	0.232** 2.473	0.250*** 3.442	0.371*** 7.447	0.230*** 3.147	0.370*** 7.429
ΔRF_t	1.268 1.523	1.268* 1.86	1.27 1.537	0.868 1.52	1.264 1.519	0.865 1.515
$\Delta SCR_t \times I_{pre-bailout}$	-0.255*** -3.172	-0.255** -2.152	-0.255*** -3.198	-0.419*** -7.642	-0.251*** -3.127	-0.418*** -7.617
$I_{pre-bailout}$	-0.065*** -3.835	-0.065** -2.447	-0.065*** -3.855	-0.047*** -4.079	-0.065*** -3.838	-0.047*** -4.079
$I_{post-Draghi}$	-0.115*** -6.253	-0.115*** -4.266	-0.115*** -6.284	-0.088*** -7.084	-0.116*** -6.264	-0.088*** -7.088
D_1	-0.023 -0.197	-0.023 -0.371	-0.025 -0.212	-0.012 -0.091		
D_2	-0.159** -2.127	-0.159* -1.861	-0.161** -2.165	-0.183** -2.087		
D_3	0.097 1.174	0.097* 1.718	0.097 1.175	0.089 0.912	0.097 1.173	0.089 0.911
D_4	-0.093 -0.567	-0.093** -2.009	-0.09 -0.553	-0.063 -0.324	-0.095 -0.577	-0.064 -0.327
DD					-0.120* -1.882	-0.134* -1.804
Constant	0.064*** 4.283	0.064** 2.528	0.063*** 4.305	0.050*** 5.023	0.064*** 4.288	0.050*** 5.024
Adj- R^2	0.069			0.046	0.069	0.046
N	871	871	871	2618	871	2618

*p<0.1, **p<0.05, ***p<0.01

Figures

(a) Pattern of Cash Flow Expectation Errors

(b) Pattern of Cash Flow Expectation Errors

Figure 3.1: Illustration of Model 1—Daniel, Hirshleifer, and Subrahmanyam (1998)

In the upper panel, the dashed line represents rational expectations, an unbiased estimate of future cash flows; the black line with an arrow represents the cash flow expectations in the model. The momentum (reversal) phase is the holding period in which winner stocks outperform (underperform) loser stocks. In the lower panel, the blue (solid) line represents the dynamics of cash flow expectation errors for winner stocks; the red (dashed) line represents the dynamics of cash flow expectation errors for loser stocks.

(a) Pattern of Cash Flow Expectations

(b) Pattern of Cash Flow Expectation Errors

Figure 3.2: Illustration of Model 2—Hong and Stein (1999)

In the upper panel, the dashed line represents rational expectations, an unbiased estimate of future cash flows; the black line with an arrow represents the cash flow expectations in the model. The momentum (reversal) phase is the holding period in which winner stocks outperform (underperform) loser stocks. In the lower panel, the blue (solid) line represents the dynamics of cash flow expectation errors for winner stocks; the red (dashed) line represents the dynamics of cash flow expectation errors for loser stocks.

Figure 3.3: Illustration of Model 3—Barberis, Shleifer, and Vishny (1998)

In the upper panel, the dashed line represents rational expectations, an unbiased estimate of future cash flows; the black line with an arrow represents the cash flow expectations in the model. The momentum (reversal) phase is the holding period in which winner stocks outperform (underperform) loser stocks. In the lower panel, the blue (solid) line represents the dynamics of cash flow expectation errors for winner stocks; the red (dashed) line represents the dynamics of cash flow expectation errors for loser stocks.

Figure 3.4: Summary of the Competing Predictions

The solid line represents the dynamics of cash flow expectation errors for winner stocks; the dashed line represents the dynamics of cash flow expectation errors for loser stocks. The dotted line represents the other possible prediction of the DHS model (see footnote 9).

Figure 3.5: Timeline for Portfolio Construction

At the end of each month t , I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Then, I sort all stocks into momentum quintile portfolios based on these breakpoints and hold the portfolios for 24 months. For example, to calculate the consensus forecast for stock i in the first month after the portfolio formation month t , in a quarter-long window from month $t+1$ to $t+3$, I collect all newly issued analyst earnings forecasts made for the fiscal year end that is closest to month $t+1$ but still at least six months away from month $t+1$. The forecast horizon thus ranges from 6 months to 18 months, with the average being approximately one year. If one analyst issues more than one such forecast in the quarter-long window, I choose the latest one. I calculate the median of these forecasts for stock i and call it the consensus forecast $AF_{t,t+1 \rightarrow t+3,T_1}^i$. Note that t signifies that stocks are sorted at time t , $t+1 \rightarrow t+3$ signifies that the forecasts are issued between month $t+1$ and month $t+3$, and T_1 signifies forecast for the fiscal year end.

Winner-minus-loser Average Returns				
Months in the holding period	1-6	7-8	9-13	14-24
Ave. Ret	0.60	0.01	-0.45	-0.24
T Stat	2.43	0.02	-1.99	-1.22
N	246	246	246	246

Figure 3.6: Differences in Cumulative Returns between Winner and Loser Portfolios

I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Then, I sort all stocks into momentum quintile portfolios based on these breakpoints and hold them for 24 months. The winner-minus-loser portfolio is formed by taking a long position in the highest quintile portfolio and a short position in the lowest quintile portfolio. Sorting is done monthly between 1988/1-2008/6. Returns are equally weighted returns. Average returns in each month of the holding period are calculated by averaging over different portfolio-formation months. Cumulative returns are calculated by summing the average monthly returns over the holding period.

Figure 3.7: Dynamics of Forecast Errors for Winner and Loser Portfolios in the Holding Period

I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Then, I sort all stocks into momentum quintile portfolios based on these breakpoints and hold them for 24 months. In overlapping quarter-long windows within the holding period, I calculate the consensus forecast by taking the median of the newly issued forecasts for the closest fiscal year end that is at least six-month away. Forecast errors are actual earnings minus the consensus forecast. I calculate the portfolio median forecast errors for each of the overlapping quarter-long windows and then calculate the time series average and the standard deviation of these forecast errors. The first dot represents the time series average of the forecast errors for forecasts made in the first quarter-long window (month 1 to month 3) in the holding period. The second dot represents the time series average of forecast errors for forecasts made in the second quarter-long window (month 2 to month 4) in the holding period. Asterisks connected by dashed lines represent the 95% confidence interval for the time series average forecast errors, using Newey-West standard errors with 18 lags.

Figure 3.8: Sum of Fama-Macbeth regression coefficients (Empirical Pattern)

This figure reports the cumulative sum of Fama-Macbeth regression coefficients in Table 3.9 over the 24 month holding period.

