Aalto University
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Forward Premium Puzzle and Firm-Level Idiosyncratic Volatility

Finance

Master's thesis

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OBJECTIVES OF THE STUDY

In this paper, I study the effects of funding constraints with respect to the uncovered interest parity (UIP) violations, i.e. the excess returns from the traditional carry strategies. More specifically, I examine the impact of the realized firm-level idiosyncratic *aggregate average* uncertainty in the United States (U.S.) economy as well as the realized firm-level idiosyncratic *average* uncertainty in the U.S. financial sector on carry trade excess returns. Moreover, I conduct a sub-period analysis with respect to the surge in the amount of speculative capital since early 2000 and the *financialization* in order to understand how sensitive the speculative community is to *unexpected* changes in systemic risk. Finally, in addition to contributing to existing research and opening new avenues for future research, I re-examine and confirm existing literature on the uncovered interest parity (UIP) violations, the role of *learning* in the forward premium puzzle, and the linkage between currency carry trades and currency crash risk.

DATA AND METHODOLOGY

The data set consists of daily spot and forward rates for 9 currencies with respect to the USD dollar from January 1996 to February 2014. In addition, I collect daily data for all listed U.S. stocks and their daily returns from CRSP for the same period in order to construct the idiosyncratic firm-level risk metrics. To test the hypotheses, I estimate several multivariate OLS regressions with varying specifications and perform numerous robustness checks.

FINDINGS OF THE STUDY

The multivariate model based upon the idiosyncratic financial sector uncertainty is statistically significant and explains 14.3% of the excess return variability of the High-minus-Low (HML3) portfolios that comprise a long position in the top three currencies and a short position in the bottom three currencies. The funding model consists of two independent explanatory variables that are both related to the realized idiosyncratic *average* firm-level uncertainty in the U.S. financial sector: a contemporaneous change and a 6-month moving average.

Moreover, a multivariate funding model based upon the conventional TED spread, a typical measure of funding constraints, and the idiosyncratic banking sector uncertainty explains 21.4% of the High-minus-Low (HML3) excess return variability. The *marginal* contribution of the latter is statistically significant once I take into account the loss in degrees of freedom.

Additionally, a *single* explanatory variable which proxies the effects of *unexpected* funding shocks, a *normalized* specification, explains 11.4% of the High-minus-Low (HML3) excess return variability for the full period from 1996 to 2013. In comparison, the *contemporaneous* TED spread explains 11.0% of the variation for the same period. The correlation coefficient among the two is 0.56. Furthermore, the explanatory power of the *normalized* specification increases from 11.4% to 22.0% in a multi-dimensional setting.

Keywords: Foreign Exchange, Forward Premium Puzzle, Carry Trades, Funding Constraints, Idiosyncratic Firm-Level Uncertainty

Tekijä Lari Palenius		
Otsikko Idiosynkraattinen yrityskohtainen riski ja sen vaikutus erilaisten valuuttastrategioiden ylituottoihin		
Tutkinto Kauppatieteiden maisteri		
Ohjelma Rahoitus		
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TUTKIELMAN TAVOITTEET

Tutkin pro gradu-tutkielmassani keskimääräisen yrityskohtaisen riskin vaikututusta valuuttamarkkinoiden ylituottoihin. Lasken yrityskohtaisen epävarmuusmittarin Yhdysvaltain osakemarkkinoille sekä erikseen Yhdysvaltain rahoitussektorille. Tarkoitukseni on tutkia toteutuneen rahoitusriskin vaikutusta erilaisten valuuttastrategioiden ylituottoihin. Lisäksi tutkin eri aikaperiodeita hyödyntäen keinottelijoiden herkkyyttä muutoksiin systeemiriskissä. Lopuksi tarkastelen keskimääräisten ylituottojen luonteenomaisia piirteitä valuuttamarkkinoilla, tutkin uncovered interest parity (UIP) - teoreettisen kehikon paikkansapitävyyttä huomioiden sekä ajan kulun että oppimisen ja perehdyn valuuttamarkkinoiden ylituottojen toteutuneen jakauman vinouteen ja sen mahdollisiin aiheuttajiin.

LÄHDEAINEISTO JA TUTKIMUSMENETELMÄT

Otokseni koostuu yhdeksästä valuuttaparista, jotka kaikki noteerataan Yhdysvaltain dollaria vastaan. Otokseni pitää sisällään valuuttakurssien ja termiinikurssien päivämuutokset aikaväliltä tammikuu 1996 ja joulukuu 2013. Lisäksi osakemarkkinaotokseni pitävät sisällään kaikki Yhdysvalloissa noteeratut julkiset yritykset ja heidän päiväkohtaiset osaketiedot samalta aikaperiodilta. Osakekohtaista dataa hyödyntäen lasken yrityskohtaiset epävarmuustekijät kuten olen yllä kuvannut. Hypoteeseja tutkiessani rakennan useita OLS monimuuttujamenetelmä eri muuttujia hyödyntäen sekä ja varmistan tuloksien tilastollista merkitsevyyttä.

TULOKSET

Rakentamani monimuuttujamenetelmä on tilastollisesti merkitsevä ja selittää 14.3% valuuttamarkkinoiden High-minus-Low portfolioiden ylituottojen muutoksista. High-minus-Low portfolio pitää sisällään pitkän position korkoerolla mitaten kolmessa kärkivaluutassa ja lyhyen position kolmessa pohjavaluutassa. Rahoitusriskiä replikoiva monimuuttujamenetelmä pitää sisällään kaksi selittävää muuttujaa, joista kummatkin liittyvät Yhdysvaltain rahoitussektorin keskimääräiseen yrityskohtaiseen epävarmuuteen.

Monimuuttujamenetelmä, joka yhdistää olemassa olevan tiedon TED rahoitusriskimuuttujan ja Yhdysvaltain rahoitussektorin keskimääräistä yrityskohtaista epävarmuutta mittaavaan rahoitusriskimuuttujan kesken, kykenee selittämään 21.4% HML portfolioiden ylikurssimuutoksista.

Lisäksi, yksittäin selittävätekijä, joka mittaa toteutuneen rahoitusriskimuuttujan odottamattoman muutoksen suuruutta kykenee selittämään 11.4% ylituottojen vaihtelusta. On myöskin varteenotettavaa, että kyseisen muuttajan selitysaste kasvaa monotonisesti 11.4%:sta 22.0%:iin ajan suhteen samanaikaisesti kuin keinottelijoiden alla olevien positioiden suuruusluokka kasvaa huomattavasti.

Avainsanat: Valuuttamarkkinat, Epänormaalit ylituotot, Erilaiset valuuttastrategiat, Rahoitusriski, Yrityskohtainen epävarmuus

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A. Introduction

A.1 Background and Motivation

Over the past few years, the lion's share of existing research on foreign exchange has been centered around three different literatures: the forward premium puzzle, funding constraints, and disaster risk. The causality goes from funding constraints and disaster risk to carry trade returns. At the same time, the relationship may characterize something called a reverse causality, where an effect actually occurs before its cause. More importantly, the topics are seemingly interconnected. Therefore, given a traditional carry trade is nothing but a risky variant of future spot rate, the decade old remarks of Meese and Rogoff (1982) on randomness are not anymore the pivotal subjects of modern research. However, this does not mean that spot exchange rates would not follow a random process, but rather that the causes of what appears to be *random*, are increasingly linked to both the funding risk and the disaster risk, especially in the aftermath of the recent financial crisis.

The first subset, the forward premium puzzle, relates to the empirical failure of the uncovered interest parity (UIP) that is the classic topic of international finance and the critical building block of most theoretical frameworks. Fama (1984) robustly captures the violations of the UIP framework and concludes that innovations relate to changes in the risk premia. The author provides future research with presumptions for the *possible* sources of risk premia but does not embark on a journey to attribute the UIP violations to any of them. The second subset, the funding constraints, attributes these UIP violations to the funding risks such as increases in margin requirements due to uncertainty, which in turn has its implications on collateralized funding and speculators' positioning. With respect to the funding constraints and asset prices, the theoretical foundation has been laid by Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), as well as Duffie and Strulovici (2012). In relation to the forward premium puzzle more specifically, Brunnermeier, Nagel and Pedersen (2009) and Filipe and Suominen (2013) link funding constraints to carry trade excess returns. The third subset, the disaster risk, relates to Dodrynskaya (2013), who concludes that the carry trade crashes occur systematically in the worst states of the world.

A potential limitation of existing studies on funding constraints is highlighted in Adrian and Shin (2002), where the authors conclude that the aggregate liquidity can be seen as a rate of change in the aggregate balance sheet of financial intermediaries. In other words, changes in financial institutions' equity prices affect their ability to lend. A simple way to measure the aggregate change is to compute a measure for the average idiosyncratic firm-level uncertainty in the financial industry as in Campbell, Lettau, Malkiel, and Xu (2001, henceforth also CLMX). This is contrary to Filipe and Suominen (2013), who proxy the funding constraints using the implied *stock market* volatility, rather than the realized *industry-specific* volatility, in measuring the uncertainty with reference to funding constraints. Similarly, Brunnermeier, Nagel and Pedersen (2009) identify states where speculators are forced to unwind positions using the CBOE VIX option implied volatility (VIX) and the TED spread. None of these studies however, measure directly the volatility of common stocks within the financial sector as proposed by Adrian and Shin (2002).

A.2 Objective and Contribution

In order to contribute to existing research, I construct two proxies for the funding risk that relate to the realized idiosyncratic firm-level *aggregate average* uncertainty in the United States (U.S.) economy as well as the realized idiosyncratic firm-level *average* uncertainty in the U.S. financial sector. In other words, both measures are a function of changes in equity prices over the period. Additionally, I derive two specifications for these funding proxies: a *directional downside* adjusted measure and a *normalized* measure. I argue that a direction is more important than dispersion, a rationale for the directional specification, and that anything that is *unexpected* must relate to a *surprise*, a rationale for the *normalized* specification. I expect that the first specification relates more to the funding constraints while the second may better proxy the disaster risk. Also, I construct a multivariate funding model that contains the *joint explanatory effect* of the funding proxies documented in Brunnermeier, Nagel and Pedersen (2009) together with the ones documented in this paper.

Furthermore, given the findings of Ang et. al. (2006 and 2009) in relation to the idiosyncratic volatility emerging from the U.S. and its ability to explain the cross-section of stock returns both in-sample and out-of-sample studies, *locally* and *globally*, raises a question related to the role of uncertainty emerging from the United States (US) as part of the forward premium puzzle. The early evidence of idiosyncratic volatility in foreign exchange is present in Guo and Savickas (2006) but is not exhaustive.

In conclusion, the objective is to contribute to existing research and potentially open new avenues for future research. Also, I re-examine existing literature on the uncovered interest parity (UIP) violations, the role of *learning* in the forward premium puzzle, and the linkage between currency carry trades and currency crash risk.

A.3 Scope and Limitations of the Study

The results of this paper are subject to the *stale price bias* given the fact that the empirical analysis on carry returns deploys the end-of-month (EOM) data on foreign exchange rates. However, given the fact that my data only includes currencies that are conceptually similar in terms of liquidity and foreign exchange regime, I believe that I have greatly mitigated this issue.

Additionally, I only proxy the uncertainty emerging from the United States though the USD dollar is not by definition a typical *funding* currency as part of the HML strategies in foreign exchange. Therefore, in addition to traditional High-minus-Low (HML) portfolios that consist of simultaneous *long* and *short* positions and are therefore USD funding neutral, I construct *long* only portfolios that are being funded via USD money markets.

Finally, my results assume that covered interest parity (CIP) holds as documented in Akram et. al. (2008).

A.4 Main Findings

The multivariate model based upon the idiosyncratic financial sector uncertainty is statistically significant and explains 14.3% of the excess return variability of the High-minus-Low (HML3) portfolios that comprise a long position in the top three currencies and a short position in the bottom three currencies. The funding model consists of two independent explanatory variables that are both related to the realized idiosyncratic *average* firm-level uncertainty in the U.S. financial sector: a contemporaneous change and a 6-month moving average.

Moreover, a multivariate funding model based upon the conventional TED spread, a typical measure of funding constraints, and the idiosyncratic banking sector uncertainty explains 21.4% of the High-minus-Low (HML3) excess return variability. The *marginal* contribution of the latter is statistically significant once I take into account the loss in degrees of freedom.

Additionally, a *single* explanatory variable which proxies the effects of *unexpected* funding shocks, a *normalized* specification, explains 11.4% of the High-minus-Low (HML3) excess return variability for the full period from 1996 to 2013. In comparison, the *contemporaneous* TED spread explains 11.0% of the variation for the same period. The correlation coefficient among the two is 0.56. Furthermore, the explanatory power of the *normalized* specification increases from 11.4% to 22.0% in a multi-dimensional setting.

A.5 Structure of the Study

This paper is structured as follows: Section B examines existing literature on the forward premium puzzle, funding constraints, disaster risk, and the role of the U.S. in asset pricing. Section C presents the data, carry trade ranking methodologies, and different carry portfolios. Section D presents the independent explanatory variables of this paper. Section E is a summary of my empirical findings and finally, section F summarises my findings.

B. Literature Review

B.1 Covered and Uncovered Interest Rate Parity

Every literature review subsumes a causal and logical structure connecting the related topics that are centered around one or more focal points. The focal point of this paper is the forward premium puzzle, which is one of the most robust findings of existing literature of international finance, showing that the forward exchange rate does not predict the subsequent, realized exchange rate change (Fama, 1984 among others). This is an undisputed fact of past and present. The pivotal causes of these violations relate to the *crash risk* (Brunnermeier, Nagel, and Pedersen, 2009) and the *funding constraints* (Filipe and Suominen, 2013). In order to look in more detail these pivotal causes, a basic understanding of covered interest parity (CIP) and uncovered interest parity (UIP) is required. It is important to fully understand these two related frameworks and their underpinning assumptions before embarking on any endeavors attempting to solve the forward premium puzzle, as the puzzle effectively violates these frameworks.

To start with, a simple theoretical framework that intuitively explains the relationship between interest rate on an asset denominated in one country's currency unit, interest rate on a similar asset *while* denominated in another country's currency unit, and the expected future spot exchange rate between the two countries is required. In other words, a model that explains the structural rationale under which today's price of foreign exchange deliverable on a specific future date is determined is detrimental. Most academics agree that if investors are *risk neutral* and hold *rational expectations*, the market's forecast of future exchange rate is implicit in differences in interest rates (Froot and Thaler, 1990).

The covered interest parity (CIP) is the simplest model for open economies that leans on the *no-arbitrage* combined with *rational expectations*. CIP simply assumes that exchange rates are market determined, all available information is present, and that investors are rational. CIP is also known as the weak version of frictionless capital mobility (Eaton and Turnovsky, 1983). Under the framework bonds are risk-free both domestically and abroad and because the model assumes *no-arbitrage* combined with *rational expectations*, market participants ought to bring the domestic interest rate *(R)* into equality with the foreign interest rate *(R')* plus the forward premium or discount of foreign exchange *(F)* (Eaton and Turnovsky, 1983). In other words, returns on 1-month money market instrument in the U.S. and in the UK are on average *equalized*. Therefore, the covered interest parity (CIP) can be written as:

$$1 + R_t = (1 + R'_t) * S_t \,/\, F_t, \tag{1}$$

where *R* , *R'*, and *F* are defined over the same maturity. The key to understanding CIP is that the 1-month money market instruments in question are effectively perfect substitutes *aside* from the currency of denomination. In other words, formula (1) assumes that investors' net returns on investments that borrow domestically and lend abroad *in similar* interest bearing assets are zero when the exchange rate uncertainty is hedged with a foreign exchange forward contract.

Generally speaking, the law of one price (LOP) requires that similar securities have a single price. If the price is defined as yield, CIP postulates that two similar securities that are denominated in different currencies must yield exactly the same return when the exchange rate uncertainty is removed. Therefore, systematic deviations from the condition (1) would not only refute LOP but also leave us to conclude that the efficient market hypothesis (EMH) does not hold.

A slightly more stringent framework derived from CIP adds an additional requirement towards the forward premium of foreign exchange forward contract. This requirement relates to the risk neutrality, either because there is a sufficient number of risk-neutral speculators providing liquidity, or because foreign exchange rate risk is perfectly diversifiable (Eaton and Turnovsky, 1983). Therefore, the stronger definition brings the forward premium (discount) on foreign exchange into equality with the expected rate of depreciation (appreciation) of the foreign currency:

$$F_t = E_t(S_{t+1}) \,/\, S_t, \tag{2}$$

where S denotes the price of one unit of domestic currency in terms of foreign currency. Substituting (2) into (1) yields:

$$1 + R_t = (1 + R'_t) * S_t \, / \, E_t(S_{t+1}), \quad (3)$$

which is also known as the *uncovered* interest parity (UIP). In other words, UIP requires that conditions (1) and (2) hold. Above, $E_t(\,)$ represent the mathematical expectation conditional on information available to the market participants at time t (Engel, 1995). In conclusion, CIP assumes perfect capital mobility, and UIP requires CIP to hold in conjunction with the risk neutrality.

