Implications of Changes in Conditional Value at Risk for the Currency Carry Trade and Equilibrium Currency Pricing

Empirical Evidence from the G10 Currencies

Dissertation

zur Erlangung des Grades eines Doktors der Wirtschaftswissenschaft

der Rechts- und Wirtschaftswissenschaftlichen Fakultät

der Universität Bayreuth

Vorgelegt

von

Daniel Hertrich

aus

Heidelberg

Dekan: Prof. Dr. Claas Christian Germelmann

Erstberichterstatter: Prof. Dr. Klaus Schäfer

Zweitberichterstatter: Prof. Dr. Friedrich Sommer

Tag der mündlichen Prüfung: 20.01.2025

Acknowledgements

There are many people whose support, guidance and inspiration have made it possible for me to explore the unknown, challenge existing beliefs, embrace failure and learn from it, always in the pursuit of discovery and understanding.

First and foremost, I would like to thank Prof. Dr. Klaus Schäfer for giving me the freedom to work on topics that fascinate me. His invaluable advice, positive attitude, patience and constant support have been crucial to my academic and personal development. He always made me feel that he had no doubts about my ability to carry out my research. Without this sense of reassurance, encouragement and, above all, his willingness to share his life experience and knowledge with me, I would not have managed to complete this thesis. I would also like to thank Prof. Dr. Friedrich Sommer for being my second reviewer and Prof. Dr. Reinhard Meckl for chairing the examination committee.

I am grateful to all the colleagues I have had the pleasure to meet for their support and guidance and, above all, for adding so much fun to my exciting time at the Chair of Banking and Finance at the University of Bayreuth. Special thanks are due to Prof. Dr. Marc Mehlhorn and Dr. Maximilian Zurek for initiating my path into scientific research at crucial points in my studies. You both have no idea how much your critical thinking and insights during my early research projects have benefited me over the years.

I would like to dedicate this thesis to my amazing wife Maria and my wonderful children Alisa, Fabian, Tobias and Isabella for being my safe haven and for believing in me even when I didn't. I would also like to thank Angelika and Eduard Christ for being incredibly great parents and grandparents. Thank you all for your love and tremendous understanding during the many hours I spent writing this thesis. Your unwavering support has been the greatest gift and the foundation of my perseverance.

Abstract

The state of the art is that non-zero excess returns in efficient foreign exchange markets reflect a time-varying risk premium for the systematic volatility risk taken, which affects current and future consumption and investment opportunities. However, the carry trade risk premium has been unexpectedly low since the global financial crisis, although its negative covariance with innovations in the state variable global FX volatility still prevails, suggesting a failure of currency pricing theory under uncertainty rather than a recovery of the conventional unbiasedness hypothesis.

According to Fama's (1991) joint hypothesis problem, both currency-specific information and market inefficiencies can lead to a failure to price risk efficiently in equilibrium, especially in the absence of any other unifying rational expectations theory. Combining these two concepts in the context of Merton's (1987) model of capital market equilibrium with incomplete information provides the core idea of this thesis, which is that the magnitude of a ‘change’ in idiosyncratic risk may have pricing power in the cross-section of currency excess returns if investors underreact to news and price adjustments occur only gradually over time.

Two approaches based on forward-looking information are proposed, a simple estimator using the moving mode of available investment currencies and the more sophisticated ‘pricing classifier’, to predict a violation of the systematic risk-based pricing model, i.e. to predict funding market states and contrarian pricing regimes when the market does not reward entering into a carry trade with sufficiently high expected excess returns. In addition, we introduce a novel sorting variable to the literature, ‘CVaR-Trend’, which captures the short- to long-term trend in CVaR forecasts and is used as a proxy for the magnitude of a recent change in the level of CVaR.

The empirical results confirm that those G10 currencies that have experienced the largest increase (decrease) in CVaR and, over the same period, the largest discount (premium) in spot prices due to the concomitant depreciation (appreciation) of the quote currency during the price adjustment, will ultimately have high (low) risk premiums to compensate for their high (low) CVaR levels. Furthermore, it is precisely when both funding and investment currencies are among those that have experienced an increase in CVaR that the ‘in equilibrium’ condition of Menkhoff et al.'s (2012a) currency pricing model is likely to be violated. Only if the discount built into spot prices by low idiosyncratic excess returns over time is sufficient to allow both investment and funding currencies to regain higher expected future excess returns, is a sufficient risk premium on the carry trade restored, and thus the risk-based explanation of the forward premium puzzle.

Finally, the three key findings, first, the pricing classifier as a mispricing indicator that signals when to avoid carry trades, second, the sorting variable CVaR-Trend that highlights the relevance of changes in individual risk for currency pricing, and third, the predictability of excess return reversals in contrarian pricing regimes that reveals price adjustments towards equilibrium, allow the development of a new currency trading strategy, the ‘contrarian pricing trade’. The contrarian pricing trade evolves the conventional carry trade investment rule and delivers economically and statistically significantly higher investment performance than the conventional carry, momentum and value FX investment styles. In addition, the contrarian pricing trade offers significantly better diversification benefits to a US investor who is internationally invested in the equities of the G10 currency economies. Overall, the favourability of the contrarian pricing trade holds not only over the entire sample period from January 1999 to June 2023 and for both conformity and contrarian pricing regimes, but also during periods of above- and below-average financial market stress as well as for the period before and after the global financial crisis.

Table of Contents

Acknowledgements . . . 1
Abstract . . . 3
Table of Contents . . . 5
List of Tables . . . 8
List of Figures . . . 9

1 Introduction . . . 11
1.1 Motivation . . . 11
1.2 Outline of the thesis . . . 14

2 Research Context . . . 17
2.1 The theoretical foundation of the carry trade . . . 17
2.1.1 Uncovered and covered interest rate parity . . . 17
2.1.2 The rejection of the unbiasedness hypothesis . . . 20
2.1.3 The stylised facts of carry trades . . . 23
2.1.4 Explanatory approaches to the forward premium puzzle . . . 25
2.2 The intertemporal relation between return and risk in foreign exchange markets 32
2.2.1 The intertemporal capital asset pricing model . . . 32
2.2.2 Common risk factors in foreign exchange markets . . . 34
2.3 Research hypotheses and key findings . . . 39
2.3.1 Theoretical framework . . . 39
2.3.2 Can mispricing be anticipated? . . . 41
2.3.3 Attribution of mispricing . . . 47
2.3.4 Does idiosyncratic risk matter? . . . 49
2.3.5 Do market inefficiencies matter? . . . 58
2.3.6 Are these findings ultimately exploitable? . . . 65

3 Carry and Conditional Value at Risk Trend . . . 69
3.1 Introduction . . . 70
3.2 Literature review . . . 73
3.3 Data and risk metric . . . 75
3.3.1 Spot and forward exchange rates . . . 75
3.3.2 Currency excess returns . . . 75
3.3.3 Risk factors . . . 76

3.3.4 CVaR-Trend . . . 77
3.3.5 Econometric framework . . . 79
3.4 CVaR-Trend and the cross-section of currency excess returns . . . 82
3.4.1 CVaR-Trend and the state of the foreign exchange market . . . 82
3.4.2 Carry and the state of the foreign exchange market . . . 87
3.4.3 CVaR-Trend in investment markets . . . 88
3.4.4 CVaR-Trend trade . . . 91
3.5 Conclusion . . . 93
4 Contrarian Currency Pricing . . . 95
4.1 Introduction . . . 96
4.2 Literature review . . . 99
4.3 Can mispricing be anticipated? . . . 102
4.3.1 Risk factors . . . 102
4.3.2 Conditional value at risk . . . 103
4.3.3 Volatility as a risk factor – signs of mispricing . . . 104
4.3.4 Pricing classifier . . . 107
4.3.5 Expectations amid global FX volatility uncertainty . . . 111
4.3.5.1 Possible scenarios . . . 111
4.3.5.2 Contrarian currency pricing . . . 113
4.3.5.3 The predictable downside of carry trades . . . 114
4.3.5.4 Contrarian currency pricing and return reversals . . . 114
4.4 Empirical Framework . . . 117
4.4.1 Data . . . 117
4.4.2 Currency and carry trade excess returns . . . 118
4.4.3 Econometric model . . . 120
4.5 Empirical results . . . 124
4.5.1 The impact of contrarian currency pricing . . . 124
4.5.2 Contrarian currency pricing and the cross-section of excess returns . . . 129
4.5.3 Predictability of return reversals . . . 133
4.5.3.1 Rationale for the choice of predictors . . . 133
4.5.3.2 Predictability of excess return reversals . . . 140
4.5.3.3 CVaR-Trend and idiosyncratic momentum . . . 143
4.6 Conclusion . . . 145

5 Diversification Benefits of the Contrarian Pricing Trade 147
5.1 Introduction 148
5.2 Literature review 150
5.3 Empirical research design 153
5.3.1 Methodology 153
5.3.2 Data and investigation period 155
5.3.3 Benchmark portfolio return. 157
5.3.4 FX investment style-adjusted benchmark portfolio return 160
5.3.5 Currency transaction costs and equity rebalancing costs 161
5.4 Foreign exchange investment styles 163
5.4.1 Carry trade 163
5.4.2 Momentum trade. 164
5.4.3 Value trade 164
5.4.4 Contrarian pricing trade. 166
5.5 Empirical results 170
5.5.1 Performance of FX investment styles 170
5.5.2 Diversification effects. 174
5.5.3 Are FX investment styles safe havens? 179
5.6 Conclusion. 184

6 Conclusion 187

Bibliography. 193

List of Tables

2.1 Uncovered interest rate parity 18

3.1 CVaR-Trend and market states 85
3.2 Forward discount and market states 87
3.3 Recent spot rate appreciation 89
3.4 Performance of high CVaR-Trend strategies 90
3.5 Performance of the CVaR-Trend trade 92

4.1 The prevalence of contrarian currency pricing regimes 126
4.2 The impact of contrarian currency pricing on future carry trade excess returns . . . 128
4.3 Pricing classifier and excess returns of portfolios sorted by forward discount 131
4.4 Pricing classifier and betas of carry trade portfolios with global FX volatility 133
4.5 Predictability of excess returns of the carry risk factor HML^{FX} 141
4.6 Pricing classifier and double sorts on CVaR-Trend and idiosyncratic momentum . . 144

5.1 Currency excess returns net of bid-ask spreads 162
5.2 Performance of FX investment styles 172
5.3 Diversification benefits of FX investment styles 175
5.4 Diversification benefits of FX investment styles in subperiods 177
5.5 Safe haven characteristics of FX investment styles 182

List of Figures

1.1 Geometric cumulative net excess return of the carry trade 12

4.1 Evolution of CVaR forecasts. 135

5.1 Geometric cumulative net excess returns of FX investment styles 171

5.2 Time series plot of the pricing classifier and financial stress indices. 180

1 Introduction

1.1 Motivation

The foreign exchange market is now the largest financial market in the world, with a daily dollar trading volume that has grown from around US$20 billion in 1973 to around US$7.5 trillion in 2022. In a nutshell, this development has been driven by the increasing globalisation of the world economy. In economic terms, globalisation has led to an increase in international trade in goods and services between countries and a reduction in their barriers to cross-border capital flows. These trends have been supported by international efforts to promote trade liberalisation and openness, as evidenced by milestones such as the General Agreement on Tariffs and Trade (GATT), signed in 1947, and its successor, the World Trade Organisation (WTO), established in 1995 (Bekaert & Hodrick, 2018; BIS, 2022b).

In theory, there should be no need to worry about forecasting exchange rate movements because, according to the unbiasedness hypothesis, forward rates should be equal to future spot rates, which implies that, in an efficient foreign exchange market, changes in interest rate differentials fully explain the cross-section of currency excess returns (e.g., Daniel et al., 2017). However, the enormous size and importance of the foreign exchange market seems to bring with it a myriad of real-world complexities that have caused the unbiasedness hypothesis to fail, as currencies with high (low) interest rates tend to appreciate (depreciate) rather than depreciate (appreciate). This empirical observation is known as the 'forward premium puzzle', which is perhaps one of the most intriguing challenges in financial theory, given the size of the foreign exchange market (Hassan & Mano, 2019, p. 397).

The most common explanation is that a non-zero expected excess return on the strategy of exploiting the forward premium puzzle through carry trades reflects a time-varying risk premium in efficient foreign exchange markets. Figure 1.1 shows that in times of market turbulence, such as during the global financial crisis or when the US sovereign credit rating was downgraded in August 2011, the carry trade experiences significantly large and sudden losses. For taking on this systematic ‘volatility risk’, investors demand positive excess returns in equilibrium as compensation (Lustig et al., 2011; Menkhoff et al., 2012a).

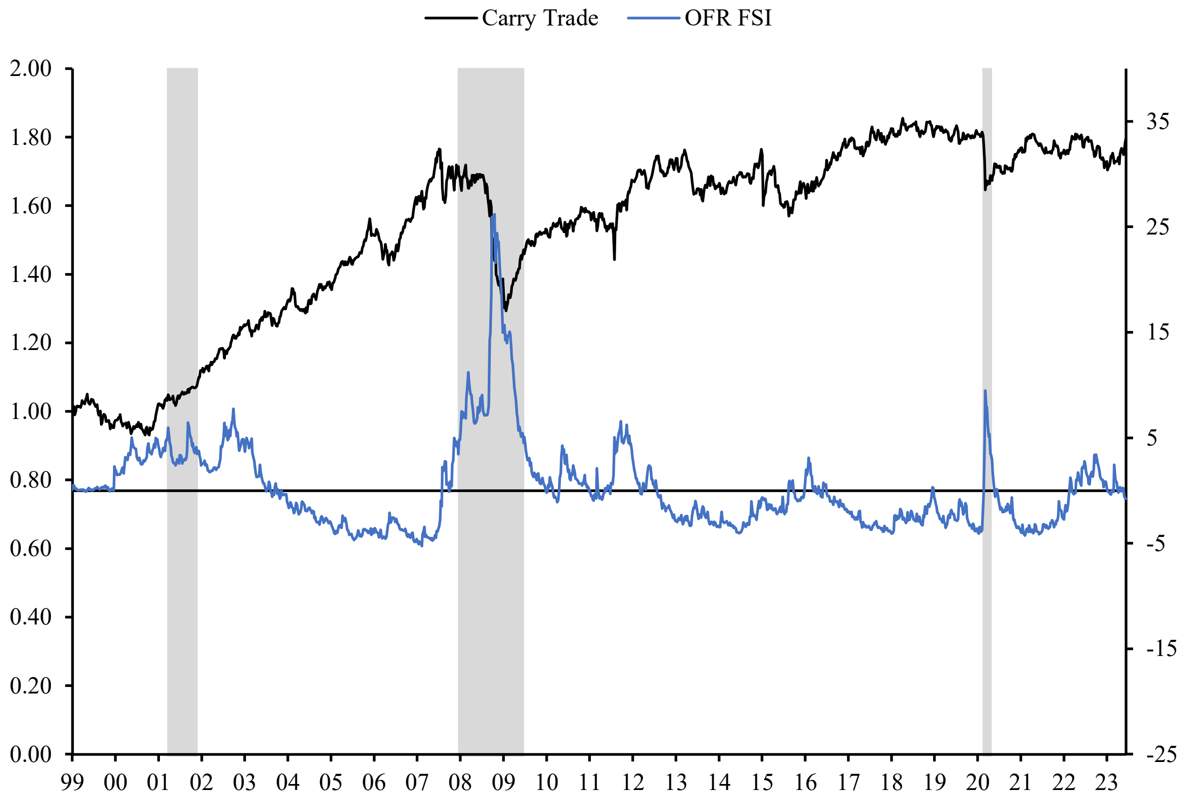

Figure 1.1. The figure shows the Office of Financial Research's Financial Stress Index (OFR FSI) on the right y-axis and the geometric cumulative excess return on $1 invested in the carry trade, constructed as described in Section 5.4.1, on the left y-axis. Discrete excess returns over the US Treasury rate are net of transaction costs. Positive (negative) values of the OFR FSI reflect above (below) average levels of financial market stress. Shaded areas in the figure correspond to NBER recessions. The sample period is January 1999 to June 2023.

However, this ‘on average’ pricing perspective (Fama, 1970, p. 409) requires the carry trade to generate positive excess returns during periods of average or below-average financial market stress. Figure 1.1 clearly shows that this was indeed the case in the period before the global financial crisis and from late 2009 to early 2013. However, for the period from around mid-2013 to mid-2023, the cumulative excess return of the carry trade only moves up and down slightly from time to time, so that on average it remains broadly unchanged. The carry trade no longer seems to offer adequate risk compensation, although its sensitivity to systematic volatility risk remains high, as the large losses following the Swiss franc shock in January 2015 or the coronavirus pandemic shock in March 2020 clearly show.

The research objective of this thesis is therefore to examine whether there is useful forward-looking information that allows us to assess whether the risk-based explanation for the cross-section of currency excess returns holds, and to understand the driving forces behind it.

Guided by the joint hypothesis problem (Fama, 1991), we are aware that there could simply be a better systematic risk-based explanation, but this seems unlikely as it would have to show how currency excess returns covary with priced risk factors in such a way that the carry trade does not sufficiently reward the still prevailing volatility risk. Moreover, the empirical support for carry and volatility risk as drivers of currency excess returns remains quite strong (e.g., Nucera et al., 2023). In particular, if deviations from equilibrium may be temporary, as suggested by Figure 1.1, it seems plausible, in line with the joint hypothesis problem, that either currency-specific information or market inefficiencies, or both, play a role alongside systematic risks (e.g., Cochrane, 2011; Daniel et al., 2020).

Accordingly, our research focuses in particular on the interplay between these two concepts, since on the one hand, in line with Merton (1987), currency-specific or idiosyncratic risks may be relevant for currency pricing and may become so significant that they even outweigh systematic risks at certain points in time. On the other hand, the key behavioural assumption of Merton (1987) is that investors have limited attention and therefore can only act on information once they are aware of it. Taken together, these two concepts highlight the potential importance of the size of a ‘change’ in risk. If market participants are slow to react to news (e.g., Daniel et al., 1998), then a large change in currency risk due to idiosyncratic information may have pricing power but will take longer to be reflected in prices. The expected excess return is then unlikely to be in equilibrium with systematic risk until the adjustment process is complete (e.g., Atilgan et al., 2020).

1.2 Outline of the thesis

The first part of Chapter 2 begins with the main theoretical concept of why we should expect carry trades to be a zero-sum game, and then reviews the empirical evidence for the failure of the unbiasedness hypothesis and the main explanations for the forward premium puzzle. The second part of Chapter 2 provides the economic rationale for recognising that, in an equilibrium model, volatility risk can be a source of systematic risk for which market participants demand a risk premium, thereby justifying the failure of the unbiasedness hypothesis. The third part of chapter two then provides a detailed description of the derivation of the four central research hypotheses of this thesis and a brief summary of the main findings. The first three research hypotheses provide an avenue for understanding the causal mechanisms through which changes in idiosyncratic risk can affect currency pricing.

Crucial to this understanding is the acceptance of the primacy of systematic volatility risk, which is why a large part of this thesis is devoted to finding evidence for the breakdown of the systematic risk explanation of currency pricing. According to the joint hypothesis problem, it should be precisely then possible to find a strong indication of the influence of currency-specific information on the pricing of currencies. The main references to the indicators developed in this thesis can be found in sections 2.3.2, 3.4.1 and 4.3.

This division of the foreign exchange market into two states, in which the risk-based explanation of the forward premium puzzle is fulfilled and in which it is not, suggests that there may be different mechanisms by which changes in idiosyncratic risk affect spot rate movements. For this reason, the third chapter examines how changes in currency-specific risk might be adequately measured, and tests whether changes in risk can price the cross-section of currency excess returns in periods when the carry trade can and cannot. The results suggest that changes in idiosyncratic risk are relevant for currency pricing in both market states, but of secondary (primary) relevance when the carry trade is (is not) a significant risk factor.

This suggests that, in line with the joint hypothesis problem, deviations from equilibrium may be temporary. For this reason, chapter four refines the mispricing indicator of chapter three, but in particular examines whether there is evidence of price adjustments that correct the mispricing and thereby restore the equilibrium of the risk-based explanation. The results suggest that a failure of the risk-based explanation does indeed seem to occur, as there are changes in idiosyncratic risk that need to be properly priced before systematic volatility risk can again become the key explanation for the carry trade driving the cross-section of currency excess returns.

The three main findings, that changes in currency-specific risk are relevant for currency pricing, albeit in different ways depending on whether the systematic risk-based explanation holds or not, and that price adjustments towards equilibrium occur, suggest that the carry trade investment rule could be improved. For this reason, chapter five develops a new currency trading strategy that builds on the carry trade but incorporates these three key insights into the investment rule. The primary objective of chapter five is then to examine whether the shortcomings of the carry trade strategy in the aftermath of the global financial crisis can actually be mitigated in a classic performance and diversification benefit study under realistic conditions. In short, the results suggest that the main findings of this thesis are indeed powerful in improving the conventional carry trade.

2 Research Context

2.1 The theoretical foundation of the carry trade

2.1.1 Uncovered and covered interest rate parity

Interest rate parity (IRP) is essentially an extension of the law of one price. While the law of one price states that in frictionless markets - a condition characterised by the absence of information asymmetry, transaction and transport costs, and legal restrictions such as differential taxes or trade barriers - a homogeneous good should trade at the same price in different locations or markets when expressed in the same currency, IRP applies this logic to the realm of international money market instruments by positing a relationship between interest rates and exchange rates that must hold when international financial markets are in arbitrage equilibrium (Bekaert & Hodrick, 2018; Eun & Resnick, 2004).

The relationship postulated by the IRP can be derived from an arbitrage transaction in which an investor sees an opportunity to exploit a positive difference between the foreign and domestic interest rates. To do this, at an initial time t, one domestic currency unit (DCU) is borrowed at the domestic interest rate i^d. This is used to buy S_t foreign currency units (FCU) at the prevailing exchange rate S_t. Note that we use quantity notation where DCU is the base currency and FCU is the quote currency. Once converted, it's immediately lent out at the foreign interest rate i^f. The arbitrage portfolio is fully self-financing, i.e. the cost of holding it is zero, since the net cash flow at time t is zero. At the end of the investment period, at time t+1, both investments are closed, i.e. the amount resulting from the foreign lending is converted back into domestic currency at the new exchange rate S_{t+1}. These proceeds are used to repay the outstanding domestic loan, together with its accrued interest. Table 2.1 summarises the current and future (maturity date) cash flows from the investment in the arbitrage portfolio, following Eun and Resnick (2004, p. 100f.).

The net cash flow of this arbitrage transaction provides several important insights into the understanding of interest rate parities and the determination of exchange rates. Uncovered interest rate parity (UIRP) is satisfied in the equilibrium state of the foreign exchange market, i.e. when there are no profitable arbitrage opportunities.

Table 2.1
Uncovered interest rate parity

Strategy	Cash flow in t = 0	Cash flow in t = 1
Borrow domestic currency	+ 1 DCU	- $(1+i^d)$ DCU
Lend foreign currency	- S_t FCU	+ $(1+i^f)$ S_t FCU
Net cash flow	= 0	= $(1+i^f)\frac{S_t}{S_{t+1}}$ - $(1+i^d)$ DCU

Note: Table 2.1 summarises the current and future (maturity date) cash flows from investing in the arbitrage portfolio, which is created by first borrowing 1 DCU in the domestic money market at the domestic interest rate and then lending the same amount abroad at the foreign interest rate.

For this equilibrium to prevail, the net cash flow from the arbitrage transaction at maturity must be zero, which implies, on the one hand, that the expected return on an uncovered foreign investment should be equal to the known return on a domestic investment and, on the other hand, that the future spot exchange rate at time t can be expected to be equal to:

$$\left(1+i^f\right)\frac{S_t}{E_t(S_{t+1})} = \left(1+i^d\right)$$

$$\Rightarrow E_t(S_{t+1}) = S_t\frac{1+i^f}{1+i^d}$$

$$\Rightarrow \frac{E_t(S_{t+1}) - S_t}{S_t} = \frac{i^f-i^d}{1+i^d} \qquad (2.1)$$

The expected percentage change in the spot rate in a given period should therefore be approximately equal to the interest rate differential between the two currencies in that period. This is because if $i_f > i_d$ ($i_f < i_d$), which favours the foreign (domestic) currency, and UIRP does not hold initially (at t=0), then arbitrageurs would seek to borrow in the domestic (foreign) currency and invest in the foreign (domestic) currency. This increased demand for the foreign (domestic) currency would put upward pressure on its current value. Over time, as the arbitrage positions mature, there will be a greater demand to convert the foreign (domestic) currency back into the domestic (foreign) currency, which will increase (decrease) the future spot rate. This expected depreciation (appreciation) of the foreign currency offsets (compensates for) the higher (lower) foreign interest rate, ensuring that the overall expected excess return equals that of the domestic investment. It is precisely this equivalence of expected excess returns between domestic and uncovered foreign investments that leads to a central conclusion of the UIRP, namely that investors are not compensated for being exposed to the uncertainty of the future spot rate, i.e. for bearing the risk that future spot rate fluctuations may adversely affect them (Bekaert & Hodrick, 2018; Eun & Resnick, 2004).

By entering into forward contracts to fix future exchange rates, investors can attempt to hedge exchange rate risk. However, the forward rate F_t, which is fixed at time t and matures at time t+1, is adjusted immediately, i.e. at time t, to eliminate possible arbitrage opportunities. This arbitrage condition, which relates the spot, forward and nominal interest rates of two currencies, is known as covered interest rate parity (CIRP). CIRP ensures that the expected returns on domestic and foreign investments hedged by forward contracts are the same. Whereas UIRP relies on anticipated movements in future spot rates to ensure parity of expected returns, CIRP relies on immediate adjustments in spot and forward rates. However, both parity conditions have in common that in an efficient market there should be no risk-free arbitrage opportunities. The arbitrage transactions of market participants guided by these parities aim to ensure that equivalent investments, whether hedged or not, earn the same return (Bekaert & Hodrick, 2018; Eun & Resnick, 2004).

Consider again an arbitrage transaction, assuming that the foreign (domestic) currency has a higher interest rate, i.e. $i_f > i_d$ ($i_f < i_d$), and CIRP is not initially satisfied. The aim of the arbitrage transaction is to take advantage of the interest rate differential. An increase in demand by arbitrageurs at time t to buy (sell) the foreign currency spot and to sell (buy) the foreign currency forward will immediately cause the spot rate to fall (rise) and the forward rate to rise (fall) so that the positive (negative) percentage difference between the forward and spot rates is approximately equal to the positive (negative) interest rate differential between the foreign and domestic currencies. This is essentially the same as replacing $E(S_{t+1})$ by F_t, which gives the following rearrangement for the net cash flow of the arbitrage portfolio:

$$\left(1+i^f\right)\frac{S_t}{F_t} = \left(1+i^d\right)$$

$$\Rightarrow F_t = S_t \frac{1+i^f}{1+i^d}$$

$$\Rightarrow \frac{F_t - S_t}{S_t} = \frac{i^f - i^d}{1+i^d} \tag{2.2}$$

Since the foreign currency is traded on the forward market at a discount (premium) to the current spot rate, i.e. $F_t > S_t$ ($F_t < S_t$), an investor who buys (sells) the foreign currency on the spot market at the lower (higher) spot rate and agrees to sell (buy) it forward at the higher (lower) forward rate will already incur a foreign exchange loss (gain) at time t that offsets (compensates for) the higher (lower) foreign interest rate (Bekaert & Hodrick, 2018; Eun & Resnick, 2004).

2.1.2 The rejection of the unbiasedness hypothesis

Assuming that market participants are risk-neutral (i.e. indifferent to risk and concerned only with expected returns) and have rational expectations (i.e. their forecasts are, on average, not systematically biased but accurate and take into account all available information), the covered and uncovered interest rate parity theories together lead to the unbiasedness hypothesis. This hypothesis states that the forward rate should be an unbiased predictor of the future spot rate. In other words, in a perfectly competitive foreign exchange market, there should be no systematic difference between the forward rate and the expected future spot rate (Bekaert & Hodrick, 2018; Daniel et al., 2017):

$$\left(1+i^f\right)\frac{S_t}{E_t(S_{t+1})} = \left(1+i^f\right)\frac{S_t}{F_t}$$

$$\Rightarrow E_t(S_{t+1}) = F_t \tag{2.3}$$

In the initial stages of the empirical investigation, the unbiasedness hypothesis was tested by conducting regressions in which the ex-post observed spot exchange rate was regressed on the ex-ante observed forward exchange rate. In addition, a constant term was included and these univariate regressions were run for each currency considered (Fu & Ruger, 2022):

$$S_{j,t+1} = \alpha_j + \beta_j F_{j,t} + \varepsilon_{j,t+1} \tag{2.4}$$

The unbiasedness hypothesis predicts for the regression coefficients α_j and β_j values close to 0 and 1, respectively. In seminal studies such as Frenkel (1976), Cornell (1977) and Levich (1979), the values of α_j and β_j were indeed found to be consistent with these predictions. However, these tests have been criticised for using non-stationary level data. This criticism has been raised in studies such as Meese and Singleton (1982) and Meese (1989). As a remedy, empirical research has begun to use a first-difference approach. This involves regressing spot returns on forward discounts and a constant (Fu & Ruger, 2022):

$$S_{j,t+1} - S_{j,t} = \alpha_j + \beta_j\left(F_{j,t} - S_{j,t}\right) + \varepsilon_{j,t+1} \tag{2.5}$$

Although the unbiasedness hypothesis still implies that $\alpha_j = 0$ and $\beta_j = 1$ in this format, subsequent empirical work has often reached different conclusions. In particular, research by Tryon (1979), Hansen and Hodrick (1980), Bilson (1981), Fama (1984), Froot and Frankel (1989), and Froot and Thaler (1990) found that the estimated values of β_j are often significantly different from unity and can even be negative. Since Fama (1984) proposes to use forward discounts as the independent variable, thereby assuming the validity of CIRP, regression (2.5) is often referred to as the ‘Fama regression’ (Engel et al., 2022, p. 3). This phenomenon indicates a failure of the unbiasedness hypothesis, as it implies that the forward rate does not equal the future spot rate as expected, which is known as the ‘forward premium puzzle’ (Hassan & Mano, 2019, p. 397).