Figure 3.9: Sum of Fama-Macbeth regression coefficients (Simulation Results)

This figure reports the cumulative sum of Fama-Macbeth regression coefficients from the simulation. 500,000 observations were simulated and divided into 500 cross sections with 1,000 observations per cross section. We repeat the same analysis on the simulated data: first decompose past six-month returns into a cash flow component and a residual component. Then I run Fama-Macbeth regressions of future returns on the two component. The cumulative sum of the FM coefficients are plotted here. Simulation parameters are $z = 15$, $j = 12$, $\sigma = 5\%$, $N=500,000$. The equilibrium $\phi = 0.1955$.

Figure 3.10: Time Series Mean of the Portfolio Median Forecast Errors for Winner and Loser Portfolios within Underreaction Ranking Quintiles

I form momentum tertile breakpoints from all NYSE firms based on their past 11-month returns. I form underreaction quintile breakpoints from stocks in my sample based on their underreaction betas. Stocks are then sorted into three momentum groups and five underreaction groups based on these breakpoints. Winner stocks are stocks in the highest momentum tertile, and loser stocks are stocks in the lowest momentum tertile. Stocks with high underreaction rankings are stocks with high underreaction betas. Portfolio median forecast errors for the holding period are calculated in a similar way as previous figures.

Figure 3.11: Time Series Mean of Winner-minus-loser Cumulative Returns across Underreaction Quintiles

I form momentum tertile breakpoints from all NYSE firms based on their past 11-month returns. I form underreaction quintile breakpoints from stocks in my sample based on their underreaction betas. Stocks are then sorted into three momentum groups and five underreaction groups based on these breakpoints. Winner stocks are stocks in the highest momentum tertile, and loser stocks are stocks in the lowest momentum tertile. Stocks with high underreaction rankings are stocks with high underreaction betas. Within each underreaction-ranking group, the winner-minus-loser portfolio is formed by taking a long position in the highest momentum tertile portfolio and a short position in the lowest momentum tertile portfolio. Sorting is done monthly from 1988/1-2008/6. Returns are equally weighted returns. Average returns in each month of the holding period are calculated by averaging over different portfolio-formation months. Cumulative returns are calculated by summing the average monthly returns over the holding period.

Figure 3.12: Dynamics of Forecast Errors for Winner and Loser Portfolios in the Holding Period (One-quarter-ahead Forecasts)

I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Then, I sort all stocks into momentum quintile portfolios based on these breakpoints and hold them for 24 months. In overlapping quarter-long windows within the holding period, I calculate the consensus forecast by taking the median of the newly issued forecasts for the closest quarter end that lies outside of the window. Forecast errors are actual earnings minus the consensus forecast. I calculate the portfolio median forecast errors for each of the overlapping quarter-long windows and then take the time series average of these forecast errors. The first dot represents the time series average of the forecast errors for forecasts made in the first quarter-long window (month 1 to month 3) in the holding period. The second dot represents the time series average of forecast errors for forecasts made in the second quarter-long window (month 2 to month 4) in the holding period. Asterisks connected by dashed lines represent the 95% confidence interval for the time series average forecast errors, using Newey-West standard errors with 18 lags.

Figure 3.13: Dynamics of Forecast Errors for Winner and Loser Portfolios in the Holding Period (Two-year-ahead Forecasts)

I form momentum quintile breakpoints from all NYSE firms based on their past 11-month returns. Then, I sort all stocks into momentum quintile portfolios based on these breakpoints and hold them for 24 months. In overlapping quarter-long windows within the holding period, I calculate the consensus forecast by taking the median of the newly issued forecasts for the fiscal year end after the next. Forecast errors are actual earnings minus the consensus forecast. I calculate the portfolio median forecast errors for each of the overlapping quarter-long windows and then take the time series average of these forecast errors. The first dot represents the time series average of the forecast errors for forecasts made in the first quarter-long window (month 1 to month 3) in the holding period. The second dot represents the time series average of forecast errors for forecasts made in the second quarter-long window (month 2 to month 4) in the holding period. Asterisks connected by dashed lines represent the 95% confidence interval for the time series average forecast errors, using Newey-West standard errors with 18 lags.

Figure 3.14: Dynamics of Forecast Revisions for Two-year-ahead Forecasts

Please refer to the description in Table A.1.

Figure 3.15: Dynamics of Forecast Revisions for the Nearest Quarterly Forecasts)

Please refer to the description in Table A.1.

Figure 3.16: Sovereign and Subnational Ratings, December 2010

Source: Standard and Poor's (black square represents sovereign rating)

Figure 3.17: Spain Sovereign Risk vs. European Risk, 2010-2013

Scaled by the value on 12/19/2011. Source: Bloomberg

Figure 3.18: Average Premium/Discount (in bps)

Figure 3.19: Bund-Länder Anleihe vs Replicated Bond (In Percent)

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Appendices

Appendix A

Appendix Tables

Table A.1: Dynamics of Forecast Revisions (Nearest quarterly forecasts)

To calculate the relevant forecast revision for one stock in the k^{th} month after portfolio formation month t , i.e., month $t + k$, I collect forecasts that are newly issued within the last quarter ending in month $t + k$, and I track the revisions of these forecasts that occur after month $t + k$ but no later than month $t + k + 3$. The period between forecasts and the corresponding revisions is called the revision period. I then normalize the revisions by the length of the revision period to get the approximate revisions in month $t + k$. I then take the median of the different analysts' revisions as the estimated revision for the stock in month $t + k$. To compare the estimated revisions across stocks, which are in the unit of earnings-per-share, I normalize them by the absolute value of forecasts. I also normalize them by different variables for the robustness purpose: the price or the standard deviations of seasonally adjusted quarterly earnings. Because the average revisions of all forecasts are negative, this non-zero average will bias the normalization results. I take out the average effect by subtracting from the revisions their average value between year -7 to year -5 (for firms don't have data earlier than year -5, use year +3 to year +5 data instead). Then I scale the demeaned revisions by the price at the formation month t or the standard deviations of seasonally adjusted quarterly earnings during the last eight quarters before the formation month t . Also for the robustness purpose, I investigate the revisions for the nearest quarterly forecasts that are at least three months away and the revisions for two-year-ahead forecasts. Winner and loser portfolios are formed in the same way as in the main test.