B.2 Forward Premium Puzzle

Mussa (1979) reports that interest differential in favor of domestic currency bonds is equal approximately to the expected rate of depreciation of domestic money in terms of foreign currency, which is in line with condition (1). By the same token, Akram et. al. (2008) investigate more recently condition (1) with three exchange rates and conclude that a typical researcher can safely assume frictionless capital mobility in foreign exchange markets when working with daily or lower frequency of data. The authors observe only short-lived, however economically significant, arbitrage opportunities and reason that the result suggest that markets exploit arbitrage opportunities rapidly. These two findings conclude that the difference between two interest rates can be approximated by the forward premium of foreign exchange:

$$\frac{F_t}{S_t} = \frac{1 + R_t}{1 + R'_t} \quad (4)$$

The CIP violations reported by Akram et. al. (2008) do not refute condition (1), and more importantly LOP and EMH, because in general terms, the price action requires a catalyst. In other words, markets are likely to diverge from the *no*-arbitrage equilibrium for a split-second when something changes investors and traders' expectations. In order to change someone's expectations, the information must be unexpected. If the information is unexpected, it must not have been priced in. Therefore, if the subsequent divergence of the equilibrium is only short-lived, it points towards markets actively seeking out opportunities to exploit. In the absence of such an efficient arbitrage vacuum, or more generally in the absence of arbitrage opportunities per se, capital could actually become binding and lead to CIP, LOP, and EMH breaking down. Therefore, the evidence of *only* short-lived violations of CIP may relate to the fact that capital is fully mobile and that market participants constantly seek arbitrage opportunities and consequently, condition (1) most hold, resulting in the resolution of the *arbitrage paradox* [1].

Hodrick (1980) and Fama (1984) on the other hand report systematic deviations from the condition (2) among several exchange rates, refuting UIP. Therefore, the forward premium is not a good proxy for the realized rate of change of spot exchange rate. If the forward exchange rate is not a good proxy for the subsequent change, risk based explanations for these empirically observed violations may solve the puzzle. If one or more risk factors would fully explain the violations, the results of Hodrick and Fama would refute the assumption of risk neutrality, while holding on rational expectations. If there is no possibility to attribute any part of the forward bias to foreign exchange risk premium, a failure to save the rational expectations would ensue. However, it is vital to understand that expectations can turn out to be incorrect under rational expectations, but they cannot systematically deviate from the realized future values as reported Hodrick (1980) and Fama (1984).

Generally speaking, the violations of UIP are hard to prove false. Mussa (1979) suggest that while the forward premium may usually be regarded as the reasonable measure of the expected spot rate change, there is some reason to believe that the forward rates may sometimes diverge from the expected future spot rates. Eaton and Turnovsky (1983) say that risk aversion among rational, fully informed speculators will create a risk premium, thereby causing condition (2) to break down. Both aforementioned presumptions attribute the forward bias to the exchange rate risk premium and indirectly refute UIP's assumption on risk neutrality. Fama (1984) reports that the realized future change in spot exchange rate is often less than the expected change observed from the forward exchange rate, supporting the risk aversion arguments. In other words, speculators seem to require a certain form of compensation to provide liquidity in the foreign exchange forward universe.

Fama (1984) decomposes the forward premium into the expected future spot rate change and the risk premia, $F_t = E(S_{t+1} \,/\, S), +P_t$, and reports that the most variation in forward premium, F_t, is the variation in risk premia, P_t. This confirms the proposition of Mussa (1979) and helps us to better understand the cause and effect dynamics behind the theoretical framework. Root and Thaler (1990) conclude that foreign exchange markets are risk averse and that exchange risk is unlikely fully diversifiable. In conclusion, the forward premium as a pure estimate of the expected change in

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[1] As discussed in Grossman and Stiglitz, if there is no noise in the market, prices convey all information, and therefore, there is no incentive to purchase or acquire information. Hence, the only possible equilibrium is one with no information. However, if everyone in uninformed, it clearly pays someone to become informed. (Grossman and Stiglitz, 1980)

future spot exchange rate is counterintuitive, but rather a sum of *expected change* and *risk premia* should be considered.

To the contrary, Mussa (1979) notes that the forward exchange rate is a function of all available information at hand at any given moment in time. As a consequence, the forward rate cannot subsume any unexpected 'new information' that arbitrarily emerges in future. If this new information is price sensitive, the predictions will be revisited. Therefore, if something alters market's expectations regarding the forward exchange rate, the current spot exchange rate should adjust by approximately the same amount or otherwise the expected return on foreign exchange as measured in the form of forward premium would become very large and induce the majority of investors to reallocate their wealth into foreign money (Mussa, 1979). This linkage between movements in spot exchange rates and *contemporaneous* movements in forward exchange rates is a well-documented, empirical regularity of 1970s (Mussa, 1979). If these information shocks in foreign exchange are regularly irregular as well as unexpected, the basis for risk neutrality is difficult to accept.

In summary, Mussa (1979), Eaton and Turnovsky (1983), Fama (1984), Root and Thaler (1990), and Engel (1995) credibly challenge the fundamental assumption of the UIP, namely the risk neutrality, and suggest that the forward premium is more likely a sum of an expected change in future spot exchange rate emerging from rational expectations and a time-varying risk premia. Engel (1995) holds on rational expectations saying that future task is to attempt to attribute the forward rate bias to a foreign exchange risk premium. However, if the rational expectations are let go, *peso problems* may be able to explain the forward premium bias.

B.3 Forward Puzzle Bias Hypothesis

The forward premium bias is usually tested by regressing the change in the exchange rate on the interest differential (Kenneth and Thaler, 1990). Another specification replaces the interest differential by the percentage difference between the current spot forward and spot exchange rates as in Fama (1984). I prefer the latter specification for its convenience and reiterate the findings of Akram et. al. (2008), concluding that CIP holds in practice. As follows

$$\Delta S_{t+k} = \alpha + \beta\left(\frac{f_{t+k}}{s_t} - 1\right) + \eta_{t+k}, \tag{5}$$

where s_t is the spot price of domestic currency at time t, f_t is the one period forward exchange rate at time t, η_t is the regression error and k is the maturity. In testing the condition (4), it is common to impose rational expectation leading to the conclusion that ΔS_{t+k} is equivalent to the mathematical expectation of change in the foreign exchange conditional on all information at time *t* (Engel, 1995). Under the null hypothesis in (4), the change in spot exchange rate is not related to the forward premium. As noted in Kenneth and Thaler (1990), a very large literature has tested the condition (4) and the average *beta* coefficient is reported to come out approximately at -0.88. Engel (1995) confirms these results. In conclusion, these findings refute the uncovered interest parity and confirm that the empirical regularity is that the coefficient β is reliably less than one.

In general, the conclusion is that forward premium is related to changes in the risk premia because a finding of $\beta < 1$ implies that a 1 percent increase in the interest rate differential is associated with less than 1 percent depreciation in the *base currency* value. To the contrary, a finding of $\beta < 0$ is fundamentally erroneous because an increase in the interest rate differential is associated with expected appreciation in the *base currency* value, resulting in larger change in risk premia. Therefore, the real problem of past and present is to explain why a change in interest rate differential ought to produce even larger change in the risk premia. Plausible explanations addressing this problem fall into two camps depending on our preference regarding rational expectations. If we assume rational expectations, plausible explanations are crash risk and funding constraints. If we refute rational expectations, plausible explanations are the 'peso problems', learning, irrational expectations, and bandwagon effect (Engel 1995).

B.4 Carry Trades, Funding Risk, and Disaster Risk Premia

Existing literature on funding constraints with respect to asset prices is supported in the theoretical research of Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), and Duffie and Strulovici (2012). Gromb and Vayanos (2002) theorize saying financial constraints limit arbitrageurs' positions as a function of wealth because arbitrageurs need to collateralize their positions in each asset separately. Brunnermeier and Pedersen (2009) provide a model, where margins are destabilizing and market liquidity and funding liquidity are mutually supportive, leading to liquidity spirals and loss spirals. Duffie and Strulovici (2012) introduce a model which states that with unexpected capital shocks, risk premia adjust severely, and then revert somewhat over time as capital is redeployed. Therefore, the tenet of these studies is that arbitrageur activity benefits all investors up to a point where liquidity suddenly dries up and leads to deleveraging.

Related to currency markets, Brunnermeier, Nagel, and Pedersen (2009, henceforth also BNP), and Filipe and Suominen (2013) link speculators' funding constraints to carry trade returns. Each study reports, *implicitly* or *explicitly*, that sudden exchange rate moves are related to unwinding of carry trades rather than fundamental news announcements. In other words, speculators tend to unwind or deleverage when funding risks loom large ahead.

Further, BNP show that currency crashes are positively correlated with implied stock market volatility (VIX) and the TED spread, an indicator for the funding liquidity. In summary, BNP results demonstrate that macroeconomic fundamentals determine long-run currency levels and that which currencies have high or low interest rates, whereas illiquidity and capital mobility lead to short-run currency *noise,* deviations from the long-run equilibrium, and occasional currency crashes.

Filipe and Suominen (2013) measure the carry trade funding risk using stock market volatility and crash risk in Japan, which is the main funding currency in foreign exchange thanks to the lost decade. The authors chose Japan because the JPY has been the main funding currency, owing to the lost decade of deflation. Interestingly, the authors' model is able to explain 42% of the monthly currency carry trade returns. The volatility measure deployed in Filipe and Suominen's model (2013) utilizes data on the option implied volatility for the *entire* Japanese stock market instead of the financial sector *alone*, due to in sufficient data. Therefore, a potential limitation of this study is related to the averaging across bias, which an important difference as reflected in CLMX where the authors show that the properties of industry-level volatility vary considerably among industries. Furthermore, there is very little reason to believe that *industry* and *market* volatility measures behave in the same way unless a certain industry, due to its scale, is effectively the whole market. In conclusion, an endeavor where the objective is to proxy the funding risk surfacing from the banking sector ought to utilize the implied option volatility data on the industry itself, and if not available, rely on the realized option volatility.

Similarly, Poti and Siddique (2013) conclude in their final remarks that the risk-capital availability predicts the time-varying excess predictability, which is line with the aforementioned.

To the contrary, Farhi et. al. (2013) link the sudden currency crashes to the disaster risk and conclude that one-third of the currency risk premia related to the disaster risk premia in advanced economies over the period of 1996 to 2011. The authors highlight the importance of disaster risk premia, especially in the aftermath of the recent financial crisis, given the emergence of option smiles that are clearly asymmetric. Actually, over the post crisis period, the disaster risk premia accounts for more than 50 percentage points of the total currency risk compensation (Farhi et. al., 2013). The conclusion is that the disaster risk premia is evident in the currency markets and requires more attention. However, the disaster risk is not a cause but rather an effect. Therefore, the funding literature seems more plausible explanation to UIP violations, because increases in funding risk may lead to disasters and subsequent increases in disaster risk premia due to naïve extrapolation.

In conclusion, existing research relates to three different literatures: the forward premium puzzle, funding constraints, and disaster risk. Generally speaking, the funding constraints relate to Bernanke (1983), confirming that the cost of credit intermediation increases during the crisis on the back of broad deterioration of *respective* balance sheets, which directly impacts the extension of credit on behalf of the banks. Therefore, in the modern financial markets, speculators are not as able to secure funding to undertake speculative investments. Similarly, Adrian and Shin (2002) conclude that aggregate liquidity can be seen as a rate of change of the aggregate balance sheet of the financial intermediaries. In other words, changes in financial institutions equity prices affect their ability to lend and therefore, we should consider measuring the idiosyncratic firm-level uncertainty in the banking sector in order to grasp the full effect of funding constraints on asset prices. On another note, disaster risk as in Farhi et. al. (2013) is most likely in some occasions related to funding constraints but can be caused by the *group behavior* due to *homogenous* positioning as well. Either or, both sources of uncertainty are most likely mutually reinforcing.

B.5 Role of United States in the Forward Premium Puzzle

Campbell, Lettau, Malkiel, and Xu (2001) introduce a disaggregated approach to study the volatility of common stocks at the market, industry, and firm levels. CLMX findings clearly show an increase in the firm-level volatility related to the market volatility. The authors' findings essentially reveal strong evidence pointing towards a positive deterministic trend in the firm-level volatility. Brandt et. al. (2008) subsequently document that the surge in the idiosyncratic volatility have completely revised and conclude that it is not a trend but rather a temporary phenomena.

The subsequent research, most interestingly Ang, Hodrick, Xing, and Zhang (2006, henceforth also AHXZ), has documented with U.S. data that recent *past* high idiosyncratic volatility coincides with low average stocks returns, *vice versa*. It other words, the authors reveal a statistically significant inverse relationship between the idiosyncratic volatility and the stock-returns. AHXZ (2009) show that the relationship exists also in international framework. Stated differently, by sorting stocks across 23 countries on *past* idiosyncratic volatility, the differences in monthly excess returns after adjusting for market, size and book-to-market factors between the highest and the lowest quintile of the idiosyncratic stocks is on average negative 1.31%. Because these results are out-of-the-sample relative to the earlier U.S. findings (AHXZ 2006), the results of AHXZ (2009) indicate that the correlation between the high idiosyncratic volatility and the low stock returns is not just a sample or country-specific effect, but rather persistent global phenomena. In other words, AHXZ (2009) show that the idiosyncratic volatility effect is simply captured by the U.S. idiosyncratic volatility factor. In summary, low returns earned by stocks with high idiosyncratic volatility around the world comove largely with the idiosyncratic volatility emerging from the U.S. The authors demonstrate that after controlling for the U.S. portfolios comprising *long* high idiosyncratic volatility stocks and *short* low idiosyncratic volatility stocks, the excess returns of the long-short portfolios positioned in international markets are *insignificant*.

Since the idiosyncratic volatility emerging from the U.S. explains the cross-section of stock returns both in-sample and out-of-sample studies (AHXZ 2006, AHXZ 2009), it may explain the cyclical variation of the currency excess returns as well. Guo and Savickas (2006) examine the relationship between idiosyncratic volatility and foreign exchange rates. The main results find early evidence pointing towards the fact that relatively high level of the U.S. industry-level or firm-level idiosyncratic volatility is usually associated with future depreciation in the U.S. dollar. The authors are of the opinion that financial variables, such as the idiosyncratic volatility, ought to provide a good measure of broad business conditions and therefore, should be less vulnerable to the omitted-variable bias. Additionally, Rapach, Strauss, and Zhou (2014, henceforth also RSZ) more recently conclude that the lagged U.S. returns significantly predict returns in numerous non-U.S. industrialized countries, whilst at the same time they display limited ability to predict U.S. returns *per se*. In summary, the results indicate that U.S. return shocks have statistically and economically significant effects on non-U.S. returns.

CLMX (2001), AHXZ (2006, 2009), Guo and Savickas (2006), and more recently RZS (2014) call explicitly for a model that incorporates the role of the United States in predicting the expected returns of foreign exchange. My objective is to confirm the findings of Guo and Savickas (2006) and subsequently extend existing research idiosyncratic volatility. A potential limitation of Guo and Savickas (2006) is that they fail to investigate this relationship on a monthly basis and therefore, the results may relate to *unintentional proxies* due to a common time trend, which are especially common in time series analysis. For instance you think that Y depends upon Z, while in reality it depends upon X.

C. Data, Ranking Methodologies, and Carry Permutations

C.1 Data

In my analysis, I scrutinize the foreign exchange carry trades on a currency by currency and on a portfolio basis. I collect daily closing spot exchange rates as well as one-month and three-month outright exchange rates with respect to the U.S. dollar from Reuters. The data set consists of 10 countries: Australia (AUD), Canada (CAD), Euro Area (EUR), Japan (JPY), New Zealand (NZD), Norway (NOK), Poland (PLN), Sweden (SEK), Switzerland (CHF), and United Kingdom (GBP). The rationale behind the data composition is based on my desire to omit currencies that are not *fully* convertible and most likely illiquid or *less* liquid. The daily observations form the raw data series, used to calculate standard deviations, semi-deviations, and variance ratios. The empirical analysis on carry returns deploys the end-of-month (EOM) data on exchange rates from January 1996 to February 2014. The EOM data is *non-sample* varying in terms of currency composition, which means that all pairs are representative for each data point. Also, I have not constructed developed and developing markets subsamples because the currencies listed above are similar conceptually: liquidity, foreign exchange regime, and monetary framework. Finally, the currencies listed above are *less* likely to suffer from the stale price bias, which refers to a situation where the end-of-month (EOM) closing quotes are available, but have not been traded in size.