As empirical research on the forward premium puzzle has progressed, increasingly sophisticated methods have been used to verify that the initial results are not just a statistical artefact. In particular, in addition to the distinction between levels and differences in assessing the unbiasedness hypothesis, the literature also addresses a problem known as the ‘multiple comparisons problem’ (Hochberg & Tamhane, 1987) when researchers simultaneously test the unbiasedness hypothesis for multiple currencies. Essentially, if many tests are performed, there's a greater chance that some results will appear to be spuriously significant. This can lead to erroneous conclusions due to sampling error (Fama, 1984).

One of the ways in which researchers have tried to address this is by running joint tests that consider several currencies together, rather than separate tests for each currency. For this reason, seemingly unrelated regression (SUR) models have been widely used (e.g., Bilson, 1981; Cornell, 1989; Fama, 1984; Hodgson et al., 2004). What's particularly useful about this method is that it recognises the relationships between different currencies, especially as most currencies are often quoted against a common benchmark currency, such as the US dollar. Given the interconnectedness of global financial markets, it therefore makes sense to take these linkages into account when testing the unbiasedness hypothesis (Fu & Ruger, 2022). In addition, other methods such as cointegrated panel regression techniques have been used (e.g., Westerlund, 2007). These methods take into account the interdependence between currencies, which makes the tests more robust. After all, as Geweke and Feige (1979) point out, a test that takes into account information from all currencies is likely to produce more reliable results than tests that look at each currency in isolation.

More recently, Fu and Ruger (2022) develop a Monte Carlo resampling procedure based on the sign and rank statistics proposed in Campbell and Dufour (1997) to test the unbiasedness hypothesis for multiple currencies jointly and for each currency separately. Interestingly, despite the sophisticated research design, Fu and Ruger (2022) broadly confirm the conclusions of previous research, as the joint test appears to robustly reject the unbiasedness hypothesis for the 13 major currencies in the period from October 1983 to December 1998 and for the G10 currencies in the period from January 1999 to June 2021 in both the level and the difference specification. It is also noteworthy that they find the Australian and New Zealand dollars to be the currencies with the most egregious p-values, and thus the main drivers of the strong rejection of the unbiasedness hypothesis in both level and difference specifications. These two currencies are prototypical investment currencies among the G10 currencies, and thus a typical G10 carry trade would hold them long. Moreover, these two currencies play a prominent role in existing explanations of carry trade returns (Bekaert & Panayotov, 2020). However, recent research also finds considerable instability in the slope parameter estimates when performing rolling regressions (Bekaert & Hodrick, 2018). Rossi (2006, 2013) examines the instability in the predictive power of the Fama regression for exchange rate changes. Indeed, there is also evidence that the slope coefficient of the Fama regression changed sign in the 2000s, especially after the global financial crisis (e.g., Engel et al., 2019; Engel et al., 2022).

2.1.3 The stylised facts of carry trades

The forward premium puzzle laid the foundation for the rise of a simple currency trading strategy, the carry trade. However, the carry trade investment rule is based on a naive interpretation of the early empirical regression results. A negative slope coefficient β_j in equation (2.5) implies that currencies with high (low) interest rates are more likely to appreciate (depreciate) rather than depreciate (appreciate), contrary to the expectation of uncovered interest parity. Under the carry trade investment rule, an investor trading in the spot market would borrow money in a currency with a low interest rate and use the borrowed money to buy a currency with a higher interest rate and invest in that currency. In the forward market, on the other hand, an investor would sell forward contracts in low interest rate currencies, which trade at a forward premium, and buy forward contracts in high interest rate currencies, which trade at a forward discount (Bekaert & Hodrick, 2018).

The idea is that if the future spot rate is the same as the current spot rate when the position is closed or at maturity, an investor will at least earn the carry, i.e. the interest rate differential that accrues during the holding period, or that the currency excess return for the investor will be even higher if the currency with the higher interest rate appreciates and the currency with the lower interest rate depreciates (Bekaert & Hodrick, 2018; Daniel et al., 2017).

However, the carry trade investment rule neglects an important information, namely that the value of the constant term α_j is usually estimated positively (negatively) in empirical tests of the unbiased hypothesis when exchange rates are expressed in quantity (price) quotation. Properly interpreted, this means that currencies with high (low) interest rates do indeed depreciate (appreciate) on average, but not as much as would be needed to offset the interest rate differential, as would be expected according to uncovered interest rate parity. Only in a few cases of very large positive (negative) interest rate differentials do currencies actually appreciate (depreciate) on average rather than depreciate (appreciate). Rather than ignoring the absolute size of the interest rate differential between two currencies, one might have expected a carry trade investment rule based on the regression tests, suggesting that the forward rate bias should be exploited primarily for currencies where the forward discount is unusually large or small relative to historical data (Bekaert & Hodrick, 2018).

If the unbiasedness hypothesis is indeed valid, i.e. if the forward discount is an accurate and unbiased predictor of the rate of depreciation of a foreign currency, then one would expect the expected currency excess return from employing the carry trade strategy to be zero (Daniel et al., 2017). However, the empirical literature has documented that the carry trade is highly profitable, as high interest rate currencies tend to have higher excess returns on average than low interest rate currencies. However, profits accumulate slowly over time, while the carry trade performs poorly in times of market turmoil and financial stress, when losses tend to be large and sudden (e.g., Bekaert & Panayotov, 2020; Brunnermeier et al., 2008; Burnside et al., 2011a; Daniel et al., 2017; Farhi & Gabaix, 2016; Lustig et al., 2011; Menkhoff et al., 2012a; Verdelhan, 2018).

2.1.4 Explanatory approaches to the forward premium puzzle

It has not yet been conclusively established whether the unbiasedness hypothesis is valid or should be rejected. However, Fama (1984) was the first to recognise that the estimated slope coefficients in tests of the unbiasedness hypothesis can be interpreted as an indication of the existence of time-varying risk premia. If the excess returns on a currency forward contract covary with systematic, e.g. non-diversifiable, risk, a non-zero currency excess return may reflect that the unbiasedness hypothesis fails because there is a time-varying compensation for the higher risk exposure of risk-averse investors, which would then be consistent with the market efficiency hypothesis (Bekaert & Hodrick, 2018).

The early empirical literature, however, had serious problems in convincingly identifying the risk factors that price these risk premia, because standard equilibrium models, such as the capital asset pricing model, were unable to generate risk premia that were as variable as the Fama regression results suggested (Bekaert, 1996; Menkhoff et al., 2012a). To understand this argument, note that the risk premium is simply the expected excess return and therefore regression (2.5) implies that:

$$E(S_{j,t+1} - S_{j,t}) - \left(F_{j,t} - S_{j,t}\right) = \alpha_j + \left(\beta_j - 1\right)\left(F_{j,t} - S_{j,t}\right) \tag{2.6}$$

Hence, the variance of the risk premium is given by $(\beta_j-1)^2\sigma^2(F_{j,t}-S_{j,t})$, and thus, as long as β_j is negative, as implied by the Fama regressions, the variance of the risk premium is greater than both the variance of the forward discount and the variance of the expected spot return, which is equal to $(\beta_j)^2\sigma^2(F_{j,t}-S_{j,t})$ (Bekaert & Hodrick, 2018). The following section discusses in more detail the intertemporal relationship between expected currency excess returns and currency risk. It will not only provide a brief and concise overview of the state of empirical research on the equilibrium risk premium that explains the dispersion of average excess returns in the cross-section of currencies. It will also provide the foundation for the core research hypotheses that this dissertation seeks to answer in the final section of this chapter.

Before doing so, however, this chapter presents other interpretations of the Fama regression results that have been discussed in the empirical literature. For example, the change over time in the estimated slope coefficients of the Fama regression suggests that the statistical analyses may not be consistent with the assumption of rational expectations of market participants. It is assumed that the sample drawn is sufficiently representative of the true but unknown distribution of spot returns. In this case, the ex-ante expectations about the distribution of spot returns are consistent with the ex-post observations. However, the actual observed distribution of spot returns may have been affected by the fact that expected events did not occur or occurred more frequently than expected (Bekaert & Hodrick, 2018).

The peso problem revolves around this discrepancy between the ex ante information set that rational investors perceived and based their decisions on, and the ex post information set that was actually realised. The name originates from the historical situation in the 1970s when the Mexican peso was pegged to the US dollar and depreciation was expected. However, depreciation did not occur as frequently as expected. As a result, the observed excess returns on peso-denominated assets appeared to be higher than would have been commensurate with the risk involved. Investors expected a depreciation (a peso event), but since it occurred infrequently in the sample, holding pesos appeared to yield a surprisingly high excess return (Lewis, 2011).

Burnside et al. (2011a) find evidence that a large part of the significant excess returns of unhedged carry trades is due to the fact that a massive depreciation of high interest rate currencies expected by market participants, the peso event, has simply not yet occurred in the observed data. They base their conclusion on the observation that the Fama-French three-factor model is unable to explain the average excess returns of unhedged carry trades. Otherwise, the average risk-adjusted excess return of the unhedged carry trade would be zero, as the peso event would have already occurred. However, once currency options are used to hedge against the peso event, the evidence for a positive alpha of hedged carry trades becomes much weaker. Neutralising the losses that will result from the impending peso event is essentially tantamount to anticipating the inevitable depreciation dictated by uncovered interest rate parity. Thus, if hedging leads to the elimination of positive risk-adjusted excess returns, this is consistent with a peso problem explanation. Consequently, as an explanatory approach, the peso problem suggests that the expected depreciation (appreciation) of the foreign currency that offsets (compensates for) the higher (lower) foreign interest rate should be perceived as a peso event simply because it has not yet occurred, or has occurred less frequently than expected over the sample period. However, if this is the case, then the realised average excess returns of high (low) interest rate currencies will be higher (lower) than expected, leading to the forward premium puzzle.

It is very important to understand that the peso problem views the expected price adjustment under uncovered interest rate parity as a rare event with a low probability of occurrence. A common misconception is to perceive the peso problem explanation as a risk-based explanation. If this were the case, part of the forward discount would reflect a risk premium that market participants receive when they buy high interest rate currencies forward as compensation for the low probability of a large depreciation in the event of a rare but catastrophic event. The hypothesis that there is a risk associated with peso events can, in principle, justify positive carry trade excess returns. However, the peso problem attributes the forward premium puzzle to a bias in the econometric tests due to the small sample size. This bias will be eliminated and the validity of the uncovered interest rate parity restored once the peso event actually occurs. Rational and risk-neutral investors expect to be compensated later for the positive (negative) excess returns of high (low) interest rate currencies accumulated before the peso event, are not better (worse) off as a result and therefore do not receive a risk premium. Risk-averse investors, on the other hand, would want to protect themselves against the unpredictability of events in which they would suffer significant losses, and would command a risk premium for holding currencies exposed to the risk of 'rare disasters'. However, in this approach, the forward premium puzzle would also occur in the population, as the puzzle is not understood as a consequence of small sample bias (Burnside et al., 2011a; Farhi & Gabaix, 2016; Lewis, 2011).

In contrast, Jurek (2014) doubts that the forward rate bias can be explained by a peso event. He uses put options to hedge long positions in high interest rate currencies against large depreciations and to isolate the component of excess return that is due to the risk of rare catastrophes. In contrast to the results of Burnside et al. (2011a), Jurek (2014) finds that high interest rate currencies generate significant excess returns even after hedging against the risk of large depreciations. Thus, a risk premium for bearing the risk of a crash that has not yet occurred therefore does not sufficiently explain the average excess returns of high interest rate currencies to conclusively identify the peso problem as the cause of the forward premium puzzle. He also draws a more sceptical conclusion about the disaster hypothesis, arguing that crash risk premia account for at most one-third of the excess returns of carry trades in G10 currencies. Daniel et al. (2017) acknowledge that generalised peso problems cannot be ruled out, but also note that a single, so far unrealised peso event is unlikely to explain the forward rate bias, as there is no statistical evidence that depreciations of high interest rate currencies are direct consequences of sudden and unpredictable crashes. Bekaert and Panayotov (2020) confirm the previous finding that options can be used to hedge crash risk without much impact on the profitability of the carry trade. Moreover, they show that the skewness of excess returns can be dramatically improved by selectively removing the prototypical currencies from the carry trade investment universe without affecting profitability. This indicates that the crash risk can, in principle, be diversified away and therefore shouldn't command a risk premium. The claim by Brunnermeier et al. (2008) that the negative skewness of carry trade excess returns cannot be diversified away and thus crash risks cannot be eliminated, which provides the basis for the existence of a crash risk premium, should therefore be treated with caution. Consequently, Bekaert and Panayotov (2020) also argue that the disaster hypothesis, according to which the profitability of carry trades reflects compensation for exposure to negative skewness of excess returns or crash risk, cannot be the sole explanation for the forward rate bias. Although it is now well established that the negative skewness of the excess returns of high interest rate currencies, and hence of carry trades, is due to unexpectedly large drawdowns, it has not yet been conclusively established whether this is the manifestation of an inevitable peso event that restores the validity of the UIRP, or a currency crash for which there is a risk premium to be rewarded. However, it is precisely these drawdowns that have led to carry trades being described as 'picking up nickels in front of steamrollers' (The economist, 2007, p. 80) or the return of a carry trade that 'goes up by the stairs and down by the lift' (Breedon, 2001, p. 151).

The ability to effectively diversify rare crash risks using currency options raises the general question of whether risks in foreign exchange markets can be perfectly diversified. In this case, there are neither systematic nor idiosyncratic risks that would justify compensation. Such a market environment reflects a consequence similar to that of perfectly risk-neutral market participants. Again, no premium for risk taking would be expected. The literature recognises that the forward rate bias may then be due to investors not having rational expectations. Lewis (1989) suggests that learning and model uncertainty can explain the forward rate bias. It is recognised that market participants are unlikely to have a correct model and therefore make biased forecasts. Given this uncertainty, market participants update their beliefs and forecasts based on incoming data, which should lead them to place more weight on the most recent observations. However, if market participants are in a continuous learning and adjustment process, both the initial misperception and the intervening updates permanently bias their expectations about future spot rates, so that the forward rate they set systematically deviates from the actual future spot rate. This bias can arise because market participants overreact to the latest data (Burnside et al., 2011b) or are slow to update their assumptions in response to new information (Al-Zoubi, 2011).

The hypothesis that market participants are irrational, e.g. that they have systematic biases in their expectations due to cognitive biases, noise trading or arbitrage limits, and thus introduce systematic mispricing in the forward market, has been taken up by a large body of empirical research in behavioural finance. Frankel and Froot (1987), among others, use survey data to examine the future expectations of market participants. They find that, in the short run, traders tend to base their expectations on recent movements (charting behaviour). In the long run, however, they tend to base their expectations on fundamentals. They conclude that this dichotomy may explain the forward rate bias. Bilson (1981) introduces the ‘speculative efficiency’ hypothesis, which states that the forward rate reflects the market consensus about the future spot rate. If the consensus is based on irrational beliefs or noise trading, then the forward rate will be distorted. Froot and Thaler (1990) examined various anomalies in the foreign exchange market, including the forward premium puzzle. They argue that the puzzle, along with other anomalies, cannot be explained by standard economic models and suggest that behavioural biases may be involved. Behavioural explanations and learning from model uncertainty are likely to be interconnected, and it is conceivable that together they contribute to the forward premium puzzle. The short-term orientation of chartists and the long-term orientation of fundamentalists suggest that there are at least two different sets of information on which expectations are based over time. Bilson's speculative efficiency argument suggests that the forward rate will initially reflect these biased views. However, learning will lead market participants to adjust their models to the new information they receive over time, often resulting in the actual future spot price deviating from the forward price originally set on the basis of different information.

2.2 The intertemporal relation between return and risk in foreign exchange markets

2.2.1 The intertemporal capital asset pricing model

Merton (1969, 1971) formulated and solved the continuous-time consumption and portfolio choice problem. An individual is assumed to make both a consumption-savings choice and a portfolio allocation decision continuously, i.e. the time interval is instantaneous. Asset prices are subject to continuous random changes, so that the distribution of returns is time-varying and investment opportunities change randomly. In this environment, individuals seek to optimise their utility from their lifetime consumption, i.e. their utility depends on their ability to consume at all future points in time. In order to maximise their utility function, individuals will continuously decide how much of their wealth to save, which will depend on their consumption preferences, and they will continuously rebalance their portfolios to adapt to changing investment opportunities. They will be concerned with the expected rate of return on their invested savings, as this will determine their future ability to consume or reinvest their accumulated wealth over time (Cochrane, 2005).

An important insight into the equilibrium pricing of assets in a multi-period, continuous-time environment is that expected asset returns satisfy the single-period capital asset pricing model (CAPM) relationship of Sharpe (1964), Lintner (1965) and Mossin (1966) only if investment opportunities are constant. In this case, however, Merton (1973) showed that the continuous-time market portfolio will be the value-weighted market portfolio implied by the single-period CAPM. Even if individuals are able to make decisions in a more realistic intertemporal environment, given constant investment opportunities, there will be only one mean-variance efficient portfolio of risky assets that is optimal for all individuals to hold in equilibrium, and they will differ only in how they allocate their total wealth between the market portfolio and the risk-free asset. However, if investment opportunities change over time, individuals' risk aversion to compromising their lifetime consumption opportunities will lead them to take into account information about the economic conditions under which assets are priced. This includes information about current consumption opportunities and the current achievable risk-return trade-off in the investment universe, as well as information about future consumption and investment opportunities, in particular how returns co-move with changes in future investment opportunities (Pennacchi, 2008).

Consequently, in equilibrium, individuals want to be compensated not only for taking market risk, but also for taking the risk of adverse changes in investment opportunities, since these changes affect the present utility of their wealth, which depends on how it can be deployed in markets in the future to realise consumption opportunities and earn investment returns. State variables capture these other, presumably multiple, sources of systematic risk that go beyond pure market risk. Innovations in these state variables can signal shifts in the investment opportunity set that affect asset prices and hence investor's utility (Merton, 1973).

Therefore, Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM) extends the CAPM relationship, in which the expected excess return of an asset depends on its sensitivity to variations in the return of the market portfolio, to include risk premia that reflect the covariances of an asset with portfolios that best hedge against changes in investment opportunities (as measured by innovations in some state variables). When Merton's (1973) ICAPM is applied to empirical studies conducted in discrete time rather than continuous time, the following equilibrium pricing equation between risk and expected return approximately holds (Cochrane, 2005; Maio & Santa-Clara, 2012)

$$E\left(r_{j,t+1}\right) - r_{f,t+1} = \gamma \, Cov\left(r_{j,t+1}, r_{M,t+1}\right) + \gamma_z \, Cov\left(r_{j,t+1}, \Delta z_{t+1}\right) \qquad (2.7)$$

where $r_{f,t+1}$ is the risk-free interest rate, known at t, $E\left(r_{j,t+1}\right) - r_{f,t+1}$ is the expected excess return on asset j between t and t+1 and $r_{M,t+1}$ denotes the return of the market portfolio. z_{t+1} represents the additional portfolio that is the one most highly correlated with the state variable of interest, and Δz_{t+1} therefore refers to the innovation or change in the state variable. γ is the price of market risk, defined as the market risk premium divided by the variance of the market portfolio return. γ reflects the additional return required by the aggregate or representative investor to bear an additional unit of variance of the market return when holding the market portfolio. γ also provides an estimate of the coefficient of relative risk aversion (RRA) of the representative investor. A higher relative risk aversion signals a greater sensitivity of the representative investor to changes in his consumption in the face of risk. The higher the RRA, the higher the price the representative investor is willing to pay for assets that hedge against adverse changes in future investment opportunities. γ_z denotes the covariance risk price and represents the price of bearing the risk associated with unexpected changes in investment opportunities, as signalled by the covariance of an asset with the state variable innovations (Maio & Santa-Clara, 2012). If there is more than one source of systematic risk beyond pure market risk, there is an additional covariance risk price in equation (2.7) for each state variable (Pennacchi, 2008).

2.2.2 Common risk factors in foreign exchange markets

The ICAPM does not directly identify the state variables underlying the risk factors. Therefore, multi-factor models that include the market risk factor as well as other risk factors have been interpreted as suitable candidates for empirical application of the ICAPM, leading Fama (1991, p. 1598) to interpret the ICAPM as a 'licence' to fish for state variables in the data. However, state variables cannot be anything because, first, they must forecast either future aggregate expected returns or return volatility and, second, if they predict positive (negative) changes in investment opportunities in time series regressions, the innovations in the risk factors corresponding to the state variable should earn a positive (negative) risk price in the cross-section of asset returns (Maio & Santa-Clara, 2012). Since the ICAPM can be applied to any risky asset, including those in the foreign exchange market (Cenedese et al., 2014), the recent empirical literature on cross-sectional currency pricing considers the parsimonious two-factor linear currency pricing model of Lustig et al. (2011) to provide a risk-based explanation for the failure of the unbiasedness hypothesis. The factors employed are the dollar risk factor (DOL), which represents the excess return on the foreign exchange market, and the excess return on the carry strategy (HML^{FX}), a carry trade that uses two currencies on both the investment and funding legs. HML^{FX} represents the risk factor that hedges against future changes in the investment opportunity set.

When currencies are sorted into portfolios in ascending order of forward discount, their betas to the dollar risk factor are monotonically close to one across interest rate levels, and the covariance risk price associated with the dollar risk factor, i.e. the coefficient γ, is indistinguishable from zero. This implies that there is no significant cross-sectional relationship between the dollar risk factor and expected currency excess returns in the cross-section of carry trade portfolios. However, the average market excess return effectively serves the same purpose as a constant, preventing common over- or underpricing in the cross-section of excess returns, which would be inconsistent with the assumptions of equilibrium asset pricing models such as the ICAPM (e.g., Lustig et al., 2011; Menkhoff et al., 2012a). In contrast, Verdelhan (2018) provides strong evidence that the dollar risk factor may nevertheless be priced into the cross-section of currency excess returns. The dollar risk factor appears to reflect some global macroeconomic level risk, which exists because shorting the dollar in a US recession is a risky strategy, even though foreign currencies then trade at a forward discount due to the risk of a sharp appreciation of the dollar as the US economy recovers, and risk-averse investors expect to be compensated for taking this risk.

Conversely, the literature finds a significant positive cross-sectional relationship between forward discount and expected currency excess returns and, consistent with this observation, a positive covariance risk price for bearing the intertemporal cross-sectional risk associated with the difference in excess returns between high and low interest rate currencies, i.e. the coefficient γ_z of the proxy state variable HML^{FX} is positive. This implies that low (high) interest rate currencies covary negatively (positively) with innovations in the state variable, reflecting that they perform particularly well (poorly) in periods of deteriorating expectations of future aggregate investment conditions, i.e. in periods when carry excess returns are low. That is, they provide (do not provide) a hedge against periods of market turbulence and hence against reinvestment risk, which increases (decreases) the investor's ability to consume at all future points in time and thus potentially increases (decreases) the investor's utility derived from lifetime consumption. Consequently, rational investors perceive low (high) interest rate currencies as less (more) risky and accordingly accept (demand) a lower (higher) risk premium, i.e. a lower (higher) expected excess return, on funding (investment) currencies for bearing less (more) carry risk (Lustig et al., 2011; Menkhoff et al., 2012a).

The HML^{FX} factor is fundamentally based on economic theory, as this difference may be related to monetary policy and interest rate differentials between countries. However, it is specific to foreign exchange markets, i.e. the HML^{FX} factor may be mainly related to volatility and uncertainty in the presence of carry shocks (Verdelhan, 2018) and therefore may not capture broader financial market risks or changes in global investment opportunities. In a highly influential paper, Menkhoff et al. (2012a) therefore suggest using the risk factor global foreign exchange volatility innovations (VOL) instead of the risk factor HML^{FX} as a proxy for a state variable describing changes in future investment opportunities in times of market turbulence. The rationale for using VOL as a pricing factor in an empirical application of Merton's ICAPM is that volatility is highly persistent and therefore aggregate market volatility innovations can be expected to contain information that predicts the future variance of market excess returns. It is therefore reasonable to assume that the covariance with volatility innovations is priced in the cross-section of currency excess returns (Maio & Santa-

Clara, 2012; Menkhoff et al., 2012a). Thus, VOL can be considered a broader, more global risk factor, as market volatility tends to reflect very quickly increased general uncertainty in financial markets and unexpected changes in the perceived future attractiveness of investment opportunities. In addition, VOL is the analogue of the aggregate volatility risk factor used by Ang et al. (2006) to price the cross-section of equity returns[1].

It is important to emphasise that VOL includes, but is not limited to, the unexpected risk of a currency crash. In addition, hedging against persistently high volatility over an extended period of time may be too complex and costly, e.g. due to transaction costs, liquidity constraints, information asymmetries or other limits to arbitrage. Thus, the pricing factor VOL as described by Menkhoff et al. (2012a) is distinct from the disaster hypothesis of Brunnermeier et al. (2008), as it goes beyond the specific crash risks that can in principle be hedged (e.g., Bekaert & Panayotov, 2020; Daniel et al., 2017; Jurek, 2014). VOL captures broader systematic volatility that reflects more fundamental economic uncertainties and shifts in the future investment opportunity set, and exposure to VOL may therefore still command a risk premium (Menkhoff et al., 2012a).

The significant negative covariance risk price associated with exposure to VOL, i.e. the coefficient γ_z of the proxy state variable VOL is negative, found in the empirical literature implies that low (high) interest rate currencies covary positively (negatively) with global FX volatility innovations. Thus, currencies with low (high) interest rates generate high (low) excess returns when future aggregate market volatility is high. Consequently, they act as a (no) hedge against market turbulence, i.e. they lead to less (more) uncertainty about future wealth for risk-averse investors, who accordingly accept (demand) a lower (higher) risk premium, i.e. a lower (higher) expected excess return, on funding (investment) currencies (Lustig et al., 2011; Menkhoff et al., 2012a).

[1] Since the seminal paper by Lustig and Verdelhan (2007), a large body of empirical research has searched for risk factors that can explain the cross-sectional excess returns of currency portfolios, in particular the profitability of carry trades, based on the existence of time-varying risk premia (see Sections 3.2 and 4.2).

Regardless of which pricing factor, HML^{FX} or VOL, better explains the cross-section of carry trade excess returns, or, equivalently, better proxies for a state variable, i.e. a source of systematic risk, that signals shifts in future investment opportunities associated with uncertainty in foreign exchange markets, both provide strong evidence for a risk-based explanation of the forward premium puzzle. If forward rates were unbiased predictors of future spot rates, there would be no risk premia, i.e. no non-zero excess returns on currencies. However, the different behaviour of currencies depending on the level of interest rates in times of market turbulence implies that currency speculation, especially the strategy of exploiting the forward premium puzzle through carry trades, is subject to considerable risk (Bekaert & Hodrick, 2018).

2.3 Research hypotheses and key findings

2.3.1 Theoretical framework

Although it is now well established that the failure of the unbiasedness hypothesis can be explained by time-varying risk premia, this dissertation addresses an important and nuanced mechanism in the context of time-continuous equilibrium asset pricing models such as the ICAPM. These models argue that in equilibrium, i.e. on average, high (low) interest rate currencies must offer a high (low) risk premium to compensate market participants for their exposure to state variables. The central concept of 'equilibrium' is that when currencies are mispriced, i.e. when they do not provide the excess return that they should, given their risk, market participants will reallocate their capital until prices adjust and the expected excess return is in balance with the risk of the currency (e.g., Daniel & Titman, 2006).

In theory, in an efficient foreign exchange market, these adjustments should be instantaneous to ensure that prices fully reflect all available information at any point in time. However, 'fully reflect' is too general to test the implications of market efficiency in its own right. One needs to specify an asset pricing model that serves as an equilibrium model and specifies the expected process of price formation in order to define more precisely what information generates expected returns. Consequently, any test of market efficiency reflects a joint test of the ability of the asset pricing model used to capture all rational variation in expected returns (Fama, 1970; 1991; for a comprehensive discussion of the joint hypothesis problem that complicates inferences about the degree of market efficiency, see Fama, 1991).

Accordingly, a divergence between the theoretical predictions of the unbiasedness hypothesis and actual spot price movements in the market would not be inconsistent with market efficiency as long as it can be explained by the presence of time-varying risk premia in the foreign exchange market, i.e. a non-zero expected currency excess return must reflect compensation for risk taking (Bekaert & Hodrick, 2018).

In the real world, however, even the predictions of an appropriate equilibrium asset pricing model can fail for a number of reasons, including liquidity shocks, investor sentiment, behavioural biases, information asymmetries and other frictions. As Merton (1987, p. 484) remarks, ‘financial models based on frictionless markets and complete information are often inadequate to capture the complexity of rationality in action’. As a result, the ‘on average’ pricing perspective (Fama, 1970, p. 409) implies that as long as the asset pricing model chosen to capture the pricing of assets in equilibrium does not suffer from systematic biases, the specified risk-return trade-off need not hold at every point in time because news may induce deviations from expectations, but should hold on average over long periods of time.