Portfolio Median Forecast Revisions for the nearest quarterly forecasts (Demeaned/Scaled by Price)													
n^{th} Month after Sorting	1	2	3	4	5	6	7	8	9	10	11	12	
Ave. Winner-Loser Diff.	0.069%	0.060%	0.051%	0.044%	0.040%	0.034%	0.029%	0.024%	0.021%	0.018%	0.014%	0.010%	
T-stat	9.41	8.13	8.26	8.47	7.49	6.67	5.85	5.86	5.33	4.32	3.64	2.89	
n^{th} Month after Sorting	13	14	15	16	17	18	19	20	21	22	23	24	
Ave. Winner-Loser Diff.	0.007%	0.006%	0.005%	0.002%	0.003%	0.002%	0.002%	0.000%	0.000%	0.001%	0.001%	0.000%	
T-stat	2.09	1.74	1.28	0.60	0.65	0.56	0.38	0.02	0.01	0.25	0.23	0.02	

Table A.2: Dynamics of Forecast Revisions (Two-year-ahead forecasts)

Portfolio		Median Forecast Revisions for Two-year-ahead forecasts (Demeaned/Scaled by Price)											
n^{th} Month after Sorting		1	2	3	4	5	6	7	8	9	10	11	12
Ave. Winner-Loser Diff.		0.235%	0.201%	0.172%	0.151%	0.131%	0.116%	0.100%	0.084%	0.071%	0.059%	0.048%	0.036%
T-stat		9.57	9.72	9.20	9.01	8.85	8.31	7.93	7.43	6.68	5.86	5.17	4.52
n^{th} Month after Sorting		13	14	15	16	17	18	19	20	21	22	23	24
Ave. Winner-Loser Diff.		0.030%	0.028%	0.022%	0.017%	0.014%	0.010%	0.005%	0.003%	0.001%	0.002%	0.000%	0.000%
T-stat		3.72	3.41	2.41	1.89	1.45	1.03	0.51	0.28	0.11	0.22	-0.03	0.02

Table A.3: Forecast Errors Regression (winsorized at 5%)

$$FE_{t+k \rightarrow t+k+2}^i = \hat{\lambda}_{t+k} mom_{i,t} + \rho_{1,k} SUE_t + \rho_{2,k} SUE_{t,L1} + \rho_{3,k} EAR_t + \rho_{4,k} EAR_{t,L1} + \rho_{5,k} REV_t + \rho_{6,k} REV_{t,L1} + \rho_{7,k} REV_{t,L2} + Yearmon_t + \eta_{t,t+h}$$

k	1	2	3	4	5	6	7	8	9	10	11	12
λ_k	0.031*** (19.05)	0.028*** (16.84)	0.025*** (14.66)	0.021*** (12.45)	0.018*** (10.53)	0.016*** (9.09)	0.014*** (7.93)	0.012*** (6.91)	0.010*** (5.81)	0.009*** (4.96)	0.008*** (4.30)	0.006*** (3.38)
EAR_t	0.125*** (4.90)	0.112*** (4.43)	0.094*** (3.53)	0.074*** (2.68)	0.053* (1.96)	0.036 (1.36)	0.024 (0.89)	0.027 (1.01)	0.018 (0.67)	0.009 (0.32)	0.014 (0.52)	0.022 (0.78)
lag EAR_t	-0.027 (-1.11)	-0.038 (-1.57)	-0.050** (-1.99)	-0.059** (-2.25)	-0.052** (-2.01)	-0.056** (-2.14)	-0.057** (-2.15)	-0.051* (-1.94)	-0.039 (-1.47)	-0.032 (-1.17)	-0.026 (-0.98)	-0.021 (-0.76)
sue	6.213*** (10.48)	5.649*** (9.48)	5.239*** (8.62)	4.834*** (7.79)	4.122*** (6.78)	3.754*** (6.06)	3.716*** (5.98)	4.066*** (6.62)	4.456*** (7.19)	4.703*** (7.35)	4.512*** (7.06)	4.212*** (6.40)
lag sue	1.756*** (3.20)	1.468*** (2.70)	1.497*** (2.64)	1.530*** (2.58)	1.965*** (3.31)	2.463*** (4.10)	2.861*** (4.61)	2.823*** (4.53)	2.677*** (4.27)	2.670*** (4.15)	2.537*** (4.16)	2.472*** (4.17)
rev1	0.302*** (21.66)	0.293*** (21.04)	0.285*** (19.88)	0.279*** (18.60)	0.277*** (18.56)	0.259*** (17.60)	0.235*** (16.15)	0.203*** (14.78)	0.168*** (12.59)	0.145*** (10.62)	0.133*** (9.82)	0.135*** (9.98)
rev2	0.167*** (13.40)	0.169*** (13.91)	0.165*** (13.30)	0.148*** (11.49)	0.118*** (10.07)	0.089*** (8.07)	0.071*** (6.21)	0.073*** (6.21)	0.085*** (7.08)	0.096*** (7.70)	0.096*** (7.99)	0.087*** (7.46)
rev3	0.109*** (8.76)	0.084*** (7.13)	0.073*** (6.18)	0.072*** (5.70)	0.079*** (6.27)	0.094*** (7.36)	0.104*** (7.94)	0.107*** (8.41)	0.104*** (8.29)	0.096*** (7.37)	0.092*** (7.00)	0.084*** (6.48)
R^2	0.143	0.13	0.119	0.108	0.099	0.09	0.084	0.08	0.077	0.076	0.075	0.074
k	13	14	15	16	17	18	19	20	21	22	23	24
λ_k	0.006*** (3.02)	0.005*** (2.87)	0.005*** (2.65)	0.005*** (2.52)	0.004*** (2.23)	0.004** (2.22)	0.005*** (2.49)	0.005** (2.51)	0.005** (2.46)	0.005*** (2.55)	0.005** (2.42)	0.005** (2.40)
EAR_t	0.015 (0.53)	0.01 (0.35)	0 (-0.01)	-0.012 (-0.40)	-0.005 (-0.19)	-0.003 (-0.10)	0.002 (0.09)	-0.001 (-0.02)	0.003 (0.09)	0.005 (0.17)	0.015 (0.56)	0.013 (0.47)
lag EAR_t	-0.022 (-0.76)	-0.013 (-0.48)	-0.007 (-0.26)	-0.004 (-0.14)	-0.004 (-0.16)	-0.005 (-0.18)	-0.01 (-0.38)	0.005 (0.17)	0.004 (0.14)	0.002 (0.09)	-0.004 (-0.17)	-0.016 (-0.57)
sue	3.923*** (5.76)	3.483*** (5.37)	3.381*** (5.37)	3.427*** (5.38)	3.488*** (5.61)	3.484*** (5.65)	3.350*** (5.36)	2.981*** (4.88)	2.638*** (4.26)	2.425*** (3.76)	2.274*** (3.58)	2.259*** (3.50)
lag sue	2.636*** (4.41)	2.796*** (4.76)	2.878*** (4.77)	2.834*** (4.47)	2.713*** (4.37)	2.241*** (3.69)	2.021*** (3.23)	1.862*** (2.98)	1.960*** (3.01)	1.915*** (2.92)	2.030*** (3.20)	1.878*** (3.03)
rev1	0.134*** (9.63)	0.136*** (9.77)	0.132*** (9.45)	0.127*** (8.85)	0.127*** (8.80)	0.122*** (8.44)	0.114*** (7.83)	0.095*** (6.77)	0.076*** (5.55)	0.058*** (4.30)	0.052*** (3.97)	0.050*** (3.90)
rev2	0.078*** (6.37)	0.073*** (6.05)	0.071*** (5.78)	0.062*** (5.06)	0.044*** (3.86)	0.030*** (2.61)	0.017 (1.50)	0.017 (1.52)	0.020* (1.77)	0.028** (2.36)	0.038*** (3.09)	0.047*** (3.76)
rev3	0.074*** (5.69)	0.053*** (4.30)	0.035*** (2.81)	0.027*** (2.12)	0.030** (2.34)	0.038*** (2.85)	0.043*** (3.10)	0.058*** (3.99)	0.071*** (4.88)	0.083*** (5.61)	0.086*** (5.98)	0.086*** (6.01)
R^2	0.075	0.074	0.074	0.073	0.072	0.071	0.071	0.071	0.071	0.071	0.072	0.073