I also collect daily stock returns, stock prices, number of shares outstanding, and Standard Industry Classification (SIC) codes for all shares quoted on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotations (NASDAQ) from the Center for Research on Security Prices (CRSP). The daily stock data is from January 1996 to December 2013. The daily stock return data is used to compute different metrics for the firm-level idiosyncratic firm-level uncertainty. I use the U.S. 3-month Treasury bill rates as a proxy for the risk free rate.

C.2 Introduction to Carry Trade Returns and Return Decomposition

As mentioned earlier, carry trade performance is measured against the U.S. dollar. In general, the exchange rate is defined as a fraction of foreign currency units (FCU) per unit of U.S. dollars. In other words, the rate tells the reader the fraction of FCU 1 USD can buy upon conversion at any point in time. I express interchangeably the U.S. dollar as *base currency* and the FCU in question as *term currency*. Additionally, a positive interest rate differential relates to a forward *premium* because I am able to enter into an agreement where I sell the USD at a higher rate in future as compared to the current spot price. Logically, a negative interest rate differential relates to a forward *discount*.

Paving the way for interpretation of the results, it is important to highlight that a positive change in spot exchange rate means that the *base currency* has appreciated versus the *term currency*. In other words, one unit of U.S. dollars is now worth a greater fraction of foreign currency in question. To avoid any confusion moving forward, I suggest the reader positions herself or himself as a U.S. based investor to whom the U.S. dollar is the functional currency.

Putting transaction cost aside, I define the currency excess returns (rx) as *ex post* deviations from the uncovered interest parity (UIP):

$$rx_{t+1} = (1 + i_t^{term})\, {}^{S_t}\!/_{S_{t+1}} - \left(1 + i_t^{base}\right), \tag{6}$$

where rx_{t+1} represents the excess returns earned at time $t+1$. The drivers of excess returns are the interest rate denominated in foreign currency, i_t^{term}, the interest rate denominated in domestic currency, i_t^{base}, and the current spot rate as well as the realized future spot rate for periods t and $t+1$, respectively. In other words, a *long* carry trade is a risky variant of the covered interest parity where the investor elects not to purchase the foreign exchange forward contract with a view that the USD will not appreciate enough to eliminate the entire profit, the forward premium (Caballero and Doyle, 2012). If the investor would enter into the forward agreement, the only source of uncertainty, which is effectively future spot rate, would be eliminated. Now, since CIP holds closely in the data at daily and lower frequency as in Akram, Rime and Sarno (2008), I re-arrange the covered interest parity (CIP) relationship and moving forward write the interest rate differential as $1 + i_t^{term} /\, 1 + i_t^{base} = f_t /\, s_t$. Therefore, from now onwards, I focus on a simple version of the carry trade where returns are measured in USD:

$$rx_{t+1} = \frac{f_t - s_{t+1}}{s_{t+1}} \tag{7}$$

I decompose excess returns into the *forward* and *spot* components to better understand the underlying return dynamics. A *forward* component is the forward premium or discount agreed at the beginning of the period and a s*pot* component is the change in spot exchange rate during the period:

$$rx_{t+1} = \frac{f_t - s_t}{s_{t+1}} - \frac{s_{t+1} - s_t}{s_{t+1}} = \frac{[f_t - s_t] - [s_{t+1} - s_t]}{s_{t+1}} = \frac{f_t - s_t - s_{t+1} + s_t}{s_{t+1}} = \frac{f_t - s_{t+1}}{s_{t+1}} \qquad (8)$$

Expressed intuitively, in a *long* carry position initiated at time t, an investor agrees to sell one unit of U.S. dollars at a premium for a future delivery and convert any payout in FCU at maturity using the current spot market rate. If the *realized* change of the spot rate in the interim, $[t, t+1]$, is less than the forward premium, the investor has effectively earned a positive return. It is important to remember that carry returns are linear when the payout is plotted in the *term currency* but are not linear when measured in terms of the *base currency*. This explains the rationale for *normalizing* the returns at maturity with the current spot rate as in (7).

In conclusion, returns are reported in the USD and monthly returns are annualized: I simply multiple the mean of the monthly returns by 12 and the standard deviation by $\sqrt{12}$. I also refer to semi-deviation, which is similar to standard deviation but only contains observations where the USD has appreciated, i.e. a measure of the downside risk in carry investing. Sharpe and Sortino ratios are defined as the ratio of the annualized mean to the annualized standard and semi-deviation, respectively.

C.3 Portfolio Strategies

I look at three different portfolio strategies, which I run on a monthly-basis. These strategies are conventional among practitioners with each resulting in different expected returns. I refer to these portfolio strategies collectively as *carry permutations*. Each ranking methodology utilizes time t information to rank currencies for the subsequent period. All carry permutations rely on the out-of-sample *excess-return-predictability,* which means that the current rankings are expected to produce good and reliable predictions of future, *expected* returns. The reason to follow such a simple and naïve strategy bows to the refutation of the UIP. As reflected upon Burnside (2011), the simple idea of sorting currencies based on the forward premium is to produce portfolios with different expected returns. If the basis of the forward premiums works, the order of expected returns ought to align with an observed return characteristic (Burnside, 2011). Henceforth, I examine the following carry permutations: *standard carry*, *forward carry*, and *normalized carry*.

The *standard* and *forward* carry strategies rank the currencies on the basis of the absolute interest rate differentials. The sharp distinction between the *standard carry* and *forward carry* is the underlying tenor. In other words, the strategies are based on maturities which have different lengths. The s*tandard carry* is based on the *current* interest rate differential derived from the spot and 1-month forward rates while the *forward carry* looks at the forward starting interest rate differential that is a function of 1-month and 3-month forward rates. Given the information used to rank the currencies is based on different parts of the *relative* term structure; each of the strategies may subsume different information and therefore, produce different expected returns and observed return characteristics.

The n*ormalized carry* is similar to the *standard carry* with one distinction, the interest rate differential is *normalized* by the three-month *realized* spot volatility. In other words, the *normalized carry* permutation is looking at the risk-adjusted differentials and is a slightly less conservative carry strategy than the permutations, which maximize the *absolute* differentials without penalizing for volatility.

Therefore, the notion for each carry permutation is:

$$rank(standard\ carry)_t = \frac{f_{t+1}}{s_t} - 1 \tag{9}$$

$$rank(forward\ carry)_t = \frac{f_{t+3} - f_{t+1}}{s_t} - 1 \tag{10}$$

$$rank(standard\ carry)_t = \left.\frac{f_{t+1}}{s_t} - 1\middle/\sigma_{s_{t-3}}\right., \tag{11}$$

where f_{t+1} is the one-month forward rate, f_{t+3} is the three-month forward rate, s_t is the current spot rate, and $\sigma_{s_{t-3}}$ is the three-month realized daily volatility.

C.4 Carry Portfolios

When carry portfolios are formed based on a given ranking methodology, I construct two sets of portfolios: *long* portfolios and *long-sort* portfolios. For the *long* portfolios, I sort all currencies into three bins according to the ranking methodology. The first bin (S1) contains the *top* three currencies, the second bin (S2) contains the *middle* three currencies, and the third bin (S3) consists of the *bottom* three currencies. This procedure produces three currency portfolios for each carry permutation. In other words, portfolios S1, S2, and S3 borrow one dollar and invest it equally in the respective elements. This is the equivalent of calculating the average excess return among the three currencies in question. For the *long-short* portfolios I apply the conventional *high-minus-low* procedure, where I borrow in the low premium currency(ies) in order to lend in the high premium currency(ies). I consider two different *long-short* portfolios. The first borrows in the bottom currency and lends in the top currency, and the second, while expected to benefit from diversification, borrows in S3 and lends in S1: these strategies are referred to HML1 and HML3, respectively. It is noteworthy to highligh that the l*ong-short* portfolio is dollar-neutral as the dollar components cancel out when taking the difference between the long and short positions. However, this is not the case with *long* portfolios S1, S2, and S3 because they are reliant on the USD funding. Transaction cost aside, the *long* and *long-sort* portfolios are zero-cost strategies, and therefore, do not incur any costs at inception.

D. Explanatory Factors

The major avenue of existing research trying to solve the *forward premium puzzle* concentrates on the risk-based explanation and aims to attribute the excess returns to different time-varying risk factors. In this section, I introduce two new risk-based explanatory variables that will be used to explain the excess returns from different carry trade portfolios, as well as more traditional ones.

D.1 Currency Volatility Factor

Menkhoff et. al. (2011) examine the relationship between the global foreign exchange volatility risk, the currency volatility factor, and the cross-section of carry trade excess returns. Their conclusion is that returns from the high forward premium currencies are negatively related to the global FX volatility, and therefore, deliver low returns in times when the realized volatility goes up, while the low forward premium currencies provide a hedge by yielding positive returns. Burnside (2011) re-examines the results of Menkhoff et. al. (2011) and concludes that the VOL factor betas, VOL is the monthly average standard deviation of the daily log changes in the values of the currencies against the USD, decrease monotonically with a move from the high forward premium portfolios towards the low forward premium portfolios. Burnside (2011) shows that the betas are statistically significant for the extreme portfolios, portfolios S1 and S5 in his study, and that the beta for the top premium portfolio is positive while the beta for the bottom premium is negative. Burnside's (2011) findings are counterintuitive in the sense that they document an increase in the performance of portfolio S1 when the currency volatility factor goes up, whereas for the other portfolios, namely S2, S3, S4, S5, the relationship is negative. The difference in Menkhoff et. al. (2011) and Burnside (2011) may emerge from the *sample selection*, as the former has a sample of 29 currencies against the USD while the latter only has 11.

I define the VOL factor as the monthly average standard deviation of the daily changes in the values of the currencies against the USD. As my sample consists of only 9 different currencies, my currency volatility factor is more *local* than *global*.

D.2 Currency Skewness Factor

For the currency skewness factor I take inspiration from Brunnermeier, Nagel, and Pedersen (2009), Burnside (2011), as well as Farhi et. al. (2013). The common avenue is that there is a strong link between currency carry trade and currency crash risk. Farhi et. al. (2013) find that the disaster risk accounts for more than one third of currency risk premia in the advanced economies. The tenet is that the carry trades are risky because the high forward premium currencies are often *all* exposed to market crashes (Burnside, 2011). Burnside (2011) computes the skewness measure by sorting the currencies into two groups, one with positive and one with negative forward premiums, and measures on a monthly basis the realized skewness by taking an average of the realized skewness statistic between the two groups.

I derive the currency skewness factor on a currency by currency basis and also on an aggregate basis for portfolios HML3 and HML1, using semi-variances in the computation. In other words, I calculate the semi-variance on a monthly basis using daily observations. The currency skewness factor is defined as V_a / V_b, where V_a and V_b are subsample measures for the realized dispersion. V_a is a sample variance for USD appreciation and V_b is a sample variance for USD depreciation:

$$r(x)_t = \begin{cases} a \ if \ x > 0 \\ omit \ if \ x = 0 \\ b \ if \ x < 0 \end{cases} \tag{12}$$

where $r(x)_t$ is the daily change, or a return for a *long* USD position. As the notation above illustrates, a positive change falls into subsample *a*, while a negative change falls into subsample *b*. If the currency skewness factor equals 1, the two dispersions are equally spread. If the currency skewness factor is greater than 1, the dispersion of *base currency* appreciation is wider. If the currency skewness factor is smaller than 1, the dispersion of *base currency* depreciation is wider. If carry currencies are exposed to crashes as mentioned above, the fractions of the HML1, HML3, and conventional carry currencies such as AUD and NZD, ought to on average be greater than 1. In summary, if the fraction is greater than one, the realized *return* distribution is *negatively* skewed.

D.3 Firm-level Idiosyncratic Risk Factor

Burnside (2011) shows that traditional stock market based risk factors do not explain carry trade returns. In most cases the issue is that the associated betas are not statistically significant once regressed on monthly returns. Burnside's (2011) conclusion is that a unifying explanation for stock market returns and carry returns does not exist. To the contrary, Guo and Savickas (2006) conclude that the U.S. idiosyncratic firm-level uncertainty predicts changes in the major currencies against the U.S. dollar. In other words, there may be grounds for a unifying explanation of stock market returns and carry trade returns, given that AHXZ (2006 and 2009) document a relationship between the U.S. idiosyncratic uncertainty and *stock* market returns globally. However, it is important to highlight that Guo and Savickas (2006) document that the relationship holds over relatively long periods of time: quarterly but more importantly, semi-annually and annually. In other words, they fail to investigate the relationship on a monthly basis. Therefore, the explanation for these results could be related to the well-known phenomena in econometrics known as the use of *unintentional proxies*, given the findings of CLMX showing that the idiosyncratic volatility covaries with the gross domestic product (GDP). In other words, if Guo and Savickas (2006) in their multivariate regressions had regressed the quarterly changes in nominal exchange rates using GDP *together with* the firm-level idiosyncratic volatility, the results may have been very different. This problem is especially common in time series analysis, where the *true* explanatory variable is subject to a time trend and you substitute, intentionally or otherwise, the *true* explanatory variable with any other variable with the *same* time trend (Dougherty, 2011). If so, the compensation of the firm-level idiosyncratic volatility may have been overestimated. One way to alleviate this problem is to shorten the interval. For example, a common way is to utilize the monthly data in order to introduce more randomness.

On another note, Brunnermeier, Nagel, and Pedersen (2009) document that currency crashes are positively correlated with implied stock market volatility (VIX). As a measure the idiosyncratic volatility is very similar to VIX in the sense that both measure a form of uncertainty. I am interested in the predictive power of the idiosyncratic firm-level uncertainty with respect to the currency crashes. However, I note that the fundamental difference between VIX and the idiosyncratic firm-level volatility is that one measures the *expected* non-diversifiable future uncertainty and the other quantifies the *realized* diversifiable uncertainty.

I apply the volatility decomposition framework introduced by Campbell, Lettau, Malkiel and Xu (2001) to decompose a return, in excess of the risk-free rate of a typical stock, into its three components: the market-wide return, an industry-specific residual, and a firm-specific residual. In other words, I break down the volatility into its simpler constituents. Based on this return decomposition, I construct a time-series of the *firm level average volatility* similar to that done by CLMX. I prefer the CLMX approach over the Fama-French framework for its convenience since the CLMX framework is by definition covariance and beta free when aggregated over industries. I denote industries as i and individual firms within a given industry i by j. In other words, a given industry i has a collection of objects j. In order to keep my logic intact, the excess return of a typical stock j that belongs to an industry i in the period t is denoted as R_{ijt}. W_{ijt} stands for the weight of the firm j within the industry i at the time t. The weighting is based on the current market values formed by taking the average of the current period. Average industry excess return of a random industry i in the period t is given by $R_{it} = \Sigma_{j \epsilon i}\, w_{ijt}\, R_{ijt}$. I aggrete the industries and denote the weight of an industry i with respect to the total market by w_{it}.

I do not reproduce the CLMX methodology in this paper but instead focus on the practicality of the framework (see CLMX for a more elaborated discussion). Following the CLMX, I calculate the daily firm-specific residual by subtracting the daily industry *i* mean return:

$$\varepsilon_{ijst} = R_{ijst} - R_{ist} \tag{13}$$

R_{ijst} is the return on day *s* in month *t* of stock *j* that belongs to industry i, and R_{ist} is the average return of industry i on day s in month *t.* Next, I sum the daily residuals to obtain a monthly idiosyncratic volatility *(IV)* for stock j:

$$FIRM\ IV_{ijt} = \sum_{s \in t} \varepsilon_{ijst}{}^2 \tag{14}$$

I calculate the value-weighted average of idiosyncratic firm level volatility for each industry *j* using monthly idiosyncratic volatility estimates of firms that belong to industry j. To obtain weights I calculate the average market capitalizations during the month t. Furthermore, I use Fama and French's SIC classification procedure to form 49 industry portfolios. Specifically:

$$IND\ IV_{it} = \sum_{j \in i} w_{ijt}\ FIRM\ IV_{ijt} \tag{15}$$

where w_{ijt} is the month *t* weight of stock *j* that belongs to industry *i*. Finally, I add up the monthly idiosyncratic volatility estimates across all industries to obtain the value-weighted average of monthly idiosyncratic volatility:

$$IV_t = \sum_{i=1}^{49} w_{it} IND\ IV_{it} \tag{16}$$

where w_{it} is the month *t* weight of industry *i*.