Daniel et al. (2020) find strong empirical evidence that the addition of two behavioural factors to the standard CAPM, which capture the commonality of mispricing due to overconfidence and limited attention, outperforms the standard factor models and the more recent extended factor models of Novy-Marx (2013), Fama and French (2015), Hou et al. (2015), and Stambaugh and Yuan (2017) in explaining the anomalies in the cross-section of stock returns studied by Hou et al. (2015). The results suggest that many of the anomalies are due to systematic mispricing. Furthermore, spanning regression tests show that the abnormal returns associated with the most of the traded factors in these factor models are fully explained by the two behavioural factors. Consistent with Fama's (1991) remark on the joint hypothesis problem that it is ambiguous whether signs of abnormal return behaviour are due to market inefficiencies or to a poor market equilibrium model, an overarching conclusion can be drawn from this evidence.

Perhaps only a few characteristics provide truly independent information about average returns, so that only a few factors are really relevant, since they already control for many characteristics in the cross-section of asset returns. Rather than assuming that any observed anomaly justifies the construction of a new factor based on the same anomaly to provide a more appropriate asset pricing model, it may be that commonalities in mispricing predict future returns due to subsequent corrections and that return differentials therefore reflect a delayed price response to information or conditional return premia due to exposure to behavioural factors rather than risk premia (Cochrane, 2011; Daniel et al., 2020).

On the one hand, these considerations imply that currencies with a high (low) sensitivity to HML^{FX} (VOL) will certainly generate higher excess returns on average to compensate for their systemic risk. On the other hand, it is quite conceivable that there will also be periods of underperformance where the necessary adjustments are not made immediately, so that there may be prolonged periods of mispricing or deviations from the predictions of equilibrium asset pricing models. For example, empirical studies have shown that low-risk (low beta or low volatility) stocks sometimes generate higher than expected returns relative to their systematic or total risk, while high-risk stocks generate lower than expected returns. This has been observed both during and outside market turmoil and is commonly referred to as the 'low-risk anomaly' in financial markets, as this observation contradicts the core tenets of equilibrium models such as the CAPM (for a comprehensive review of the current state of research on the low-risk anomaly, see, e.g., Blitz et al., 2020). This framework provides the theoretical basis for the 'four' central research hypotheses of this dissertation.

2.3.2 Can mispricing be anticipated?

According to the risk-based explanation of Menkhoff et al. (2012a), a long (short) position in currencies with high (low) systematic risk, as in the case of holding the risk factor HML^{FX}, would result in a difference portfolio with a highly negative exposure to VOL. Consequently, both positions holding long the investment currency and engaging in a carry trade covary negatively with VOL and therefore command a positive risk premium in equilibrium to compensate for the high systematic volatility risk taken.

However, as mentioned in the last section, it is well established that there may be periods in which even a generally sound equilibrium model fails to capture certain aspects of currency pricing, as the empirical finance literature has found a plethora of possible anomalies or market inefficiencies to explain why the theoretical prediction of equilibrium asset pricing models does not always hold as a reliable indicator of the risk-return trade-off in real markets (e.g., Daniel et al., 2020; Hou et al., 2015).

The ‘first’ central research hypothesis of this dissertation therefore asks, in principle as an implicit consequence of this empirical evidence, whether there are periods in which the market does not reward entering into a carry trade with sufficiently high expected excess returns.

To answer this research question, two ex-ante indicators are proposed that signal a change in the relationship between systematic risk and expected excess returns. Addressing this central research hypothesis contributes to a unified explanation of the cross-section of G10 currency excess returns, as both indicators suggest that it would be beneficial for currency pricing models to condition on two different foreign exchange market states or regimes.

We find clear implications for a reduced equilibrium model in the periods denoted by ‘funding market states’ and ‘contrarian pricing regimes’, where one would favour omitting the systematic HML^{FX} risk factor to better explain the cross-section of G10 currency excess returns. This is because the empirical evidence in both tables, Panel B of Table 3.2 and Table 4.3, suggests that both the excess return and the risk-adjusted excess return of the carry trade strategy, i.e. the risk factor HML^{FX}, are economically and statistically insignificant in these periods. Consequently, HML^{FX} contributes positively to the ability of the currency pricing model used to capture all rational variation in the cross-section of G10 currency excess returns only in the other market states or regimes, denoted by ‘investment market states’ and ‘conformity pricing regimes’.

Section 3.4 proposes the first approach to distinguish between investment and funding foreign exchange market states. This first indicator is based on a rolling estimate of the mode of the number of investment currencies and signals an investment (funding) market state if the mode is greater (less) than one in the 42 weeks prior to the respective start of the strategy's holding period.

The rationale behind this indicator is that there can be no positive risk premium for holding investment currencies that negatively covary with global FX volatility innovations in the absence of such investment currencies. The expectation is that in these zero-investment currency market states, i.e. in times when the market can be characterised as a funding environment, the carry trade decision rule should lead to suboptimal allocations, as borrowed funds would have to be invested in currencies with negative interest rate differentials. This should lead to inferior portfolio allocation decisions, as funding currencies positively covary with global FX volatility innovations and are therefore expected to trade at a premium in equilibrium, resulting in a low expected excess return of the long leg of the carry trade strategy in funding market states.

While this first indicator is very effective in identifying pronounced funding market states and thus quite powerful in signalling when the inclusion of HML^{FX} in an equilibrium model tends to have little power to correctly price G10 currencies, it captures only a very narrow set of events, essentially assuming that the source of systematic risk in the market has disappeared when the market no longer needs to reward currencies with high systematic risk with a positive risk premium because such currencies have disappeared.

Section 4.3 therefore develops this indicator by addressing more directly when the risk premium offered by the investment currencies available in the market may be insufficient. To this end, we work with the two core predictions of the two-factor currency pricing model of Menkhoff et al. (2012a). We aim to derive conditions under which causal relationships may be present in the data that contradict the predictions of the VOL risk factor for the cross-section of G10 currencies.

Why should it be beneficial to be aware ex ante of a contradiction to the risk-based concept underlying such a currency pricing model? In general, empirical asset pricing aims to predict cross-sectional variation in future excess returns by postulating that the cross-sectional level of an asset's exposure to pricing factors determines its future level of excess returns. The competition between these models is about which factors are the main drivers of future prices, i.e. which risk-based explanation can dominate over the others. However, whether individual assets will behave as predicted by their exposure to pricing factors can only be determined with the benefit of hindsight. That is, if the asset pricing model adequately predicts future excess returns in the cross-section, one would expect that in regressions in which the ex-post observed excess returns of portfolios composed of assets with different risk exposures, typically captured by different levels of the manifestation of certain characteristics (e.g. forward discount levels or beta levels with market excess return), are regressed on the risk premia of commonly accepted pricing factors, the performance of the portfolios would be fully attributable to these pricing factors (Bali et al., 2016).

However, this is an ex-post perspective, and we would generally be interested in whether there is exploitable forward-looking information that would allow us to derive assessments of how likely it is that we can rely on the underlying risk-based explanation for the cross-sectional variation in future excess returns in our portfolio allocation decisions. This question is less about competition between different asset pricing models than it is about when and why which risk-based explanation should work, i.e. can we expect certain effects to materialise only under certain circumstances or not? The literature is much less concerned with this issue, because it erroneously loses relevance if the validity of pricing factors in explaining cross-sectional variations in future excess returns is tested only over the entire sample period, i.e. over a long time horizon, since then possible contradictions to the underlying risk-based explanatory theory present in the data are eliminated by the 'on average' or 'in equilibrium' pricing perspective.

Note that we prefer to work with the currency pricing model of Menkhoff et al. (2012a) over that of Lustig et al. (2011), i.e. the risk factor VOL is preferred to HML^{FX} as the slope coefficient of the currency pricing model, even though HML^{FX} is close to the factor-mimicking portfolio of VOL. Theoretically, a non-return factor such as VOL cannot outperform its own factor-mimicking portfolio (Cochrane, 2005). Therefore, HML^{FX} typically outperforms VOL in explaining the positive relationship between forward discounts and currency excess returns in the cross-section of G10 currencies (e.g., Lustig et al., 2011; Menkhoff et al., 2012a). However, we prefer VOL for two reasons. First, VOL appears to be superior to HML^{FX} in terms of (small) pricing errors, i.e. the combination of VOL and DOL has a significantly higher cross-sectional R^2 than the combination of HML^{FX} and DOL. This is mainly due to the fact that both factors, HML^{FX} and DOL, capture information on the variation in funding and investment currencies. Not only does HML^{FX} capture similar information on cross-sectional variation as DOL, but it even seems to capture so much of it that it renders DOL rudimentary for explaining the cross-section of G10 currencies (e.g., Lustig et al., 2011; Menkhoff et al., 2012a). See also Section 4.3.3 for a discussion. Second, this shows that HML^{FX} captures a very broad range of cross-sectional information, such that VOL is more specific than HML^{FX} in capturing information about cross-sectional variation conditional on the level of financial market stress. The ability to properly disentangle how currencies should behave due to their exposure to systemic market volatility from other sources of systemic, i.e. market-wide, risk is crucial to the argumentation and development of the second mispricing indicator.

This second indicator, called the ‘pricing classifier’, defines a minimum requirement for the contribution of the long position in the investment currency to the expected risk-adjusted performance of the carry trade, and a value of the pricing classifier greater (less) than zero indicates a ‘conformity’ (‘contrarian’) pricing regime.

The rationale behind the pricing classifier is that if the second (first) core prediction of Menkhoff et al.'s (2012a) two-factor currency pricing model is violated in contrarian pricing regimes, which are periods of low (high) global FX volatility innovation. Then we should find that for the funding and investment currencies that together form the carry trade strategy, the difference in excess returns between periods of high and low global FX volatility innovation should be significantly larger, i.e. more positive for funding currencies and less negative for investment currencies, in contrarian than in conformity pricing regimes. However, this consequence would be conceptually difficult to reconcile with the currency pricing model of Menkhoff et al. (2012a), as it essentially implies that both the negative effect of high global FX volatility innovations on currency excess returns and thus the relevance of systematic risk, i.e. the negative exposure of investment currencies to volatility risk, is significantly reduced in contrarian pricing regimes. We refer to this phenomenon as ‘contrarian currency pricing’ when the negative effect of high global FX volatility innovations is absent. Similar to the first indicator, this second indicator identifies when the inclusion of HML^{FX} in an equilibrium model tends to have little power to correctly price the G10 currencies, but covers a wider range of periods in which systematic mispricing prevails, as it does not require that the exposure to systematic volatility and/or the investment currencies disappear.

It is important to note that the fact that the cross-section of G10 currency excess returns cannot be explained by sorting currencies by forward discount does not necessarily imply that the unbiasedness hypothesis holds in these funding market states or contrarian pricing regimes. This is because the portfolio-based carry trade anomaly is not the cause of the regression-based forward premium puzzle, but only a consequence of it (e.g., Hassan & Mano, 2019). Since in these states or regimes low (high) interest rate currencies still covary positively (negatively) with global FX volatility innovations, it is not consistent with the unbiasedness hypothesis that low interest rate currencies consequently outperform high interest rate currencies in periods of high global FX volatility. Rather, in these states or regimes, investment currencies are unable to contribute sufficiently to the risk premium that the conventional carry trade must provide to compensate for the risk of particularly poor performance in periods of unexpectedly high market volatility.

2.3.3 Attribution of mispricing

The indicators in sections 3.4 and 4.3 help to anticipate potential mispricing and to identify periods when the use of investment currencies leads to a deterioration in the risk-return trade-off for the conventional carry trader. However, given the joint hypothesis problem, it is not possible to prove unambiguously that the failure of HML^{FX} to price the cross-sectional excess returns of G10 currencies in funding market states or contrarian pricing regimes is due to either market inefficiencies or an incorrect specification of the market equilibrium model.

Consequently, the 'second' central research hypothesis of this dissertation asks whether it is a misspecification of the market equilibrium model due to the omission of idiosyncratic risk that explains the first central findings of this dissertation.

Subsequently, the 'third' central research hypothesis of this dissertation asks, essentially as a consequence of the joint hypothesis problem, whether there are additional market inefficiencies that affect the relevance of idiosyncratic risk.

It is important to note that, in principle, the results of both indicators could also be the consequence of an apparent lack of adequate systematic pricing factors. However, it is not straightforward to reconcile the results of this dissertation with a systematic risk-based explanation. That is, on the one hand, the findings may well imply that forward discounts are a poor proxy for 'interest rate differentials', implying that HML^{FX} is simply the wrong risk factor in funding market states or contrarian pricing regimes, even if the rational expectations framework is correct (Daniel & Titman, 2006; Fama, 1991). For example, Hassan and Mano (2019) find that the unbiasedness hypothesis can be restored if past looking models are corrected for uncertainty about future average interest rates when estimating interest rates. Investors then always expect high interest rate currencies to depreciate rather than appreciate, which means that after optimising the measurement of forward discounts, portfolios sorted by these augmented forward discounts may no longer have any exposure to VOL. In the absence of systematic risk, there is no need to provide risk premia, which would be entirely consistent with the unbiasedness hypothesis. However, such an approach does not provide a direct explanation for our findings using an empirical research design that is well established in the financial economics literature. Rather, it casts doubt on the appropriateness of the methods. It remains to be seen whether an adjustment of the measures will find a general consensus in the literature.

On the other hand, if it were possible to recover the well-established positive relationship between forward discounts and future currency excess returns in funding market states or contrarian pricing regimes by simultaneously controlling for other sources of systematic risk, this would imply that the market equilibrium model is incomplete and that there are omitted state variables affecting currency pricing (Fama, 1991). However, as there are few generally accepted common pricing factors for currency excess returns, it may not be straightforward to argue theoretically for a particular omitted state variable that needs to be controlled for and upon which an accurate interpretation of the excess returns of portfolios sorted by forward discount in funding market states or contrarian pricing regimes crucially depends. This may be all the more true as Lustig et al. (2011) find that HML^{FX} explains most of the cross-sectional variation in foreign currency excess returns. In fact, Nucera et al. (2023) provide strong evidence for a rather reverse causality, i.e. that HML^{FX} may be the most important state variable, as the most risk factors have significant exposure to the carry risk factor. This implies that they only have statistically significant risk premia when the carry risk factor is excluded.

Apparently, it is not possible to rule out a priori the existence of a rational expectations theory that would justify a systematic state variable that contributes more than carry to explaining the cross-sectional variation of currency excess returns in funding market states or contrarian pricing regimes. However, the results in sections 3.4 and 4.5 provide strong evidence that a generally acceptable systematic risk-based explanation must show how currency excess returns covary with priced risk factors in funding market states and contrarian pricing regimes in such a way that the most important common risk factor, carry, becomes too weak to price the cross-section of currency excess returns, and currencies still significantly covary with global FX volatility innovations, while currency-specific risks (and risk premia) decrease (increase) with the realisation of positive (negative) idiosyncratic excess returns and the core predictions of Menkhoff et al.'s (2012a) two-factor currency pricing model are essentially rejected.

2.3.4 Does idiosyncratic risk matter?

The ‘second’ central research hypothesis of this dissertation conjectures that the predictability of currency excess returns associated with the two proposed foreign exchange market classification indicators may, at least in part, be attributable to the impact of idiosyncratic risk on currency pricing. However, traditional equilibrium asset pricing models, including CAPM, ICAPM and also arbitrage pricing theory (Ross, 1976), assume that investors can diversify away asset-specific risks and are therefore only exposed to the systematic risks that affect the whole capital market. Consequently, these asset pricing theories postulate a positive relationship between expected return and systematic risk, as market participants demand a risk premium for taking on exposure to sources of systematic risk. Thus, idiosyncratic risk should not command a risk premium, nor should measures of idiosyncratic risk be related to future asset returns. Therefore, contrary to the expectation formulated in the second research hypothesis, there should be no predictability resulting from the inclusion of idiosyncratic risk in a market equilibrium model. However, the privilege of not having to worry about the risks of individual assets depends crucially on all investors having 'complete information', i.e. having immediate access to all publicly available information and being able to react immediately to new information. But this requires markets to be truly 'frictionless', meaning that there are no transaction costs, no taxes and no restrictions on borrowing and short selling (Bali et al., 2016).

Merton (1987) is one of the first to develop an equilibrium asset pricing model that weakens these highly idealised premises, recognising that in reality the behaviour of market participants is affected by transaction costs, information acquisition and processing costs, incomplete and delayed information diffusion, and numerous other frictions. Merton's model assumes that investors behave rationally, i.e., and this will be relevant to the third central research hypothesis, that they seek to use the available information, as soon as they become aware of it, to derive forecasts that are not systematically biased on average, in order to make decisions that maximise their utility. However, Merton's model explicitly assumes that investors are affected by incomplete information, i.e. that they don't have access to the same or all relevant information and therefore have to base their decisions on different sets of information. Since different investors have access to different levels and qualities of information, they can only include in their optimal asset allocation those assets for which they have adequate information. This information asymmetry implies that there are assets that are unknown to most investors or that are not demanded by most investors due to insufficient information. Merton refers to these assets as assets of low ‘investor recognition’. It follows that market clearing can only take place if informed and interested investors take large and undiversified positions in these assets. However, investors with concentrated portfolios cannot completely eliminate unsystematic risk through diversification. They therefore require not only compensation for systematic risk, but also higher expected returns to compensate for the higher exposure to idiosyncratic risk associated with these concentrated positions in their portfolios (Lehavy & Sloan, 2008; Merton, 1987).

To date, there is no specific study that directly demonstrates a positive relationship between idiosyncratic currency risk and expected excess returns from the perspective of Merton's capital market equilibrium with incomplete information. However, various strands of the empirical and theoretical literature suggest that investors in foreign exchange markets may (first) have incomplete information, which (second) should contribute to the emergence of idiosyncratic risks from various sources. As a result, it seems infeasible for investors to hold optimal currency allocations at all times, which would (third) allow them to diversify away all currency-specific risks. Consequently, they will demand higher expected returns to compensate for taking on more idiosyncratic risk within concentrated portfolio allocations, which is why (fourth) idiosyncratic risk is likely to have an impact on currency pricing.

It is by no means possible to provide an exhaustive list of all the sources of idiosyncratic risk that may affect currency pricing. For example, there are numerous studies on the global dominance of the US dollar and its impact on the international financial system, which may lead to incomplete information in foreign exchange markets. Given the prominent international position of the US dollar, Gourinchas and Rey (2007) describe the US as a ‘world banker’ with substantial excess returns on foreign assets, granting the US an 'exorbitant privilege' (e.g., Caballero & Krishnamurthy, 2009; Gourinchas et al., 2019). One reason for the dominance of the dollar is seen in the invoicing of international trade in dollars (e.g., Goldberg & Tille, 2008; Gopinath & Stein, 2020). On the other hand, the dollar's dominance may be due to its safe haven status, which increases demand for the dollar in times of global uncertainty (e.g., Caballero et al., 2017; Jiang et al., 2021). The dominance of the dollar is also reinforced by the fact that corporate debt, that is, global bond portfolios, are increasingly denominated in dollars (e.g., Bruno & Shin, 2017; Eren & Malamud, 2022). Consequently, other currencies may be subject to specific risks that are difficult to predict or account for in portfolio allocation. These risks may arise from factors specific to particular economies, political dynamics or changes in trading patterns. Investors may not be able to fully understand or incorporate into their decision-making models the impact of global economic changes, trade policies or geopolitical events on currency pricing. This may be particularly true for country-specific effects when their magnitude depends largely on the covariation of the local currency with the dominant US dollar.

In another strand of the literature, Ready et al. (2017) provide evidence that real exchange rates between final goods-producing economies, such as Japan and Switzerland, and commodity-producing economies, such as Australia and New Zealand, are dominated by business cycle fluctuations in the final goods-producing economies. During expansions in the final goods-producing economies, their comparative productivity advantage increases due to technological differences, and the global price of commodities rises above the local price in the commodity-producing economy, allowing the commodity currency to appreciate. However, in times of recession in the final goods-producing economies, this is reversed and the commodity currencies depreciate. This is because commodity consumption in the final goods-producing economies falls faster than in the commodity-producing economies, as the commodity country can shift local resources to the production of final goods domestically, albeit at the expense of efficiency. Ready et al. (2017) point out that the more inelastic the trade channels, the more this consumption effect depends on productivity shocks in the final goods-producing economies, so the commodity currency is risky and commands a risk premium. To diversify away these country-specific, i.e. idiosyncratic, risks, it would be necessary to internalise a common source of systematic risk that fully reflects all relevant information about comparative productivity differentials and, as Ready et al. (2017) show, also information about the future impact of nonlinear trade frictions in an equilibrium currency pricing model. Whether this is possible is questionable.

Given that there are numerous potential sources of idiosyncratic volatility, it seems reasonable to assume that, as Merton (1987) showed, exposure to idiosyncratic volatility should matter to investors in the foreign exchange market if they are under-diversified. But how likely are investors to hold concentrated portfolios that do not sufficiently eliminate these unsystematic risks through diversification?

For equity markets in particular, it is well established in the literature that individual investors are generally not well diversified. Odean (1999), Barber and Odean (2001), Polkovnichenko (2005) and Goetzmann and Kumar (2008) report that US individual investors hold concentrated, i.e. under-diversified, portfolios. Dorn and Huberman (2005, 2010) find that German individual investors do not hold well-diversified portfolios. Dimmock et al. (2016) find that ambiguity aversion depends on stock ownership and is associated with portfolio under-diversification. More recently, Dimmock et al. (2021) examine the relationship between under-diversification and probability weighting, a behaviour in which investors overestimate the probability of extreme returns. They find that overweighting small probabilities of occurrence leads investors either not to invest or to hold positively skewed portfolios. This leads to portfolio under-diversification and hence high heterogeneity in realised returns, which could potentially exacerbate wealth inequality.

It is important to note, however, that it is not only individual or retail investors with small portfolios who tend to be under-diversified. In theory, institutional investors should be able to achieve better diversification because the degree of diversification can increase with the level of wealth. However, recent theoretical work argues that, contrary to traditional asset pricing theory, institutional investors' portfolios can be under-diversified but still optimal if the institutional investor exploits an information advantage in the decision-making process. This theory of information advantage argues that institutional investors hold concentrated portfolios because they use their initial information advantage to learn and specialise in markets where they can add the most value (Van Nieuwerburgh & Veldkamp, 2009, 2010). This exploitation of investment specialisation is consistent with Merton (1987), who notes that it is expensive to obtain information about securities and therefore investors may not be able to consider all securities in the market when making their decisions. More recently, Choi et al. (2017) found strong support for the information advantage theory using security holdings data for 10,771 institutional investors from 72 countries. The results show that portfolio concentration, i.e. the deliberate deviation from a well-diversified global market portfolio, increases risk-adjusted returns for institutional investors worldwide. Consequently, it may be optimal for institutional investors to focus their investment strategies on the home country, the foreign country or the sector. They also examine the degree of learning of institutional investors and find that higher levels of learning (i.e. more skilled investors) lead to more concentrated portfolios, especially in foreign markets and sectors.

In addition to the strong evidence for the existence of under-diversification among institutional and individual investors in equity markets, there is also evidence of under-diversification in foreign exchange markets. For example, the carry trade strategy itself encourages investors to hold concentrated currency allocations by focusing only on certain currency pairs with favourable interest rate differentials. Prototypical funding currencies among the liquid G10 currencies are the Swiss franc and the Japanese yen, which almost always have the lowest interest rates and would therefore be shorted in a typical G10 carry trade. Prototypical investment currencies are the New Zealand and Australian dollars, which typically have the highest interest rates and would be bought (Bekaert & Panayotov, 2020).

A preference for liquidity could also lead to a concentration in a few highly liquid currency pairs, leading to under-diversification in foreign exchange markets. Recently, Ranaldo and de Magistris (2022), for example, examine the liquidity of the global foreign exchange market and find, on the one hand, that trading volume has an impact on price formation. On the other hand, they examine violations of no-arbitrage conditions and find that mispricing increases systematically with increasing illiquidity, suggesting that a high price impact of trading volume limits arbitrage. Therefore, currencies with a lower price impact of trading volume are able to maintain a higher degree of price efficiency. In addition, currency pairs involving the euro, which tend to be traded in less liquid markets, concentrate the illiquidity frictions that lead to arbitrage deviations. This is not the case for currency pairs involving the US dollar, where the impact on trading is less pronounced, so that trading in these currency pairs makes it possible to avoid a negative impact on prices, which promotes price efficiency. Consequently, their findings suggest that currency pairs that are highly liquid, because they involve large trading volumes and many market participants, make it easier to enter and exit trades at the desired prices with minimal impact on the currency's price. This can lead to under-diversification as traders and investors, seeking to reduce the risk of slippage and achieve efficient trade execution, concentrate their activity on these liquid pairs rather than diversifying their trades across a wider range of currencies.

Irrespective of the potential reasons for under-diversification, data from the Bank for International Settlements (BIS) on the volume and structure of global turnover in over-the-counter foreign exchange markets clearly show that foreign exchange trading is highly concentrated in the major currency pairs. Turnover is a measure of market activity. It is therefore an indicator of market liquidity and allows the analysis of concentration effects (e.g., BIS, 2022b). According to the BIS's triennial survey of central banks (BIS, 2022a), the US dollar remains the most traded currency in the world. Average daily global OTC foreign exchange turnover involving the US dollar on one side of the trade has increased significantly, from USD 5.8 trillion in April 2019 to USD 6.6 trillion in April 2022. The US dollar is thus a component of 88.5% of the total USD 7.5 trillion average daily global OTC FX turnover across FX swaps, spot and forward markets, currency options and currency swaps. The second most traded currency is the euro, which accounts for 30.5% of average daily global OTC FX turnover in April 2022, followed by the Japanese yen with a share of 16.7%. Taken together, the currencies of the liquid Group of Ten (G10) account for 86.0% of average daily global OTC foreign exchange turnover. Transactions involving only the US dollar against the other G10 currencies account for 63.80% of average daily global OTC foreign exchange turnover. Notably, the top nine most traded currency pairs all involve the US dollar in one leg of the currency pair. This means that the largest shares of average daily global OTC FX turnover involve trading the US dollar against, in descending order of turnover, EUR, JPY, GBP, CNY, CAD, AUD, CHF, HKD and SGD, with these transactions together accounting for 71.4% of average daily global OTC FX turnover in April 2022.

But even if the average investor in the foreign exchange market is likely to hold currency portfolios with concentrated exposure to idiosyncratic risk, because the presence of incomplete information makes it impossible to control for all plausible sources of currency-specific risk, the question is how relevant can idiosyncratic risk be, or in other words, how much is idiosyncratic risk relative to systematic risk?

Campbell et al. (2001) were among the first to find that when separating the contributions of market, industry and idiosyncratic volatility to the total volatility of US stocks, idiosyncratic volatility is the most dominant. In particular, they contribute to the financial literature by showing that in periods when the share of idiosyncratic volatility in total volatility increases, this implies that the average correlation of returns across assets has decreased and the number of assets required to achieve a target level of portfolio risk through diversification has increased. This demonstrates that highly under-diversified investors are exposed to significantly higher unsystematic risk, particularly during such periods. More recently, Campbell et al. (2023) confirm their earlier findings that idiosyncratic volatility is a crucial determinant of total volatility over a period of almost 100 years.

The relevance of idiosyncratic risk is also highlighted by Herskovic et al. (2016), who show that there is a common idiosyncratic volatility factor that is priced into the cross-section of equity returns. This implies that, even after controlling for state variables, there remains a large exposure to idiosyncratic volatility that is undiversifiable and aggregates into a return-driving commonality in the cross-section. Although it should not exist according to asset pricing theory, it is considered a relevant asset pricing factor and has even led Duarte et al. (2014) to refer to it as an 'unaccounted systematic risk factor'. Herskovic et al. (2016) find that only 11% of the average total volatility is explained by a five principal component model, with idiosyncratic volatility accounting for the remaining 89% for a large sample of US stocks over the period 1926-2010. The same is true for the market model and the Fama and French three-factor model, where common risk factors explain only 8% and 9% of average total volatility, respectively. Remarkably, they find that the volatility of residual returns, after eliminating all common return variations, has essentially the same volatility structure as total returns. Herskovic et al. (2016) thus confirm the findings of Campbell et al. (2001, 2023), but also show that the relevance of idiosyncratic volatilities is so significant that it even has an impact on asset pricing. Although the literature on the common idiosyncratic volatility factor is still limited, there is some initial empirical evidence that this factor is also likely to be relevant for currency pricing (e.g., Tessari, 2020). Indeed, the third and fourth chapters of this dissertation provide theoretical justification and empirical evidence that currency-specific risk, i.e. largely purely idiosyncratic risk, is of significant importance in explaining the variation in excess returns in the cross-section of G10 currencies. Finally, chapter five provides evidence that exploiting this information in idiosyncratic currency risk, in particular the information in changes in currency-specific CVaR, allows the construction of a highly profitable trading strategy that not only outperforms other more traditional currency trading strategies, but also adds significant diversification benefits to a global equity portfolio.

2.3.5 Do market inefficiencies matter?

In line with the fundamental financial principle that a risk-averse investor requires higher (lower) future excess returns to hold currencies with higher (lower) future risk, Merton's (1987) model of capital market equilibrium suggests that if investors hold concentrated portfolios and are thus likely to be under-diversified with respect to higher-order moments of the excess return distribution due to their inability to correctly incorporate all relevant information into their decision-making models, currencies with higher left-tail risk should be priced lower to compensate for the higher probability and magnitude of large losses associated with them (Atilgan et al., 2020).

Consequently, in theory, an increase (decrease) in the predicted conditional value at risk (CVaR) should be associated with an instantaneous depreciation (appreciation) of the quote currency, providing the necessary discount (premium) in spot prices, as investors demand (accept) a higher (lower) risk premium, i.e. a higher (lower) expected excess return, to be willing to hold the quote currency with high (low) left-tail risk (e.g. Fama, 1970; Menkhoff et al., 2012a). However, the ‘third’ central research hypothesis of this dissertation conjectures that there may be market inefficiencies at work that affect both the process or speed of this price adjustment and hence the impact of idiosyncratic risk on currency pricing.