Table A.4: Forecast Errors Regression (winsorized at 5%/Scaled by Price)

$$FE_{t+k \rightarrow t+k+2}^i = \hat{\lambda}_{t+k} mom_{i,t} + \rho_{1,k} SUE_t + \rho_{2,k} SUE_{t,L1} + \rho_{3,k} EAR_t + \rho_{4,k} EAR_{t,L1} + \rho_{5,k} REV_t + \rho_{6,k} REV_{t,L1} + \rho_{7,k} REV_{t,L2} + Yearmon_t + \eta_{t,t+h}$$

k	1	2	3	4	5	6	7	8	9	10	11	12
λ_k	0.227*** (24.90)	0.201*** (22.11)	0.175*** (19.28)	0.152*** (16.82)	0.132*** (14.56)	0.116*** (12.90)	0.103*** (11.62)	0.091*** (10.27)	0.077*** (8.66)	0.063*** (7.56)	0.059*** (6.50)	0.049*** (5.31)
EAR_t	0.491*** (3.95)	0.432*** (3.61)	0.357*** (2.98)	0.313*** (2.57)	0.254** (2.19)	0.166 (1.44)	0.107 (0.94)	0.118 (1.05)	0.112 (0.96)	0.108 (0.87)	0.163 (1.34)	0.221* (1.78)
lag EAR_t	-0.13 (-1.10)	-0.159 (-1.41)	-0.168 (-1.47)	-0.173 (-1.45)	-0.103 (-0.89)	-0.074 (-0.64)	-0.022 (-0.19)	0.035 (0.31)	0.075 (0.65)	0.072 (0.59)	0.049 (0.41)	0.067 (0.56)
sue	0.654*** (10.11)	0.574*** (9.10)	0.509*** (8.17)	0.469*** (7.49)	0.407*** (6.75)	0.381*** (6.33)	0.368*** (6.28)	0.385*** (6.74)	0.405*** (7.14)	0.418*** (7.12)	0.400*** (6.82)	0.378*** (6.43)
lag sue	0.241*** (4.15)	0.238*** (4.14)	0.248*** (4.28)	0.251*** (4.27)	0.274*** (4.76)	0.294*** (5.14)	0.306*** (5.35)	0.298*** (5.29)	0.280*** (5.03)	0.285*** (5.05)	0.284*** (5.18)	0.266*** (4.96)
rev1	1.506*** (16.15)	1.418*** (15.31)	1.346*** (14.46)	1.277*** (13.53)	1.200*** (12.84)	1.052*** (11.51)	0.868*** (9.86)	0.693*** (8.41)	0.555*** (6.87)	0.446*** (5.43)	0.400*** (4.76)	0.431*** (4.95)
rev2	0.583*** (7.66)	0.547*** (7.32)	0.467*** (6.40)	0.352*** (4.91)	0.230*** (3.49)	0.137** (2.12)	0.067 (1.01)	0.091 (1.33)	0.172** (2.38)	0.242*** (3.24)	0.292*** (4.01)	0.276*** (3.75)
rev3	0.236*** (3.23)	0.157** (2.25)	0.160** (2.29)	0.184** (2.54)	0.233*** (3.16)	0.330*** (4.31)	0.417*** (5.36)	0.454*** (5.99)	0.442*** (5.73)	0.403*** (4.99)	0.360*** (4.40)	0.335*** (4.16)
R^2	0.146	0.132	0.121	0.112	0.104	0.098	0.096	0.093	0.091	0.092	0.091	0.09
k	13	14	15	16	17	18	19	20	21	22	23	24
λ_k	0.042*** (4.55)	0.040*** (4.36)	0.036*** (3.87)	0.032*** (3.44)	0.030*** (3.19)	0.028*** (2.99)	0.031*** (3.33)	0.033*** (3.58)	0.034*** (3.60)	0.038*** (3.90)	0.041*** (4.17)	0.045*** (4.43)
EAR_t	0.198 (1.56)	0.181 (1.47)	0.165 (1.34)	0.145 (1.14)	0.102 (0.83)	0.066 (0.53)	0.066 (0.53)	0.029 (0.24)	-0.01 (-0.08)	-0.044 (-0.33)	-0.073 (-1.05)	-0.141 (-1.05)
lag EAR_t	0.071 (0.57)	0.072 (0.61)	0.051 (0.42)	0.04 (0.32)	0.044 (0.37)	-0.003 (-0.02)	-0.079 (-0.65)	-0.072 (-0.61)	-0.118 (-0.96)	-0.136 (-1.05)	-0.158 (-1.26)	-0.191 (-1.49)
sue	0.360*** (6.07)	0.343*** (5.97)	0.325*** (5.79)	0.311*** (5.51)	0.310*** (5.68)	0.294*** (5.32)	0.269*** (4.84)	0.246*** (4.52)	0.216*** (3.94)	0.189*** (3.37)	0.182*** (3.31)	0.177*** (3.30)
lag sue	0.255*** (4.73)	0.248*** (4.75)	0.249*** (4.57)	0.236*** (4.13)	0.227*** (4.12)	0.206*** (3.83)	0.183*** (3.42)	0.169*** (3.27)	0.184*** (3.48)	0.194*** (3.60)	0.203*** (3.86)	0.183*** (3.54)
rev1	0.456*** (5.16)	0.463*** (5.27)	0.449*** (5.06)	0.447*** (4.87)	0.440*** (4.72)	0.441*** (4.75)	0.431*** (4.69)	0.378*** (4.34)	0.339*** (3.99)	0.277*** (3.29)	0.279*** (3.42)	0.310*** (3.79)
rev2	0.241*** (3.13)	0.208*** (2.68)	0.206*** (2.66)	0.175** (2.31)	0.128** (1.84)	0.111 (1.64)	0.089 (1.31)	0.099 (1.50)	0.128* (1.89)	0.181** (2.58)	0.228*** (3.09)	0.262*** (3.42)
rev3	0.300*** (3.85)	0.260*** (3.54)	0.226*** (3.08)	0.227*** (3.02)	0.248*** (3.30)	0.287*** (3.75)	0.318*** (4.01)	0.384*** (4.63)	0.430*** (4.97)	0.468*** (5.17)	0.459*** (5.08)	0.433*** (4.78)
R^2	0.09	0.089	0.089	0.089	0.091	0.091	0.092	0.092	0.093	0.094	0.096	0.098