D.4 Banking Sector Idiosyncratic Risk Factor

Brunnermeier and Pedersen (2009) provide a model in which traders provide liquidity, but their ability to do so depends on their availability of funding. Brunnermeier, Nagel, and Pedersen (2009) show that a sudden unwinding of carry trades leads to currency crashes and is caused by funding constraints. Specifically, increases in the TED spread, which is the 3-month USD LIBOR minus the 3-month T-Bill yield, is shown to have a positive correlation with currency crashes. Now, because carry trades are risky variants on future spot rate, currency crashes will deteriorate carry returns as well. Therefore, in the concluding remarks the authors proclaim that new macroeconomic models are needed to take into account the fact that the risk premia is affected by both market liquidity and funding liquidity.

Filipe and Suominen (2013) answer the call and derive a funding risk metric by using the implied stock market volatility and crash risk in Japan. They chose Japan because the JPY has been the main funding currency, owing to the lost decade of deflation. Interestingly, the authors' model is able to explain 42% of the variation in the monthly excess returns. The volatility measure deployed in Filipe and Suominen's model (2013) is the option implied volatility for the *entire* Japanese stock market instead of the financial sector *alone*, due to insufficient data.

In order to capture the *idiosyncratic* information within the banking sector, I propose an alternative metric using the daily stock market data to calculate a measure for the average firm-level uncertainty within the banking sector. This measure is not affected by *averaging across bias* as potentially reflected in Filipe and Suominen's research (2013). This is an important remark as reflected in CLMX, where the authors show that the properties of industry-level volatility vary considerably among industries. Additionally, the proposed measure is based in this paper is based upon *realized* rather than *implied* volatility, a potential caveat. However, the focus is not on the debate of whether *realized* volatility is a better estimate for the unforeseeable uncertainty in short horizons, but rather the *source* of uncertainty. In other words, I concentrate on the fact that there is very little reason to believe that the *industry* and *market* volatility measures behave in the same way unless a certain industry, due to its scale, is effectively the whole market. In order to study the idiosyncratic risk in the banking sector, I amend the return composition as I am no longer averaging over firms and industries. Therefore, I need a composition that includes the banking sector beta:

$$R_{ist} = \beta_{mi}\, R_{mst} + \varepsilon_{ist} \tag{17}$$

$$R_{ijst} = \beta_{mi}\, R_{mst} + \varepsilon_{ist} + \varepsilon_{ijst} \tag{18}$$

$$\varepsilon_{ijst} = R_{ijst} - \beta_{mi}\, R_{mst} - \varepsilon_{ist} \tag{19}$$

$$FIRM\ LEVEL\ AGGREGATE\ RESIDUAL_{ijt} = \sum_{s\,\epsilon\,t} {\varepsilon_{ijst}}^{2} \tag{20}$$

$$FIRM\ LEVEL\ VOLATILITY_{it} = \sum_{j\,\epsilon\,i} w_{ijt}\ FIRM\ LEVEL\ AGGREGATE\ RESIDUAL_{ijt} \tag{21}$$

Equations 11 and 12 show the decomposition of excess returns, including a beta for each industry (CLMX). Equation 13 computes daily firm-specific residuals, while 14 sums daily residuals to obtain monthly firm-level volatility for stock *j*. What is evident in the notation above is that I only need one additional parameter to derive the average firm-level idiosyncratic uncertainty metric. In other words, $FIRM\ LEVEL\ VOLATILITY_{it}$ only contains information about the *average* firm-level uncertainty within the industry in question as opposed to the *average* firm-level volatility across all industries.

As a consequence, the *firm-level idiosyncratic* risk factor measures the average firm-level uncertainty, whilst the *banking sector idiosyncratic* risk factor measures the average firm-level uncertainty within the banking sector. I use the latter as a proxy for the funding risk in order to explain currency excess returns and currency crashes.

D.5 Downside Idiosyncratic Risk Factors

Motivated by Dodrynskaya (2013), I define the *downside adjusted* idiosyncratic firm-level risk factors. Dodrynskaya (2013) concludes that carry trade crashes occur systematically in the worst states of the world. If these return and risk characteristics are predominant in different currency blocks, Dodrynskaya's (2013) sample consists of 42 countries while my sample contains 10 countries, I would expect to find that the downside idiosyncratic market factors better fit the excess return data.

The computation of the *downside adjusted* idiosyncratic risk factors is rather straightforward as they measure the magnitude of *directional* average firm-level uncertainty. Therefore, in (7) and (13) the sample of R_{ijst} only contains negative observations. Other than that, the methods in C.3 and C.4 are similar.

E. Research questions

The research questions are motivated by the observed, empirical regularities in the behavior of foreign exchange markets. My first objective is to confirm the validity and soundness of my data as well as to test the classic topic of international finance, the uncovered interest parity (UIP), which is a critical building block of most theoretical models of modern finance. The second objective is to assess if floating exchange rates are affected by learning and potentially reassure that UIP is no longer such a dismal empirical failure. My third and fourth objectives revolve around the time-varying characteristics of the risk premia in foreign exchange. I examine whether the risk-based explanatory factors, each introduced in section C, explain the risk-return profile of the different carry trade permutations. More specifically, I focus on whether the time-varying exchange risk premia relates to the funding constrains.

E.1 Testing the Forward Premium Puzzle

The first hypothesis is well-known and appears frequently in previous literature, seminally in Fama (1984). The hypothesis relates to the forward premium bias, also known as the *forward premium puzzle*. My intention is straightforward in assessing a potential bias of future spot estimate in today's forward exchange rate. In other words, I test the forward premium bias and determine if expectations among market participants are rational. The null hypothesis is that $\beta = 1$ and that $\alpha = 0$. If the expectations are rational and investors are risk neutral, I would expect to find that the realized depreciation (appreciation) of FCU is equal to the forward premium (discount), plus a purely random error term with zero mean as in Froot and Thaler (1990) and Engel (1995). The hypothesis tests the bias by regressing the *realized* change in the spot exchange rate on the contemporaneous forward premium:

$$\frac{S_{t+k}}{s_t} = \alpha + \beta\left(\frac{f_{t+k}}{s_t} - 1\right) + \eta_{t+k}, \tag{22}$$

where S_t is the spot price of domestic currency at time t, S_{t+k} is the spot price of domestic currency at $t+k$, f_t is the one period forward exchange rate at time t for delivery at time $t+k$, η_t is the regression error, and k alone is the tenor which equals 1-month forward.

H0: Uncovered Interest Parity (UIP) does hold and violations average out resulting in zero excess returns.

H1: Uncovered Interest Parity (UIP) does not hold and violations result in non-zero excess returns.

E.2 Testing the Properties of Exchange Rates as Predictors of Future Spot Rates

The second hypothesis is inspired by the findings of Eugene F. Fama (1984) showing that the properties of forward exchange rates as predictors of future spot rates are no different in *chronological* subsample comparison. As Fama (1984) pointed out, investors are not in the process of learning about floating exchange rates and henceforth, the forward predictions are not affected by learning. In other words, the market's assessment of ΔS_{t+k} in F_{t+k} / S_t is consistently perverse vis-à-vis the realized change in the spot exchange rate. Fama (1984) concludes that inefficiency is persistent in time and that forecasting bias is not cured by continued experience with flexible exchange rates.

This occurrence is perplexing and could be settled in more recent time series study, because today, twenty-years after Fama's study, floating exchange rates and managed floating rates are the norm. Suppose that market participants have accumulated considerably *more* experience via similarity and associative learning with flexible exchange rate regimes since 1980s. If true, the forward exchange rate ought to show increased efficiency in predicting future spot exchange rate. I measure the fit of F_{t+k} / S_t in predicting ΔS_{t+k} over three non-overlapping subperiods in order to determine if learning plays a role. NBER recessions drive a wedge between these respective periods because people have a tendency to learn from failure as it generally causes them to pay more general attention to basic rules and counterfactual analysis.

H0: The forward exchange rates subsume increased ability to predict future spot exchange rates.

H1: The forward exchange rates do not subsume increased ability to predict future spot exchange rates.

E.3 Testing the Time-varying Conditional Skewness

As discussed in the literature review, Brunnermeier, Nagel, and Pedersen (2009) report a strong linkage between currency carry trades and currency crash risk. The authors provide evidence of unfavourably skewed returns emerging from a standard carry trade strategy. Similarly, Eaton and Turnovsky (1983) conclude that factors encouraging speculation, such as an increase in the number of speculators and an increase in the amount of speculative capital, are likely to reduce the overall risk aversion and increase the exchange rate volatility.

More recently, Poti and Siddique (2013) conclude in their final remarks that the risk capital availability predicts the time-varying excess predictability, which is consistent with recent theories on limited risk capital mobility (Duffie and Strulovici, 2012). In conclusion it seems that the currency carry crashes are driven by the availability of funding and accumulation of speculative positions.

I am interested in the time-varying characteristics of the conditional skewness and its covariance with the average forward premium. I expect higher average forward premiums to absorb more speculative capital and result in greater currency skewness factors.

H0: Carry currencies are associated with negative return skewness which varies with and is driven by the attractiveness of the standard carry trade.

H1: Carry currencies are not associated with negative return skewness.

E.4 Testing the New Funding Risk Proxies

Inspired by Felipe and Suominen (2013), I examine the relationship between carry excess returns and average banking sector firm-level uncertainty *as well as* carry excess returns and average firm-level uncertainty across all industries. The firm-level uncertainty surfaces from the U.S. economy, and I define the banking sector using the Fama and French's SIC classification procedure. As mentioned earlier, Adrian and Shin (2002) conclude that aggregate banking sector liquidity can be seen as a rate of change of the aggregate balance sheet of the financial intermediaries, and therefore, changes in financial institutions equity prices affect ability to lend. Consequently, the banking sector idiosyncratic firm-level risk factor may contain unique information relating to *current* funding conditions. On the other hand, the average firm-level uncertainty across all industries ought to proxy the average uncertainty within the U.S. economy, which might tame bank's appetite and reduce liquidity. Generally speaking, the banking sector and across-all-industries idiosyncratic factors may be considered *endogenous* and *exogenous* funding proxies, respectively.

My objective is to test whether these two *new* explanatory variables contain information that is not present in the conventional explanatory variables, such as the TED spread and VIX. I also examine whether there is a relationship between the two and the currency skewness factor. I extend existing research and investigate the contribution of these new funding proxies, and their specifications, on the *forward premium puzzle*.

H0: The proposed new risk factors contain new information about the carry returns and currency skewness factors

H1: The proposed new risk factors do not contain new information about the carry returns and currency skewness factors as it is already present in existing explanatory variables

F. Empirical Findings

F.1 Forward premium puzzle and different carry permutations

The starting point of my analysis is the traditional, well-documented currency carry trade. I scrutinize the performance of the three slightly different carry permutations. I intend to reinforce past research, showing that future change is generally unrelated to forward premium. Additionally, I want to confirm the validity and soundness of my data as previously stated.

Before embarking on a journey into the rather perplex world of foreign exchange, I restate the underpinning assumptions of UIP. Mainly, UIP hypothesizes that interest rate differentials and subsequent spot returns have an inverse relationship such as currencies with positive interest rate differentials ought to depreciate, and *vice versa*. If true in practice, different carry permutations should not deviate from UIP, *on average*. To the contrary, if UIP does not hold, a *potential* gain from a carry position is a function of two interest rates and equals the forward rate for the period, while a *realized* gain is a risky variant of change in spot exchange rate in the interim. If *realized* gains are persistent in time, a rational conclusion is that the foreign exchange markets are risk-averse or rational expectations are false. If we assume rational expectations, we must attempt to attribute the forward rate bias to a foreign exchange risk premium and subsequently risk-neutrality would be rejected. If we reject rational expectations, possible explanations for forward rate bias include *peso problems*, *learning*, as well as *speculative bubbles* and *group-think*, which are not the topics of focus in this paper.

I report excess returns (RX), spot returns (RS), and average forward premium (AFP) for each carry strategy. The three competing carry strategies are the *standard carry* (figure I top), *normalized carry* (figure I middle) and *forward carry* (figure I bottom). Each strategy in figure I executes the traditional High-Minus-Low (HML3) strategy utilizing time *t* information to rank currencies based on alternative permutations for a chosen tenor, and subsequently investing in currencies with the highest forward premium, whilst funding via currencies with the lowest forward premium. Generally speaking these portfolios are zero cost at inception and USD neutral. I rebalance the portfolios on a monthly basis.

The dotted grey line in figure I depicts the cumulative average forward premium. By looking at the plotted time series, it seems that AFP exhibit a high degree of serial correlation whilst the average spot change is likely to follow a random walk. In order to confirm my presumption, I calculate autocorrelations with three different lag lengths, i = (1, 2, 3). I note that the results are assertive enough to conclude that there is a strong dependence between the output variable and its own previous values in the case of AFP, but not so much in RS, which is in line with the empirical regularities of Mussa (1979).[2] The solid red line shows the average spot return, showing signs of a random process with no serial dependence. UIP effectively stipulates that the dotted line, the average forward premium, and the solid red line, the spot change, should always be superimposed, assuming an unbiased estimate of future change. If this were true, the cumulative excess returns, the solid blue line, ought to form a straight horizontal line with a zero slope coefficient for in the time series.

In other words, the ballistic-like *non-zero* cumulative excess returns among different carry strategy permutations refute the equilibrium state hypothesized by UIP. Therefore, it seems sensible that the previous research defines the expected future change as the sum of the expected change and risk premium, such as in Fama (1984) and Jensen (1990). At this point, figure I gives the impression that the idea of risk neutrality, the mail principle of UIP, should be abandoned. However, in order to avoid hasty generalizations and reaching conclusions based on insufficient evidence, I am going to turn my attention to the summary statistics in table I.

2 The results are available by request with the author.

Figure I: High-minus-Low 3 Portfolios Deploying Different Carry Strategies

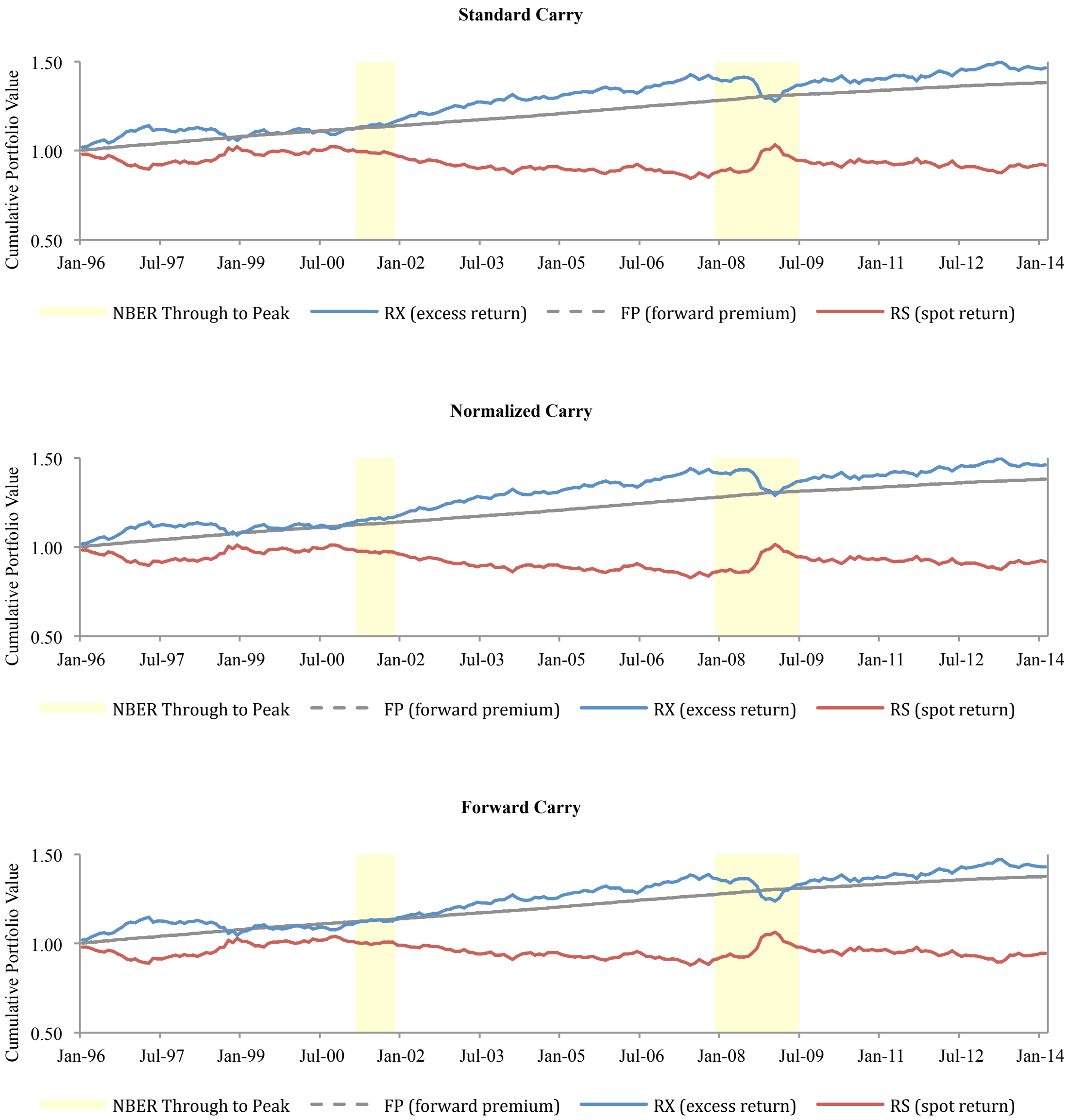

Figure I plots three different HML3 strategies, each deploying different carry permutations. HML3 portfolios comprise a long position in top three currencies and short position in bottom three currencies. The dotted line is the cumulative forward premium collected from the long and short positions formed at time t. The solid red line depicts the cumulative average spot return of the long-short portfolio. The solid blue line depicts the cumulative excess returns that under UIP should effectively be zero. Excess Return is the differential between the expected appreciation and the realized spot change. The areas highlighted in yellow reflect the NBER recession cycles.