Why might this be the case? Indeed, it is precisely Merton's (1987) key behavioural assumption that investors have limited attention and thus can only act on information they are aware of (Lehavy & Sloan, 2008). Section 3.1 explains in more detail that, due to their limited attentional capacity, they may perceive and process new information about changes in the level of currency-specific CVaR with a time lag, resulting in delayed market price behaviour. This means that if investors underreact to persistent changes in CVaR, a discount (premium) to account for an increase (decrease) in CVaR will not be immediately reflected in spot prices through the sale (purchase) of the quote currency, but will only materialise over time as information about a persistent change in CVaR gradually diffuses through the market. As a result, there is a greater likelihood that the quote currency will continue to depreciate (appreciate) in the future, with further increases (decreases) in CVaR, as long as expectation errors remain unresolved and the necessary price adjustment is in progress but has not yet fully taken place. This assumed causality is consistent with a large body of literature documenting an asymmetric volatility effect, i.e. the observation that price changes and volatility changes are negatively correlated (e.g., Glosten et al., 1993; Wang & Yang, 2009). Indeed, Panel A of Table 3.3 provides significant empirical support for this hypothesis, as an increase (decrease) in CVaR follows a recent depreciation (appreciation) of the quoted currency.

These considerations highlight the potential importance of time-varying ‘changes’ in risk. This is because a change in CVaR over time can only be relevant to currency pricing if spot prices do not adjust instantaneously to changes in risk levels, but only over time. Consequently, investors who demand a higher (lower) risk premium to be willing to hold the higher (lower) risk currency will, in the presence of an underreaction to the persistence of

CVaR, be compensated by a higher (lower) excess return at a later point in time than would be implied by asset pricing theory assuming an instantaneous price adjustment.

To address this third research hypothesis, section 3.3 of this dissertation is concerned with the construction of a new sorting variable called 'CVaR-Trend', which aims to measure the magnitude of a recent change in the level of CVaR forecasts. By relating the most recent CVaR forecast to previous forecasts to capture the short- to long-term upward or downward trend in CVaR forecasts, we capitalise on the information contained in two well-established trend-following rules, namely the time series momentum (TSMOM) rule of Moskowitz et al. (2012) and the variable length moving average (VMAR) rule of Brock et al. (1992).

Brock et al. (1992) use a long-period and a short-period moving average to infer whether a trend movement is initiated in the underlying time series. A buy (sell) signal reflecting the initiation of an upward (downward) trend movement is generated when the short-period moving average rises above (or falls below) the long-period moving average. Typically, the most popular moving average rules are those in which the short period simply represents the most recent, i.e. a single, observation of the level of the time series of interest (e.g., Han et al., 2016). It is common practice to apply technical trading rules to the price level of assets in order to predict future changes in the price level (e.g., Han et al., 2016; Marshall et al., 2017). In this dissertation, however, we shift the focus to applying these rules to the level of CVaR forecasts in order to capture the magnitude of a recent change in the level of currency risk (see Section 3.3). Therefore, at the end of week t, we calculate the signal associated with the VMAR of Brock et al. (1992) as follows, where L is the window length of the moving average $MA_{t,L}$ or 'look-back' period (e.g., Marshall et al., 2017):

$$\begin{aligned} VMAR_{t,L} &= \widehat{CVaR}_\alpha(Y_t) - MA_{t,L} \\ &= \widehat{CVaR}_\alpha(Y_t) - \frac{\widehat{CVaR}_\alpha(Y_{t-L+1}) + \ldots + \widehat{CVaR}_\alpha(Y_t)}{L} \end{aligned} \tag{2.8}$$

Moskowitz et al. (2012) highlight that cross-sectional momentum, which focuses on the relative performance of assets in the cross-section, fails to capture information from many prominent behavioural and rational asset pricing theories, such as Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999). These theories focus on a single risky asset and therefore have direct implications for time series rather than cross-sectional predictability. As a result, they propose to focus solely on an asset's own past return trend and suggest that a buy (sell) signal reflecting the beginning of an upward (downward) trend movement is generated when the excess return over the look-back period L is positive (negative). As a result, when the TSMOM signal from Moskowitz et al. (2012) is applied to CVaR forecasts, it is calculated as follows:

$$TSMOM_{t,L} = \widehat{CVaR}_{\alpha}(Y_t) - \widehat{CVaR}_{\alpha}(Y_{t-L}) \tag{2.9}$$

Obviously, by simply taking the difference between the moving average at time t and the moving average at time t-1, i.e. by calculating the change in the moving average, we obtain:

$$\begin{aligned} \Delta MA_{t,L} &= MA_{t,L} - MA_{t-1,L} \\ &= \frac{\widehat{CVaR}_{\alpha}(Y_t) - \widehat{CVaR}_{\alpha}(Y_{t-L})}{L} \\ &= \frac{TSMOM_{t,L}}{L} \end{aligned} \tag{2.10}$$

Consequently, we can also write the VMAR as:

$$VMAR_{t,L} = \widehat{CVaR}_{\alpha}(Y_t) - \left[\frac{TSMOM_{t,L}}{L} + MA_{t-1,L}\right] \tag{2.11}$$

Rearranging gives:

$$\widehat{CVaR}_{\alpha}(Y_t) - MA_{t-1,L} = VMAR_{t,L} + \frac{TSMOM_{t,L}}{L} \tag{2.12}$$

We refer to the expression on the left side of (2.12) as the trend signal $CS_{t,L}$ as defined in (3.6) of Section 3.3. Section 3.4 then provides evidence that the risk of variation in spot exchange rate risk is important in explaining the cross-section of G10 currency excess returns in funding market states, as the empirical evidence shows a strong positive relationship between CVaR-Trend and expected currency excess returns in funding markets. These results are consistent with rational expectations, as an increasing (decreasing) CVaR following negative (positive) excess returns indicates high (low) future excess returns. However, due to investors' underreaction to the persistence of CVaR, the price adjustment only occurs slowly over time. It is precisely for this reason that those currencies that have experienced the greatest increase (decrease) in CVaR and, at the same time, the greatest discounts (premiums) in spot prices due to the concomitant depreciation (appreciation) of the quote currency are most likely to have, and, as the empirical evidence in chapter 3.4 shows, will ultimately have, high (low) risk premiums to compensate for their high (low) CVaR levels.

However, section 3.4 documents a novel and intriguing phenomenon. The preferences associated with the fundamental financial principle seem to be reversed for funding currencies, as investors require higher (lower) future excess returns to hold currencies with lower (higher) future risk. Table 3.3 provides evidence that the asymmetric volatility effect appears to be reversed for funding currencies, as funding currencies with a high CVaR-Tend have recently experienced strong spot rate appreciation, while funding currencies with a low CVaR-Tend have recently experienced strong spot rate depreciation. Both chapters three and five of this dissertation provide evidence that this phenomenon occurs only in periods when the HML^{FX} risk factor is a significant driver of the cross-section of G10 currency excess returns, i.e. only in investment market states and in conformity pricing regimes.

Our interpretation is that the asymmetric investment preferences associated with high and low forward discounts are likely to cause this phenomenon. If investors tend to go short rather than long in currencies with low forward discounts in order to use the negative interest rate differential to fund their long position, they are likely to perceive an appreciation of a funding currency as riskier than a depreciation. However, the risk-based rational expectations framework of the two-factor currency pricing model of Menkhoff et al. (2012a) also provides a consistent explanation for this seemingly contradictory phenomenon of an inverse asymmetric volatility effect for funding currencies. Periods of high global FX volatility are likely to be periods in which funding currencies experience an increase in CVaR. This is almost certainly due to the construction of this risk factor (Menkhoff et al., 2012a). Low future excess returns following periods of increasing CVaR may therefore simply reflect the fact that during periods of market turmoil, funding currencies have appreciated, providing a hedge against volatility risk, and investors are then willing to pay a premium, i.e. accept low risk premia, for insurance against future systematic volatility risk.

Consequently, if investors underreact to the persistence of CVaR, the price adjustment will occur slowly over time. However, those funding currencies that have experienced the largest increase (decrease) in CVaR and, at the same time, the largest premium (discount) in spot prices due to the concomitant appreciation (depreciation) of the quote currency are most likely to have, and, as the empirical evidence in sections 3.4 and 5.5 shows, will ultimately have, low (high) risk premiums to compensate for their high (low) CVaR levels.

In Chapter 4, another dimension of mispricing emerges, as the pricing classifier may capture mispricing by predicting contrarian pricing regimes when the predicted performance of the investment or, at the same time, of the funding currencies is low. This is because, according to the asymmetric volatility effect perspective, if the predicted CVaR is high and therefore the predicted performance is low, the currencies may have experienced low average excess returns in the past, providing the discount to allow for higher excess returns in the future. Conversely, if currencies have low predicted excess returns and therefore low predicted performance, they may trade at a premium and have low CVaR because they have experienced high average excess returns in the past.

These considerations therefore highlight the potential relevance of time-varying ‘changes in risk’ as a consequence of ‘momentum’ in excess returns, with the relationship between the two arising from the asymmetric volatility effect. In particular, in section 4.5 we are interested in whether CVaR has increased (decreased) in contrarian pricing regimes to an extent that would not have been expected if excess returns had not been so low (high) in the recent past. This question is important because, if markets are at least ‘on average’ efficient, financial theory would suggest that pricing imbalances cannot persist for long, and the results in Section 4.5 confirm the earlier findings in Section 3.4, i.e. that those currencies that have experienced large increases (decreases) in CVaR will ultimately have high (low) risk premia to compensate for their high (low) CVaR levels.

However, chapter four goes beyond chapter three by first showing that the cross-sectional average level of idiosyncratic momentum (CVaR-Trend) negatively (positively) predicts short-term excess returns of the carry risk factor HML^{FX} in contrarian pricing regimes, which turn out to be periods of low global FX volatility innovation. This is evidence that a persistent low performance of both funding and investment currencies, as captured by the pricing classifier, ultimately leads to lower (higher) expected future excess returns on the strategy of shorting the funding currency (buying the investment currency), which is necessary to restore the second core prediction, i.e. the ‘in equilibrium’ condition of Menkhoff et al.'s (2012a) currency pricing model (e.g., Pennacchi, 2008). Second, chapter four documents that information about impending excess return reversals is contained in idiosyncratic rather than systematic excess returns. This is consistent with Zhang’s (2022) evidence that in contrarian pricing regimes, following low carry trade excess returns, investment currencies are more likely to be sorted into the short leg of momentum strategies, thus shorting the carry risk factor and making it more likely that factor or systematic momentum will remain low, i.e. it cannot be a good predictor of impending excess return reversals.

2.3.6 Are these findings ultimately exploitable?

The results of chapters three and four make several contributions to the literature on currency pricing models. In particular, the pricing classifier in Section 4.3 as a mispricing indicator that signals when to avoid carry trades, the sorting variable CVaR-Trend in Section 3.3 that highlights the relevance of changes in risk for currency pricing, and the predictability of excess return reversals in Section 4.5 that reveals price adjustments towards equilibrium, improve our understanding for explaining the cross-section of G10 currency excess returns.

Consequently, Section 5.4.4 explains in more detail that these three key findings around the carry trade investment rule allow for the construction of a new currency trading strategy, sometimes referred to as an FX investment style (e.g., Kroencke et al., 2014).

This is because the finding that the carry trade performs poorly in contrarian pricing regimes suggests that the forward discount sorting should be omitted and replaced by a conditional double sorting on CVaR-Trend and idiosyncratic excess return momentum in order to benefit from excess return reversals that bring prices in line with the risk-based explanation of Menkhoff et al. (2012a). As contrarian currency pricing is the driving force behind the construction of this FX investment style, we refer to it as the contrarian pricing trade. Thus, in contrarian pricing regimes, the contrarian pricing trade could be seen as a specialised currency reversal strategy that buys (sells) those currencies that have unexpectedly become riskier (less risky) while they have experienced low (high) average idiosyncratic excess returns in the past, providing the discount (premium) to allow for higher (lower) excess returns in the future. In conformity pricing regimes, i.e. in periods when the carry risk factor HML^{FX} prices the cross-section of G10 currency excess returns, it makes perfect sense to use the standard investment rule of a carry trade as a basis. Thus, in conformity pricing regimes, the first sort on the forward discount as the control variable forms the basis for the contrarian pricing trade. Then, however, a dependent second sort on CVaR-Trend as the risk dimension to be priced helps the contrarian pricing trade to avoid buying (selling) investment (funding) currencies that offer (command) a discount (premium) that is insufficient to compensate for the higher probability and magnitude of large losses (gains) associated with their higher CVaR level.

It is clear from this brief description that all the details involved in constructing the contrarian pricing trade are by no means trivial. Rather, the contrarian pricing trade adds to the growing body of recent literature suggesting that dynamic, sophisticated econometric models that exploit the predictability of currency excess returns arising from currency characteristics and risk premia can successfully contribute to the construction of currency strategies that are not only profitable in their own right, but can also provide performance benefits for diversifying an equity portfolio (e.g., Barroso et al., 2021; Cho et al., 2019; Kroencke et al., 2014; Opie & Riddiough, 2020; Polak & Ulrych, 2024).

Consequently, the 'fourth' central research hypothesis of this dissertation asks whether the contrarian pricing trade is profitable and an attractive diversification instrument.

Whether this is the case is by no means certain, given the three key findings on which its construction is based. In all cases, the key component is the forecast of CVaR and, in the case of the pricing classifier, also the forecast of future excess returns. While CVaR forecasts may be much more persistent than return forecasts, forecasting joint multivariate distribution functions is still uncertain and difficult. Consequently, the moving averages derived from these forecasts may be far from perfect, especially in an out-of-sample framework. In addition, even good CVaR forecasts are much less persistent than other currency characteristics such as interest rate differentials (carry) or five-year changes in purchasing power parity (value). This means that the contrarian pricing trade is likely to have higher turnover than traditional carry or value trading strategies, perhaps even as high as that for the momentum trade.

Consequently, when assessing the stand-alone performance of the contrarian pricing trade or its diversification benefits for an equity portfolio, the outcome will strongly depend on whether we choose a realistic framework, i.e. one that takes into account the transaction costs that arise in real investment strategies when dynamic portfolio rebalancing takes place (e.g., Menkhoff et al., 2012b). In addition, forward contracts have margin requirements that must be met from available investment capital. This creates a trade-off between investments in domestic equities, foreign equities and currencies, as the required margin reduces the investment capital available for equity investments. However, margin requirements are often ignored in the literature, especially when empirical studies use leverage. Barroso and Santa-Clara (2015) suggest a currency positioning of 594%. Kroencke et al. (2014) use a leverage of two, i.e. the FX investment styles they use have an absolute demand for forward contracts of 200%. Opie and Riddiough (2020) do the same. More seriously, for their main results, Kroencke et al. (2014) do not report portfolio weights for FX investment styles, although they use an optimal mean-variance allocation, which is known to generate extreme positioning even with short selling constraints (e.g., DeMiguel et al., 2009). However, ignoring margin requirements results in higher portfolio weights for both equity and FX investment styles than is actually possible, thereby overstating their performance contribution to a fully hedged or FX style augmented equity portfolio. Consideration of margin requirements therefore raises the bar for FX investment styles, as they must provide diversification benefits without dominating the portfolio composition. It is not possible to choose FX exposures that are many times the value of the underlying equity positions, as this would significantly reduce the investment capital available to build these equity positions. Margin requirements thus prevent the use of excessive leverage to create deviations from the benchmark that most active managers are unable or unwilling to pursue, given their mandates and concerns about performance relative to their peers (e.g., Barroso et al., 2021).

For these reasons, in order to assess the performance of the contrarian pricing trade in a realistic framework, chapter 5 takes into account rebalancing costs for equities, transaction costs for currencies and margin requirements for forward contracts.

The results of this performance study show that the contrarian pricing trade economically and statistically increases the Sharpe ratio of the benchmark equity portfolio when added, not only over the entire sample period from January 1999 to June 2023 and for both conformity and contrarian pricing regimes, but also during periods of above- and below-average financial market stress and for the periods before and after the global financial crisis.

In contrast, we find that carry and value trades do not provide diversification benefits in periods of below-average excess returns, but at least have the safe haven property of providing positive excess returns to investors in periods of market turmoil when global equity prices are falling. However, as we cannot predict the future level of financial market stress and thus the optimal entry point to take advantage of the safe haven characteristics of these two FX investment styles, the contrarian pricing trade has a significant advantage over carry and value trades as a diversification instrument for global equity investors. For the momentum trade, however, we find no diversification benefits, regardless of the time period or market conditions considered.

These results show, on the one hand, that the performance loss experienced by the three traditional FX investment styles, carry, momentum and value, since the global financial crisis (e.g., Fan et al., 2022; Opie & Riddiough, 2020; Zhang, 2022) has also significantly impaired their ability to be good diversifiers. On the other hand, these results are particularly interesting because the contrarian pricing trade incorporates, at least to some extent, elements of the carry trade. Consequently, the extension of the standard carry trade investment rule by the central findings of this dissertation does indeed help to mitigate the shortcomings of this strategy since the global financial crisis.

3 Carry and Conditional Value at Risk Trend

Capturing the short-, intermediate-, and long-term trends of left-tail risk forecasts[2]

[2] This chapter has been published in the *Journal of International Financial Markets, Institutions and Money, Volume 82, January 2023, https://doi.org/10.1016/j.intfin.2022.101710*.

3.1 Introduction

The excess return of a currency can be decomposed into carry and spot exchange rate appreciation (Koijen et al., 2018). The well-known carry trade strategy aims to exploit deviations from uncovered interest parity (UIP), a non-arbitrage equilibrium condition. According to UIP, in the absence of transaction costs and other market imperfections for risk-neutral investors with rational expectations, the expected change in an exchange rate over a given period should be equal to the interest rate differential between the two currencies for the same period. However, empirical evidence suggests that changes in exchange rates do not offset the interest rate differential, and, therefore, UIP does not hold. Instead, the empirical evidence suggests that high (low) interest rate currencies appreciate (depreciate) rather than depreciate (appreciate). This is often referred to as the 'forward premium puzzle' (Fama, 1984; Hassan & Mano, 2019) and implies positive excess returns for a carry trade, that borrows in low nominal short-term interest-rate (funding) currencies and invests the proceeds in high-yielding (investment) currencies (e.g., Burnside et al., 2011a; Darvas, 2009; Della Corte et al., 2009). A key characteristic of the carry trade is that the strategy's excess returns are exposed to the risk of adverse spot exchange rate movements. However, the allocation process only relies on interest rate differentials.

As a consequence, the carry trade ignores the fundamental financial principle that a risk-averse investor requires higher (lower) future excess returns to hold currencies with higher (lower) future risk (e.g., Pennacchi, 2008). This paper provides new insights into the relationship between the two determinants of currency excess returns. We address the second excess return determinant, the appreciation of the spot exchange rate, by specifically investigating how the risk of variation in spot exchange rate risk and expected currency excess returns are related. With this research question, we first address the empirical evidence that currency excess return volatility and correlation aren't static but time-varying (Engle, 1982; Engle, 2002), with stationarity implying mean-reverting dynamics, i.e., both are expected to converge to their unconditional mean in the long run. High persistence, in turn, allows shocks that push variance and/or correlation away from their unconditional mean to persist for a long time. Second, we base our approach on the finding that investors underreact to news (e.g., Barberis et al., 1998; Daniel et al., 1998; Harris & Raviv, 1993; Hong & Stein, 1999), specifically, to negative news or downside risk (e.g., Atilgan et al., 2020; Chan, 2003; Hong et al., 2000). Due to its future importance as the primary risk measure for calculating minimum capital requirements for market risk as a result of the fundamental review of the trading book (Basel Committee on Banking Supervision, 2019), we choose the conditional value at risk (CVaR) as the risk measure of interest.

Considering these two empirical findings, we argue that if information diffuses through the market only gradually and is initially perceived by only a small fraction, prices are likely to underreact to news of a forecasted increase (decrease) in the time-varying CVaR. As a result, investors initially overestimate the level of mean-reversion of CVaR, which leads to a failure to adjust prices immediately. However, if a change in the level of CVaR is persistent, investors will eventually recognize the mispricing and update their prior expectations about the level of CVaR over time; probably to varying degrees and at different adaptation rates. Thus, an underreaction to CVaR persistence causes a delay in the market's anticipation of high (low) future CVaR. It follows that an underreaction to CVaR persistence for a cross-sectionally low (high) CVaR level does not yet indicate a need for price adjustment, provided that this absolute level has remained unchanged. Rather, the magnitude of a recent change in the level of CVaR indicates a need for price adjustment in the future. The greater the persistence and increase (decrease) in forecasted CVaR, the more likely it is that spot prices will exhibit a full discount (premium), reflecting the news about CVaR changes, only after a time lag. That is, the probability that the quote currency will continue to experience depreciations (appreciations) in the future will be higher, as long as expectation errors are not resolved and, consequently, the price adjustment has not yet fully occurred. Atilgan et al. (2020) similarly argue that an underreaction of left-tail risk's persistence leads investors to justify higher (lower) prices for stocks with recently higher (lower) left-tail risk because they prematurely expect that the recent high (low) left-tail risk will soon revert to a lower (higher) future left-tail risk. This subsequently leads to a negative relationship between left-tail risk and expected stock returns. Based on these conjectures, we introduce a new variable 'CVaR-Trend' into the literature by relating the most recent CVaR forecast to previous forecasts to capture the short- to the long-term upward or downward trend in CVaR forecasts, which is used as a proxy for the magnitude of a recent change in the level of CVaR.

This paper contributes to the existing literature in the following aspects. We find that CVaR-Trend captures a persistent cross-sectional characteristic of G10 currency excess returns. However, the relationship between CVaR-Trend and expected currency excess returns depends on the state of the foreign exchange market, crucially. We distinguish between two states of the foreign exchange market, investment and funding market. In investment markets, the relationship between CVaR-Trend and expected currency excess returns appears to be non-linear, conditional on carry. In contrast, we find a linear and positive relationship between CVaR-Trend and expected currency excess returns in funding markets. Based on these findings, we propose a new currency trading strategy, the CVaR-Trend trade, which buys (sells) the high CVaR-Trend currencies among the high (low) forward discount currencies in investment markets and buys (sells) the high (low) CVaR-Trend currencies in funding markets. We show that the excess return of the CVaR-Trend trade cannot be explained by exposure to the most common risk factors in currency markets. The remainder of the paper is organized as follows. Section 3.2 discusses related literature. Section 3.3 presents the data, the calculation of excess returns, the risk factors, the methodology used to construct the CVaR-Trend, and the econometric model used to forecast CVaR. Section 3.4 examines the relationship between the CVaR-Trend and currency excess returns using univariate and bivariate portfolio analyses. Section 3.5 concludes the paper.

3.2 Literature review

Finance theory states that a risk-averse investor should be compensated by the provision of a risk premium if additional risk is taken. According to the risk based explanation, the positive mean excess returns to the carry trade should correspond to compensation for bearing risk. However, Burnside (2012) shows that conventional risk factors used to price stock returns do not seem to be appropriate for pricing currency excess returns. Therefore, many studies have searched for risk factors that can explain the cross-sectional returns of currency portfolios.

This paper contributes to three branches of literature. First, this paper is related to the literature that develops tradable and replicable self-financing currency risk factors. Particularly influential is the evidence in Lustig et al. (2011), Lustig et al. (2014) and Verdelhan (2018) that two risk factors, the Dollar risk factor and the $HML^{(FX)}$ factor, as a proxy for the currency market and the carry trade excess return itself, covary with the expected carry trade excess returns in the time series and in the cross-section. Menkhoff et al. (2012a) propose aggregate global FX volatility, a risk factor directly motivated by the persistence of volatility, within the framework of standard asset pricing theory and find that carry trades provide a time-varying risk premia because they perform particularly poorly during periods of unexpectedly high market volatility. Similarly, Burnside (2012) find global FX skewness and Dupuy (2015) finds global FX Value at Risk to explain carry trade excess returns. More recently, Gao et al. (2019) find that the beta relative to an index of global ex ante tail risk concerns drives cross-sectional variation in currency excess returns, and Fan et al. (2022) find that an option-based equity tail risk factor is priced in the cross-section of currency returns. We contribute to this branch of the literature by examining the implications of the time evolution of tail risk forecasts of individual currencies that satisfy the minimum capital requirements for market risk (Basel Committee on Banking Supervision, 2019) for the cross-section of currency excess returns and, in particular, for the construction of the carry risk factor.

Our work is also related to the strand of literature studying crash risks in foreign exchange markets. Brunnermeier et al. (2008) find evidence that carry trades are exposed to high crash risk. Following on from this observation, Burnside et al. (2011a), Jurek (2014) and Farhi and Gabaix (2016) argue that the high average excess returns of carry trades can be explained by peso problems, i.e. the high average excess returns correspond to compensation for events that only occur with a very low probability but are then accompanied by large losses. In particular, we contribute to this part of the literature by showing that a large increase in tail risk for individual currencies over time is able to predict significant future spot price movements in the cross-section.

Finally, this paper contributes to the literature that focuses on optimizing the construction of carry trades instead of explaining carry trade excess returns. Clarida et al. (2009) find evidence that carry trades can be improved, as their study shows that currencies violate UIP mainly in times of low volatility, much less in times of high volatility. Bakshi and Panayotov (2013) find trading signals generated using commodity index returns, exchange rate volatility, and global liquidity to enhance the risk-return profile of conventional carry trades. Similarly, Ready et al. (2017) find that the Baltic Dry Index, an index of shipping costs, predicts the excess returns of carry trades. More recently, Bekaert and Panayotov (2020) progressively test whether reducing the set of G10 currencies improves the historical Sharpe ratio, and then implement ‘good’ carry trades equally weighted with fewer currencies, while ‘bad’ carry trades include only the currencies prototypical of standard carry trades.

In a similar work, Mulder and Tims (2018) adjust the set of investable currencies in regimes of high FX volatility. Dupuy (2021) constructs improved strategies based on forward discount timing and volatility timing and finds that both signals improve the Sharpe ratio of the carry trade to a similar extent. We contribute to this strand of literature by showing, on the one hand, that conditioning on different regimes of FX forward discount is important to successfully use tail risk information. On the other hand, we use this information specifically to change currency selection relative to the standard carry strategy and show that this leads to a strategy that generates a significantly positive average risk-adjusted return.

3.3 Data and risk metric

3.3.1 Spot and forward exchange rates

The dataset consists of 1-week forward rates and the corresponding weekly spot rates. To avoid week-end effect (Dao et al., 2016) we collect Wednesday closing exchange rates from WM/Refinitiv (formerly WM/Reuters), sourced from Refinitiv Eikon Datastream. The data on spot rates spans from July 11, 1990, to February 09, 2022, and the data on forward rates range from January 6, 1999, to February 09, 2022. To avoid issues of selection bias, we focus on the most liquid currencies, the G10 currencies. The foreign currencies in the sample are the Australian Dollar (AUD), British Pound (GBP), Canadian Dollar (CAD), Euro (EUR), Japanese Yen (JPY), New Zealand Dollar (NZD), Norwegian Krone (NOK), Swedish Krona (SEK) and the Swiss Franc (CHF). Following Burnside et al. (2011a), the GBP/FCU quotes are multiplied by USD/GBP quotes to obtain the longer spot rate sample against the dollar.

3.3.2 Currency excess returns

We implement the currency excess returns in terms of forward currency contracts, as suggested in Burnside et al. (2011a), Lustig et al. (2011), Bakshi and Panayotov (2013), and

Koijen et al. (2018). We adopt the perspective of a US investor. Let $F_{t,t+1}$ denote the log one-week forward rate in units of foreign currency per US dollar at time t and maturity in t+1 and S_t the corresponding log spot rate at time t. As long as the covered interest parity (CIP) applies, an assumption well-established by empirical evidence in Akram et al. (2008), forward and spot exchange rates can be used to compute forward discounts FD_t at time t, which are approximately equal to the interest rate differentials

$$FD_t = i_t^* - i_t \approx F_{t,t+1} - S_t \tag{3.1}$$

where i_t^* and i_t stand for the foreign and domestic interest rates, respectively, in week t. Following the extant literature since Fama (1984), we work in logarithms of spot and forward rates for ease of exposition and notation. For the regression analyses, however, log returns are transformed into discrete returns. The log excess return RX_{t+1} on buying the foreign currency at time t in the forward market and selling it at time t+1 after one week in the spot market is defined as:

$$RX_{t+1} = i_t^* - i_t - \Delta S_{t+1} \approx (F_{t,t+1} - S_t) - \Delta S_{t+1} \approx F_{t,t+1} - S_{t+1} \tag{3.2}$$

3.3.3 Risk factors

Following the literature, we consider the dollar risk factor (DOL) and Lustig et al.'s (2011) excess return to the carry strategy (HML^{FX}) as well as global FX volatility innovations (VOL) of Menkhoff et al. (2012a) as common risk factors in foreign exchange markets that can predict the cross-section of expected currency excess returns.

The dollar risk factor (DOL) is the average excess return of a trading strategy in which all foreign currencies are bought in equal parts against the dollar by borrowing funds in the United States. A carry trade is a long-short portfolio constructed by selecting currency pairs with the largest difference in forward discount. The investor, therefore, purchases the portfolio, which contains the currencies with the highest interest rate differential (largest forward discounts), and finances these purchases by selling the portfolio, which contains the currencies with the lowest interest rate differential (smallest forward discounts). At any point in time, this results in a zero-cost trading strategy with zero net currency exposure, as the investment and funding legs are equally weighted.