Table A.5: Forecast Errors Regression (winsorized at 2.5%)

$$FE_{t+k \rightarrow t+k+2}^i = \hat{\lambda}_{t+k} mom_{i,t} + \rho_{1,k} SUE_t + \rho_{2,k} SUE_{t,L1} + \rho_{3,k} EAR_t + \rho_{4,k} EAR_{t,L1} + \rho_{5,k} REV_t + \rho_{6,k} REV_{t,L1} + \rho_{7,k} REV_{t,L2} + Yearmon_t + \eta_{t,t+h}$$

k	1	2	3	4	5	6	7	8	9	10	11	12
λ_k	0.035*** (14.9)	0.033*** (13.4)	0.030*** (12.1)	0.027*** (10.6)	0.024*** (9.1)	0.022*** (8.0)	0.020*** (7.3)	0.018*** (6.6)	0.016*** (5.7)	0.014*** (5.1)	0.013*** (4.6)	0.011*** (3.8)
EAR_t	0.149*** (4.0)	0.136*** (3.6)	0.114*** (2.9)	0.090** (2.1)	0.059 (1.4)	0.036 (0.9)	0.023 (0.6)	0.033 (0.8)	0.02 (0.5)	0.015 (0.3)	0.021 (0.5)	0.026 (0.6)
lag EAR_t	-0.047 (-1.29)	-0.063* (-1.73)	-0.085** (-2.26)	-0.093** (-2.33)	-0.079** (-2.01)	-0.082** (-2.03)	-0.089** (-2.12)	-0.085** (-2.08)	-0.067 (pd62)	-0.052 (-1.22)	-0.051 (-1.26)	-0.043 (-1.04)
sue	8.631*** (9.7)	7.895*** (8.7)	7.346*** (7.8)	6.729*** (6.9)	5.546*** (5.9)	5.085*** (5.4)	5.122*** (5.3)	5.674*** (6.0)	6.464*** (6.6)	6.713*** (6.7)	6.170*** (6.2)	5.488*** (5.4)
lag sue	1.994** (2.5)	1.451* (1.8)	1.299 (1.6)	1.328 (1.6)	2.123** (2.5)	2.876*** (3.3)	3.490*** (3.8)	3.257*** (3.6)	2.867*** (3.1)	2.861*** (3.0)	3.009*** (3.3)	3.153*** (3.6)
rev1	0.466*** (21.1)	0.457*** (20.2)	0.438*** (18.9)	0.429*** (17.5)	0.427*** (17.5)	0.400*** (16.9)	0.365*** (15.5)	0.316*** (14.1)	0.264*** (12.0)	0.222*** (10.1)	0.199*** (9.4)	0.205*** (9.8)
rev2	0.258*** (12.9)	0.269*** (13.5)	0.262*** (13.1)	0.236*** (11.3)	0.188*** (9.8)	0.144*** (8.0)	0.112*** (6.1)	0.114*** (6.2)	0.131*** (7.0)	0.151*** (7.7)	0.150*** (7.8)	0.143*** (7.5)
rev3	0.176*** (8.9)	0.141*** (7.4)	0.123*** (6.5)	0.117*** (5.9)	0.122*** (6.2)	0.142*** (7.1)	0.162*** (7.8)	0.168*** (8.4)	0.168*** (8.5)	0.158*** (7.5)	0.147*** (6.9)	0.135*** (6.4)
R^2	0.125	0.112	0.1	0.089	0.08	0.071	0.065	0.061	0.057	0.055	0.053	0.053
k	13	14	15	16	17	18	19	20	21	22	23	24
λ_k	0.010*** (3.5)	0.010*** (3.3)	0.009*** (3.1)	0.009*** (2.9)	0.008*** (2.6)	0.008** (2.5)	0.009*** (2.9)	0.009*** (2.9)	0.009*** (2.8)	0.009*** (2.7)	0.008** (2.5)	0.009** (2.6)
EAR_t	0.014 (0.3)	-0.001 (-0.02)	-0.015 (-0.35)	-0.029 (-0.65)	0 (0.0)	0.024 (0.6)	0.032 (0.7)	0.02 (0.5)	0.009 (0.2)	0.005 (0.1)	0.023 (0.5)	0.028 (0.7)
lag EAR_t	-0.039 (-0.90)	-0.018 (-0.45)	0.003 (0.1)	0.017 (0.4)	0.01 (0.3)	-0.003 (-0.07)	-0.022 (-0.51)	0.004 (0.1)	0.011 (0.3)	0.017 (0.4)	-0.005 (-0.13)	-0.039 (-0.91)
sue	5.035*** (4.8)	4.478*** (4.5)	4.492*** (4.5)	4.567*** (4.7)	4.593*** (4.8)	4.552*** (4.8)	4.289*** (4.5)	3.699*** (4.0)	3.278*** (3.4)	2.729*** (2.8)	2.363** (2.5)	2.311** (2.4)
lag sue	3.454*** (3.9)	3.688*** (4.2)	3.754*** (4.0)	3.473*** (3.6)	3.298*** (3.4)	2.739*** (2.9)	2.492** (2.5)	2.195** (2.3)	2.147** (2.1)	2.056** (2.0)	2.241** (2.2)	2.005** (2.0)
rev1	0.207*** (9.7)	0.217*** (9.9)	0.218*** (9.8)	0.215*** (9.2)	0.216*** (9.1)	0.209*** (8.8)	0.194*** (8.1)	0.164*** (7.1)	0.135*** (5.9)	0.111*** (4.9)	0.098*** (4.4)	0.093*** (4.2)
rev2	0.129*** (6.4)	0.124*** (6.0)	0.122*** (5.8)	0.108*** (5.1)	0.080*** (4.1)	0.057*** (3.0)	0.037* (1.9)	0.035* (1.9)	0.041** (2.1)	0.055*** (2.6)	0.078*** (3.7)	0.091*** (4.3)
rev3	0.116*** (5.6)	0.083*** (4.1)	0.056*** (2.8)	0.048** (2.3)	0.051** (2.5)	0.064*** (3.0)	0.073*** (3.2)	0.101*** (4.2)	0.118*** (4.9)	0.137*** (5.7)	0.133*** (5.8)	0.122*** (5.3)
R^2	0.052	0.05	0.05	0.048	0.047	0.047	0.046	0.045	0.045	0.045	0.046	0.046