I report aggregate carry trade statistics in annualized form in table I for HML1, HML3, S1, S2, and S3 portfolios across different carry permutations. The aggregated results confirm the existence of positive, *non*-zero excess returns across different HML1 and HML3 portfolios. As table I indicates, over the historical sample, the HML3 carry trade strategy, depending on the permutation, had an average annual excess return in the range of 2.37% - 2.55%, with a standard deviation ranging from 3.93% to 4.08% and a Sharpe ratio of 0.59 – 0.65. HML1 permutations yield in two instances higher returns than their respective HML3 strategies: *standard carry* 2.60% against 2.55%, *normalized carry* 2.48% against 2.55%, and *normalized carry* 3.25% against 2.37%; HML1 and HML3, respectively. HML1 portfolios have significantly greater standard deviations due to the lack of *diversification*, and therefore, it is not surprising that the HML3 portfolios produce superior Sharpe ratios, while HML1 over performs on an absolute basis. I argued earlier that if the basis of the forward premiums works to produce portfolios with different expected returns, then the ordering of the expected returns ought to align with an observed characteristic. If I take a closer look at the average forward premiums and average excess returns for HML1 and HML3 within different permutations, I can conclude that in two out of three instances the observed characteristics are aligned with the expected returns. The only exception is *forward carry*, where the HML3 portfolio yields greater average excess returns than the HML1 portfolio.

In summary, I conclude that HML3 and HML1 performances are anonymously driven by the fact that the *realized* spot change is on average *less* than the implied change at time *t* for the subsequent period *t, t*+1. In 4 out of 6 instances the average spot change is actually negative. These *consistent* prediction errors require a rational explanation in order to save the forward rate from a dismal failure in predicting future level of foreign exchange. One attempt is to attribute the forward rate bias to a foreign exchange risk premium or alternatively refute rational expectations. On the contrary, it is important to bear in mind that the forward rate *only* takes into account information that is available at inception, and therefore, any *new information* that emerges in the interim must have been unexpected at the time the forward rate was established. As a result, it is intuitive to expect that only a small portion of the realized change is actually attributable to the expected change due to the continuous arrival of information.

Long portfolios S1, S2, and S3 properties are aligned with HML3 and HML1. However, there are a few interesting points to highlight. First of all, the excess returns and forward premiums are monotonously increasing between S3 and S1, which precisely shows that the basis of the forward premium is aligned with the observed outcome. Secondly, the excess return volatility increases monotonically with the average forward premium. Finally, the average spot return is always negative regardless of the forward premium.

The risk-adjusted properties conclude that the *forward carry* permutation's HML3 portfolio yields the greatest risk-adjusted average performance. This is contrary to my expectation that the *normalized carry* strategy would have returned superior risk-adjusted returns because the other two strategies do not penalize for the realized spot exchange rate volatility.

In summary, return and risk go hand in hand, and free lunches, average positive excess returns, are not actually free. Given the properties of different long and long-sort portfolios, it is intuitive to conclude that forward rates are induced by risk premia.

Furthermore, I see a need to modify the Sharpe ratio that penalizes *equally* both upside and downside volatility, by differentiating between *negative* and *positive* volatility, as investors have a tendency to prefer avoiding losses to acquiring gains. In other words, I calculate a semi-deviation, capturing the *positive* observations that are fundamental as any long and long-sort portfolio is effectively a risky variant on future base currency *appreciation*. Expressed differently, any USD appreciation erodes the potential gains at maturity and therefore, a carry investor is taking chances on the directional future volatility. Once I normalize the returns with the modified measure, I report less attractive HML3 and HML1 portfolios in a risk-return spectrum across different permutations. For instance, the standard carry HML3 and HML1 portfolios have the Sharpe ratios of 0.63 and 0.38 whilst the Sortino ratios are 0.57 and 0.31, respectively. This sort of ratio is known as the Sortino ratio as opposed to Sharpe ratio.

Here I use a *non-parametric* one sample Wilcoxon signed rank test [3] to determine if there is evidence showing that HML3 performance among different permutations is statistically different to zero. The rationale for a zero hypothesized value emerges from UIP. In the standard carry example with 218 degrees of freedom, the corresponding significance is less than 1%. As a result, I conclude that the average performance of *standard carry* strategy is not only economically, but also statistically different to zero. Similarly, the average returns from the *forward carry* and the *normalized carry* are statistically different to zero. In conclusion, I have shown that different carry permutations yield *economically* and *statistically* different positive average performance in time series, which refutes UIP.

[3] My results until now show violations of normality.

Table I: Monthly Carry Trade Return Summary Statistics

	HmL3	HmL1	S3	S2	S1
Standard Carry					
Excess Return: $(F_t / S_{t+1}) -1$					
Average	2.55%	2.60%	-0.84%	0.90%	4.26%
Standard Deviation	4.08%	6.77%	8.12%	8.89%	10.55%
Semi-Deviation	4.50%	8.46%	7.50%	9.04%	10.55%
Skewness *	-0.92	-1.35	0.32	-0.25	-0.44
Kurtosis *	2.98	4.66	-0.17	1.66	2.44
Sharpe Ratio	0.63	0.38	-0.10	0.10	0.40
Sortino Ratio	0.57	0.31	-0.11	0.10	0.40
Spot Change: $(S_{t+1} / S_t) -1$					
Mean	-0.45%	0.60%	-1.08%	-0.86%	-1.98%
Standard Deviation	4.09%	6.79%	8.07%	8.84%	10.49%
Semi-Deviation	3.58%	5.24%	9.05%	8.68%	10.31%
Forward Premium: $(F_t / S_t) -1$					
Average	2.10%	3.19%	-1.93%	0.04%	2.28%
Standard Deviation	0.14%	0.25%	0.48%	0.37%	0.38%
Forward Carry					
	HmL3	HmL1	S3	S2	S1
Excess Return: $(F_t / S_{t+1}) -1$					
Average	2.55%	2.48%	-0.93%	1.08%	4.17%
Standard Deviation	3.93%	6.73%	8.29%	8.72%	10.46%
Semi-Deviation	4.37%	8.35%	7.68%	8.90%	10.46%
Sharpe Ratio	0.65	0.37	-0.11	0.12	0.40
Sortino Ratio	0.58	0.30	-0.12	0.12	0.40
Spot Change: $(S_{t+1} / S_t) -1$					
Mean	-0.45%	0.71%	-0.99%	-1.04%	-1.89%
Standard Deviation	3.94%	6.74%	8.23%	8.67%	10.41%
Semi-Deviation	3.41%	5.18%	9.21%	8.47%	10.23%
Forward Premium: $(F_t / S_t) -1$					
Average	2.10%	3.18%	-1.92%	0.04%	2.28%
Standard Deviation	0.14%	0.25%	0.47%	0.37%	0.38%
Normalized Carry					
	HmL3	HmL1	S3	S2	S1
Excess Return: $(F_t / S_{t+1}) -1$					
Average	2.37%	3.23%	-0.89%	1.37%	3.84%
Standard Deviation	4.01%	6.62%	8.20%	8.93%	10.39%
Semi-Deviation	4.45%	7.31%	7.65%	8.89%	10.36%
Sharpe Ratio	0.59	0.49	-0.11	0.15	0.37
Sortino Ratio	0.53	0.44	-0.12	0.15	0.37
Spot Change: $(S_{t+1} / S_t) -1$					
Mean	-0.29%	-0.21%	-1.01%	-1.32%	-1.59%
Standard Deviation	4.02%	6.63%	8.15%	8.88%	10.33%
Semi-Deviation	3.58%	5.77%	9.10%	8.91%	10.08%
Forward Premium: $(F_t / S_t) -1$					
Average	2.07%	3.03%	-1.90%	0.05%	2.25%
Standard Deviation	0.14%	0.25%	0.47%	0.38%	0.37%

* Results show similar tendency amongst the other carry permutations

Table I reports the annualized summary statistics for standard carry, normalized carry, and forward carry. High-Minus-Low portfolios, e.g. HML3, consist of a long position in the top three and a short position in the bottom three currencies. I also report the statistics for long sub-portfolios. For instance SI comprises the top three currencies and S3 contains the bottom three currencies. I utilize end-of-month data (EOM) from January 1996 to February 2014. Exchange rates are from Reuters. All the portfolios are rebalanced on a monthly-basis.

Similarly, I compare competing permutations to assess whether their absolute excess return averages differ from zero. In other words, I test the hypothesis that two distributions are the same, that is, *standard carry* equals to *forward carry*. If the distributions are the same in *statistical* terms, the choice of the permutation is *irrelevant* as they contain the same information about the *expected* returns. As expected, *standard carry* and *forward carry* strategies are effectively the same and the results are similar to *normalized carry* strategy. In conclusion, in terms of out-of-the-sample excess return predictability, there is no difference among the three permutations.

Third and fourth moments, *skewness* and *kurtosis*, of the *long* and *long-sort* portfolios for the *standard carry* strategy confirm the findings of *currency crash* literature, by showing that a higher average forward premium is accompanied with greater negative *return* skewness and greater *directional* volatility.

F.2 Subperiod results and Effects of Learning

Previously, I have highlighted the *ballistic* shape of excess returns in figure I. In other words, it seems that the excess returns emerging from the different carry permutations deteriorate over time. I take this as a pre-evidence, suggesting that the excess returns are not *constant* but rather *time-varying* or alternatively subject to *learning*.

In order to conduct a more detailed analysis on this matter, I construct three sequential *non*-overlapping time series to study the performance of the standard carry strategy. The choice of carry strategy is trivial because the correlations among across different strategies are close to 1 as seen in table II.

Table II: Correlation Coefficients amongst Different Carry Strategies

	Standard Carry	Normalized Carry	Forward Carry
	Excess Return: (Ft / St+1 - 1)		
	Standard Carry	Normalized Carry	Forward Carry
Standard Carry	1.00		
Normalized Carry	0.98	1.00	
Forward Carry	0.99	0.97	1.00
	Spot Change: (St+1 / St - 1)		
	Standard Carry	Normalized Carry	Forward Carry
Standard Carry	1.00		
Normalized Carry	0.97	1.00	
Forward Carry	0.99	0.97	1.00
	Forward Premium*: (Ft / St - 1)*		
	Standard Carry	Normalized Carry	Forward Carry
Standard Carry	1.00		
Normalized Carry	0.99	1.00	
Forward Carry	0.99	0.98	1.00

Table II reports Pearson's correlation coefficients between different carry permutations. Pearson's correlation coefficients are defined as the covariance of the two variables in question divided by the respective product of their standard deviations.

The first panel in figure II (Panel I) consists of the end-of-month data from January 1996 to April 2001, the second panel (Panel II) goes from November 2001 to December 2007, and the final panel (Panel III) starts June 2009 and ends February 2014. I set the timing of the entry, as well as the exit point, not to coincide with the U.S. business cycle contractions as reported by the NBER[4]. The rationale to exclude the periods of NBER contractions relates to the occurrence of *crash risk* during the worst states of the world as reported in Dodrynskaya (2013) and depicted in figure I. In other words, I want to study the effects of learning during the "normal times". Moreover, NBER recessions drive a wedge between periods, and should therefore, be valuable if learning plays a role. This is because people tend to learn from failure as they *typically* ought to pay more attention to basic rules and counterfactual analysis.

4 The National Bureau of Economic Research, US Business Cycle Expansions and Contractions

Figure II: High-minus-Low 3 Standard Carry Subperiod Comparison

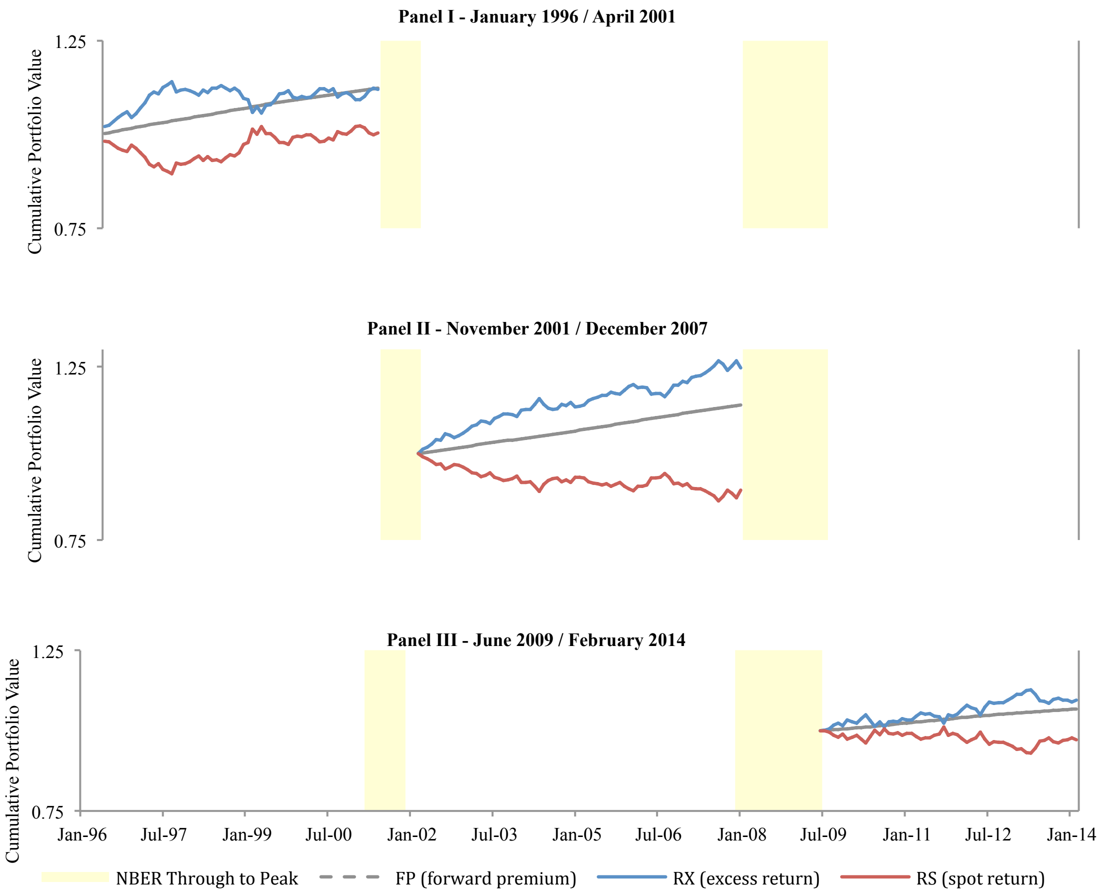

Figure II illustrates the subperiod excess returns and its elements for the HML3 standard carry portfolios.

I summarize the subperiod results in table III and confirm that the traditional carry strategy is not suffering from *fading profitability*, but rather *time-varying* excess returns. The average excess return variation is evident in the *long* portfolios: portfolio S1 excess returns range from -4.08% to 12.05%. The results of S1 in panel I demonstrate that carry investing is a double-edged sword. In other words, following an aggressive strategy can be one's rise or downfall. More specifically, the subperiod results highlight the importance of diversification in carry investing, and therefore, it is not surprising that HML3 yields the most *consistent* performance. Generally speaking, the observed variation in excess returns is most likely related to the variation in risk premia as explained in Fama (1984). Eaton and Turnovsky (1983) suggest that factors encouraging speculation, and more importantly the amount of speculative capital, are likely to reduce overall risk aversion and increase exchange rate volatility. In summary, it seems that risk-taking is greatly encouraged in certain time periods and that without fault very high returns go to those who take the greatest risk.