HML^{FX} is a carry trade that uses two currencies on both the investment and funding leg. Global FX volatility innovations (VOL) is an aggregated measure of unexpected increases in global currency volatility and is defined as the residual time series from an estimated AR(1) process for the level of a global FX volatility proxy. This proxy is first created by averaging the daily cross-sectional averages of the absolute log changes in the spot rate $|\Delta S_t|$, calculated for each currency on each day, up to the weekly frequency.

3.3.4 CVaR-Trend

In this section, we outline our approach to constructing a trend indicator for estimating the magnitude of a recent change in the CVaR level, called CVaR-Trend. CVaR-Trend serves as a proxy for the likelihood that prices require adjustment as a result of a change in the CVaR level and is used as a sorting variable in the empirical analyses that follow. Let the random vector $\mathbf{Y}_t = (Y_{1,t},\ldots,Y_{n,t})'$ denote the log spot return of the $j = 1,\ldots,n$ currencies at time t, that is, $Y_{j,t} = \log S_{j,t} - \log S_{j,t-1} = \Delta S_{j,t}$. Throughout this article, we assume all return distributions to be continuous. The conditional cumulative distribution function of $Y_{j,t}$ is denoted by $F_j(y_{j,t}) = P(Y_{j,t} \leq y_{j,t})$ and the corresponding marginal density function by $f_j(y_{j,t})$. The quantile function of $Y_{j,t}$ is given by $F^{-1}_{j,t}(\alpha)$. The Value at Risk (VaR) at the confidence level $\alpha \in (0,1)$ is defined as the conditional quantile of $Y_{j,t}$ evaluated at α (Bayer & Dimitriadis, 2020):

$$VaR_\alpha(Y_{j,t}) = F^{-1}_{j,t}(\alpha) = \inf \{y_j \in R : F_j(y_j) \geq \alpha\} \tag{3.3}$$

Although VaR has been considered the industry standard for risk measurement and management, the Basel Committee on Banking Supervision (2019) decided to replace Value at Risk with an expected shortfall (ES) measure as the primary risk measure for calculating minimum capital requirements for market risk because VaR is unable to capture tail risks beyond the α-quantile. In addition, the fact that ES is a coherent risk measure (Artzner et al., 1999) and thus satisfies meaningful axioms for a natural or reasonable risk measure speaks in favour of taking it into account. The ES coincides with CVaR which was introduced in Rockafellar and Uryasev (2000) if the return distribution is continuous.

CVaR at confidence level α is defined as the expected mean of returns smaller than the VaR associated with α (Bayer & Dimitriadis, 2020):

$$CVaR_{\alpha}(Y_{j,t}) = E_t(Y_{j,t}|Y_{j,t} < VaR_{\alpha}(Y_{j,t})) \tag{3.4}$$

Assume for each currency scenarios of size m of one-step-ahead spot returns $\widehat{Y}_t = (\hat{y}_{j,k,t}) \in \mathbb{R}^{nxm}$, j = 1,…, n and k = 1,…, m, are available. A one-step-ahead forecast of the α-CVaR corresponds to the mean of the spot returns less than the α-quantile (Stoyanov et al., 2007)

$$\widehat{CVaR}_{\alpha}(Y_{j,t}) = \frac{1}{\lfloor M\alpha \rfloor} \sum_{k=1}^{\lfloor M\alpha \rfloor} (-1)\, \hat{y}_{j,(k),t} \tag{3.5}$$

where $\hat{y}_{j,(k),t}$ represents the return scenarios sorted in ascending order and $\lfloor M\alpha \rfloor$ is the largest integer less than or equal to Mα, where Mα indicates the location of the α-VaR. Following the Basel Accords, we choose α to be 2.5%. The evolution of the series $\{\widehat{CVaR}_{\alpha}(Y_{j,t})\}$ is used to indicate, based on a trend signal, whether CVaR increases or decreases through time. To address concerns about data snooping, we do not intend to come up with an optimized measure to determine the magnitude of a recent change in CVaR. Instead, we use a rather standard trend indicator, i.e., the trend signal $CS_{j,t,L}$ indicates that CVaR increases (decreases) if the most recent CVaR forecast for time t is larger (smaller) than the moving average of the L one-step-ahead CVaR forecasts during the period t-L through t-1:

$$CS_{j,t,L} = \widehat{CVaR}_{\alpha}(Y_{j,t}) - \frac{\widehat{CVaR}_{\alpha}(Y_{j,t-L}) + \ldots + \widehat{CVaR}_{\alpha}(Y_{j,t-1})}{L} \tag{3.6}$$

We exclude the most recent CVaR forecast from averaging for two reasons. First, it removes the mechanical correlation between the short- and long-period moving averages, which could have potentially undesirable effects on the statistical analyses. Second, $CS_{j,t,L}$ in this definition relies on the most popular trend-following rules applied in the finance literature, namely, time-series momentum (TSMOM) as defined by Moskowitz et al. (2012) and variable-length moving average rules (VMAR) proposed by Brock et al. (1992):

$$CS_{j,t,L} = VMAR_{j,t,L} + \frac{TSMOM_{j,t,L}}{L} \tag{3.7}$$

We mitigate concerns about data mining by, first, not preselecting an optimal lag length L, but instead applying the most common lag lengths. Since we use weekly data, the lag lengths considered are 1-, 2-, 4-, 10-, 21-, 31-, and 41-weeks, corresponding to 5-, 10-, 20-, 50-, 100-, 150-, and 200-days, respectively (Brock et al., 1992; Han et al., 2016). Moreover, to avoid data mining by an additional measure, we do not select the best trend signal, but follow the suggestion of Han et al. (2016) and simply combine all trend signals for each currency. To this end, we average them for each currency to obtain CVaR-Trend signals ($CT_{j,t}$) at time t.

3.3.5 Econometric framework

The construction of CVaR-Trend requires weekly forecasts of CVaR for each currency. Since we explicitly base our analysis on the empirical evidence that CVaR is time-varying, and since the time-varying CVaR of an individual asset depends not only on its own time-varying behavior but also on its time-varying dependence to other assets, in particular on the dependence in the tails of the distribution (e.g., Embrechts et al., 1999a, 1999b), we use a highly flexible time-varying t-copula with skewed t-GJR-GARCH margins that can account for dynamic correlations, volatility persistence, heteroskedasticity, the leverage effect, and leptokurtic and asymmetric return distributions. With this model, we take into account recent findings on the importance of proper calibration of multivariate density forecasts in order to obtain a correct forecast of tail risk (e.g., Dovern & Manner, 2020; Kim et al., 2021). Indeed, the results of the one-sided and two-sided intercept expected shortfall regression backtests of Bayer and Dimitriadis (2020) (for the sake of brevity, we only mention the main conclusion, but detailed results are available upon request from the author) show that this model accurately predicts CVaR for G10 currencies.

In the following, we outline the framework for forecasting the joint distribution of G10 currencies to derive CVaR forecasts. Through the application of the probability integral transform to each random variable of $\mathbf{Y}_t$, the marginal distributions of the random vector $\mathbf{U}_t = (U_{1,t},\ldots, U_{n,t})' = (F_1(Y_{1,t}),\ldots, F_n(Y_{n,t}))'$ are uniformly distributed on [0,1]. The n-dimensional copula $C(\mathbf{u}_t) = C(u_{1,t},\ldots, u_{n,t})$ of $\mathbf{Y}_t$ is the joint cumulative distribution function on $[0,1]^n$ of $\mathbf{U}_t$. According to Sklar (1959) and Patton (2006) the joint distribution $F(\mathbf{y}_t)$ of $\mathbf{Y}_t$ can be constructed by connecting together disparate marginal distributions with a copula:

$$F(y_{1,t},\ldots,y_{n,t}) = C(F_1(y_{1,t}),\ldots,F_n(y_{n,t})) \tag{3.8}$$

A copula models the dependence structure between the marginals, so all individual marginal distributions can be modelled independently from each other and their dependence structure to account for univariate characteristics.

It is assumed that the joint distribution of $\mathbf{Y}_t$ can be modelled by a time-varying Student t-copula $C(u_{1,t},\ldots,u_{n,t};R_t,\eta)$ with conditional correlation matrix R_t and unconditional shape parameter η. The conditional correlation matrix R_t is assumed to follow the dynamic conditional correlation model (DCC) of Engle (2002). In this model the conditional variance-covariance matrix H_t is decomposed as $H_t = D_tR_tD_t$, where $D_t = \text{diag}\{\sqrt{h_{j,t}}\}$ represents the diagonal matrix of the conditional standard deviations to separate univariate and multivariate dynamics, thus allowing for a two-step estimation process. The marginal distributions are modelled in the first stage. The conditional mean is described by an AR(1) with constant to capture the autocorrelation in the univariate return series. The conditional variances $h_{j,t}$ are estimated by the GJR-GARCH(1,1) model of Glosten et al. (1993):

$$Y_{j,t} = \varphi_j + \delta_j Y_{j,t-1} + \varepsilon_{j,t},$$

$$\varepsilon_{j,t} = \sqrt{h_{j,t}} Z_{j,t}, \qquad \text{where } Z_{j,t} \sim T_j(z_{j,t};0,1,\xi_j,\nu_j),$$

$$h_{j,t} = \omega_j + \alpha_j \varepsilon^2_{j,t-1} + \gamma_j \varepsilon^2_{j,t-1} I(\varepsilon_{j,t-1} < 0) + \beta_j h_{j,t-1} \tag{3.9}$$

The indicator function I allows to model the effect of positive and negative error terms on the conditional variance $h_{j,t}$ asymmetrically, so γ_j captures the 'leverage'.

The usual GARCH restrictions employed are ($\omega_j>0$, $\alpha_j \geq 0$, $\beta_j \geq 0$) to ensure positivity of $h_{j,t}$ and $|\delta_j|<1$ as well as $\alpha_j+\beta_j+\gamma_j\kappa_j<1$ to ensure stationarity, where κ_j is the expected value of the standardized residuals $\mathbf{Z}_t = (Z_{1,t},\ldots, Z_{n,t})'$ below zero. $Z_{j,t}$ are assumed to follow the standardized skewed Student distribution of Fernandez and Steel (1998) to capture the asymmetry of the marginal distributions. ξ_j and ν_j denote the unconditional skew and shape parameter, respectively (Laurent, 2002).

Compared to the original DCC, the use of a copula allows individual degrees of freedom and skew parameters for the first stage estimation. Due to the invariance property of copulas, R_t corresponds to the correlation matrix of the random vector $\mathbf{Z}^*_t = (Z^*_{1,t},\ldots, Z^*_{n,t})'$, where $Z^*_{j,t} = T^{-1}_{j,t}(T_j(Z_{j,t};0,1,\xi_j,\nu_j);\eta)$ is transformed to have a Student t-distribution with η degrees of freedom. To allow for time-varying correlations, an autoregressive, moving-average process is modelled in the second stage

$$Q_t = (1\text{-}a\text{-}b)\overline{Q} + a\mathbf{Z}^*_{t-1}\mathbf{Z}^{*'}_{t-1} + bQ_{t-1} \tag{3.10}$$

with $a,b \geq 0$ and the restriction $a+b < 1$ imposed to ensure stationarity and positive definiteness of Q_t and R_t. $\overline{Q}$ is the unconditional correlation matrix of $\mathbf{Z}^*_t$, that is $E(\mathbf{Z}^*_t\mathbf{Z}^{*'}_t)$, which is estimated with the sample covariance matrix of $\mathbf{Z}^*_t$ (Ausin & Lopes, 2010; Engle, 2002).

The quasi-correlations Q_t have to be rescaled to ensure that the diagonal elements equal 1 and the off-diagonal elements lie in [-1,1] at all times, so R_t is obtained by (Engle, 2002):

$$R_t = \text{diag}(Q_t)^{-\frac{1}{2}} Q_t \, \text{diag}(Q_t)^{-\frac{1}{2}} \tag{3.11}$$

The joint density function of $\mathbf{Y}_t$ is then given by (e.g., Ausin & Lopes, 2010):

$$f(\mathbf{y}_t; \mu_t, h_t, R_t, \eta) = \frac{t(z^*_{1,t}, \ldots, z^*_{n,t}; R_t, \eta)}{\prod_{j=1}^{n} t_j\left(z^*_{j,t}; 0,1,\eta\right)} \prod_{j=1}^{n} \frac{1}{\sqrt{h_{j,t}}} t_j\left(z_{j,t}; 0,1,\xi_j,\nu_j\right) \tag{3.12}$$

The estimation is carried out in two steps with the 'Inference Functions for Margins' (Joe & Xu, 1996). First, the log-likelihoods of the marginal densities are maximized individually, i.e., each separately, to obtain the parameters of all univariate density model specifications, and then the parameters of the copula are estimated using $\mathbf{Z}^*_t$ from the first step. One-ahead forecasts $\widehat{Y}_t$ for $\mathbf{Y}_t$ are then generated by simulation.

3.4 CVaR-Trend and the cross-section of currency excess returns

3.4.1 CVaR-Trend and the state of the foreign exchange market

In this section, we present our main results by examining the cross-sectional relationship between CVaR-Trend and currency excess returns conditional on the state of the foreign exchange market. In December 2015, the Federal Open Market Committee (FOMC) initiated the process of 'normalization' with the aim of raising the federal funds rate to a level that is 'neither expansionary nor contractionary'. This development culminated in a period between 2018 and 2020 when G10 investment currencies were temporarily unavailable to US investors. In the case of zero investment currencies, the carry trade decision rule leads to suboptimal allocations, since borrowed funds would have to be invested in currencies with negative interest rate differentials.

For times when the carry strategy is deprived of the prerequisite for success, it seems reasonable to assume that the first determinant, carry, exerts less influence on currency excess returns. Section 3.4.2 provides empirical support for this conjecture. To avoid look-ahead bias, we follow the empirical approach of Cooper et al. (2005) to construct an ex ante estimator for inferring two states of the foreign exchange market. To do so, we count the number of available investment currencies for each week in the period from January 06, 1999, to February 16, 2022, and define the state of the market as 'investment' ('funding') in the period from October 20, 1999, to February 09, 2022, if the mode of investment currencies is greater than or equal to (less than) one over the 42 weeks before each start of the strategy's holding period. The use of 42 weeks ensures that the derivation of market states is consistent with the construction of CVaR-Trend. We use a moving window approach for two reasons. First, a moving window allows us to capture the trend in the number of investment currencies over time, thus accounting for the likelihood that information about a change in market state is perceived only with a time lag. Second, it smoothens the time series of investment currencies, avoiding frequent changes in market state and short market state durations due to fluctuations in forward discounts.

Since our currency dataset contains the euro, the first estimation is performed on January 6, 1999, the first business Wednesday of the Euro, to avoid look-ahead bias. The estimation uses data from July 11, 1990, to January 06, 1999, to obtain CVaR forecasts for each currency for the week January 07, 1999, to January 13, 1999. The most recent forecasts are from February 02, 2022, resulting in a total of 1205 weekly CVaR forecasts for each currency. The portfolio analyses start on October 20, 1999, because the construction of the time series of CVaR-Trend requires a lead time of 42 weekly forecasts.

Note that forecasting is performed in an out-of-sample framework with expanding window length. This means that to avoid look-ahead bias at time t-1, only historical observations that are already available at time t-1 are used for estimation and forecasting. Then, we perform a univariate regression analysis by allocating all currencies in the G10 sample into nine portfolios based on an ascending sort of CVaR-Trend each week from October 20, 1999, to February 02, 2022. The holding period is one week, so portfolios are rebalanced at the end of each week. Portfolio 1 contains the currency with the lowest CVaR-Trend (highest decrease or at least smallest increase in CVaR) and portfolio 9 contains the currency with the highest CVaR-Trend (highest increase or at least smallest decrease in CVaR).

At first, we regress the excess returns of these nine portfolios and the long-short portfolio H/L^{CT}, that is long in portfolio 9 and short in portfolio 1, on the appropriate risk factors DOL, HML^{FX}, and VOL, and a constant. Next, we regress the risk-adjusted excess returns on an investment and a funding dummy variable with no intercept to test if the alphas are equal to zero in each state.

Panel A of Table 3.1 shows that conditioning on the state of the market has substantially different cross-sectional implications for future excess returns of CVaR-Trend strategies. Univariate sorting by CVaR-Trend suggests a positive relationship between CVaR-Trend and excess returns, but only in funding markets. In funding markets, the difference portfolio H/L^{CT} generates an economically large and statistically significant alpha of 0.31% per week. In contrast, the univariate analysis fails to detect a relationship between CVaR-Trend and excess returns in investment markets, as the difference portfolio generates an alpha that is neither large in magnitude nor statistically significant.

These findings for investment markets are inconsistent with the prediction of a positive relationship between CVaR-Trend and excess returns. Given the suitability of the carry trade decision rule, we expect carry as the first determinant of currency excess returns to be most pronounced in investment markets.

Table 3.1
CVaR-Trend and market states

Panel A: Excess returns to portfolios sorted on CVaR-Trend

	1	2	3	4	5	6	7	8	9	H/L^{CT}
Funding Markets										
Mean	-0.31***	-0.14	-0.16	-0.14	-0.18	-0.09	-0.11	0.16	-0.03	0.28**
α	-0.22**	-0.03	-0.05	-0.02	-0.06	0.01	0.01	0.28**	0.09	0.31**
Investment Markets										
Mean	0.05	0.05	0.03	0.01	0.02	0.06	0.02	0.02	0.03	-0.02
α	0.02	0.01	0.00	-0.02	-0.01	0.01	0.00	-0.01	0.01	-0.01

Panel B: Excess returns to portfolios sorted on forward discount and CVaR-Trend

Funding Markets

		Forward Discount		
	Mean	1	2	3
CVaR-Trend	1	-0.16**	-0.17	-0.09
	2	-0.09	-0.11	-0.21
	3	-0.06	0.06	-0.18
	$H/L^{CT\|FD}$	0.10	0.23**	-0.08

		Forward Discount		
	α	1	2	3
CVaR-Trend	1	-0.09	-0.06	0.05
	2	-0.01	0.01	-0.05
	3	0.03	0.17**	-0.03
	$H/L^{CT\|FD}$	0.12	0.23**	-0.08

Investment Markets

		Forward Discount		
	Mean	1	2	3
CVaR-Trend	1	0.03	0.01	0.06
	2	0.02	0.00	0.05
	3	-0.06	0.04	0.12***
	$H/L^{CT\|FD}$	-0.09*	0.03	0.06

		Forward Discount		
	α	1	2	3
CVaR-Trend	1	0.04	-0.03	0.00
	2	0.03	-0.03	-0.03
	3	-0.05*	0.01	0.05**
	$H/L^{CT\|FD}$	-0.09*	0.04	0.05

Note: Panel A shows the average excess return and the average risk-adjusted excess return (in percent per week) for each of the portfolios formed by sorting on CVaR-Trend (CT), and for the long-short difference portfolio H/L^{CT}, following funding and investment markets. Panel B shows equivalent information for portfolios dependent sorted by forward discount (FD) and CVaR-Trend, as well as for the long-short difference portfolios $H/L^{CT|FD}$ in each forward discount tertile. *, ** and *** indicate significance according to Newey-West (1994) HAC standard errors at the 10, 5 and 1% levels. The sample period is October 1999 to February 2022.

Therefore, we further analyse the performance of portfolios formed by sorting dependently on forward discount as the control variable (the first sort variable) and CVaR-Trend as the risk dimension to be priced (the second sort variable) to control for the effect of carry on the relationship between CVaR-Trend and excess returns. We follow the literature (e.g., Koijen et al., 2018; Lustig et al., 2011; Menkhoff et al., 2012a) and use sorting on forward discount because it is equivalent to sorting on interest rate differentials under covered interest parity and therefore appropriate to indicate the carry of currencies, i.e., the return on a futures position if the price remains constant over the holding period. Due to the small sample of currencies, we choose a tertile sort on CVaR-Trend within forward discount tertiles to avoid biases induced by specific portfolio sorting choices. This breakpoint selection produces control variable portfolio group sizes comparable to Lustig et al. (2011). Each week in the time range from October 20, 1999, to February 02, 2022, all currencies are allocated into three groups based on an ascending sort of forward discount as the control variable. Within each control variable group, the three currencies are sorted into three equal-weighted portfolios based on an ascending sort of CVaR-Trend. A currency is classified as 'low CVaR-Trend' ('high CVaR-Trend') if it has a CVaR-Trend lower (higher) than two-thirds of the currencies in the same forward discount tertile.

We then regress the risk-adjusted excess returns relative to the risk factors DOL, HML^{FX}, and VOL of these nine portfolios and the long-short portfolios $H/L^{CT|FD}$ that are long in portfolio 3 and short in portfolio 1 in each forward discount tertile on an investment dummy variable and a funding dummy variable with no intercept to test if the alphas are equal to zero in each state. Panel B of Table 3.1 shows that the double sorts uncover some interesting patterns in 1-week currency excess returns. In investment markets, the alpha of -0.09% of $H/L^{CT|FD}$ per week suggests that currencies in the low forward discount tertile perform particularly poorly when they become riskier (exhibit higher levels of CVaR-Trend). In contrast, currencies from the high forward discount tertile appear to perform particularly well precisely when they become riskier, as evidenced by the statistically significant alpha of 0.05% per week of the high forward discount, high CVaR-Trend portfolio.

3.4.2 Carry and the state of the foreign exchange market

In the previous analyses, we assumed that conditioning on market state is important for the effectiveness of the carry trade. To test this more rigorously, we estimate the forward discount (FX^{FD}) of the foreign exchange market as an equally weighted average of currency forward discounts. Thus FX^{FD} corresponds to the forward discount of the DOL portfolio.

Table 3.2
Forward discount and market states

Panel A: Foreign exchange market average forward discount

	Funding	Investment
FX^{FD}	-0.03***	0.01

Panel B: Excess returns to portfolios sorted on forward discount

	1	2	3	4	5	6	7	8	9	HML^{FX}
Funding Markets										
Mean	-0.08	-0.05	-0.18*	-0.05	-0.02	-0.15	-0.17	-0.13	-0.17	-0.09
α	-0.04	0.02	-0.07	0.04	0.09	-0.02	-0.03	0.02	-0.01	0.01
Investment Markets										
Mean	-0.01	0.00	0.00	0.03	0.03	-0.01	0.02	0.10**	0.10**	0.11***
α	-0.07*	-0.05*	-0.03	-0.01	0.01	-0.02	0.00	0.10***	0.09***	0.15***

Note: Panel A of Table 3.2 reports the average forward discount (in percent per week) of the foreign exchange market following funding and investment markets. Panel B of Table 3.2 shows the average excess return and the average risk-adjusted excess return (in percent per week) for each of the portfolios formed by sorting on forward discount, and for the carry strategy HML^{FX}, following funding and investment markets. *, ** and *** indicate significance according to Newey-West (1994) HAC standard errors at the 10, 5 and 1% level, respectively. The sample period is October 1999 to February 2022.

We regress FX^{FD} on an investment dummy variable and a funding dummy variable with no intercept to test if the mean global FX forward discounts are equal to zero in each state. Panel A of Table 3.2 confirms that in funding markets currencies trade at a discount on average. In funding markets, therefore, the basic idea of the carry trade is called into question, and interest differentials should thus drive currency excess returns less than in investment markets.

To test this, we examine the relationship between forward discount and expected currency excess returns conditional on the state of the foreign exchange market. Each week in the period from October 20, 1999, to February 02, 2022, all currencies are allocated into nine portfolios based on an ascending sort of forward discounts. Following Menkhoff et al. (2012a), we regress the excess returns of these nine portfolios and of HML^{FX} on the risk factors DOL and VOL, and a constant. Next, we regress the risk-adjusted excess returns on an investment and a funding dummy variable with no intercept to test if the alphas are equal to zero in each state. Panel B of Table 3.2 shows a strong positive cross-sectional relationship between forward discount and currency excess returns in investment markets, but there is no significant relationship between forward discount and currency excess returns in funding markets. These results are consistent with the expectation that the first determinant, carry, is a key driver in the cross-section of currency excess returns only in investment markets.

3.4.3 CVaR-Trend in investment markets

Panel B of Table 3.1 implies that the excess returns of funding and investment currencies in investment markets behave in opposite ways when they become riskier. In this section, we examine in more detail how the second determinant of currency excess returns, the appreciation of the spot rate, evolves in the wake of a change in the CVaR level to provide an explanation for our findings. To this end, over the period from October 20, 1999, to February 02, 2022, we measure an increase (decrease) in spot returns as the positive (negative) difference between the spot return in week t-1, i.e., the most recent spot return used to forecast CVaR for week t, and the moving average of spot returns over the period t-L to t-2. The lag lengths considered are 2-, 4-, 10-, 21-, 31- and 41-weeks, and we average over these indicators to obtain a measure of the magnitude of a recent change in spot returns that is consistent with the time periods used to calculate CVaR-Trend.

Panel A of Table 3.3 shows that low (high) CVaR-Trend currencies have recently experienced large appreciation (depreciation), indicated by the highly statistically significant average spot depreciation of the difference portfolio. The high excess returns of the difference portfolio H/L^{CT} in funding markets and the high excess returns of high CVaR-Trend investment currencies in investment markets are therefore consistent with the expectation that once the market anticipates a future lower (higher) CVaR level associated with an increasing overvaluation of the quote (base) currency, a premium (discount) to spot prices will materialise through the sale (purchase) of the base currency, resulting in low (high) future excess returns of the quote currency.

Table 3.3
Recent spot rate appreciation

Panel A: Appreciation of portfolios univariate sorted on CVaR-Trend

	1	2	3	4	5	6	7	8	9	H/L^{CT}
Mean	-0.07**	-0.07**	-0.06**	0.02	-0.01	0.02	0.06	0.10**	0.13***	0.20***

Panel B: Appreciation of portfolios bivariate sorted on forward discount and CVaR-Trend

Funding Markets

		Forward Discount		
	Mean	1	2	3
CVaR-Trend	1	0.04	-0.05	-0.14
	2	-0.04	-0.04	0.12*
	3	0.02	-0.01	0.11
	$H/L^{CT\|FD}$	-0.02	0.04	0.25***

Investment Markets

		Forward Discount		
	Mean	1	2	3
CVaR-Trend	1	0.08***	-0.01	-0.13***
	2	0.00	-0.01	0.01
	3	-0.05	0.09**	0.15***
	$H/L^{CT\|FD}$	-0.13***	0.10***	0.28***

Note: Panel A of Table 3.3 reports the average spot rate appreciation (Mean) at time t-1 (in percent per week) for each of the portfolios formed by univariate sorting on CVaR-Trend (CT) and for the long-short difference portfolio H/L^{CT}. Panel B of Table 3.3 shows the average spot rate appreciation at time t-1 for portfolios dependent sorted using forward discount (FD) and CVaR-Trend, as well as for the long-short difference portfolios $H/L^{CT|FD}$ in each forward discount tertile, following funding and investment markets. *, ** and *** indicate significance according to Newey-West (1994) HAC standard errors at the 10, 5 and 1% level, respectively. The sample period is October 1999 to February 2022.

However, the poor performance of low forward discount but high CVaR-Trend currencies is in contrast to this. Given the significant relationship between forward discount and currency excess returns in investment markets, a plausible explanation for this observation could arise from the asymmetric investment preferences associated with high and low forward discount levels. If investors are more likely to go short than long in low forward discount currencies to capture the negative interest differential to fund their investment leg, they will perceive an appreciation (depreciation) of a funding (investment) currency as more risky than a depreciation (appreciation). In investment markets, therefore, funding (investment) currencies should become more volatile in the wake of appreciations (depreciations). Panel B of Table 3.3 provides empirical support for this conjecture. The statistically highly significant average spot appreciation in week t-1 of the difference portfolio $H/L^{CT|FD}$ in the low forward discount tertile indicates that CVaR-Trend of funding currencies is larger (smaller) following recent appreciation (depreciation).

Table 3.4
Performance of high CVaR-Trend strategies

	Funding Markets	Investment Markets
Mean	-0.11	0.18^{***}
α	-0.06	0.10^{**}

Note: Table 4 shows the average excess return and the average risk-adjusted excess return (in percent per week) of a long-short portfolio $HH^{CT|FD}$ - $HL^{CT|FD}$ that is long (short) the high CVaR-Trend currency within the high (low) forward discount tertile following investment and funding markets. *, ** and *** indicate significance according to Newey-West (1994) HAC standard errors at the 10, 5 and 1% level, respectively. The sample period is October 1999, to February 2022.

Consequently, the contrasting trend in the excess returns of funding and investment currencies evident in panel B of Table 3.1 can be seen as an expression of opposing investor behaviour in investment markets when information about an increase in CVaR is to be incorporated into spot prices. To account for a future higher CVaR level of funding (investment) currencies associated with a rising overvaluation of the quote (base) currency, investors buy (sell) funding (investment) currencies, whereby the negative relationship between CVaR-Trend and future currency excess returns on funding currencies in investment markets emerges. These results suggest that large return spreads can be achieved in investment markets by trading the high risk 'corners' of a double sort on forward discount and CVaR-Trend. Indeed, Table 3.4 shows that the alpha of a long-short trading strategy $HH^{CT|FD}$ - $HL^{CT|FD}$ that buys the high CVaR-Trend portfolio in the third forward discount tertile and sells the high CVaR-Trend portfolio in the first forward discount tertile in investment markets is 0.10% per week, which is large in magnitude and statistically significant.