Table A.6: Forecast Errors Regression (winsorized at 5%/Scaled by Price)

$$FE_{t+k \rightarrow t+k+2}^i = \hat{\lambda}_{t+k} mom_{i,t} + \rho_{1,k} SUE_t + \rho_{2,k} SUE_{t,L1} + \rho_{3,k} EAR_t + \rho_{4,k} EAR_{t,L1} + \rho_{5,k} REV_t + \rho_{6,k} REV_{t,L1} + \rho_{7,k} REV_{t,L2} + Yearmon_t + \eta_{t,t+h}$$

k	1	2	3	4	5	6	7	8	9	10	11	12
λ_k	0.280*** (24.4)	0.248*** (21.9)	0.217*** (19.2)	0.190*** (16.8)	0.165*** (14.6)	0.146*** (13.0)	0.131*** (11.8)	0.118*** (10.7)	0.102*** (9.3)	0.092*** (8.4)	0.082*** (7.4)	0.070*** (6.4)
EAR_t	0.655*** (4.1)	0.605*** (4.0)	0.521*** (3.4)	0.444*** (2.9)	0.367** (2.5)	0.243* (1.7)	0.167 (1.1)	0.167 (1.2)	0.137 (0.9)	0.109 (0.7)	0.176 (1.1)	0.26 (1.6)
lag EAR_t	-0.14 (-0.93)	-0.188 (-1.30)	-0.204 (-1.40)	-0.204 (-1.34)	-0.126 (-0.85)	-0.118 (-0.80)	-0.06 (-0.40)	0.005 (0.0)	0.036 (0.3)	0.03 (0.2)	-0.005 (-0.03)	0.033 (0.2)
sue	0.660*** (9.9)	0.583*** (9.0)	0.518*** (8.1)	0.479*** (7.6)	0.426*** (6.9)	0.399*** (6.5)	0.386*** (6.4)	0.392*** (6.8)	0.412*** (7.1)	0.419*** (7.0)	0.399*** (6.6)	0.387*** (6.3)
lag sue	0.261*** (4.5)	0.249*** (4.3)	0.258*** (4.5)	0.258*** (4.4)	0.273*** (4.8)	0.287*** (5.0)	0.297*** (5.2)	0.294*** (5.1)	0.280*** (5.0)	0.296*** (5.2)	0.296*** (5.3)	0.270*** (5.0)
rev1	1.311*** (13.4)	1.254*** (12.7)	1.207*** (12.1)	1.164*** (11.6)	1.117*** (11.3)	0.985*** (10.5)	0.817*** (9.1)	0.669*** (8.0)	0.551*** (6.7)	0.456*** (5.5)	0.414*** (4.8)	0.412*** (4.6)
rev2	0.599*** (7.2)	0.562*** (7.1)	0.481*** (6.5)	0.367*** (5.2)	0.254*** (3.9)	0.184*** (2.9)	0.123* (1.8)	0.135* (1.9)	0.194** (2.6)	0.233*** (3.1)	0.264*** (3.6)	0.258*** (3.5)
rev3	0.265*** (3.5)	0.183** (2.6)	0.183** (2.6)	0.202*** (2.7)	0.239*** (3.1)	0.304*** (3.8)	0.370*** (4.6)	0.390*** (5.0)	0.378*** (4.9)	0.346*** (4.3)	0.307*** (3.8)	0.284*** (3.7)
R^2	0.126	0.114	0.103	0.096	0.088	0.082	0.078	0.075	0.073	0.073	0.073	0.072
k	13	14	15	16	17	18	19	20	21	22	23	24
λ_k	0.064*** (5.8)	0.061*** (5.5)	0.056*** (5.0)	0.051*** (4.6)	0.049*** (4.3)	0.045*** (4.1)	0.047*** (4.2)	0.048*** (4.2)	0.049*** (4.1)	0.052*** (4.2)	0.055*** (4.4)	0.059*** (4.6)
EAR_t	0.242 (1.5)	0.225 (1.4)	0.199 (1.3)	0.181 (1.1)	0.128 (0.8)	0.098 (0.6)	0.102 (0.6)	0.086 (0.5)	0.054 (0.3)	-0.017 (-0.10)	-0.071 (-0.42)	-0.156 (-0.93)
lag EAR_t	0.062 (0.3)	0.062 (0.4)	0.056 (0.4)	0.051 (0.3)	0.063 (0.4)	0.01 (0.1)	-0.091 (-0.58)	-0.08 (-0.52)	-0.157 (-1.00)	-0.188 (-1.14)	-0.233 (-1.46)	-0.278* (-1.73)
sue	0.376*** (6.1)	0.349*** (5.8)	0.324*** (5.5)	0.314*** (5.2)	0.317*** (5.6)	0.307*** (5.4)	0.287*** (5.1)	0.275*** (4.9)	0.252*** (4.4)	0.237*** (4.0)	0.232*** (4.0)	0.234*** (4.1)
lag sue	0.254*** (4.7)	0.254*** (4.9)	0.262*** (4.9)	0.268*** (4.7)	0.261*** (4.7)	0.245*** (4.5)	0.231*** (4.2)	0.220*** (4.0)	0.235*** (4.2)	0.242*** (4.2)	0.243*** (4.4)	0.215*** (4.0)
rev1	0.408*** (4.5)	0.415*** (4.6)	0.421*** (4.7)	0.419*** (4.6)	0.402*** (4.4)	0.404*** (4.6)	0.388*** (4.6)	0.351*** (4.4)	0.299*** (3.8)	0.261*** (3.3)	0.251*** (3.2)	0.280*** (3.5)
rev2	0.233*** (3.1)	0.209*** (2.8)	0.207*** (2.9)	0.172** (2.5)	0.141** (2.2)	0.118* (1.8)	0.092 (1.4)	0.085 (1.3)	0.114* (1.7)	0.164** (2.3)	0.220*** (2.9)	0.253*** (3.1)
rev3	0.260*** (3.6)	0.231*** (3.3)	0.196*** (2.8)	0.202*** (2.7)	0.213*** (2.9)	0.244*** (3.2)	0.292*** (3.7)	0.378*** (4.4)	0.428*** (4.7)	0.452*** (4.7)	0.430*** (4.5)	0.404*** (4.3)
R^2	0.071	0.07	0.07	0.07	0.071	0.071	0.072	0.073	0.073	0.074	0.076	0.078

Table A.7: Dynamics of Forecast Errors (Two-year-ahead forecasts)

Portfolio		Median Forecast Errors for Two-year-ahead forecasts											
n^{th} Month after Sorting	1	2	3	4	5	6	7	8	9	10	11	12	
Ave. Winner-Loser Diff.	22.1%	19.2%	16.4%	14.0%	12.1%	10.4%	8.7%	7.3%	6.2%	5.1%	4.7%	4.0%	
T-stat	9.5	8.7	7.5	6.4	5.6	4.6	4.0	3.3	2.8	2.3	2.1	1.8	
n^{th} Month after Sorting	13	14	15	16	17	18	19	20	21	22	23	24	
Ave. Winner-Loser Diff.	3.3%	3.2%	3.1%	2.9%	2.9%	2.7%	2.9%	3.2%	3.2%	3.0%	2.8%	2.6%	
T-stat	1.4	1.4	1.3	1.4	1.4	1.4	1.6	1.8	1.8	1.6	1.5	1.3	