Table III: Monthly Carry Trade Return Panel Data Summary Statistics

	HmL3	HmL1	S3	S2	S1
Panel I - January 1996 / April 2001					
Excess Return: $(F_t / S_{t+1}) -1$					
Average	2.33%	0.96%	-8.73%	-5.88%	-4.08%
Standard Deviation	4.04%	6.82%	8.16%	7.08%	6.91%
Semi-Deviation	4.61%	9.13%	8.01%	7.40%	7.02%
Sharpe Ratio	0.58	0.14	-1.07	-0.83	-0.59
Sortino Ratio	0.50	0.10	-1.09	-0.79	-0.58
Spot Change: $(S_{t+1} / S_t) -1$					
Average	0.07%	2.81%	4.92%	4.83%	5.07%
Standard Deviation	4.04%	6.82%	8.19%	7.07%	6.85%
Semi-Deviation	3.29%	4.63%	10.39%	7.19%	6.78%
Forward Premium: $(F_t / S_t) -1$					
Average	2.40%	3.77%	-3.81%	-1.05%	0.99%
Standard Deviation	0.09%	0.17%	0.14%	0.15%	0.27%
Panel II - November 2001 / December 2007					
	HmL3	*HmL1*	S3	S2	S1
Excess Return: $(F_t / S_{t+1}) -1$					
Average	4.12%	7.26%	3.81%	8.34%	12.05%
Standard Deviation	3.20%	5.52%	7.46%	7.80%	8.44%
Semi-Deviation	3.04%	6.26%	6.43%	6.26%	7.30%
Sharpe Ratio	1.29	1.31	0.51	1.07	1.43
Sortino Ratio	1.35	1.16	0.59	1.33	1.65
Spot Change: $(S_{t+1} / S_t) -1$					
Average	-1.78%	-3.81%	-5.67%	-8.12%	-9.23%
Standard Deviation	3.20%	5.52%	7.42%	7.74%	8.38%
Semi-Deviation	3.14%	5.21%	8.46%	8.82%	9.40%
Forward Premium: $(F_t / S_t) -1$					
Average	2.34%	3.45%	-1.87%	0.22%	2.82%
Standard Deviation	0.06%	0.13%	0.43%	0.47%	0.38%
Panel III - June 2009 / February 2014					
	HmL3	*HmL1*	S3	S2	S1
Excess Return: $(F_t / S_{t+1}) -1$					
Average	2.05%	2.13%	2.47%	1.70%	6.56%
Standard Deviation	3.89%	5.22%	7.82%	8.69%	12.21%
Semi-Deviation	3.67%	5.15%	7.29%	9.18%	12.78%
Sharpe Ratio	0.53	0.41	0.32	0.20	0.54
Sortino Ratio	0.56	0.41	0.34	0.18	0.51
Spot Change: $(S_{t+1} / S_t) -1$					
Average	-0.59%	-3.81%	-2.75%	-1.08%	-3.92%
Standard Deviation	3.88%	5.52%	7.82%	8.69%	12.19%
Semi-Deviation	3.90%	5.21%	8.28%	8.28%	11.44%
Forward Premium: $(F_t / S_t) -1$					
Average	1.46%	2.09%	-0.27%	0.62%	2.64%
Standard Deviation	0.07%	0.14%	0.05%	0.11%	0.13%

Table III represents the annualized summary statistics of the standard carry permutation for the subperiods. The sample period for panels I, II, and III is Jan-96 – Apr-01, Nov-01 – Dec-07, and Jun-09 – Feb-14, respectively. Data is end-of-month data (EOM). Exchange rates are from Reuters. I use information at time t to determine the rankings and report the returns for the period of t, t+1. All portfolios are rebalanced on a monthly-basis.

Inspired by Fama (1984) I now re-examine the role of *learning* in foreign exchange. In other words, I examine if past excess returns were partly induced by the market participants' overestimation of the *frequency* as well as the *magnitude* of the reported sudden reversals. If so, the argument supporting the willingness to take on the '*same'* risk with *less* compensation is plausible. My hypothesis is that the uncovered interest rate parity (UIP) has become a more *efficient* predictor of future spot rate, and that this increased *efficient* can be attributed to *learning*. On a currency by currency basis, I compute the ordinary least squares (OLS) regression for each subperiod and compare the goodness-of-fit measures, by regressing the realized spot change on forward premium. A progressively *higher* R-squared measure would imply that the accumulated experience with flexible exchange rates has alleviated the forecasting bias, and consequently, today's estimate is more robust.

The statistical inferences of the results partly confirm my thoughts. The impression is that *predictability* increases as I move from panel I towards panel III, but since the R-squared measures *on average* remain extremely low and none of the coefficients are statistically significant, I conclude that *learning* does not play a role. Expressed differently, I report that the goodness-of-fit measures *on average* improve over time, but since the proposed model *on average* is not statistically significant, the forward premium does not show an *increased ability* to explain subsequent change in spot rates, at least not in *statistical* terms. Furthermore, of the full sample of coefficients, 9 are negative, which concludes that the proposed and theoretically-sound inverse relationship between the forward premium and the subsequent spot change does not hold in practice. In consonance, with the huge amount of literature on the forward premium puzzle and the bias hypothesis, I conclude that the coefficient is reliably less than one. My average coefficient for the full sample is -1.60.

Additionally, even when I split the full sample into subperiod results in order to alleviate the problem of non-constant variance during the full sample period, there is no evidence of a robust relationship between today's forward premium and a subsequent change in spot rate. Moreover, the subsample III results are extremely counter-intuitive owing to the harmony of subsamples I and II. The average coefficient across the 9 currency pairs in the subsample III is 6.92. This implies, for example, that when the interest rate differential increases by 1 percentage point, the *base currency* subsequently tends to appreciate at an annual rate of almost 7 percent.

In summary, I have so far concluded that the UIP does not hold and excess returns are time-varying. If I continue assuming that rational expectations hold, the only way to save the UIP from dismal failure is to attribute excess returns to different risk factors.

Table IV: OLS Regressions Testing Conditional Forward Premium Bias [a]

	Full Sample	Sub-Samples I, II, and III		
	January 96 - February 14	January 96 - April 01	November 01 - December 07	June 09 - February 14
AUD	-2.06	-5.89	-0.17	-4.51
	(0.007)	(0.0231)	(0.0000)	(0.0074)
CAD	-1.89	-2.04	0.05	6.22
	(0.004)	(0.0093)	(0.0000)	(0.0059)
CHF	-2.77	1.54	-2.35	-23.94
	(0.014)	(0.0008)	(0.0099)	(0.0168)
EUR	-3.33	-3.20	-2.25	8.23
	(0.015)	(0.0049)	(0.0142)	(0.0062)
GBP	-1.11	-0.85	0.42	28.44
	(0.002)	(0.0008)	(0.0004)	(0.0128)
JPY	-0.24	-1.67	-1.61	15.75
	(0.000)	(0.0005)	(0.0087)	(0.0062)
NOK	-0.93	-2.20	-1.17	13.65
	(0.003)	(0.0154)	(0.0080)	(0.0121)
NZD	-0.13	-0.65	-1.71	16.53
	(0.000)	(0.0012)	(0.0017)	(0.0060)
SEK	-1.92	-1.40	-1.90	1.92
	(0.007)	(0.0041)	(0.0131)	(0.0012)

[a] Estimate of Beta (goodness of fit)

Beta coefficient = St+1 - St = i + a(Ft - St) + e2

***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

Table IV represents the annualized summary statistics for beta coefficients and goodness-of-fit measures (in parenthesis). The sample period for panels I, II, and III is January 1996 – April 2001, November 2001 – December 2007, and June 2009 – February 2014, respectively.

F.3 Linkage between Currency Carry Trades and Currency Crash Risk.

In addition to the properties of the time-varying average carry strategy profitability, I am interested in the presence of non-normality in foreign exchange and its relationship with the average forward premium. As previously stated, the carry excess returns tend to suffer from negative conditional skewness. I calculate monthly variance ratios (currency skewness factors) on the back of daily spot returns. If the bandwagon effect is prevalent, on average across the full sample, currencies with higher average forward premiums should have greater variance ratios, an evidence supporting the existence of crash risk. If so, the underlying positioning is likely to be *clustered* and *homogenous*, fueling speculative bubbles. For example, if greater forward premiums on average attract more speculative money, the clustered positioning may create momentum to the adverse spot movements, amplifying speculator losses.

The results suggest that the variance ratio, which is a conditional positive variance divided by a conditional negative variance, varies over time. Remember that investors overall prefer avoiding losses to acquiring gains, and therefore, a positive variance is less desirable. If a positive variance is greater than a negative variance, the explanation is that the *base currency* appreciation has been more prevalent during the sample period. After all, a carry investor hopes the *base currency* to depreciate, or alternative appreciate, but only to a certain extent, in order to enjoy positive returns over the period.

In table V, variance ratios and average forward premiums provide interesting evidence during normal periods (outside the NBER recessions cycles), supporting existing literature on *crash risk*. Variance ratio, which is effectively an average realized risk premia, exhibits rather high variability in time series and across currencies. For example, take AUD, GBP, NOK, and NZD. For each of these currencies, the average forward premium is positive throughout the sample accompanied with the realized VR ratios that are greater than 1. To the contrary, the same metrics for HML1 and HML3, which isolate the U.S. funding bias potentially present in the results, confirm that the carry strategies as well suffer from negative return skewness.

In conclusion, my results are consistent with the fact that carry trades are exposed to crash risk during normal times. My results suggest that the failure of the uncovered interest parity (UIP) may potentially relate to the compensation that investors require for providing liquidity.

Table V: Variance Ratios and Average Forward Premiums

	Full sample		Panel I - January 1996 / April 2001		Panel II - November 2001 / December 2007		Panel III - June 2009 / February 2014	
	Variance Ratio (VR) *	Average Forward Premium (AFP) **	VR	AFP	VR	AFP	VR	AFP
Currency skewness measures on a currency by currency basis								
AUD	1.408	2.12%	1.563	0.03%	1.275	2.50%	1.300	3.70%
CAD	1.223	-0.04%	1.163	-1.02%	1.016	0.18%	1.361	0.62%
CHF	1.264	-2.01%	1.322	-3.92%	0.985	-1.99%	1.565	-0.45%
EUR	1.271	-0.46%	1.310	-1.68%	1.039	-0.19%	1.516	0.03%
GBP	1.221	0.91%	1.242	0.62%	1.101	1.55%	1.317	0.24%
JPY	1.447	-2.97%	1.163	-5.49%	1.211	-2.98%	2.091	-0.31%
NOK	1.332	0.98%	1.457	-0.20%	1.111	0.82%	1.544	1.59%
NZD	1.321	2.69%	1.268	1.27%	1.338	3.61%	1.153	2.57%
SEK	1.277	-0.08%	1.239	-1.33%	1.066	-0.09%	1.444	0.94%
Currency skewness measures for long-short portfolios								
HML3	1.349	2.55%	1.323	2.33%	1.445	4.12%	1.288	2.05%
HML1	1.375	2.60%	1.341	0.96%	1.497	7.26%	1.223	2.13%

Table V represents the annualized summary statistics for variance ratios and average forward premiums. The sample period for panels I, II, and III is January 1996 – April 2001, November 2001 – December 2007, and June 2009 – February 2014, respectively. Variance ratio is calculated from daily spot return data.

F.4 Excess Returns and Different Sources of Risk Premia

I begin by computing traditional Pearson's correlation coefficients between the excess returns from different portfolios deploying the *standard carry* ranking methodology and unique risk factors. I also analyze average currency skewness metrics for all 9 currencies, and separately for HML1 and HML3 portfolios. Pearson's correlation coefficients are defined as the covariance of the two variables in question, divided by the respective product of their standard deviations. Intuition suggests that negative loadings on the explanatory variable should emerge when the variables are defined over the same period, i.e. the causal channel goes through *contemporaneous* changes rather than *lagged* changes. To the contrary, I expect positive loadings on the respective risk factors against the average skewness metrics.

Looking at table VI, I can confirm that this thinking makes sense. In HML1 and HML3 columns of table VI a negative correlation coefficient emerges between implied volatility, idiosyncratic volatility, *downside* adjusted idiosyncratic volatility, TED spread, banking sector idiosyncratic volatility, *downside* adjusted banking sector idiosyncratic volatility, banking sector idiosyncratic surprise, and realized currency basket volatility (VOL).

For *long* portfolios S1, S2, and S3 the results are similar except that implied volatility has a positive correlation with the excess returns which seems counter-intuitive. A possible explanation may relate to the fact that the implied volatility measures future uncertainty. In other words, a *contemporaneous* measure for implied volatility is most likely misspecified as there is no time between the cause and effect.

Additionally, both *downside adjusted* measures have greater correlation coefficients, suggesting that the *direction* is more important than the *dispersion* per se. However, the surprise measure, banking sector idiosyncratic surprise, produces the greatest correlation coefficients among the different banking sector idiosyncratic uncertainty measures. In summary, the *unexpected directional advers*e specification has the highest relative correlation coefficient with the carry trade excess returns.

To the contrary, the currency skewness factors have a positive correlation coefficient with different risk metrics. A sturdy explanation, similar to existing *crash literature*, is that investors are more likely to unwind their carry positions amid increasing uncertainty. In other words, if investors simultaneously unwind positioning in the same currency, the supply-and-demand dynamics would cause further damage to existing positions. Since the correlation coefficients are very close to zero, there is a possibility the *contemporaneous* relationship is misspecified. Also, the correlation coefficient of the implied volatility holds an opposite sign with respect to the rest of the pack and is possibly related to the pre-emptive reduction in liquidity: speculators discount a higher probability for future crash; liquidity drops in FCU before the event because people avoid any excessive exposure in the given currency; and the *base currency* depreciates.

Table VI: Portfolio Excess Returns and Risk Factors

Predictor Variables Correlation with the Dependent Measure								
	HML1	**HML3**	**S1**	**S2**	**S3**	**SKW**	**SKWHML1**	**SKWHML3**
Implied Volatility	-0.12	-0.02	0.05	0.03	0.08	0.07	-0.08	-0.14
Idiosyncratic Volatility	-0.20	-0.14	-0.20	-0.18	-0.12	0.02	0.02	0.00
Downside Idiosyncratic Volatility	-0.20	-0.17	-0.23	-0.21	-0.14	0.02	0.03	0.01
TED	-0.39	-0.33	-0.27	-0.19	-0.01	0.04	0.12	0.12
Banking sector idiosyncratic volatility	-0.26	-0.20	-0.19	-0.19	-0.05	0.07	0.01	-0.03
Banking sector downside idiosyncratic volatility	-0.28	-0.23	-0.23	-0.23	-0.07	0.08	0.01	-0.02
Banking sector idiosyncratic surprise	-0.28	-0.34	-0.36	-0.36	-0.13	0.09	0.08	0.14
VOL	-0.39	-0.31	-0.17	-0.05	0.09	-0.01	0.05	0.05

Implied Volatility is the VIX index and measures the subjective probability distribution of future uncertainty

Idiosyncratic Volatility measures the average idiosyncratic firm-level shocks across different industries

Banking sector idiosyncratic volatility measures the average idiosyncratic firm-level shocks within the banking sector

TED spread measures the availability of liquidity, which is the 3-month USD LIBOR minues 3-month T-Bill yield

DOL measures the average excess return across portfolios S3, S2, and S1

Banking sector idiosyncratic surprise equals banking sector downside firm-level uncertainty divided by period t-1 implied volatility

Table VI represents the correlation coefficients between the dependent measures (portfolio returns) and independent variables (sources of uncertainty). The sample period is from January 1996 to December 2013.

Table VII: Risk Factor Correlation Matrix

	Implied Volatility	**Idiosyncratic Volatility**	**Downside Idiosyncratic Volatility**	**TED**	**Banking sector idiosyncratic volatility**	**Banking sector downside idiosyncratic volatility**	**Banking sector idiosyncratic surprise**	**VOL**
Implied Volatility	1.00	0.53	0.51	0.43	0.69	0.67	0.15	0.42
Idiosyncratic Volatility		1.00	0.99	0.46	0.71	0.71	0.53	0.36
Downside Idiosyncratic Volatility			1.00	0.45	0.70	0.71	0.55	0.35
TED				1.00	0.67	0.67	0.56	0.50
Banking sector idiosyncratic volatility					1.00	0.99	0.69	0.49
Banking sector downside idiosyncratic volatility						1.00	0.73	0.49
Banking sector idiosyncratic surprise							1.00	0.32
VOL								1.00

Table VII represents the correlation matrix for different independent variables (risk factors). The sample period is from January 1996 to December 2013.