3.4.4 CVaR-Trend trade

The previous results suggest that a trading strategy that buys (sells) the high CVaR-Trend currency within the high (low) forward discount tertile in investment markets and buys (sells) the high (low) CVaR-Trend currencies in funding markets should outperform conventional carry trade strategies that rely only on forward discount as the sole selection criterion and disregard tail risk. We refer to this trading strategy as CVaR-Trend trade (CTT). Each week when the market state is classified as 'investment', all currencies are sorted into three groups based on an ascending sort of forward discount. Within each forward discount tertile, all currencies are sorted into three portfolios based on an ascending sort of CVaR-Trend. The CVaR-Trend trade is the portfolio that buys (sells) the currency with a high CVaR-Trend in the high (low) forward discount tertile. And when the market state is classified as 'funding', all currencies in the G10 sample are sorted into portfolios based on an ascending sort of CVaR-Trend. The CVaR-Trend trade is then the long-short portfolio that is long (short) in the currencies with the highest (lowest) CVaR-Trend.

The CVaR-Trend Trade is a zero-cost trading strategy with zero net currency exposure, as the investment and funding legs are equally weighted. Panel A of Table 3.5 shows the results of time-series regressions employing the excess returns of the CVaR-Trend trade. The CVaR-Trend trade generates average excess returns and average risk-adjusted excess returns between 0.12% and 0.21% per week after controlling for the risk factors DOL, VOL, and H/L^{FX}, which are both economically large and highly statistically significant regardless of the specification. Panel B of Table 3.5 reports the results of the time-series regression of the alpha relative to each specification on an investment dummy variable and a funding dummy variable to test if the alphas are equal to zero in each state. The results show that the conclusion of the previous analysis holds in both market states, as the CVaR-Trend trade generates an economically large and statistically significant alpha in each market state.

Table 3.5
Performance of the CVaR-Trend trade

Panel A: Time-series regression results

	Dependent variable		
	CTT		
Independent variables	(1)	(2)	(3)
Intercept	0.19***	0.21***	0.12***
DOL		0.34***	0.04
VOL		-0.87***	0.41
HML^{FX}			0.66***
adj.-R^2		0.06	0.37

Panel B: Risk-adjusted excess return of the CVaR-Trend trade in the market states

	Dependent variable		
	CTT		
Independent variables	(1)	(2)	(3)
Funding Markets	0.28**	0.34***	0.33**
Investment Markets	0.18***	0.20***	0.10**

Note: Panel A reports time-series regression results employing the excess returns to the CVaR-Trend trade. Panel B presents results from the time-series regression of the risk-adjusted excess return to each specification on an investment dummy variable and a funding dummy variable. *, ** and *** indicate significance according to Newey-West (1994) HAC standard errors at the 10, 5 and 1% level, respectively. The sample period is October 1999 to February 2022.

3.5 Conclusion

This study examines the relationship between the trend of left-tail risk and the cross-section of expected G10 currency excess returns. A univariate portfolio analysis shows a strong positive relationship between CVaR-Trend and expected currency excess returns in funding markets. This result is consistent with the expectation that once the market anticipates a future lower (higher) CVaR level associated with an increasing overvaluation of the quote (base) currency, a premium (discount) is applied to spot prices, resulting in low (high) future excess returns of the quote currency.

In investment markets, however, there is no linear relationship. Bivariate portfolio analysis in investment markets shows that funding (investment) currencies perform particularly poorly (well) when they become riskier. Since we find strong empirical support for carry being an important factor in the cross-section of currency excess returns only in investment markets, a plausible explanation for this finding may lie in the asymmetric investment preferences associated with high and low forward discount levels. If investors tend to go short rather than long in low forward discount currencies in order to use the negative interest rate differential to finance their long position, they are likely to perceive an appreciation (depreciation) of a funding (investment) currency as riskier than a depreciation (appreciation). Indeed, in investment markets we find empirical evidence, that funding (investment) currencies with high CVaR-Trend have recently experienced strong spot rate appreciation (depreciation) while funding (investment) currencies with low CVaR-Trend have recently experienced strong spot rate depreciation (appreciation). Consequently, the contrasting trend in the excess returns of funding and investment currencies can be seen as an expression of opposing investor behaviour in investment markets when incorporating information about an increase in CVaR into spot prices. Confronted with a future higher CVaR level of funding (investment) currencies associated with an increasing overvaluation of the quote (base) currency, investors buy (sell) funding (investment) currencies, resulting in the negative relationship between CVaR-Trend and future currency excess returns for funding currencies in investment markets.

Our findings suggest a new currency trading strategy, named CVaR-Trend trade, constructed in funding markets by univariate sorting on CVaR-Trend and in investment markets by bivariate sorting on forward discount and CVaR-Trend. In investment markets, therefore, CVaR-Trend trade can be considered an enhancement of the carry trade. Finally, we show that the excess returns of the CVaR-Trend trade cannot be explained by exposure to the most common risk factors in currency markets.

From a practical point of view, our results have important implications for portfolio management investing in G10 currencies. One of the prevailing currency strategies is the carry trade strategy, which has worked well in the past. However, interest rate differentials across G10 currencies have narrowed significantly. This development makes it increasingly difficult to identify and exploit entry opportunities based on the carry trade investment rule. In this sense, our novel sorting variable CVaR-Trend can make an important contribution to expanding the investment opportunity set of currency managers. Future research on CVaR-Trend could be extended to other asset classes, such as equities. According to the Intertemporal Capital Asset Pricing Model (ICAPM) of Merton (1973), risk premia should be associated with the conditional covariances between asset returns and innovations in state variables reflecting time variation in investment opportunities. To the extent that investors' utility is affected by time-varying changes in left-tail risk, our reasoning about the CVaR-Trend may conceal a potential pricing factor that remains to be identified. These are questions that our work would like to leave open for future research.

4 Contrarian Currency Pricing

When risk tells you to expect mispricing[3]

[3] This chapter corresponds to a working paper of the same title published as a preprint on the *Social Science Research Network, https://dx.doi.org/10.2139/ssrn.4577434*.

4.1 Introduction

The core motivation to engage in a carry trade is based on the ‘forward premium puzzle’ (Hassan & Mano, 2019), i.e. the empirical evidence that the uncovered interest parity (UIP) is violated. According to the UIP, risk-neutral investors with rational expectations should be indifferent between holding the high or low interest rate currency, because a higher (lower) interest rate should compensate for an expected depreciation (appreciation) of the exchange rate, and thus currencies are assumed to have the same expected excess returns. However, if the UIP does not apply, the carry trade aims to earn at least the ‘carry’, i.e. the ex ante observable positive interest rate differential between two countries that accrues during the holding period, or that the currency excess return for the investor will be even higher if the high interest rate currency depreciates against the low interest rate currency by less than the interest rate differential, or if high (low) interest rate currencies actually appreciate (depreciate) rather than depreciate (appreciate) (Bekaert & Hodrick, 2018).

The empirical literature has documented that the carry trade is profitable on average, but its profits accumulate slowly over time, while the carry trade performs poorly in times of market turmoil and financial stress, when losses tend to be large and sudden (e.g., Bekaert & Panayotov, 2020; Brunnermeier et al., 2008; Burnside et al., 2011a; Daniel et al., 2017; Farhi & Gabaix, 2016; Lustig et al., 2011; Menkhoff et al., 2012a; Verdelhan, 2018). Menkhoff et al. (2012a) show that currencies with low (high) interest rates covary positively (negatively) with global FX volatility innovation (VOL), reflecting that they offer lower (higher) excess returns in equilibrium because they perform well (poorly) when global FX volatility is high. Consequently, the different covariation of currencies with the risk factor VOL depending on the level of their interest rates suggests that the unbiasedness hypothesis fails because there are time-varying risk premia for bearing systematic, i.e. non-diversifiable, volatility risk, which is consistent with the market efficiency hypothesis (Bekaert & Hodrick, 2018). The central research hypothesis of this paper asks, in principle as an implicit consequence of this empirical evidence, whether there are periods in which conditions prevail that contradict the equilibrium condition of the two-factor currency pricing model of Menkhoff et al. (2012a) and imply that the market does not reward entering into a carry trade with sufficiently high expected excess returns.

This research question differs from standard empirical asset pricing studies, which test whether individual assets behave as predicted by their exposure to pricing factors with the benefit of hindsight. In these studies, the competition is about which asset pricing model adequately predicts future excess returns in the cross-section, i.e. which risk-based explanation might dominate over the others (e.g., Harvey et al., 2016; Hou et al., 2015). However, this is an ex-post perspective, and we would generally be interested in whether there is exploitable forward-looking information that would allow us to derive assessments of how likely it is that we can rely on the underlying risk-based explanation for the cross-sectional variation in future excess returns in our portfolio allocation decisions. This concern is indeed justified, as a number of possible market anomalies or inefficiencies are known, suggesting that the theoretical predictions of equilibrium asset pricing models do not always hold as a reliable indicator of the risk-return trade-off in real markets. Consequently, it may be that commonalities in mispricing predict future returns due to subsequent corrections and that return differentials therefore reflect a delayed price response to information rather than risk premia (e.g., Cochrane, 2011; Daniel et al., 2020). Our research question is therefore less concerned with the competition between different currency pricing models than with the conditions under which the predictions of an appropriate currency pricing model may fail to materialise, even though the underlying source of systematic risk is still present. The literature is much less concerned with this issue, because it erroneously loses relevance when the validity of pricing factors in explaining the cross-section of asset returns is tested only over the entire sample period, i.e. over a long time horizon, since then possible contradictions to the underlying risk-based explanatory theory present in the data are eliminated by the 'on average' or 'in equilibrium' (Fama, 1970, p. 409) pricing perspective.

We contribute to the existing literature by first developing an indicator, called the 'pricing classifier', which is derived from the 'in equilibrium' condition of the Menkhoff et al. (2012a) currency pricing model and predicts periods in which the two core predictions of this currency pricing model are likely to be violated. Second, we show that it is precisely for this reason that the pricing classifier can predict 'contrarian pricing regimes', i.e. periods in which both the negative impact of high global FX volatility innovations on currency excess returns and thus the relevance of systematic volatility risk diminish, a phenomenon we refer to as 'contrarian currency pricing'. Third, we find that the systematic risk factor HML^{FX} cannot explain the cross-section of G10 currency excess returns in contrarian pricing regimes, suggesting a reduced equilibrium model where omitting HML^{FX} is beneficial. As a result, the conventional carry trade strategy performs poorly, and an investor who takes advantage of the predictive information contained in the pricing classifier would prefer not to enter into a carry trade in contrarian pricing regimes. Finally, we find that contrarian pricing regimes contain cross-sectional information about reversal adjustments, which in turn aligns prices more closely with the risk-based explanatory approach of the currency pricing model of Menkhoff et al. (2012a). This information can be used to construct a highly profitable reversal strategy.

The remainder of the paper is structured as follows. Section 4.2 presents how our work relates to previous research. Section 4.3 introduces currency risk factors, conditional value at risk (CVaR), the theoretical framework and the construction of the pricing classifier. Section 4.4 presents the data, the calculation of currency excess returns and the econometric model used to implement the pricing classifier. Section 4.5 then examines the implications of the pricing classifier and presents the empirical results. Section 4.6 concludes.

4.2 Literature review

Fama (1984) was among the first to recognise that the estimated slope coefficients in tests of the unbiasedness hypothesis can be interpreted as an indication of the existence of time-varying risk premia. If forward rates were unbiased predictors of future spot rates, there would be no risk premia, i.e. no non-zero excess returns on currencies. However, the different behaviour of currencies depending on their exposure to systematic risk implies that currency speculation is subject to considerable risk and the risk premium represents compensation for investors who take on exposure to these sources of uncertainty in foreign exchange markets (Bekaert & Hodrick, 2018).

Since the seminal paper by Lustig and Verdelhan (2007), recent research has applied asset pricing to currency returns, highlighting in particular the significance of the dollar risk factor and the HML^{FX} risk factor in explaining the cross-section of currency excess returns and providing estimates of the price of currency risk (e.g., Lustig et al., 2011; Lustig et al., 2014; Verdelhan, 2018). Such currency risk factors are self-financing, replicable and tradable as they represent the excess return combinations associated with currency investment strategies. Another line of research is increasingly concerned with non-tradable risk factors, i.e. factors that are not based on returns, so that, unlike tradable risk factors, their price of risk is not equal to the time-series average of their excess returns (Cochrane, 2005). In particular, recent research highlights the long-standing relevance of risk factors designed to capture the information contained in the volatility of currency excess returns to explain the profitability of carry trades based on the existence of a time-varying risk premium (e.g., Chernov et al., 2023; Nucera et al., 2023).

Our study differs from typical asset pricing studies in that we do not attempt to uncover an anomaly for an established currency pricing model in order to argue for the construction of a new systematic risk factor based on that anomaly, which would then provide a more appropriate model for currency pricing. By contrast, in line with Cochrane (2011) and Harvey et al. (2016, 2021), we tend to accept that perhaps only a few characteristics provide truly independent information about average returns, so that only a few factors are truly relevant, as they already control for many characteristics in the cross-section of asset returns. Consequently, our starting point is to first acknowledge the theoretical suitability and performance of a parsimonious two-factor currency pricing model, such as that of Lustig et al. (2011) or Menkhoff et al. (2012a), for the risk-based explanation of carry trade excess returns. This view is well supported by Nucera et al. (2023) and their findings on the optimal factor model for currency pricing when accounting for omitted variable and measurement error biases. They find that the optimal pricing kernel includes latent factors that are closely related to, but not identical to, the observable and tradable dollar and carry risk factors. In addition, their findings highlight the relevance of uncertainty and volatility measures, in particular the global FX volatility factor of Menkhoff et al. (2012a).

Against this view, Burnside (2012) argues that global FX skewness or Dupuy (2015) argues that global FX Value at Risk may better explain carry trade excess returns than global FX volatility innovations. In addition, Rafferty (2012), Lettau et al. (2014) and Dobrynskaya (2014, 2015) also construct crash risk factors to price currency returns on the basis of skewness, kurtosis and downside risk. Bekaert and Panayotov (2020) measure crash risk using skewness. They show that crash risk is predictable and that it is possible to construct profitable good carry trades with low crash risk, which can serve as risk factors explaining the cross-section of currency excess returns. Jurek (2014) also casts doubt on the ability of crash risk to explain carry trade excess returns, finding that high interest rate currencies generate significant excess returns even after hedging against the risk of large depreciations. Related studies construct mean-variance optimised portfolios and find that they are profitable, have low exposure to crash risk, and correctly price currency risk, suggesting that crash risk, which underlies Menkhoff et al.'s (2012a) risk-based explanation, may not be all that important in pricing currency risk (e.g., Ackermann et al., 2017; Chernov et al., 2023; Maurer et al., 2022, 2023).

Another branch of the literature argues that volatility is more of an indirect measure of FX liquidity and attributes cross-sectional risk premia to exposure to global FX liquidity rather than to risk variables (e.g., Karnaukh et al., 2015). Mancini et al. (2013) also find a strong relationship between liquidity risk and carry trade excess returns. Other studies argue that risk factors derived from information about the risk characteristics of equity or derivatives markets may be more powerful in explaining the cross-section of currency excess returns (e.g., Fan et al., 2022; Gao et al., 2019; Lustig et al., 2011). Non-tradable risk factors also include macroeconomic risk factors that reflect a country's economic conditions and are therefore considered to be linked to currency excess returns (e.g., Hassan, 2013), in particular to the cross-section of currency excess returns (e.g., Dahlquist & Hasseltoft, 2020). Text-based factors such as the US Economic Policy Uncertainty Index of Baker et al. (2016) may also be related to sources of currency risk (Nucera et al., 2023).

In this paper, we shift the focus away from this competition between different currency pricing models or risk-based explanations. Specifically, we ask whether there are certain predictable conditions embedded in the underlying risk-based explanation of the two-factor currency pricing model of Menkhoff et al. (2012a) that shed light on when and why this risk-based explanation may or may not apply. In particular, we show that HML^{FX} cannot explain the cross-section of G10 currency excess returns in contrarian pricing regimes, i.e. in periods when the two core predictions of Menkhoff et al.'s (2012a) two-factor currency pricing model are violated. The impact is severe, as investment currencies in contrarian pricing regimes cannot adequately compensate for their negative exposure to the global FX volatility innovation risk factor of Menkhoff et al. (2012a).

This makes the carry trade in contrarian pricing regimes an unattractive trading strategy. In the spirit of Cochrane (2011) and Daniel et al. (2020), we call for a thorough analysis of the core predictions of established asset pricing models in order to fully exploit the potential of their expected implications for explaining the cross-section of asset prices, even when apparent inconsistencies are observed. This approach could help to avoid the misconception that the perceived abnormal return behaviour reflects a weakness in the benchmark pricing model, rather than a systematic mispricing that is likely to resolve itself over time. It could also prevent the all-too-common practice of prematurely discarding established models in favour of new pricing factors or more appropriate risk-based explanatory approaches.

4.3 Can mispricing be anticipated?

4.3.1 Risk factors

In line with the existing literature, we examine the dollar risk factor (DOL), Lustig et al.'s (2011) excess return on the carry trade (HML^{FX}), and Menkhoff et al.'s (2012a) global FX volatility innovations (VOL) as common risk factors in foreign exchange markets. These factors are known to have the potential to predict the cross-section of currency excess returns (Brunnermeier et al., 2021). The risk factor DOL is the average excess return of a trading strategy in which all foreign currencies are bought equally against the dollar using funds borrowed in the United States. The risk factor HML^{FX} of Lustig et al. (2011) is a carry trade strategy that uses two currencies in each of the two legs, the investment leg and the funding leg. Menkhoff et al.'s (2012a) VOL risk factor captures unexpected increases in global FX volatility. It is defined as the residual time series of an estimated AR(1) process applied to the level of a proxy for global FX volatility. To construct this proxy, the daily cross-sectional averages of the absolute log changes in the spot rate $|\Delta s_\tau|$, computed individually for each currency on each day, must be averaged up to a weekly frequency.

4.3.2 Conditional value at risk

In section 4.3.4, we use Expected Shortfall (ES) or CVaR as a measure of risk because it is based on objective and concrete risk concepts that take into account loss aversion (Artzner et al., 1999; Rockafellar et al., 2006). In particular, the use of CVaR provides a coherent and consistent measure of risk by satisfying the axioms of translation invariance, positive homogeneity, subadditivity and monotonicity. Coherence ensures that CVaR is well behaved, mathematically consistent and captures important risk characteristics, including the component of risk due to heavy tails (Artzner et al., 1999; Rockafellar & Uryasev, 2000). From a regulatory perspective, another argument can be made for the use of CVaR. Due to the lack of coherence of VaR and its inability to capture tail risks beyond the α-quantile, the Basel Committee on Banking Supervision (2019) has decided to replace VaR with ES as the primary risk measure for calculating minimum capital requirements for market risk as a result of the fundamental review of the trading book, which is expected to further increase the importance and prevalence of ES in the future. Given the information set $\mathcal{F}_t$ at the end of week t, the random vector $\mathbf{Y}_t = (Y_{1,t},\ldots,Y_{n,t})'$ denotes the log spot return of the $j = 1,\ldots,n$ G10 currencies at the end of week t, i.e. $Y_{j,t} = \log s_{j,t} - \log s_{j,t-1} = \Delta s_{j,t}$. We assume that all return distributions are continuous. Let $F_j(y_{j,t}) = P(Y_{j,t} \leq y_{j,t})$ be the conditional cumulative distribution function of $Y_{j,t}$ and $f_j(y_{j,t})$ the corresponding marginal density function. $F_{j,t}^{-1}(\alpha)$ is the quantile function of $Y_{j,t}$. CVaR at the confidence level $\alpha \in (0,1)$ is defined as the expected mean of returns smaller than the Value at Risk (VaR) associated with α

$$CVaR_\alpha(Y_{j,t}) = E_t(Y_{j,t}|Y_{j,t} < VaR_\alpha(Y_{j,t})) \tag{4.1}$$

where the Value at Risk (VaR) at the confidence level α is defined as the conditional quantile of $Y_{j,t}$ evaluated at α (Bayer & Dimitriadis, 2020):

$$VaR_\alpha(Y_{j,t}) = F_{j,t}^{-1}(\alpha) = \inf \{y_j \in R : F_j(y_j) \geq \alpha\} \tag{4.2}$$

4.3.3 Volatility as a risk factor – signs of mispricing

Menkhoff et al. (2012a) find a significant negative covariance risk price associated with exposure to global FX volatility innovations, implying that currencies with low (high) interest rates covary positively (negatively) with global FX volatility innovations. Thus, low (high) interest rate currencies generate high (low) excess returns when future aggregate market volatility increases. They therefore act as a (no) hedge against market turbulence, i.e. they lead to less (more) uncertainty about future wealth for risk-averse investors. Consequently, the main predictions of this currency pricing model are, on the one hand, that investors accept low risk premia, i.e. a low expected excess return, for taking less systematic volatility risk when holding funding currencies. That is, they are willing to pay a premium because funding currencies provide insurance against systematic volatility risk. On the other hand, investors demand high risk premia (a high expected excess return) for taking more systematic volatility risk when holding investment currencies, i.e. they demand compensation because investment currencies expose them to systematic volatility risk. Menkhoff et al. (2012a) thus show that the positive cross-sectional relationship between forward discount and currency excess returns can be understood by the covariance of carry portfolios with global FX volatility innovations. The carry trade strategy, i.e. the difference portfolio, is profitable in equilibrium because the two strategies involved in the carry trade, a long position in the investment currency and a short position in the funding currency, both covary negatively with global FX volatility innovations and therefore the combination of the two is expected to generate high risk premia in equilibrium. Thus, if the two-factor currency pricing model of Menkhoff et al. (2012a) explains the cross-section of future currency excess returns, the first core prediction is that during periods of high global FX volatility, the strategy of engaging in a conventional carry trade will provide a lower expected negative excess return per unit of systematic risk (i.e. volatility risk) taken than the strategy of shorting the funding currencies.

This is because in periods of high global FX volatility, the funding currencies are expected to generate rather low positive excess returns, as they are supposed to be hedges. Therefore, in periods of high global FX volatility, it should be more profitable, or at least less unprofitable, to short the funding currencies than to buy the investment currencies in a carry trade, which are expected to worsen the performance of the carry trade in particular. This prediction is consistent with equilibrium asset pricing theory, according to which assets with low (high) systematic risk benefit less (more) from market upturns in good times, but are also less (more) affected by market downturns in bad times (e.g., Pennacchi, 2008).

This prediction is also supported by the fact that low-interest rate currencies covary less with the dollar risk factor than high-interest rate currencies and therefore underperform less when the market does, i.e. during periods of high global FX volatility. Although less acknowledged in the literature, these betas with the dollar risk factor are not equal to one in the two-factor currency pricing model of Menkhoff et al. (2012a). In contrast to the currency pricing model of Lustig et al. (2011), where VOL is replaced by HML^{FX}, DOL therefore plays a more important role in explaining the cross-sectional variation in expected currency excess returns in the Menkhoff et al. (2012a) model, effectively serving more than the purpose of a constant, implying that the dollar risk factor is important for more than just the level of average excess returns.

The second core prediction is that, on average, and therefore particularly during periods of low or moderate global FX volatility, the strategy of engaging in a conventional carry trade will generate a higher expected positive excess return per unit of systematic risk (i.e. volatility risk) taken than the strategy of shorting the funding currencies.

This follows from the fact that the risk premium of carry trades depends crucially on whether the investment currencies offer their investors, on average, high, clearly positive excess returns, i.e. high compensation, which they have to generate in times of low or moderate global FX volatility. This is because, on average, investors in funding currencies have to accept low or even slightly negative returns as they pay a premium for their hedge properties against volatility risk. It follows, also supported by their low but positive beta to DOL, that their excess returns should not be so negative that the funding currencies contribute much to the risk premium of the carry trade when shorted in periods of low or moderate global FX volatility.

In conclusion, if there are pronounced market phases in which these two core predictions do not hold, it would be conceptually difficult to reconcile the consequences with the currency pricing model of Menkhoff et al. (2012a). This is because, from the perspective of the two-factor currency pricing model of Menkhoff et al. (2012a), both decisions - to enter into a carry trade instead of shorting the funding currencies in periods of high global FX volatility and to short the funding currencies instead of entering into a carry trade in periods of low or moderate global FX volatility - imply that the absolute betas of the funding currencies with global FX volatility innovations are significantly higher than the absolute betas of the investment currencies with global FX volatility innovations. But this would imply that, in these periods, funding currencies with high positive betas on global FX volatility innovations would offer large hedging profits in turbulent markets and therefore command high premiums for insurance against volatility risk. Conversely, investment currencies with much smaller negative betas on global FX volatility innovations would only need to offer small compensation, as they would experience rather small losses in turbulent markets.

Consequently, funding currencies would be subject to much higher volatility than investment currencies, making them effectively more risky than investment currencies during these periods. But this would challenge the risk-based explanation of Menkhoff et al. (2012a), as it essentially suggests that the relevance of systematic risk, i.e. the negative exposure of investment currencies to volatility risk, has diminished significantly in these periods.

4.3.4 Pricing classifier

Suppose that at the end of week t, i.e. at the beginning of the next strategies' holding period, we forecast the excess return of both the carry trade strategy and the strategy of shorting only the funding currencies for the next week t+1. Note that the two strategies are comparable in terms of the size of the investment and therefore result in the same absolute demand for one dollar of forward contracts. Assuming that equality is unlikely, there are two possible outcomes. Either the predicted excess return of the carry trade is greater than or less than the predicted excess return of shorting only the funding currencies.

However, anticipating future periods of high or low global FX volatility innovations is inherently difficult, if not unpredictable. This insight is addressed by Menkhoff et al. (2012a), who define innovations in global FX volatility as the residuals of an AR(1) process that are not autocorrelated, i.e. not correlated with their own lags. As a result, we may well be surprised by periods of high global FX volatility, but we cannot predict them accurately. Therefore, given the uncertainty about future global FX volatility, any prediction of future currency excess returns, for the two strategies as well, should essentially be based on the second core prediction of the Menkhoff et al. (2012a) currency pricing model, as this is the 'on average', i.e. 'in equilibrium' expectation.

Consequently, if at the end of week t, the carry trade offers a higher (lower) predicted excess return per unit of systematic volatility risk taken than the strategy of shorting only the funding currencies, we classify the following week t+1 as a conformity (contrarian) pricing regime because it would appear advantageous (not advantageous) to engage in a carry trade, which is consistent (contrary) to the 'in equilibrium' expectation of Menkhoff et al.'s (2012a) two-factor currency pricing model. It follows that if we normalise the positive and large (small positive or negative) expected excess returns of the carry trade (the strategy of shorting the funding currencies) by their negative estimated factor betas with global FX volatility innovations to one unit of systematic risk to account for the difference in beta levels between the two strategies, we expect the left side to be smaller than the right side of the following inequality:

$$\frac{\widehat{rx}_t^{CT}}{\hat{\beta}_t^{CT}\widehat{CVaR}_\alpha(Y_t^{CT})} < \frac{\widehat{rx}_{F,t}^{S}}{\hat{\beta}_t^{S}\widehat{CVaR}_\alpha(Y_{F,t}^{S})} \tag{4.3}$$

$\widehat{rx}_t^{CT}$ ($\widehat{rx}_{F,t}^{S}$) and $\widehat{CVaR}_\alpha(Y_t^{CT})$ ($\widehat{CVaR}_\alpha(Y_{F,t}^{S})$) are the one-step-ahead forecasts of the mean excess return and the CVaR of spot returns of the carry trade (short position in the funding currency) at the end of week t. And $\hat{\beta}_t^{CT}$ ($\hat{\beta}_t^{S}$) are the estimated factor betas of the conventional carry trade (short position in the funding currency) with global FX volatility innovations.

Note that in this paper we do not intend to develop superior predictors of excess returns, covariation or tail risk, but rather to derive an indicator of mispricing from the core predictions of the two-factor currency pricing model of Menkhoff et al. (2012a). Therefore, for the intended task, we use rather standard and well-established techniques in the financial economics literature to avoid data snooping or pre-optimisation. Consequently, we adopt the approach of Lustig et al. (2011) and Menkhoff et al. (2012a) and use rolling estimates of the factor betas, i.e. at the end of week t, we estimate the betas with global FX volatility innovations using the latest 156 weeks of available data, corresponding to three years. Note that we estimate the AR(1) process for the level of the global FX volatility proxy at the end of each week t using an expanding window. This updates the VOL risk factor each week as new data become available. In this way, we avoid look-ahead bias and estimate the betas with global FX volatility innovations out-of-sample (Menkhoff et al., 2012a).

Furthermore, we standardise the predicted mean excess returns by the CVaR of the spot returns, resulting in a risk-adjusted predictor of the risk premium related to the STARR or CVaR ratio (Stoyanov et al., 2007), as the mean spot returns and hence the mean excess returns can only be predicted under uncertainty. When comparing the estimated mean excess return of the two strategies on a weekly basis, the standardisation by CVaR helps to capture the risk that adverse movements in spot rates during the strategy's holding period may result in a significant deviation between the predicted mean excess return, i.e. the uncertain risk premium, and the actual excess return subsequently realised. This is all the more important given that the Spearman rank correlation coefficient between the long and short legs of the carry trade is -0.30. As a result, the average spot return CVaR of the conventional carry trade is statistically significantly lower than the average spot return CVaR of the strategy of shorting the funding currencies.

Note that we use the CVaR of spot returns rather than the CVaR of excess returns to standardise predicted excess returns because the forward discount is known in advance and modelling excess returns assuming a stochastic rather than a constant forward discount would lead to misspecification (see Section 4.4.3). Furthermore, we use CVaR because it allows us to capture both the potential losses from extreme events and the upside rewards and downside risks at the same time. As the distribution of currency spot returns deviates significantly from the normal distribution, the mathematical properties of CVaR provide a comprehensive assessment of risk and adequately reflect investor preferences compared to other risk measures such as variance (Brunnermeier et al., 2008; Rachev et al., 2007).