Table A.8: Dynamics of Forecast Errors (Nearest quarterly forecasts)

Portfolio Median Forecast Errors for the nearest quarterly forecasts													
n^{th} Month after Sorting	1	2	3	4	5	6	7	8	9	10	11	12	
Ave. Winner-Loser Diff.	9.0%	8.0%	6.8%	5.9%	5.1%	4.2%	3.4%	2.7%	2.0%	1.6%	1.4%	1.2%	
T-stat	6.5	6.2	6.3	5.6	4.9	4.7	4.4	3.8	3.5	3.3	3.1	2.5	
n^{th} Month after Sorting	13	14	15	16	17	18	19	20	21	22	23	24	
Ave. Winner-Loser Diff.	1.0%	0.5%	0.2%	0.2%	0.1%	-0.2%	0.1%	-0.2%	-0.4%	-0.5%	-0.4%	-0.4%	
T-stat	2.0	1.2	0.4	0.3	0.3	-0.4	0.1	-0.5	-0.8	-1.1	-0.9	-1.0	

Table A.9: Data Description

Variable	Data	Quotes	Time Stamp	Source	Frequency
Sovereign Credit Risk	CDS 5y	mid	1:00 p.m. ET	Bloomberg	Daily
CDS liquidity	CDS 5y	bid/ask	1:00 p.m. ET	Bloomberg	Daily
Regional Credit Risk	Regional bond yields	mid	12PM ET	Bloomberg	Daily
Regional Bond liquidity	Regional bond yields	bid/ask	12PM ET	Bloomberg	Daily
General Risk Aversion	iTraxx Index	mid	1:00 p.m. ET	Bloomberg	Daily
Short Term Interest Rate	EURIBOR	ask	6pm ET	EBF	Daily
4 Groups of 14 Event Dummies 1/	Set to 1 on respective event day			Bloomberg News	Daily
Period Dummy 1 (PD1)	Set to 1 until 12/19/2011				Daily
Period Dummy 2 (PD2)	Set to 1 after 7/26/2012				Daily

Table A.10: *Event Dummies*

D1: Government Pledges of Support		
1/17/2012	15:48 GMT	Prime Minister announces a broad agenda to address regional liquidity issues (Ross-Thomas, 2012a)
3/27/2012	12:22GMT	Economy Minister is considering joint bond issuance, backed by the treasury (Benoit, 2012c)
D2: Concrete Bailout Measures		
1/4/2012	16:30GMT	Treasury provides a "verbal guarantee" for Valencia's loans (Sills, 2012)
2/3/2012	12:45 GMT	ICO sets up a credit line of 15 billion euros (Baigorri, 2012)
3/2/2012	12:56GMT	FFPP is set up to pay regions' debt to suppliers (Benoit, 2012b)
7/13/2012	14:05GMT	FLA is set up to provide 18 billion euros in liquidity (Benoit, 2012d)
7/20/2012	13:28GMT	Valencia announces that it will tap FLA-the first region to do so (Sills and Ross-Thomas, 2012)
D3: Subnational Credit Negative Events		
12/19/2011	20:42GMT	Moody's downgrades Valencia (Moody's, 2011)
1/12/2012	10:22GMT	Moody's downgrades Valencia, puts 6 others on downgrade watch (Benoit, 2012a)
5/17/2012	17:02 GMT	Moody's downgrades several regions but confirms Valencia (Moody's, 2012)
5/19/2012	8:31 GMT	Negative general government fiscal deficit revision, caused by 3 regions (Ross-Thomas, 2012b)
5/25/2012	14:00 GMT	Catalonia requests additional government support, calls for "Hispanos" (Sparkes, 2012)
7/9/2012	6:31 GMT	Valencia announces that it may default without government support (Smyth, 2012)
D4: ECB Announcement		
7/26/2012	13:50 GMT	Draghi: "ECB will do what's needed" to preserve the euro (Black and Randow, 2012)

Table A.11: Unit Root Tests

Spanish CDS	Phillips-Perron w/ 5 lags	trend	MacKinnon approximate p-value	0.6147
		no trend	MacKinnon approximate p-value	0.2216
Valencia's bond yield	Phillips-Perron w/ 5 lags	trend	MacKinnon approximate p-value	0.9847
		no trend	MacKinnon approximate p-value	0.6496

Appendix B

Appendix for Chapter 2

B.1 GMM Standard Errors

Table 1 reports the first four unconditional moments of the basic carry trades as well as their Sharpe ratios. This Appendix explains the construction of the standard errors. Let μ denote the sample mean, σ denote the standard deviation, γ_3 denote sample standardized skewness, and γ_4 denote sample standardized kurtosis. The orthogonality conditions are

$$\begin{aligned} E(r_t) - \mu &= 0 \\ E[(r_t - \mu)^2] - \sigma^2 &= 0 \\ \frac{E[(r_t - \mu)^3]}{\sigma^3} - \gamma_3 &= 0 \\ \frac{E[(r_t - \mu)^4]}{\sigma^4} - \gamma_4 - 3 &= 0 \end{aligned}$$

Let $\theta = (\mu, \sigma, \gamma_3, \gamma_4)^\top$, let $g_T(\theta)$ denote the sample mean of the orthogonality conditions for a sample of size T , and let S_T denote an estimate of the variance of the sample moments. We estimate S_T using the method of Newey-West (1987) with three leads and lags. Hansen

(1982) demonstrates that choosing the parameter estimates to minimize $g_T(\theta)^\top S_T^{-1} g_T(\theta)$ produces asymptotically unbiased estimates with asymptotic variance, $\frac{1}{T}(D_T^\top S_T^{-1} D_T)^{-1}$, where D_T is the gradient of $g_T(\theta)$ with respect to θ . The Sharpe ratio is defined to be $SR = \frac{\mu}{\sigma}$, and the variance of SR is found by the delta method:

$$\text{var}(SR) = \frac{1}{T} \begin{bmatrix} \frac{1}{\sigma} & \frac{-\mu}{\sigma^2} & 0 & 0 \end{bmatrix} (D_T^\top S_T^{-1} D_T)^{-1} \begin{bmatrix} \frac{1}{\sigma} & \frac{-\mu}{\sigma^2} & 0 & 0 \end{bmatrix}^\top$$