My next question explores to what extent the information embedded in the different risk factors is unique. One way to address this question is to construct a correlation matrix for the *independent* variables. If the correlation coefficient is close to +1, the conclusion would be that the two risk factors contain the exact same information and I may omit one of them.

First, I note that none of the correlation coefficients are anyway near one, which means that I may not omit any of the risk factors without risking a possibility of *marginal* contribution.

Furthermore, I am interested in the correlation coefficients between the banking sector idiosyncratic firm-level uncertainty and the TED spread *as well as* the idiosyncratic firm-level uncertainty and the implied volatility.

Looking at the latter first, it is important to remember that the fundamental difference between the implied volatility and the idiosyncratic uncertainty is that the implied volatility measures *non-diversifiable* uncertainty, while the idiosyncratic uncertainty quantifies the *diversifiable* uncertainty. Also, the implied volatility reflects the *expectation of future* uncertainty, whereas the idiosyncratic volatility measures the *realization of past* uncertainty. As seen in table VII, the correlation coefficient is 0.53 for the latter pair. Therefore, if changes in the idiosyncratic uncertainty explain changes in the carry excess returns, part of the excess return variability may be attributed to the average firm-level shocks, resulting in a potentially statistically significant *marginal* contribution to the explanatory power of the model. For the *downside adjusted* idiosyncratic uncertainty the correlation is 0.51 and the remarks on the subject are the same.

By the same token, the TED spread and the banking sector idiosyncratic uncertainty are both related to existing literature on *funding constraints*. As already mentioned, the TED spread is a measure of liquidity constraints in the economy. Generally speaking, increases in the TED spread are related to reduced risk tolerance. The banking sector idiosyncratic firm-level uncertainty measures the firm-level volatility in the banking sector and can be linked to funding constraints, credit risk, and systemic risk. In summary, both risk factors are related to the same underlying uncertainty, speculators' willingness and ability to *keep* or *put* capital at risk. Since the correlation coefficient with the TED spread is 0.67, which is high but clearly less than one, I suggest that the banking sector average firm-level volatility may contain information that is related to excess return variability, but is not present in the TED spread. For the *downside adjusted* idiosyncratic banking sector volatility the correlation is 0.67 and for the banking sector idiosyncratic surprise the correlation is 0.56.

In conclusion, it is worth conducting regression analysis to measure the degree of relationship among the *idiosyncratic volatility* and *banking sector idiosyncratic volatility* in time series *vis-à-vis* the excess returns, given that both risk factors have similar characteristics, but are not the same, to the implied volatility (VIX) and the TED spread, respectively.

Table VIII: Mutually Exclusive Single Explanatory Variable Regression Models

	Average	Implied Volatility	Idiosyncratic Volatility	Downside Idiosyncratic Volatility	TED	Banking sector idiosyncratic volatility	Banking sector downside idiosyncratic volatility	Banking sector idiosyncratic surprise	VOL
Excess returns and risk factors									
HML1	2.60%	-0.03*	-0.036***	-0.053***	-1.891***	-0.038***	-0.059***	-0.016***	-0.238***
r^2		{0.015}	{0.039}	{0.040}	{0.155}	{0.070}	{0.080}	{0.076}	{0.154}
HML3	2.55%	-0.003	-0.015**	-0.027**	-0.96***	-0.017***	-0.029***	-0.012***	-0.114***
r^2		{0.000}	{0.018}	{0.028}	{0.110}	{0.040}	{0.054}	{0.114}	{0.096}
S1	-0.58%	0.018	-0.057***	-0.096***	-1.982***	-0.043***	-0.076***	-0.032***	-0.164**
r^2		{0.002}	{0.040}	{0.055}	{0.070}	{0.037}	{0.055}	{0.128}	{0.030}
S2	-0.77%	0.01	-0.042***	-0.072***	-1.17***	-0.037***	-0.063***	-0.028***	-0.042
r^2		{0.001}	{0.031}	{0.044}	{0.035}	{0.038}	{0.054}	{0.133}	{0.003}
S3	1.51%	0.023	-0.027	-0.043*	-0.061	-0.009	-0.017	-0.009*	0.063
r^2		{0.006}	{0.015}	{0.019}	{0.000}	{0.002}	{0.005}	{0.016}	{0.008}
Currency skewness measures and risk factors									
SKW	1.16	0.318	0.073	0.115	3.373	0.199	0.309	0.096	-0.066
r^2		{0.005}	{0.000}	{0.001}	{0.001}	{0.006}	{0.006}	{0.008}	{0.000}
SKWHML1	1.25	-0.437	0.107	0.174	13.056*	0.025	0.051	0.11	0.642
r^2		{0.006}	{0.001}	{0.001}	{0.013}	{0.000}	{0.000}	{0.007}	{0.002}
SKWHML3	1.19	-0.483	-0.006	0.038	7.795*	-0.053	-0.061	0.115**	0.384
r^2		{0.020}	{0.000}	{0.000}	{0.013}	{0.001}	{0.000}	{0.020}	{0.002}

*****, **, and * denote significance at 1%, 5% and 10% levels, respectively.**

Table VIII holds the single regression model summary statistics. Beta coefficients are expressed with the significance at 1%, 5% and 10%. R-squared metrics are expressed in parenthesis. The sample period is from January 1996 to December 2013.

Using the excess returns and risk factors section in table VIII, I conclude that the statistical inferences of the single linear regressions on excess returns are intriguing. Firstly, with respect to the implied volatility and the idiosyncratic volatility, the results of the latter are *more often* statistically significant with varying degrees of significance, whilst the former only reaches the required threshold *once*. In other words, on average, the null hypothesis is true and I conclude that the observed relationship between the *contemporaneous* implied volatility (VIX) and the excess returns is likely related to sampling error (a random chance), or alternatively, to misspecification (a *contemporaneous* measure versus a *lagged* measure). To the contrary, the *contemporaneous* measure for the idiosyncratic volatility is more likely to reflect the actual characteristics of the underlying excess returns since the beta coefficients are statistically significant for HML1, HML3, S1, and S2. Therefore, I refute the null hypothesis and conclude that the results are *not* a by-product of randomness. Furthermore, when I look at the goodness-of-fit measure, r^2, the idiosyncratic volatility better explains the variability of excess returns in all five instances (HML1, HML3, S1, S2, and S3). I propose an out-of-the-box explanation linked to CLMX, which I leave open for future research, where a possible explanation may be related to the fact that arbitrageurs, who trade to exploit the mispricing of individual stocks rather than aim to hold well-diversified portfolios, are more exposed to the idiosyncratic return volatility, and not the aggregate market volatility, due to the lack of *diversification*. If so, during times of increased firm-level uncertainty, a unifying explanation for stock market returns and carry returns may be present. For instance, it is possible that the portfolio manager's choices for liquidation are limited to the most marketable holdings such as foreign exchange carry trades.

Secondly, the banking sector volatility and the TED spread are both likely to match the characteristics of the underlying excess returns via the funding constraints linkage. The funding constraints linkage relates to tightness of margin constraints, or an increase in funding risk, and should be associated with poor carry trade returns as explained in Filipe and Suominen (2013). In general, I report that the coefficients are significant with normal levels of significance, while the TED spread over performs in terms of goodness-of-fit in three out of five regressions. However, with respect to the correlation matrix in table VI, it is very likely that the banking sector volatility contains unique information, which is not captured by the TED spread, and therefore, may provide existing multivariate models on the excess return variability with a statistically significant *marginal* contribution. Moreover, I argue that the banking sector uncertainty is potentially associated with causality through the changes in financial institutions equity prices, where the change in the variable results in the *contemporaneous* change with respect to their ability to lend to other market participants such as speculative accounts. This causality is not necessarily present in the TED spread.

Thirdly, the basket realized volatility, VOL, explains the excess returns with varying success with respect to both *long-short* and *long* strategies. VOL performs particularly well in explaining the HML1 and HML3 portfolio excess returns, which makes sense given that the volatility is the only caveat of foreign exchange carry strategies.

Moreover, I find that the risk premia is monotonically increasing in the level of the average interest rate differential across the board. In other words, the high average interest rate differential portfolios such as HML1 and S1 have relative greater beta coefficients with respect to the different risk factors. Also, the *downside adjusted* measures of idiosyncratic uncertainty have superior explanatory power leading to a conclusion that the *downside adjusted* measures similar to Dodrynskaya (2013) better fit the excess return data.

Next I briefly turn my attention to the bottom section, currency skewness measures and risk factors, of table VII. SKW is the average skewness of the 9 currencies, and SKWHML1 as well as SKWHML3 relate to the High-Minus-Low strategies, which have USD neutral funding. My interpretation of the results is that in most cases, excluding a few exceptions, there is no linkage between the different risk factors and the currency skewness metrics: the TED spread holds statistically significant betas for SKWHML1 and SKWHML3 but the explanatory power remains very low, while the banking sector idiosyncratic surprise measure explains SKWHML3. Since the explanatory power is close to zero, there is a possibility the *contemporaneous* relationship is misspecified and time should be allow between *cause* and *effect*.

E.5 Multivariate Funding Risk Analysis

In section E.4 I restricted my analysis to simple regression models, *implicitly* assuming that the dependent variable was related to one explanatory variable. In general, the excess returns are most likely attributable to several, perhaps many, explanatory variables. For this reason, I scrutinize the *joint explanatory* power among the different funding parameters: the TED spread and the banking sector *downside adjusted* firm-level uncertainty. I start off with a model of two explanatory variables. I presume that the excess returns are influenced by a *contemporaneous* change in the funding uncertainty and a moving average of funding uncertainty.

A *contemporaneous* funding uncertainty relates to *short-run* implications, such as unexpected *shocks* to the entire financial system. These shocks may cause speculators to deduce from this simple observation that a systemic risk event is more feasible. For example, a sudden increase in the *average* banking sector firm-level uncertainty disseminates a message to speculative accounts that there is an increased likelihood of systemic risk, such as the bankruptcy of Lehman Brothers, encouraging pre-emptive reduction in positioning. Expressed differently, the losses that emanate from a financial sector *alone* increase the likelihood of severe instability or collapse of an entire industry, resulting in deleveraging, where speculators unwind their existing positions. In other words, changes in financial institutions equity prices directly affect their ability to lend to other market participants (Adrian and Shin, 2010). Similarly, Duffic and Strulovici (2012) consider that unexpected changes in the amount of capital available to speculators result in severe adjustment in risk premia. My assessment is that the practical repercussions are similar to the funding spirals introduced in Brunnermeier and Pedersen (2009). A funding spiral per se instigates speculators to unwind, resulting in *further* losses. Explained differently, I consider the *short-run* effects are destabilizing during the *current* period.

To the contrary, I presume that the moving average of funding uncertainty relates to the *long-run* effects such as the availability of liquidity. In other words, the causality between the dependent variable and the moving average of the independent variable is most likely related to factors regulating the amount of speculative capital as compared to the *short-run* effects. In other words, an increase in the *average* firm-level uncertainty in the banking sector is likely to reduce banks' appetite to extend credit to speculative accounts. Similarly to Duffie and Strulovici (2012), I presume that an abundance of capital results in low risk premium. Therefore, if a credit extension becomes and more importantly remains binding, a straightforward implication is to discourage speculation and consequently, increase the overall risk aversion, which in turn would lead to a higher risk premium. In other words, a higher risk premium translates into greater excess returns given the relationship between expected and observed return characteristics discussed earlier in this paper. Intuitively, if most of the speculators are providing liquidity at the same time, the compensation for proving liquidity must be less on a *relative scale* as compared to a situation where liquidity is scarce.

The relationship between the excess returns from various *standard carry* portfolios and the different funding proxies is:

$$rx(y)_t = \beta_1 + \beta_2\, TED_t + \beta_3\, TED\ 6M\ MA_t + u_t \tag{12}$$

$$rx(y)_t = \beta_1 + \beta_2\, BANK_t + \beta_3\, BANK\ 6M\ MA_t + u_t, \tag{13}$$

where *rx* is the excess return for *period t* whereas $y = \{HML1, HML3, S1, S2, S3\}$, *TED* and *BANK* are the contemporaneous measures for the funding uncertainty in *period t*, and *TED 6M MA* and *BANK 6M MA* relate to the 6-month moving average measures.

The results of the multiple regression results depicted in tables IX-A and IX-B confirm my thoughts. In other words, the 6-month moving average measures have statistically significant *positive* betas while the *contemporaneous* measure coefficients have statistically significant *negative* betas. The results confirm that the two funding proxies have similar characteristics, when putting the differences in explanatory fit aside. Moreover, the topline of the results in tables IX-A and IX-B are that the TED model better explains the excess returns for portfolios HML1 and HML3, whereas the banking sector *downside adjusted* model does a better job of explaining excess returns in the long portfolio S1, S2, and S3. Since U.S. dollar is not a traditional funding currency, I suggest that the banking sector funding proxy ought to be computed using the stock market data from Switzerland or Japan since the currencies of these two countries are considered *the* traditional funding. Moreover, it is worth to mention that the bottom currency, when I perform the rankings with the *standard carry* methodology, is in each and every case either CHF or JPY, which means that the HML portfolios are *never* funded via U.S. On the same token, McGuire and von Peter (2009) conclude that a stress on banks' balance sheets can cause shortage on funding in a given currency and therefore, a strong relationship between the U.S. funded carry portfolios and the U.S. idiosyncratic banking sector uncertainty seems plausible. However, I leave this question unanswered and subject to future research to address.

I also consider various specifications for the explanatory variables in question such as lagged values, lognormal transformation, and percentage changes, but conclude that the *contemporaneous* and 6-month moving average specifications best fit the data. However, the problem with the *contemporaneous* or *instantaneous* relationship is that it is possible that the *dependent variable* and the *independent variables* are both correlated with a third, unknown variable. Therefore, I should allow for the possibility that time might elapse between the cause and effect. For the avoidance of doubt, I confirm that the one-period lagged measure of the *contemporaneous* parameter remains statistically significant for both funding proxies.[5] Nevertheless, in my opinion it is reasonable to assume that foreign exchange markets rapidly incorporate new information, implying that if the

[5] r^2 measures for the lagged banking sector downside firm-level uncertainty for portfolios HML1, HML3, S1, S2, and S3 are 0.0600, 0.0502, 0.0374, 0.0323, and 0.0007, respectively. All coefficients excluding S3 are statistically significant with 1 percent significance level. The results for the TED spread show a similar trend, i.e. there is a reduction in the goodness-of-fit measure from table VIII.

banking sector uncertainty *unexpectedly* deteriorates during the current period, the price action take place *instantaneously*. In other words, because funding problems in future are now more *probable*, a pre-emptive risk-off motivated reduction in positioning is likely to ensue during the same period and lead to the *loss spirals*. In summary, I argue that the most likely causal channel goes through *contemporaneous* changes rather than *lagged* changes. My remarks are open to debate.

Table IX-A: Funding Model I

Variables	HML1	HML3	S1	S2	S3
Banking sector downside firm-level uncertainty	-0.1143***	-0.0859***	-0.206***	-0.1451***	-0.0342
Std. Err.	(0.0249)	(0.0146)	(0.0385)	(0.0330)	(0.0313)
6-month MA banking sector downside firm-level uncertainty	0.0763***	0.0777***	0.1788***	0.1128***	0.0234
Std. Err.	(0.0287)	(0.0168)	(0.0442)	(0.0379)	(0.0360)
r^2	0.1104	0.1431	0.1235	0.0921	0.0069
Model F	0***	0***	0***	0.0006***	0.4881

Table IX-B: Funding Model II

Funding Model II on excess returns					
Variables	HML1	HML3	S1	S2	S3
TED spread	-2.8781***	-1.9864***	-3.516***	-1.772**	0.4561
Std. Err.	(0.5340)	(0.3203)	(0.8728)	(0.7548)	(0.6978)
6-month MA TED spread	1.3822**	1.439***	2.146**	0.837	-0.7334
Std. Err.	(0.6115)	(0.3666)	(0.9994)	(0.8643)	(0.7990)
r^2	0.1743	0.1709	0.0898	0.0390	0.0042
Model F	0***	0***	0.0001***	0.016**	0.6461

*****, **, and * denote significance at 1%, 5% and 10% levels, respectively.**

Tables IX-A and IX-B represent the funding models I and II. I am not running a horse race comparison but rather show that the observed characteristics of both models are very similar, while the TED model better fits the data. The sample period is from January 1996 to December 2013.