Since a violation of the second core prediction of Menkhoff et al.'s (2012a) two-factor currency pricing model suggests that either the investment or the funding currencies, or both, perform worse than expected (see Section 4.3.3), we develop (4.3) in a way that allows us to separate their individual performance contributions. To do this, we first multiply (4.3) by $\hat{\beta}_t^{CT}$. We then seek to obtain an additive decomposition of the CVaR ratio of the carry trade on the left side of (4.3) in order to separate the contributions of the long and short legs to the predicted CVaR ratio of the carry trade and express them as weightings of their own CVaR ratios. This can be achieved by first applying (4.9) from Section 4.4.2 to the left side of (4.3) and then multiplying the first resulting term by $\widehat{CVaR}_\alpha(Y^L_{I,t})/\widehat{CVaR}_\alpha(Y^L_{I,t})$ and the second resulting term by $\widehat{CVaR}_\alpha(Y^S_{F,t})/\widehat{CVaR}_\alpha(Y^S_{F,t})$, i.e. by 1 in both cases:

$$\frac{\widehat{CVaR}_\alpha(Y^L_{I,t})}{\widehat{CVaR}_\alpha(Y^{CT}_t)}\frac{\widehat{rx}^L_{I,t}}{\widehat{CVaR}_\alpha(Y^L_{I,t})}+\frac{\widehat{CVaR}_\alpha(Y^S_{F,t})}{\widehat{CVaR}_\alpha(Y^{CT}_t)}\frac{\widehat{rx}^S_{F,t}}{\widehat{CVaR}_\alpha(Y^S_{F,t})}\geq\frac{2\hat{\beta}^{CT}_{t+1}\widehat{rx}^S_{F,t}}{\hat{\beta}^S_t\widehat{CVaR}_\alpha(Y^S_{F,t})} \tag{4.4}$$

$\widehat{rx}^L_{I,t}$ and $\widehat{CVaR}_\alpha(Y^L_{I,t})$ denote the one-step-ahead forecasts of the mean excess return and the CVaR of spot returns of a long position in the investment currency at the end of week t.

It is important to note that the ratio $\hat{\beta}^{CT}_t/\hat{\beta}^S_t$ on the right is high when $\hat{\beta}^S_t$ is low, because the beta of the conventional carry trade with global FX volatility innovations is equal to the sum of the betas of the funding and investment currencies, i.e. $\hat{\beta}^{CT}_t=\hat{\beta}^S_t+\hat{\beta}^L_t$. This reflects that if the contribution of the long leg to the factor beta of the conventional carry trade with global FX volatility innovations is high, then the contribution of the long leg to the compensation (second core prediction) of the carry trade on the left side of (4.4) must be correspondingly high.

Consequently, we can rearrange (4.4) to isolate the contribution of the long leg to the CVaR ratio of the conventional carry trade on the left side of the inequality:

$$\frac{\widehat{CVaR}_\alpha(Y^L_{I,t})}{\widehat{CVaR}_\alpha(Y^{CT}_t)}\frac{\widehat{rx}^L_{I,t}}{\widehat{CVaR}_\alpha(Y^L_{I,t})}\geq\left(\frac{2\hat{\beta}^{CT}_t}{\hat{\beta}^S_t}-\frac{\widehat{CVaR}_\alpha(Y^S_{F,t})}{\widehat{CVaR}_\alpha(Y^{CT}_t)}\right)\frac{\widehat{rx}^S_{F,t}}{\widehat{CVaR}_\alpha(Y^S_{F,t})} \tag{4.5}$$

It follows from (4.5) that in periods when this inequality is false, there is a risk that the investment currencies will not meet the minimum requirement for their contribution to the predicted CVaR ratio of the conventional carry trade. This is when either the predicted performance of the investment currencies is actually too poor, or the predicted performance of the funding currencies is too poor, i.e. shorting only the funding currencies seems too profitable, or both. We use a four-week moving average for both sides of the inequality in order to smooth the time series and capture their short-term trends.

This is in line with the literature, which tends to use monthly data, and also helps to stabilise the trend so as to avoid frequent changes in the assessment of this inequality, especially in the course of a regime change. In addition, to infer the predicted pricing regime at the end of week t, we construct an indicator we call the ‘pricing classifier’. To do this, we take the difference between the two four-week moving averages, so that a value of the pricing classifier greater (less) than zero indicates a conformity (contrarian) pricing regime.

4.3.5 Expectations amid global FX volatility uncertainty

4.3.5.1 Possible scenarios

Recall the ambiguity that, given the unpredictability of innovations in global FX volatility, we cannot predict whether week t+1 is a period of low or high global FX volatility. This is true regardless of whether week t, at the end of which the forecasts of the components of inequality (4.5) are generated, is classified as a period of low or high global FX volatility. This unpredictability of global FX volatility innovations allows us in this section to derive four scenarios from the intersection of the predictions of the pricing classifier and the two-factor currency pricing model of Menkhoff et al. (2012a).

If it turns out that week t+1 is a period of low global FX volatility, i.e. the ‘on average’ or ‘in equilibrium’ expectation holds in t+1. Then we would expect the carry trade to actually generate a higher (lower) future excess return in the following week t+1 than the strategy of shorting only the funding currencies if we predict a conformity (contrarian) pricing regime, i.e. if inequality (4.5) is true (false).

Therefore, the first scenario, in which the forecast predicts a conformity pricing regime and the subsequent week is actually a week of low global FX volatility, is essentially consistent with the second core prediction and thus reflects the ‘on average’ or ‘in equilibrium’ expectation of Menkhoff et al.'s (2012a) two-factor currency pricing model.

However, the second scenario in which a violation of inequality (4.5) occurs during periods of low global FX volatility, i.e. a prediction of a contrarian pricing regime when the following week is actually a week of low global FX volatility, would be inconsistent with the second core prediction of Menkhoff et al.'s (2012a) two-factor currency pricing. This is because it would suggest that either only investment currencies underperform precisely when they are supposed to compensate for their exposure to systematic volatility risk, or that funding currencies also underperform precisely when they are supposed to generate low excess returns, but their excess returns should not be so negative as to make it competitively profitable to short them.

On the other hand, if we are surprised by high global FX volatility in the following week t+1, i.e. the 'on average' or 'in equilibrium' expectation does not materialise in t+1. Then the third scenario of possible outcomes would be that the forecast predicts a conformity pricing regime and the following week is actually a week of high global FX volatility. However, if we expect currencies with low (high) interest rates to generate low (high) excess returns in the following week. It is then likely that the full impact of the unexpectedly high global FX volatility will materialise in the market in the following week t+1. Currencies with low (high) interest rates should then be expected to perform rather well (poorly) in week t+1 amid a surprise increase in global FX volatility. Therefore, the third scenario is essentially consistent with the first core prediction and thus reflects the expectation of the Menkhoff et al.'s (2012a) two-factor currency pricing model for unexpectedly high systematic volatility shocks.

However, in the fourth scenario, where the forecast predicts a contrarian pricing regime and the following week is actually a week of high global FX volatility, the prediction of a contrarian pricing regime would unexpectedly coincide with the actual impact of high global FX volatility. Therefore, similar to scenario three, investment (funding) currencies should perform poorly (well) in week t+1 because they covary negatively (positively) with global

FX volatility innovations. However, there is a very important difference between the third and fourth scenarios. In contrast to the third scenario, we already expect a contrarian pricing regime at the end of week t when inequality (4.5) is predicted, i.e. we already expect the performance of the investment currencies to be too poor to compete with the strategy of shorting only the funding currencies, which is expected to be more profitable. Consequently, in the fourth scenario, the effect of unexpectedly high global FX volatility innovations may be weaker in scenario four than in scenario three, which would be inconsistent with the first core prediction of Menkhoff et al.'s (2012a) two-factor currency pricing.

4.3.5.2 Contrarian currency pricing

If the second (first) core prediction of Menkhoff et al.'s (2012a) two-factor currency pricing model is indeed violated in contrarian pricing regimes, which are periods of low (high) global FX volatility innovation. Then we should find that for the funding and investment currencies that together form the carry trade strategy, the difference in excess returns between periods of high and low global FX volatility innovation should be significantly larger, i.e. more positive for funding currencies and less negative for investment currencies, in contrarian than in conformity pricing regimes.

Consequently, we refer to this phenomenon as ‘contrarian currency pricing’ when the negative effect of high global FX volatility innovations is absent. If the negative effect of high global FX volatility innovations is absent for the most extreme carry trade portfolios, then it is likely to be absent for the portfolios in between, where it is less pronounced anyway (e.g., Menkhoff et al., 2012a), and thus for the entire cross-section of currency excess returns. In section 4.5.1, we test for the presence of contrarian currency pricing.

4.3.5.3 The predictable downside of carry trades

Regardless of whether the following week t+1 is a period of low or high global FX volatility, if the pricing classifier predicts a contrarian pricing regime at the end of week t, the incentive to enter into a carry trade should be low, as it does not appear to be profitable. Consequently, the prediction of a contrarian pricing regime may provide valuable ex ante information about when it is likely to be a bad decision to enter into a carry trade. This is in contrast to scenarios one and three, because since we cannot avoid being surprised by high global FX volatility innovations in scenario three, we have to hope for scenario one, i.e. hope that the following week t+1 will be a period of low rather than high global FX volatility innovations, if the pricing classifier predicts a conformity pricing regime. This is essentially the same dilemma of decision making under uncertainty as in the case without the pricing classifier.

As a result, the pricing classifier should contribute to better decision making by allowing investors to reduce their exposure to both periods of unexpectedly high global FX volatility (scenario four) and periods of low compensation for the systematic volatility risk taken (scenario two) by excluding those holding periods where the carry trade is a priori expected to perform too poorly and it is therefore undesirable to expose investment capital to the negative systematic volatility risk of the carry trade. We examine the profitability of the carry trade strategy under the four possible scenarios in section 4.5.2.

4.3.5.4 Contrarian currency pricing and return reversals

How should we interpret contrarian currency pricing? Theoretically, Fama's (1991) remark on the joint hypothesis problem highlights that it is ambiguous whether observed anomalies or abnormal return behaviour are due to market inefficiencies or to a limitation of the asset pricing model's ability to capture all relevant systematic risk factors. Consequently, we cannot rule out the existence of a rational expectations theory that would justify a systematic state variable that contributes to explaining the cross-sectional variation of currency excess returns in contrarian pricing regimes. However, a generally acceptable systematic risk-based explanation must show how currency excess returns covary with priced risk factors in contrarian pricing regimes in such a way that the most important common risk factor, carry, presumably becomes too weak to price the cross-section of currency excess returns under the 'in equilibrium' expectation of Menkhoff et al.'s (2012a) two-factor currency pricing model, and currencies still significantly covary with global FX volatility innovations as assumed by the model, while its core predictions are essentially rejected.

Therefore, we argue that contrarian currency pricing may signal a failure of the market to price risk efficiently, and if the prediction of contrarian pricing regimes essentially reflects the anticipation of mispricing, we should also find evidence of mean-reverting dynamics. In fact, financial theory would suggest that we should not expect periods of contrarian currency pricing to persist for long, as investors will increasingly engage in (buy) the strategy of shorting the funding currencies and sell the strategy of buying the investment currencies. They do so because continued shorting of the funding (investment) currencies leads to a lower (higher) expected future excess return on the strategy of shorting the funding currency (buying the investment currency), which is necessary to restore the second core prediction, i.e. the 'in equilibrium' condition of Menkhoff et al.'s (2012a) currency pricing model (e.g., Pennacchi, 2008).

Indeed, the pricing classifier may capture pricing imbalances by predicting contrarian pricing regimes when the predicted performance of investment or at the same time also funding currencies is low. This is because if the predicted CVaR is high and therefore the predicted performance is low, currencies may have experienced low average excess returns in the past, providing the discount to allow for higher excess returns in the future. Conversely, if currencies have low predicted excess returns and thus low predicted performance, they may trade at a premium and have low CVaR because they have experienced high average excess returns in the past.

Why should average excess returns in the past affect CVaR and lead to inverse excess returns in the future? Glosten et al. (1993) show that stocks are more volatile following negative returns than following positive returns. This may be because bad news (shocks) at the market level increase volatility more than good market news due to the interaction of volatility feedback and leverage effects, while for news at the firm level it is mainly the opposite leverage effect that amplifies (offsets) the volatility associated with bad (good) shocks (Bekaert & Wu, 2000).

As greater uncertainty about future price changes increases the risk of providing liquidity or engaging in arbitrage, a higher CVaR may be more likely to prevent the correction of mispricing, causing underperforming currencies to deviate further from their intrinsic value than outperforming currencies. Therefore, the priced discount for currencies with high CVaR and low past excess returns may be even larger than the priced premium for currencies with low CVaR and high past excess returns, ultimately leading to larger reversals as prices realign to allow for higher future carry trade excess returns again, consistent with the underlying risk-based explanatory approach (e.g., Cheng et al., 2017). In Section 4.5.3, we examine whether contrarian pricing regimes reveal a predictable reversal component in currency excess returns.

4.4 Empirical Framework

4.4.1 Data

To ensure efficient estimation of the econometric model presented in section 4.4.3, we use a weekly rather than the more common monthly data frequency. Higher data frequencies are not used because they tend to be very noisy, which can affect the estimation results. Dao et al. (2016) find that spot prices of seven major currency pairs overreact over the weekend. To avoid the weekend effect caused by unusually high or low weekend price gaps and subsequent price reversals, we do not use Friday's close or Monday's open prices in calculating currency excess returns, but collect one-week closing forward and spot exchange rates on Wednesday (e.g., Chong & Miffre, 2010).

Our data set comes from WM/Refinitiv, which is sourced from Refinitiv Eikon Datastream. The spot rates used to estimate the econometric model cover the period from June 6, 1990 to February 8, 2023. The forward rates used to calculate excess returns cover the period from 6 January 1999 to 8 February 2023. Following Burnside et al. (2011a), we multiply GBP/FCU quotes by USD/GBP quotes to obtain the longer sample of spot rates against the dollar. We choose 6 January 1999 as the starting date for our out-of-sample study in order to avoid biased cross-sectional estimation results that could arise from extrapolating relationships to significantly different samples before and after the introduction of the euro and from using data or information that was not available or known during the study period, as would be the case, e.g., if the euro were included through a proxy time series prior to its introduction.

We do not consider emerging market currencies because first they are intertwined with the credit risk of their respective sovereigns, and the composition of their currency risk premia is therefore different from that of more established currencies (Daniel et al., 2017). Second, we find that some emerging market currencies temporarily violate the covered parity condition (see also Bakshi & Panayotov, 2013). Therefore, in order to avoid problems of selection bias and to make our study more comparable with the literature, we follow the recent literature (e.g., Bekaert & Panayotov, 2020; Chernov et al., 2023) and consider the liquid Group of Ten (G10) currencies (AUD, CAD, CHF, EUR, GBP, JPY, NZD, NOK, SEK and USD), as these are the most commonly used currencies for constructing carry trades both in the financial economics literature and in professional portfolio management.

4.4.2 Currency and carry trade excess returns

From the perspective of a US investor, the currency excess return of a foreign investment over a domestic investment at the US interest rate is equal to the residual return that results if, at the end of week t, money is borrowed in US dollars (USD) at the domestic interest rate i^d, that amount is converted into foreign currency units (FCU) at the exchange rate S_t and invested at the foreign interest rate i^f, the proceeds are finally converted back into USD at the exchange rate S_{t+1} at the end of week t+1, and the debt is repaid (Bekaert & Hodrick, 2018). Let F_t denote the one-week forward rate in FCU per USD at the end of week t and maturity at the end of week t+1, where $F_t = S_t \cdot \frac{1+i_t^f}{1+i_t^d}$. Following the literature (e.g., Menkhoff et al., 2012a), we denote discrete spot (forward) rates as S_t (F_t) and log spot (forward) rates as s_t (f_t) and use logarithms in the following sections for ease of presentation, but use discrete excess returns in the cross-sectional portfolio analyses. For a long position, it is agreed at time t to purchase F_t FCU after one week at time t+1 at the forward rate F_t in the forward market against payment of $\frac{F_t\ \text{FCU}}{F_t \frac{\text{FCU}}{\text{USD}}} = 1$ USD. These F_t FCU are then sold in the spot market at time t+1 at the spot rate S_{t+1} for $\frac{F_t\ \text{FCU}}{S_{t+1} \frac{\text{FCU}}{\text{USD}}} = \frac{F_t}{S_{t+1}}$ USD. Consequently, the log currency excess return is (e.g., Bekaert & Hodrick, 2018):

$$rx_{t+1}^L = \ln\left(\frac{\frac{F_t}{S_{t+1}} - 1}{1}\right) = \ln\left(\frac{F_t - S_{t+1}}{S_{t+1}}\right) = f_t - s_{t+1} \tag{4.6}$$

For a short position, on the other hand, it is agreed at time t to sell F_t FCU after one week at time t+1 at the forward rate F_t in the forward market for $\frac{F_t\ FCU}{F_t \frac{FCU}{USD}} = 1$ USD. In order to do this, F_t FCU must first be purchased in the spot market at the spot rate S_{t+1} at time t+1 against payment of $\frac{F_t\ FCU}{S_{t+1} \frac{FCU}{USD}} = \frac{F_t}{S_{t+1}}$ USD. Thus, the log currency excess return is:

$$rx_{t+1}^{S} = \ln\left(\frac{1 - \frac{F_t}{S_{t+1}}}{\frac{F_t}{S_{t+1}}}\right) = \ln\left(\frac{S_{t+1} - F_t}{F_t}\right) = s_{t+1} - f_t \tag{4.7}$$

The log forward discount fd_t at the end of week t indicates whether a foreign currency is traded at a discount (premium) in the forward market, i.e. whether it is cheaper (more expensive) to buy in the forward market than in the spot market (e.g., Bekaert & Hodrick, 2018; Lustig et al., 2011):

$$fd_t = \ln\left(i_t^f - i_t^d\right) \approx f_t - s_t \tag{4.8}$$

To construct a carry trade, we follow the literature and sort all foreign currencies in ascending order of forward discount. We use the forward discount to sort currencies because it is equivalent to sorting by the interest rate differential under covered interest rate parity and is therefore appropriate to indicate the carry of currencies, i.e. their excess return if their spot price remains unchanged over the holding period (e.g., Koijen et al., 2018; Lustig et al., 2011; Menkhoff et al., 2012a). The carry trade is then the long-short portfolio formed by purchasing a portfolio of currencies with the largest forward discounts and simultaneously selling a portfolio of currencies with the smallest forward discounts.

As the weights of the carry trade portfolio sum to zero, it is a zero-cost strategy that is dollar-neutral as its excess return is unaffected by the bilateral exchange rate of the US dollar against all other currencies (e.g., Hassan & Mano, 2019). Following Bakshi and Panayotov (2013), we assume an absolute demand for forward contracts of size one dollar in each period, reflecting the interpretation that one bets half a dollar on both the investment and funding leg of the carry trade. Thus, at the end of week t+1, the log excess return of a carry trade that aims to exploit the widest spread in forward discounts and therefore uses one currency on each leg is, in USD terms, as follows

$$rx_{t+1}^{CT} = \frac{rx_{I,t+1}^{L} + rx_{F,t+1}^{S}}{2} \tag{4.9}$$

where $rx_{I,t+1}^{L}(rx_{F,t+1}^{S})$ is the log excess return of a long (short) position in the investment (funding) currency.

4.4.3 Econometric model

The assumption of Markowitz (1952) in the Modern Portfolio Theory and Fama (1970) in the Efficient Markets Hypothesis that asset returns are normally distributed and random, i.e. in particular that they exhibit no distorting ‘effects’, has been shown to be unrealistic by a large body of empirical evidence (e.g., Cont, 2001). Well-known stylised facts such as autocorrelation in returns, heteroskedasticity, leptokurtic and asymmetric return distributions as well as the leverage effect of volatility and dynamic correlations lead to a complex behaviour in currency spot return dynamics that deviates considerably from the i.i.d. assumption (e.g., Engle, 1982; Engle, 2002).

To avoid misspecification with the consequences of biased weekly one-step-ahead forecasts of the currencies’ mean spot return and CVaR, we use a time-varying t-copula with skewed t-GJR-GARCH margins to forecast the joint distribution of spot returns of the G10 currencies. In doing so, we take into account recent findings that recommend appropriate modelling of the multivariate return distribution to capture both univariate stylised facts and time-varying dependencies in the tails of the marginal distributions (e.g., Dovern & Manner, 2020; Kim et al., 2021). Further, Hertrich (2023) finds that this model correctly predicts the CVaR for G10 currencies, i.e. neither underestimates nor overestimates the CVaR, as the null hypothesis of correct forecasts at the 2.5% α-quantile of both the one-sided and two-sided intercept expected shortfall regression backtest of Bayer and Dimitriadis (2020) cannot be rejected.

In this model, based on Sklar (1959) and Patton (2006), the joint distribution $F(\mathbf{y}_t)$ of $\mathbf{Y}_t$ is modelled by associating the probability integral transformed uniformly distributed random variables of $\mathbf{Y}_t$, which have individual marginal distributions to account for univariate properties, with a dependence structure given by a time-varying n-dimensional Student t-copula $C(\mathbf{u}_t;R_t,\eta)$ with conditional correlation matrix R_t and unconditional shape parameter η:

$$F(y_{1,t},\ldots,y_{n,t}) = C(F_1(y_{1,t}),\ldots,F_n(y_{n,t});R_t,\eta) \tag{4.10}$$

R_t is assumed to follow the dynamic conditional correlation model (DCC) of Engle (2002), where the conditional variance-covariance matrix H_t is decomposed as $H_t = D_tR_tD_t$ and $D_t = \text{diag}\{\sqrt{h_{j,t}}\}$ represents the diagonal matrix of the conditional standard deviations to separate univariate and multivariate dynamics, thus allowing for a two-step estimation process.

In the first stage, the conditional mean of the marginal distributions is described by an AR(1) process with constant to capture the autocorrelation in the univariate return series. The conditional variances $h_{j,t}$ are estimated using the GJR-GARCH(1,1) model of Glosten et al. (1993) to account for asymmetric effects of positive and negative error terms on $h_{j,t}$:

$$Y_{j,t} = \varphi_j + \delta_j Y_{j,t-1} + \varepsilon_{j,t},$$

$$\varepsilon_{j,t} = \sqrt{h_{j,t}}Z_{j,t}, \text{where } Z_{j,t} \sim T_j(z_{j,t};0,1,\xi_j,\nu_j),$$

$$h_{j,t} = \omega_j + \alpha_j\varepsilon_{j,t-1}^2 + \gamma_j\varepsilon_{j,t-1}^2 I(\varepsilon_{j,t-1} < 0) + \beta_j h_{j,t-1} \tag{4.11}$$

The usual GARCH restrictions employed are ($\omega_j>0$, $\alpha_j\geq0$, $\beta_j\geq0$) to ensure positivity of $h_{j,t}$ and $|\delta_j|<1$ as well as $\alpha_j+\beta_j+\gamma_j\kappa_j<1$ to ensure stationarity, where κ_j is the expected value of the standardized residuals $\mathbf{Z}_t = (Z_{1,t},\ldots, Z_{n,t})'$ below zero. $Z_{j,t}$ are assumed to follow the standardized skewed Student distribution of Fernandez and Steel (1998) to capture the asymmetry of the marginal distributions. ξ_j and ν_j denote the unconditional skew and shape parameter, respectively. κ_j equals $1/1+\xi_j^2$ (Laurent, 2002).

R_t corresponds to the correlation matrix of the random vector $\mathbf{Z}_t^* = (Z_{1,t}^*,\ldots, Z_{n,t}^*)'$ due to the invariance property of copulas. $Z_{j,t}^* = T_{j,t}^{-1}(T_j(Z_{j,t};0,1,\xi_j,\nu_j);\eta)$ is transformed to have a Student t-distribution with η degrees of freedom. To allow for time-varying correlations, an autoregressive, moving-average process is modelled in the second stage

$$Q_t = (1\text{-}a\text{-}b)\bar{Q} + a\mathbf{Z}_{t-1}^*\mathbf{Z}_{t-1}^{*'} + bQ_{t-1} \tag{4.12}$$

with $a,b \geq 0$ and the restriction $a+b < 1$ imposed to ensure stationarity and positive definiteness of Q_t and R_t. $\bar{Q}$ is the unconditional correlation matrix of $\mathbf{Z}_t^*$, that is $E(\mathbf{Z}_t^*\mathbf{Z}_t^{*'})$, which is estimated with the sample covariance matrix of $\mathbf{Z}_t^*$. The quasi-correlations Q_t have to be rescaled to ensure that the diagonal elements equal 1 and the off-diagonal elements lie in [-1,1] at all times, so R_t is obtained by (Ausin & Lopes, 2010; Engle, 2002):

$$R_t = \mathrm{diag}(Q_t)^{-\frac{1}{2}}\, Q_t\, \mathrm{diag}(Q_t)^{-\frac{1}{2}} \tag{4.13}$$

The joint density function of $\mathbf{Y}_t$ is then given by (e.g., Ausin & Lopes, 2010):

$$f(\mathbf{y}_t;\, \mu_t,h_t,R_t,\eta) = \frac{t(z_{1,t}^*,\ldots,z_{n,t}^*;\, R_t,\eta)}{\prod_{j=1}^{n} t_j\left(z_{j,t}^*;\, 0,1,\eta\right)} \prod_{j=1}^{n} \frac{1}{\sqrt{h_{j,t}}}\, t_j\left(z_{j,t};\, 0,1,\xi_j,\nu_j\right) \tag{4.14}$$

Using the 'Inference Functions for Margins' (Joe & Xu, 1996), the log-likelihoods of the marginal densities are first maximised to obtain the univariate parameters, and then the parameters of the copula are estimated using $\mathbf{Z}_t^*$ from the first step.

To construct the pricing classifier, we need both a one-step-ahead forecast of the mean excess return and the CVaR of spot returns. To obtain the latter, discrete scenarios of size m of one-step-ahead spot returns $\hat{y}_{j,k,t} \in \mathbb{R}^{nxm}$, $j = 1,\ldots, n$ and $k = 1,\ldots, m$ for $\mathbf{Y}_t$ are generated by simulation at the end of week t. To this end, uniformly distributed random variables are first simulated from the estimated copula using a forecast of the conditional correlation matrix $\widehat{R}_t$. Then, standardised innovations are generated by inserting the uniformly distributed random variables into each quantile function of the standardised marginal distribution using the estimated individual currency shape and skew parameters. Standardised innovations and forecasts of the conditional variances are then inserted into the conditional mean equations to obtain $\widehat{Y}_t$. Note, $\hat{y}_{j,k,t}$ must be multiplied by -1 to obtain the simulated scenario spot returns associated with a short position. A one-step-ahead forecast of the CVaR corresponds to the mean of spot returns below the α-quantile (Stoyanov et al., 2007)

$$\widehat{CVaR}_\alpha(Y_{j,t}) = \frac{1}{\lfloor M\alpha \rfloor} \sum_{k=1}^{\lfloor M\alpha \rfloor} (-1)\, \hat{y}_{j,(k),t} \tag{4.15}$$

where $\hat{y}_{j,(k),t}$ represents the return scenarios sorted in ascending order and $\lfloor M\alpha \rfloor$ is the largest integer less than or equal to $M\alpha$, where $M\alpha$ indicates the location of the VaR at the confidence level α. We set α at 2.5%, in line with the Basel Accord (Basel Committee on Banking Supervision, 2019). Finally, a one-step-ahead forecast of the mean excess return for a long position and a short position is calculated as follows

$$\widehat{rx}_{j,t}^{L} = f_{j,t} - s_{j,t} - \widehat{\varphi}_j - \widehat{\delta}_j y_{j,t-1}$$

$$\widehat{rx}_{j,t}^{S} = s_{j,t} - f_{j,t} + \widehat{\varphi}_j + \widehat{\delta}_j y_{j,t-1} \tag{4.16}$$

where $\widehat{\varphi}_j$ and $\widehat{\delta}_j$ correspond to the parameters of the mean equation estimated at the end of each week t. Since the forward rate f_t maturing at the end of week t+1 is known in advance at the end of week t, we compute the one-step-ahead forecast of the mean excess return by using the one-step-ahead forecast of the mean spot return generated by the GJR-GARCH(1,1) model (4.11) within the first step of maximising the joint density function of $\mathbf{Y}_t$ (4.14). This means that we model spot returns rather than excess returns, since assuming a stochastic rather than a constant (ex ante known) forward discount would lead to misspecification.

4.5 Empirical results

4.5.1 The impact of contrarian currency pricing

In this section, we test whether, in contrarian pricing regimes, there is indeed a contrarian currency pricing effect in the cross-section of currency excess returns due to the violation of the two core predictions of Menkhoff et al.'s (2012a) two-factor currency pricing model. To do this, we first sort all G10 currencies into nine portfolios each week from 6 January 1999 to 15 March 2023, based on an ascending order of forward discounts as calculated in (4.8). Portfolios are rebalanced at the end of each week, i.e. after a holding period of one week. Second, to capture contrarian and conformity pricing regimes, we define two dummy variables, one for each pricing regime of interest. The Contrarian (Conformity) dummy variable takes the value one if the pricing classifier at the end of week t is negative (positive), thus predicting a contrarian (conformity) pricing regime for the subsequent holding period. Note that only historical observations already available at the end of each week are used for estimation and forecasting, in order to avoid a look-ahead bias. Consequently, the first estimation of the econometric model and the first forecasts of the mean spot return and CVaR for each currency to compute the pricing classifier are made on 6 January 1999, the first business Wednesday of the euro. We use data from 6 June 1990 to 6 January 1999 to obtain the first one-step-ahead forecasts of the mean spot return and CVaR for each currency for the end of the week from 7 January 1999 to 13 January 1999. The latest forecasts are from 15 March 2023 for the end of the week from 16 March 2023 to 22 March 2023, resulting in a total of 1263 weekly forecasts. Third, to capture periods of low and high global FX volatility innovations, we adopt the approach of Menkhoff et al. (2012a) and define periods of high global FX volatility innovations as the 25% of weeks with the highest realisations. We choose this approach to avoid customised methods and to ensure comparability. The HighVOL (LowVOL) dummy variable takes the value one if the realisation of the risk factor

VOL at the end of week t+1, i.e. if the innovation of the global FX volatility at the end of the holding period of the strategy is higher (lower) than the upper quartile of all realisations of VOL.