B.2 Cumulants of a random variable

$$\begin{aligned} g_X(t) &= \ln(E(e^{tX})) \\ &= \sum_{n=1}^{\infty} \kappa_n \frac{t^n}{n!} \end{aligned}$$

$$\kappa_1 = E(X) = \gamma_1^d$$

$$\kappa_2 = E(X - \kappa_1)^2 = \gamma_2^d$$

$$\kappa_3 = E(X - \kappa_1)^3 = \gamma_3^d$$

$$\kappa_4 = E(X - \kappa_1)^4 - 3[E(X - \kappa_1)^2]^2$$

$$g_{X+Y}(t) = g_X(t) + g_Y(t)$$

Therefore,

$$\begin{aligned}
 skew^d &= \frac{\gamma_3^d}{(\gamma_2^d)^{\frac{3}{2}}} \\
 skew^m &= \frac{\gamma_3^m}{(\gamma_2^m)^{\frac{3}{2}}} \\
 &= \frac{\kappa_3(r_1^d) + \dots + \kappa_3(r_{21}^d)}{(\kappa_2(r_1^d) + \dots + \kappa_2(r_{21}^d))^{\frac{3}{2}}} \\
 &= \frac{1}{\sqrt{21}} \frac{\gamma_3^d}{(\gamma_2^d)^{\frac{3}{2}}} \\
 &= \frac{1}{\sqrt{21}} skew^m \\
 Kurt^d &= \frac{\gamma_4^d}{(\gamma_2^d)^2} \\
 &= \frac{\kappa_4(r_1^d) + 3\kappa_2(r_1^d) + \dots + \kappa_4(r_{21}^d) + 3\kappa_2(r_{21}^d)}{(\kappa_2(r_1^d) + \dots + \kappa_2(r_{21}^d))^2} \\
 &= \frac{1}{21} Kurt^m
 \end{aligned}$$

Appendix C

Appendix for Chapter 3

C.1 General data description

The sample comprises daily data from 1/1/2010 to 6/25/2013.

We use CDS data for 12 countries: Austria, Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Portugal, Spain, Sweden, and United Kingdom; and regional bond yields for Andalucía, Catalonia, and Valencia (which had sufficiently frequent quotes).

We use the most liquid bond for each region and apply a few data cleaning steps: i) we take the absolute value of the bid/ask spreads because in a few occasions the spreads are negative, suggesting the bid/ask quotes are put in reverse order; ii) we use the Bloomberg “BGN” quotes whenever they are available and “BVAL” quotes otherwise (“BGN” quotes are trade-based and “BVAL” quotes are synthetic).

We use the Markit iTraxx Europe index, which is an equally weighted index of 125 investment grade corporate CDSs in Europe.¹

Period Dummy 1 (PD1) captures the time period before the sub-national debt crisis (*pre-bailout*) and Period Dummy 2 (PD2) the time period after ECB president Draghi’s speech (*post-Draghi*).

C.2 Events studied

We use the Bloomberg news search function to determine the exact timing of the first news break for each of the events. We then organize these news events into four groups (Table A.10). The first group comprises news events about the central government’s pledges of support (without any concrete commitments). The second group comprises news events about concrete government guarantees or bailout mechanisms. The third group comprises events

¹For a complete description see <http://www.markit.com/assets/en/docs/products/data/indices/credit-and-loan-indices/iTraxx/Markit%20iTraxx%20Europe%20Index%20Rules%20S19.pdf>

that are bad news from a regional credit risk point of view. The last event is ECB president Draghi's speech that reconfirmed the ECB's "unlimited" commitment to preserving the euro (widely interpreted to refer to continued purchases of sovereign bonds with excessively high yields). In our robustness checks we also pool D1 and D2 into a joint dummy (DD).

C.3 GERMANY'S BUND-LÄNDER ANLEIHEN

As Spanish regions were shut out of debt markets and the sovereign rescue unfolded, the issuance of joint bonds by the central government and regions (so-called *Hisapabonos*) was also being discussed. The recent issuance of the first joint federal-state government bond in Germany offers an illustration of how joint borrowing of sovereign and state governments results in a subsidy to the latter—similar to the increase in sovereign borrowing costs we found to coincide with outright bailouts—but much more circumscribed and mainly applicable to the specific joint debt issue.²

In June 2013, the German federal government and 10 states jointly issued a *Bund-Länder Anleihe*, with each entity being liable on a pro rata basis for their respective share.³ As the joint bond has been traded in the market, we can observe the financing cost charged by the market both for the joint bond as well as for each individual issuer.⁴ Figure 3.18 shows that the joint bond commands a yield that is higher than the federal government yield, but lower than most of the individual Länder yields. Specifically, since the debut of the bond,

²The impact on general risk premia could be assessed. Most likely, results will be driven by the significance of the new potential liability for central government finances as a whole.

³The bond has a maturity of 7 years and a size of 3 billion euros. Shares are as follows: Federal government (13.5%); Berlin (13.5%); Brandenburg (6.75%); Bremen (13.5%); Hamburg (5.25%); Mecklenburg-Vorpommern (3.25%); NRW (20%); Rheinland-Pfalz (6.75%); Saarland (6.75%); Sachsen-Anhalt (2.75%); Schleswig-Holstein (8%). Source: Deutsche Finanzagentur (2013).

⁴We download daily data of the bond yields for the joint bond, individual bond, and jumbo bond from Bloomberg. Data are from 2013/6/23 to 2013/7/26.

the data indicate that the federal government has to pay 50 basis points more by financing through the joint bonds, while in doing so most of the Länder can get a discount over their own financing cost, ranging from 8 basis points to 12 basis points.⁵

Since the joint bonds and the individual bonds differ in terms of size, liquidity, maturity, and other aspects, we double-check our result by calculating a weighted average of the interpolated individual bond yields according to each state's share. We find that the weighted average yield tracks the actual joint bond yield very closely (Figure 3.19). This implies that the market's risk assessment of individual entities does not seem to have changed, and for the Länder to pay less in interest, the federal government has to make up the difference.

Summing up, while it does not constitute a risk transfer scheme as the one we identified in Spain, this example illustrates the subsidy that would be paid by any entity as a result of pooling its borrowing with lesser-rated entities.⁶ However, joint borrowing by sovereigns and sub-entities is a rare exception in financing arrangements in federations (Palomba et al 2013).⁷

⁵Bremen does not issue fixed rate coupon bonds, so it could not be included in our calculations. Weights are adjusted accordingly. There are a number of caveats: Given the size of the joint bond, its liquidity is relatively low, and no other bond will have the exact same maturity. However, to get around the latter issue we linearly interpolate individual bond yields to match the maturity of the joint bond.

⁶In the case of this bond the subsidy is maximized as it particularly attracted financially weaker states while financially stronger states (such as Bayern or Baden-Wuerttemberg) did not opt to participate.

⁷The same phenomenon has occurred with a slightly different twist when separate states with separate financial histories join a federation. For example, Collet (2012) examines Italian states' bond premia during Italy's unification process in the 19th century and finds that Naples' previously low borrowing costs increased substantially as it joined the highly indebted unitary state.