I now extend my earlier model to allow for the possibility that excess returns are *simultaneously* influenced by the banking sector idiosyncratic firm-level uncertainty *and* the TED spread. However, because my explanatory variables are correlated and conceptually similar, issues related to the multicollinearity may pose a problem. I simply test whether multicollinearity is a problem by running a regression with all the four variables in question. As expected, it turns out that the t-statistics for the coefficients are not always significant, although regression on the HML3 portfolio excess returns is an exception, yet the overall F-statistics are significant. These results together with relatively high pairwise correlations in table VII are indicators that the *multicollinearity* is potentially a problem. One way to deal with correlated independent explanatory variables is to orthogonalize them. Therefore, I use the residual values as an orthogonalized additional explanatory variable:

$$TED = \beta_1 + \beta_2\, BANK_t + u_t, \tag{14}$$

where u_t captures the *unique* information that is not present in *BANK*. I compute (14) by regressing *BANK* on *TED* as well in order to capture the capture the *unique* information that is not present in *TED*.

I report the results from this extension in tables X-A and X-B. I have two tables because *BANK* fits the S1, S2, and S3 data better than *TED*, whereas *TED* better explains HML1 and HML3 as seen in IX-A and IX-B. In other words, I have one funding model for the *long* portfolios that are funded in the USD, and another for the USD neutral *long-short* portfolios. However, my intention is not to run a horse race in order to conclude which one of the *funding proxies* is superior, but rather to understand if information content is *complementary* at any level.

I start off with the *long* portfolios in table X-A. The first observation is that I have produced a satisfactory model for the *long* portfolios in which all explanatory variables are significant.[6] More importantly, the orthogonalized residuals are statistically significant and multicollinearity is no longer a threat. Nevertheless, I cannot conclude *yet* that the *marginal* explanatory power, an improvement in the model fit, is any better because even if the new variable truly belongs in the model, its correlation with the other model variables may be high, and therefore, the *marginal* explanatory power is low, or in some cases, statistically insignificant.

I report that the *joint* marginal contribution of the new orthogonalized variable is *not* significant once I take into account the loss in degrees of freedom. In other words, the improvement in fit from IX-A S1 to X-A S1 is the reduction in the residual sum of squares, 0.17497 - 0.17186, and the cost equals one degree of freedom because I have estimated an additional parameter. The number of degrees of freedom remaining after adding the new variable is 208 – 1 = 207. Therefore, $F(1{,}207) =$

[6] I am not interested in long portfolio S3 anymore but document the results for the sake of consistency.

$\frac{(0.17497-0.17186)/1}{0.17186/\ 207} = 3.75$ and because *F(1,207)* must be *higher* than *F(1,250)*, which is 3.88 at the 5 percent level, I cannot refute H_0 and conclude that the residual variable capturing the unique information content in TED does have significant *joint* explanatory power, i.e. the improvement in model fit is *not* statistically significant. In conclusion, a more complex model for the excess returns of the *long* USD funded carry portfolios is not statistically any better in terms of goodness-of-fit, which means that the unique information content in the TED spread is not *complementary* at normal levels of statistical significance.

In summary, the explanatory power of the *long* portfolio model in X-A, *F*, is slightly greater when compared to IX-A, which means that the inclusion of the additional parameter has increased the goodness of fit, but as already mentioned, the *marginal* contribution to the explanatory power is not statistically significant. However, Dougherty (p. 173, 2011) notes that if a parameter in question has a significant coefficient, it is likely to belong to the model, and dropping it could distort the results by giving rise to the omitted variable bias. Nevertheless, the *downside adjusted* banking sector idiosyncratic firm-level uncertainty specifications covary with the carry trade excess returns.

Table X-A: Funding Model III

Variables	HML1	HML3	S1	S2	S3
Banking sector downside firm-level uncertainty	-0.1078***	-0.0827***	-0.2012***	-0.1442***	-0.0357
Std. Err.	(0.0240)	(0.0143)	(0.0383)	(0.0331)	(0.0314)
6-month MA banking sector downside firm-level uncertainty	0.0674**	0.0734***	0.1722***	0.1115***	0.0254
Std. Err.	(0.0277)	(0.0165)	(0.0441)	(0.0381)	(0.0361)
Residuals from regressing TED on banking sector downside firm-level uncertainty	-1.682***	-0.8152***	-1.2544*	-0.2355*	0.3761
Std. Err.	(0.4065)	(0.2418)	(0.6477)	(0.5595)	(0.5311)
r^2	0.1783	0.1877	0.1391	0.0929	0.0093
Model F	0***	0***	0***	0.0002***	0.5864

*****, **, and * denote significance at 1%, 5% and 10% levels, respectively.**

Table X-A represents the funding model I that utilizes the unique information in TED. The sample period is from January 1996 to December 2013.

I now turn my attention to the *long-short* portfolios in table X-B. In brief, all explanatory variables are significant and multicollinearity is no longer a threat. To begin with, I assess the *marginal* contribution. First, the improvement in fit from IX-B HML3 to X-B HML3 is the reduction in the residual sum of squares, 0.02446 - 0.02375, and the cost is *again* one degrees of freedom. The number of degrees of freedom remaining after adding the new variable is 208 – 1 = 207. Therefore, $F(1{,}207) = \frac{(0.02446 - 0.02375)/1}{0.02375/\ 207} = 6.19$, and because *F(1,207)* must be *lower* than *F(1,250)*, which is 3.88 at the 5 percent level, I refute H_0 and conclude that the residual variable capturing the unique information content in the banking sector downside adjusted firm-level uncertainty does have significant *joint* explanatory power, i.e. the improvement in the model fit is statistically significant. To the contrary, for HML1 the results are the exact opposite. Nevertheless, I argue that while the model itself is already highly significant before the inclusion of the new funding parameter, the *unique* information content captured by the banking sector *downside adjusted* firm-level uncertainty increases the explanatory power of the model. Therefore, I have statistically significant evidence of the *complementary* fit with respect to the TED spread and the banking sector downside adjusted firm-level uncertainty.

Table X-B: Funding Model IV

Funding Model IV on excess returns					
Variables	HML1	HML3	S1	S2	S3
TED spread	-3.2839***	-2.3321***	-4.4707***	-2.7407***	0.1935
Std. Err.	(0.5805)	(0.3455)	(0.9413)	(0.8094)	(0.7627)
TED spread 6-month MA	1.9472***	1.921***	3.474***	2.1846**	-0.3678
Std. Err.	(0.6899)	(0.4106)	(1.1188)	(0.9620)	(0.9064)
Residuals from regressing Banking sector downside idiosyncratic volatility on TED	-0.0343*	-0.0292**	-0.0806**	-0.0817***	-0.0222
Std. Err.	(0.0200)	(0.0117)	(0.0319)	(0.0274)	(0.0259)
r^2	0.1861	0.1949	0.1169	0.0783	0.0077
Model F	0***	0***	0***	0.0007***	0.6583

*****, **, and * denote significance at 1%, 5% and 10% levels, respectively.**

Table X-B represents the funding model II that utilizes the unique information in banking sector firm-level uncertainty. The sample period is from January 1996 to December 2013.

Finally, I include the orthogonalized residuals from the moving average measure as well and report the results for the funding model V in table XI, concluding that the *marginal* contribution in the model fit from adding two new parameters is statistically significant for HML3. The critical value of F is $F(2{,}206) = \frac{(0.024457-0.023179)/2}{0.023179/\ 206} = 6.19$ and because the critical value of *F(2,206)* must be *smaller* than *F(2,200)*, which is 4.71 at the 1 percent level, I refute H_0 and conclude that the contribution from both residual parameters is statistically significant at 1 percent level. The contribution of the explanatory power as regards to HML1 is not significant at the normal levels of significance, while the respective results for S1 and S2 are statistically significant at the 1 percent level.

Table XI: Funding Model V

Funding Model V on excess returns					
Variables	HML1	HML3	S1	S2	S3
TED spread	-3.3005***	-2.3534***	-4.537***	-2.7848***	0.1697
Std. Err.	(0.5806)	(0.3423)	(0.9290)	(0.8040)	(0.7625)
6-month MA TED spread	2.068***	2.0754***	3.9554***	2.5041***	-0.1953
Std. Err.	(0.6996)	(0.4124)	(1.1195)	(0.9688)	(0.9187)
Residuals from regressing banking sector downside firm-level uncertainty on TED	-0.0541**	-0.0545***	-0.1595***	-0.1341***	-0.0504
Std. Err.	(0.0275)	(0.0162)	(0.0439)	(0.0380)	(0.0361)
Residuals from regressing 6m MA banking sector downside firm-level uncertainty on 6m MA TED	0.0346	0.0442**	0.1377**	0.0914**	0.0493
Std. Err.	(0.0333)	(0.0196)	(0.0533)	(0.0462)	(0.0438)
r^2	0.1904	0.2142	0.1446	0.0955	0.0138
Model F	0***	0***	0***	0.0004***	0.5796

*****, **, and * denote significance at 1%, 5% and 10% levels, respectively.**

Table XI represents the funding model II that utilizes the unique information in funding model I. The sample period is from January 1996 to December 2013.

In conclusion, the results in this paper offer an interesting addition to existing *funding constraints* literature and a small step to the right direction with respect to solving the *forward premium puzzle*. For future research, I urge people to explore alternative approaches on the realized *banking sector idiosyncratic* firm-level uncertainty because to the best of my knowledge, this paper is the first work that shows the relationship between the banking sector firm-level uncertainty and the carry trade excess returns.

F.6 Multi-Dimensional Regression Analysis on Funding Risk

Finally, I suspect that the carry trade community, in other words speculators whose role is to provide liquidity in foreign currency, simply respond, without feedback, to the adverse *unexpected* developments in the financial sector by *deleveraging existing positions*. If these reactions are *collective*, a loss spiral is likely to ensue as in Brunnermeier and Pedersen (2009). Therefore, the interactions in the aftermath of the adverse *unexpected* developments in the financial sector may be as follows: the initial *unexpected* idiosyncratic shock within the banking sector increases market illiquidity and leads to speculator losses, speculator positions are *reduced* collectively without feedback, prices drop further, losses on existing positions, speculators encounter funding problems due to the deteriorating conditions in the banking sector, forced selling and reduction in speculator positions ensue, and so on.

To the contrary, and according to the Triennial Central Bank Survey 2013, global foreign exchange market turnover indicates that the daily average trading volumes of outright forward agreements trended up to $680 billion in 2013 from $128 billion in 1998, a 431% increase. As mentioned in the Triennial survey, the measurement of speculative positioning is subject to inaccuracy, but my assessment is that we can *safely* assume that the turnover by the speculative community has surged up as well. [7] In conclusion, today every attractive opportunity is being eyed by many more investors than in the past. Additionally, I presume that the importance of the *banking sector* in asset pricing has monotonically increased during recent years of *financialization*. *Financialization* relates to ever-larger and more-complex financial systems which may be prone to crashes, leading to *systemic crashes*.

Therefore, the relationship between the surge in the amount of speculative capital and *financialization* is of interest. I report the results by regressing the HML3 excess returns on different *funding proxies* in a multi-dimensional setting in table XII. Firstly, I report that all coefficients have the same sign and that results are statistically significant at the 1% significance level. Surprisingly, the banking sector idiosyncratic surprise variable's explanatory power increases *monotonically* in the multi-dimensional setting, whereas both the TED spread and other specifications for the banking sector idiosyncratic variable remain fairly constant.

In conclusion, a possible explanation is that speculative investors have become increasingly sensitive to the conditions in the banking sector, indicating that the uncertainty spillovers from the financial sector drive asset prices in cross-section. Also, it is evident and obvious in today's world that the financial sector has become more *interconnected*. Alternatively, pressure to maximize

[7] The average daily trading volumes of outright forwards: $128 billion (1998), $130 billion (2001), $209 billion (2004), $362 billion (2007), $475 billion (2010), $680 billion (2013). The numbers are adjusted for local and cross-border inter-dealer double-counting (net-net basis). Source *Triennial Central Bank Survey 2013*.

short-term returns may lead to trigger-happy behaviour in foreign exchange, where speculators and investors unwind positions before the forward premium is fully absorbed.

Table XII: Multi-Dimensional Regression Analysis on Funding Constraints

Multi-Dimensional Regression Analysis of Time-Series Data on HML3 Excess Returns			
	Panel I: 1996 - 2013	**Panel II: 2000 - 2013**	**Panel III: 2005 - 2013**
High-minus-Low 3 (HML3) Excess Returns			
Banking sector idiosyncratic surprise	-0.012***	-0.013***	-0.015***
r^2	{0.114}	{0.171}	{0.220}
Banking sector downside idiosyncratic volatility	-0.029***	-0.026***	-0.028***
r^2	{0.054}	{0.057}	{0.071}
Banking sector idiosyncratic volatility	-0.017***	-0.015***	-0.016***
r^2	{0.040}	{0.038}	{0.047}
TED	-0.96***	-0.881***	-0.893***
r^2	{0.110}	{0.117}	{0.130}
N	215	155	95

Banking sector surprise equals banking sector downside firm-level uncertainty divided by period t-1 implied volatility

Banking sector idiosyncratic volatility measures the average idiosyncratic firm-level shocks within the banking sector

TED spread measures the availability of liquidity, which is the 3-month USD LIBOR minues 3-month T-Bill yield

N equals the number of end-of-month (EOM) observations in the sample

*****, **, and * denote significance at 1%, 5% and 10% levels, respectively.**

G. Concluding remarks

In this paper, I look at the banking sector idiosyncratic firm-level uncertainty emerging from the United States as a possible explanation for the non-zero carry trade excess returns. The causality between the dependent variable, *carry excess returns*, and the independent variables, *funding proxies*, is most likely related to factors regulating, *endogenously* and *exogenously,* the amount of speculative capital.

Expressed differently, an increase in the *average* firm-level uncertainty in the banking sector is likely to reduce a bank's appetite to extend credit to speculative accounts. Similarly to Duffie and Strulovici (2012), I assume that an abundance of capital results in a low risk premium. Therefore, if a credit extension becomes, and more importantly remains binding, a straightforward implication is to discourage speculation and consequently, increase the overall risk aversion, which in turn would lead to a higher risk premium. In other words, a higher risk premium translates into greater excess returns given the relationship between expected and observed return characteristics. These are the *long-run* implications of the *average* banking sector firm-level uncertainty on the carry trade excess returns. A *short-run* implication relates to unexpected *shocks* that may cause speculators to deduce that systemic risk is more probable. For example, a sudden increase in the *average* banking sector firm-level uncertainty disseminates a message to speculative accounts that there is a greater likelihood of a systemic shock such as the bankruptcy of Lehman Brothers, encouraging a pre-emptive reduction in positioning and resulting in *loss spirals*. Stated otherwise, the *short-run* effects are destabilizing during the *current* period.

The multivariate model constructed in this paper is statistically significant and explains 14.3% of the excess return variability of the High-minus-Low (HML3) portfolio that comprises a long position in the top three currencies and a short position in the bottom three currencies. The model utilizes the information embedded in the realized firm-level idiosyncratic *average* uncertainty in the U.S. financial sector. Moreover, a *joint* multivariate funding model that combines the information of the *conventional* TED spread and the banking sector idiosyncratic firm-level uncertainty emerging from the U.S. explains 21.4% of the High-minus-Low (HML3) excess return variability.

Additionally, a *single* explanatory variable which proxies the effects of *unexpected* funding shocks explains 11.4% of the High-minus-Low (HML3) excess return variability for the full period from

1996 to 2013. By comparison, the *contemporaneous* TED spread explains 11.0% of the excess return variation for the same period. The correlation coefficient among the two is 0.56. Moreover, the explanatory power of the banking sector idiosyncratic surprise measure increases from 11.4% to 22.0% in a multi-dimensional setting. Finally, I introduce an alternative metric for the CBOE VIX option implied volatility (VIX).

In summary, I consider the results in this paper to be an interesting addition to existing literature on *funding constraints* and a small step in the right direction in solving the *forward premium puzzle*.

In addition to opening new avenues for future research, I confirm existing literature on the uncovered interest parity (UIP) violations, the role of *learning* in the forward premium puzzle, and the linkage between currency carry trades and currency crash risk.

In future, I urge further exploration of alternative approaches to the *banking sector idiosyncratic volatility* because to the best of my knowledge, this paper is the first piece of research that shows the relationship between banking sector firm-level uncertainty and excess returns from foreign exchange carry strategies.

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