We then stack the excess returns and dates of, on the one hand, all carry trade portfolios (Dollar sample, as this essentially reflects the composition of the Dollar risk factor, i.e. the entire cross-section of currency excess returns) and, on the other hand, only the investment and funding currencies (HML sample) and run the following pooled panel regression for both samples:

$$rx^{L}_{j,t+1} = \beta_1 + \beta_2 Contrarian_{t+1} + \beta_3 HighVOL_{t+1} + \beta_4 Contrarian_{t+1} \times HighVOL_{t+1} + \varepsilon_{j,t+1} \quad (4.17)$$

These pooled panel regressions allow us to compare the contrarian pricing regimes with the conformity pricing regimes, correcting the difference in excess returns between periods of high and low global FX volatility innovation in the contrarian pricing regimes by accounting for the difference in excess returns between periods of high and low global FX volatility innovation in the conformity pricing regimes.

In essence, this reflects a difference-in-difference regression approach, with the contrarian pricing regimes thus representing the treatment group that presumably experienced a change in the environment and thus exhibit currency pricing that is inconsistent with the prediction of Menkhoff et al.'s (2012a) two-factor currency pricing model. The conformity pricing regimes represent the non-treated control group. This approach is based on the parallel trend assumption that in the absence of the contrarian pricing effect, i.e. the average treatment effect on the treated (ATT), the difference in excess returns between periods of high and low global FX volatility innovation would have been the same in both regimes. The imputation of this counterfactual outcome trend has raised concerns about producing biased difference-in-difference estimates if the observed trend in the outcomes of the control units does not adequately capture the trend in the outcomes of the treatment units had they received no treatment (Baker et al., 2022). However, from the perspective of the two core predictions of Menkhoff et al.'s (2012a) currency pricing model, there is no theoretical justification why the cross-section of carry trade portfolios should behave differently in contrarian pricing regimes than in conformity pricing regimes. This is because, on the one hand, Table 4.1 shows that conformity and contrarian pricing regimes contain almost equal proportions of periods of low (715/953 vs. 230/310) and high (238/953 vs. 80/310) global FX volatility innovation. Therefore, the ‘on average’ effect of global FX volatility innovations should be similar in contrarian pricing regimes if they had not been treated as in conformity pricing regimes.

Table 4.1
The prevalence of contrarian currency pricing regimes

	Contrarian	Conformity	
LowVOL	230	715	945
HighVOL	80	238	318
	310	953	1263

Note: Table 4.1 shows the number of observations in the periods covered separately by the LowVOL, HighVOL, Conformity and Contrarian dummy variables. The sample period is January 1999 to March 2023.

On the other hand, a violation of the two core predictions of the currency pricing model of Menkhoff et al. (2012a) is expected to lead to homogeneous treatment effects across all carry trade portfolios. That is, in principle, for the entire cross-section of carry trade portfolios, the difference in excess returns between periods of high and low global FX volatility innovation should be significantly larger when treated (in a contrarian pricing regime) than when not treated (in a conformity pricing regime).

Following the financial literature (Petersen, 2009; Thompson, 2011), we compute standard errors clustered by time and group. We account for time effects, i.e. errors may be arbitrarily correlated across currencies at any point in time, which seems appropriate given that periods of high or low market volatility typically affect the financial market as a whole, and thus all carry trade portfolios are simultaneously sensitive to global FX volatility innovations. We also allow standard errors to account for within-currency correlation, i.e. errors for a given currency may be arbitrarily correlated over time. This seems appropriate given that unobserved currency-specific effects may affect all observations for that currency over time. Such idiosyncratic characteristics of currencies may be reflected in persistent interest rate differentials, which typically define prototypical investment and funding currencies (e.g., Bekaert & Panayotov, 2020), or in persistent comparative productivity advantages between final goods-producing and commodity-producing economies (e.g., Ready et al., 2017).

Since we have a large number of time periods, we follow Thompson (2011) and also account for the potential correlation between different currencies in different weeks, i.e. for persistent common shocks. Therefore, as suggested by Thompson (2011), we account for common effects that may affect the error term for up to two months, assuming that after two months the correlation between shocks should have decayed sufficiently to be ignored. Overall, the computed standard errors are robust to any dependence structure within each currency or within each week, and to the cross-serial correlation between the excess returns of different currencies up to two lagged months (Croissant & Millo, 2019). As a result, they may be too conservative, but they reduce the risk of overestimating the significance of the results and prevent erroneous inferences.

Table 4.2 shows that the estimated coefficient β_4 of the interaction term in the Dollar sample (HML sample) is 0.27% (0.29%) per week, implying that the effect of contrarian currency pricing is both economically very large and statistically significant. Consequently, the difference in excess returns between periods of high and low global FX volatility innovations is, on average, significantly larger, i.e. less negative, in the contrarian pricing regimes than in the conformity pricing regimes. This poses a serious challenge to the risk-based explanation of Menkhoff et al. (2012a), as it essentially implies that the negative effect of high global FX volatility innovations on currency excess returns in both the Dollar and the HML sample is significantly lower and even diminishes in contrarian pricing regimes (0.035% and 0.081%) than in conformity pricing regimes (-0.235% and -0.21%).

Table 4.2
The impact of contrarian currency pricing on future carry trade excess returns

Dollar sample				HML sample			
	Contrarian	Conformity			Contrarian	Conformity	
LowVOL	-0.064	0.086*	-0.15**	LowVOL	-0.047	0.095	-0.142**
HighVOL	-0.029	-0.149	0.12	HighVOL	0.034	-0.115	0.149
	0.035	-0.235**	0.27*		0.081	-0.21	0.291**

Note: Table 4.2 shows coefficients estimates of the impact of contrarian currency pricing on the average excess returns (in percent per week) of carry trade portfolios. The Dollar sample includes all nine portfolios formed by sorting on forward discount, while the HML sample includes only the portfolios 1,2,8 and 9, i.e. the portfolios that form the carry trade strategy HML^{FX}. Following Thompson (2011), standard errors are clustered by time and at the portfolio level and are robust to persistent common shocks of up to two months. *, ** and *** indicate significance at the 10%, 5% and 1% level. The sample period is January 1999 to March 2023.

Furthermore, Table 4.2 provides evidence that the carry trade portfolios in the Dollar sample (HML sample) perform on average 0.12% (0.149%) per week better in periods of high global FX volatility innovations when these periods are predicted as contrarian pricing regimes than when these periods are predicted as conformity pricing regimes. The differences may not be statistically significant, but in economic terms they are large. Consequently, at least the economic intuition implies a violation of the first core prediction of the two-factor currency pricing model of Menkhoff et al. (2012a), as investment (funding) currencies generate substantially less negative (more positive) excess returns than expected, making it more profitable, or at least less unprofitable, to engage in a carry trade instead of only shorting funding currencies during contrarian pricing regimes that turn out to be periods of high global FX volatility innovations.

Table 4.2 also provides evidence that the carry trade portfolios in the Dollar sample (HML sample) perform on average -0.15% (-0.142%) per week worse in periods of low global FX volatility innovations when these periods are predicted as contrarian pricing regimes than when these periods are predicted as conformity pricing regimes. This underperformance is both economically large and statistically significant. Consequently, these findings imply a violation of the second core prediction of the two-factor currency pricing model of Menkhoff et al. (2012a), as investment (funding) currencies generate significantly less positive (more negative) excess returns than expected, making it more profitable to only short funding currencies instead of engaging in a carry trade during contrarian pricing regimes that turn out to be periods of low global FX volatility innovations.

4.5.2 Contrarian currency pricing and the cross-section of excess returns

In this section, we conduct a univariate portfolio analysis to examine the cross-sectional relationship between forward discount and currency excess returns, conditional on the regime prediction of the pricing classifier. The main objective is to test whether a contrarian pricing regime is indeed an unfavourable period for carry trades.

Following Menkhoff et al. (2012a), we regress the excess returns of the nine forward discount sorted portfolios and HML^{FX} on the risk factors DOL and VOL and a constant. We then regress both the excess returns and the risk-adjusted excess returns of the portfolios on the two global FX volatility dummy variables without an intercept to test whether the excess returns and alphas are zero in each volatility regime. The same is done using the pricing regime dummy variables and interaction terms between global FX volatility and pricing regime dummy variables.

Consistent with the two-factor currency pricing model of Menkhoff et al. (2012a), Table 4.3 shows that in periods of high global FX volatility innovation, the alpha of HML^{FX} is insignificant because investment (funding) currencies perform particularly poorly (well) when the average excess return of the dollar risk factor is low and high global FX volatility innovations decrease (increase) their performance. Consequently, the performance of HML^{FX} cannot be explained by the two risk factors, DOL and VOL, in periods of low global FX volatility innovation because investment (funding) currencies compensate for their exposure to volatility risk (demand a premium to hedge against volatility risk).

However, the main observation in Table 4.3 is that the average excess return and the average alpha of HML^{FX} are only statistically significant in the conformity pricing regime, but not in the contrarian pricing regime. This is striking because the conformity and contrarian pricing regimes contain almost equal proportions of periods of low and high global FX volatility innovation, and thus the impact of contrarian currency pricing weakens the relationship between forward discounts and currency excess returns to an extent that would not be expected purely from the perspective of Menkhoff et al.'s (2012a) currency pricing model.

In particular, in contrarian pricing regimes, which turn out to be periods of low global FX volatility innovation, we find that the excess returns of HML^{FX}, both in terms of raw and risk-adjusted excess returns, are low precisely when they should be high according to Menkhoff et al.'s (2012a) currency pricing model.

Looking at sections five and seven of Table 4.3, we see that the average systematic excess return of carry trade portfolio nine (one) falls from 0.13% (0.00%) per week in the conformity pricing and low global FX volatility regimes to -0.05% (-0.11%) per week in the contrarian pricing and low global FX volatility regimes. Similar conclusions apply to portfolios four to eight. The average risk-adjusted excess return, i.e. the average idiosyncratic excess return not explained by risk factors, falls much less sharply for carry trade portfolio 9, from 0.09% to 0.04% per week. For carry trade portfolio 1, it even increases slightly from -0.07% to -0.03% per week. Similar conclusions apply to portfolios two and three.

Table 4.3
Pricing classifier and excess returns of portfolios sorted by forward discount

	1	2	3	4	5	6	7	8	9	HML^{FX}
Low global FX volatility regime										
rx	-0.08**	-0.03	0.02	-0.01	0.07	0.06	0.07	0.19***	0.17***	0.24***
α	-0.06*	-0.05	-0.03	-0.04	0.01	-0.01	0.00	0.10***	0.08***	0.14***
High global FX volatility regime										
rx	0.20*	0.01	-0.01	0.01	-0.14	-0.29***	-0.19*	-0.30***	-0.22	-0.36***
α	-0.07	-0.05	-0.04	0.03	0.01	-0.06	0.06	0.04	0.08	0.12
Conformity pricing regime										
rx	0.00	-0.03	-0.02	0.02	0.05	-0.01	0.03	0.10*	0.11*	0.12***
α	-0.07*	-0.07**	-0.05	-0.02	0.03	-0.02	0.02	0.09***	0.09***	0.16***
Contrarian pricing regime										
rx	-0.04	0.01	-0.05	-0.08	-0.10	-0.09	-0.07	-0.03	-0.04	-0.02
α	-0.04	0.03	0.00	-0.04	-0.04	-0.02	0.01	0.05	0.04	0.05
Conformity pricing and low global FX volatility regime										
rx	-0.07	-0.03	0.04	0.04	0.10**	0.09**	0.12**	0.25***	0.22***	0.28***
α	-0.07*	-0.07**	-0.04	-0.03	0.01	-0.02	0.00	0.11***	0.09**	0.17***
Conformity pricing and high global FX volatility regime										
rx	0.18	-0.05	-0.20*	-0.04	-0.10	-0.31***	-0.23*	-0.35**	-0.25	-0.37**
α	-0.07	-0.08	-0.07	0.00	0.07	-0.04	0.06	0.03	0.10	0.14
Contrarian pricing and low global FX volatility regime										
rx	-0.14**	-0.06	-0.07	-0.17**	-0.05	-0.03	-0.06	0.01	-0.01	0.10
α	-0.03	0.02	-0.01	-0.10**	0.01	0.02	-0.01	0.05	0.04	0.05
Contrarian pricing and high global FX volatility regime										
rx	0.24	0.19	0.01	0.18	-0.24	-0.25	-0.09	-0.15	-0.14	-0.36
α	-0.07	0.07	0.03	0.11	-0.19	-0.11	0.05	0.07	0.05	0.06

Note: Table 4.3 shows the average excess return and the average risk-adjusted excess return (in percent per week) for each of the portfolios formed by sorting by forward discount and for the carry trade strategy HML^{FX}. First, the results are shown for the periods covered separately by the LowVOL, HighVOL, Conformity and Contrarian dummy variables. Then the results are shown for the periods resulting from the intersection of the two corresponding categorical effects. *, ** and *** indicate significance according to Newey-West (1994) HAC standard errors at the 10%, 5% and 1% levels, respectively. The sample period is January 1999 to March 2023.

This implies that the underperformance of HML^{FX} in contrarian pricing regimes with low global FX volatility, as predicted by the pricing classifier, is to a significant extent due to the much lower systematic excess returns of the investment currencies.

To summarise, these univariate regression analyses provide evidence that in the 310 weeks, i.e. almost a quarter of the entire period under consideration, in which the pricing classifier predicts a contrarian pricing regime at the end of week t, an investor should indeed avoid entering into a carry trade for the following week t+1. This is because, for these holding periods, it is not only predicted, but will actually be the case, that the average compensation of the investment currencies will be too low and the average premium of the funding currencies too unfavourable to risk exposing the investment capital to the negative systematic volatility risk of the carry trade. Consequently, exclusively following the conventional investment rule of the carry trade, while ignoring the predictive information contained in the pricing classifier, would run a significant risk of impairing the investor's wealth accumulation, as the 'on average' or 'in equilibrium' expectation of the two-factor currency pricing model of Menkhoff et al. (2012a) overestimates, i.e. does not optimally exploit, the profit opportunity of the carry trade, i.e. the forward premium, in contrarian pricing regimes.

In Section 4.3.3, we discussed that contrarian currency pricing may be consistent with the core predictions of Menkhoff et al.'s (2012a) currency pricing model when the absolute betas of funding currencies with global FX volatility innovations are significantly higher than the absolute betas of investment currencies. However, Table 4.4 shows that while the negative betas of high interest rate currencies appear to be slightly less negative, the positive betas of low interest rate currencies are also less positive. Overall, as the differences between the two pricing regimes are mostly insignificant, they cannot explain the cross-sectional excess return differences between contrarian and conformity pricing regimes.

Table 4.4
Pricing classifier and betas of carry trade portfolios with global FX volatility

	1	2	3	4	5	6	7	8	9	HML^{FX}
Conformity pricing regime (n = 953)										
β^{VOL}	1.17^{***}	0.65^{***}	0.21^{***}	0.23^{***}	-0.19^{***}	-0.17^{***}	-0.38^{***}	-0.81^{***}	-1.02^{***}	-1.82^{***}
Contrarian pricing regime (n = 310)										
β^{VOL}	1.13^{***}	0.50^{***}	0.32^{***}	0.37^{***}	-0.24^{**}	-0.39^{***}	-0.56^{***}	-0.69^{***}	-0.78^{***}	-1.55^{***}
Difference	0.04	0.15	-0.11	-0.14	0.05	0.22^{**}	0.18^{*}	-0.12	-0.24^{*}	-0.27

Note: Table 4.4 shows, for each of the portfolios formed by sorting by forward discount and for the carry trade strategy HML^{FX}, the average beta with global FX volatility innovations in conformity and contrarian pricing regimes, as well as the difference in betas between the two pricing regimes. Factor betas are estimated at the end of week t using a rolling window of 156 weeks. *, ** and *** indicate significance according to Newey-West (1994) HAC standard errors at the 10%, 5% and 1% levels, respectively. The sample period is January 1999 to March 2023.

4.5.3 Predictability of return reversals

4.5.3.1 Rationale for the choice of predictors

To derive the first predictor, we need to decide how to determine whether a currency has become more (less) risky during a period of low (high) excess returns. In particular, we are interested in whether CVaR has increased (decreased) to an extent that would not have been expected if excess returns had not been so low (high) in the recent past. To this end, we use a measure recently proposed by Hertrich (2023), as this measure uses a combination of well-known and fairly standard trend-following rules, namely the time-series momentum of Moskowitz et al. (2012) and the variable-length moving average rules of Brock et al. (1992), to determine the magnitude of a recent change in CVaR. The general idea behind this measure is that currency excess return volatility is time-varying (e.g., Engle, 1982; Engle, 2002), with stationarity implying mean-reverting dynamics. This assumption also underlies the GJR-GARCH(1,1) model of Glosten et al. (1993) used in Section 4.4.3. Stationarity implies that the variance at each level will always converge to its unconditional mean in the long run, even though new information in the form of an additional innovation may disrupt the return path, depending on its strength and intensity.

We refer to Hertrich (2023) for more details on the construction of this measure, but note here that we use the same CVaR forecasts as in the pricing classifier to predict the pricing regime for the following week t+1, but for all G10 currencies, not just funding and investment currencies. That is, we first subtract from the one-step-ahead CVaR forecasts at the end of week t the moving average of the L previous one-step-ahead CVaR forecasts to obtain the trend signal $CS_{j,t,L}$ at lag length L:

$$CS_{j,t,L} = \widehat{CVaR}_{\alpha}(Y_{j,t}) - \frac{\widehat{CVaR}_{\alpha}(Y_{j,t-L}) + \ldots + \widehat{CVaR}_{\alpha}(Y_{j,t-1})}{L} \tag{4.18}$$

Second, following the suggestion of Han et al. (2016), we average over all trend signals at lag lengths of 1-, 2-, 4-, 10-, 21-, 31-, and 41-weeks, corresponding to 5-, 10-, 20-, 50-, 100-, 150-, and 200-days, to obtain the indicator $CT_{j,t}$, named CVaR-Trend. As volatility, and therefore CVaR, is persistent, the CVaR-Trend indicator captures not only large and persistent deviations from a level that may be appropriate for CVaR based on its recent trajectory. CVaR-Trend also contains information on the magnitude of the price decrease (increase) required to account for the discount (premium) that allows for higher (lower) expected excess returns (e.g., Bekaert & Wu, 2000). Indeed, Hertrich (2023) shows that low (high) CVaR-Trend currencies have recently experienced large appreciations (depreciations), which is consistent with the asymmetric volatility effect.

Next, we sort all G10 currencies into nine portfolios in ascending order of CVaR-Trend at the end of each week over the period from 6 January 1999 to 15 March 2023. Figure 4.1 shows the most recent 42 weekly one-step-ahead forecasts of the spot CVaR used to construct CVaR-Trend for the G10 currencies prior to portfolio construction, i.e. on the basis of which currencies are allocated to these nine univariate portfolios at the end of each week t. In particular, if CVaR-Trend indicates an increase (decrease) in the level of CVaR at the end of week t compared to the reference period of the previous 41 weeks, the shift in CVaR appears to become significant around 12 weeks or around 3 months earlier, and the upward (downward) evolution of this trend then increases (decreases).

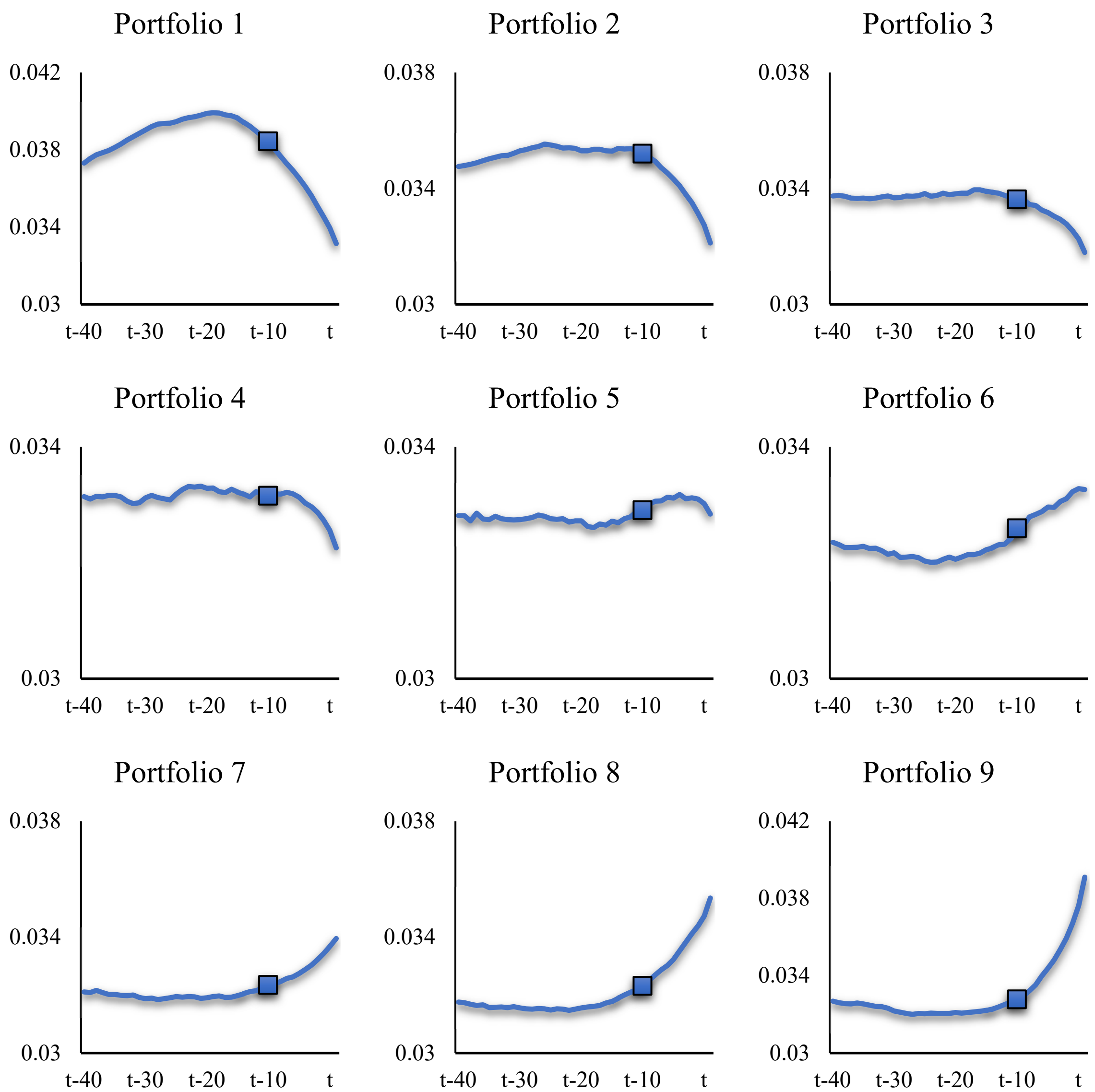

Figure 4.1. Evolution of CVaR forecasts. This figure shows the most recent 42 weekly one-step-ahead CVaR forecasts for the spot rate of the currency assigned to each of the portfolios, sorted by CVaR-Trend at the end of week t. The data point that marks the beginning of the 12-week period prior to the calculation of CVaR-Trend is highlighted by a rectangle. The sample period is January 1999 to March 2023.

Importantly, linking the change in a currency's CVaR to its past excess return is obviously related to the momentum effect, as this 12-week or three-month period is consistent with the empirical evidence that currency excess returns contain momentum, especially for this period, as a longer formation period does not provide any additional benefit (Menkhoff et al., 2012b). Raza et al. (2014) also find strong evidence in favour of short-term momentum and against short-term reversals in weekly currency excess returns. In addition, Zhang (2022) finds that 'on average' systematic excess returns contain strong momentum in the first twelve months after portfolio formation, but idiosyncratic excess returns do not, so the momentum in total excess returns arises from the momentum in currency risk factors and only summarises their autocorrelation.

If we revisit the finding in Table 4.3 that the impact of contrarian currency pricing is largely driven by the low average systematic excess returns of investment currencies. Then the evidence from Zhang (2022) implies that in contrarian pricing regimes, following low carry trade excess returns, investment currencies are more likely to be sorted into the short leg of momentum strategies, which thus short the carry risk factor and make it more likely that factor or systematic momentum will continue to be low. Consequently, if low average excess returns in the past are indicative of the incorporation of a discount to account for an increase in CVaR and predict higher future excess returns, it is more likely to be the idiosyncratic excess returns rather than the systematic excess returns that contain this information about impending excess return reversals.

To ensure that the first predictor variable is a measure of the global (aggregated) change in the level of CVaR, i.e. that it captures the cross-sectional variation in changes in CVaR, we calculate the average CVaR-Trend across all foreign currencies at the end of week t:

$$CT_t^{FX} = \frac{1}{n}\sum_{j=1}^{n} CT_{j,t} \tag{4.19}$$

To decompose currency excess returns into systematic excess returns driven by currency risk factors and idiosyncratic excess returns unexplained by risk factors, we follow Zhang (2022). That is, we regress the excess returns of the G10 currencies on the systematic risk factors

DOL, VOL and HML^{FX} and a constant at the end of each week. Note that unlike Zhang (2022), we also include the VOL risk factor, as global FX volatility and the HML^{FX} risk factor are not identical, as they are negatively correlated (Menkhoff et al., 2012a). The omission of VOL may therefore prevent a proper decomposition of total excess returns into their systematic and idiosyncratic components. For consistency, we use the same rolling regression scheme as for the construction of the pricing classifier, i.e. at the end of each week t we estimate the following regression using the latest 156 weeks of available data, with the VOL risk factor updated each week as new data become available:

$$rx_{j,t} = [\text{systematic excess return}] + [\text{idiosyncratic excess return}]$$

$$= \left[\hat{\beta}_j^{DOL} \cdot DOL_t + \hat{\beta}_j^{VOL} \cdot VOL_t + \hat{\beta}_j^{HML^{FX}} \cdot HML_t^{FX}\right] + \left[\hat{\alpha}_j + \hat{\varepsilon}_{j,t}\right] \tag{4.20}$$

We standardise the residual excess returns over the three-year estimation period:

$$rx_{j,t}^{idio} = \frac{\hat{\varepsilon}_{j,t}}{\sqrt{\sum_{t-155}^{t}\left(\hat{\varepsilon}_{j,t}-\bar{\hat{\varepsilon}}_j\right)^2}} + \hat{\alpha}_j \tag{4.21}$$

Standardisation takes into account the empirical evidence that raw residual excess returns can be noisy, as it improves the quality of interpretation of the residual excess return as true currency-specific information by reducing possible biases due to pure noise (Gutierrez & Prinsky, 2007). Idiosyncratic momentum is then obtained as the average of volatility-scaled idiosyncratic log excess returns in the 12-week period prior to the prediction of the pricing regime at the end of week t:

$$iMOM_{j,t} = \frac{1}{12}\sum_{\tau=11}^{0} rx_{j,t-\tau}^{idiosyncratic} \tag{4.22}$$

Accordingly, using (4.20), the systematic momentum is as follows:

$$sMOM_{j,t} = \frac{1}{12}\sum_{\tau=11}^{0} rx_{j,t-\tau}^{systematic} \tag{4.23}$$

Similar to CT_t^{FX} we obtain global (aggregated) predictor variables for idiosyncratic momentum $iMOM_t^{FX}$ and systematic momentum $sMOM_t^{FX}$ as the averages of $iMOM_{j,t}$ and $sMOM_{j,t}$ across all currencies.

In addition to these predictors derived from the hypothesised relationship between currency excess returns and contrarian currency pricing, we consider as controls three additional theoretically motivated predictor variables that have been shown to be able to predict carry trade excess returns (e.g., Bakshi & Panayotov, 2013; Opie & Riddiough, 2020). The fourth predictor variable we use is the average log return of the S&P GSCI industrial metals spot price index in the 12-week period prior to the prediction of the pricing regime at the end of week t:

$$\Delta GSCI_t = \frac{1}{12} \ln\left(\frac{GSCI_t}{GSCI_{t-11}}\right) \tag{4.24}$$

The use of a commodity-based predictor is motivated by the fact that there are several ‘commodity currencies’ among the G10 investment currencies, such as AUD, NOK and NZD (Chen & Rogoff, 2003). When the prices of their commodities rise, their export revenues increase, leading to an improvement in their ‘terms of trade’, which is often associated with an appreciation of their currencies, which is why higher commodity prices predict higher carry trade excess returns for G10 currencies (e.g., Bakshi & Panayotov, 2013; Ready et al., 2017).

The fifth predictor variable we use is the average log change in the level of aggregated global FX volatility, i.e. the proxy before the AR(1) process is estimated to obtain the VOL risk factor (see Section 4.3.1), in the 12-week period prior to the prediction of the pricing regime at the end of week t:

$$\Delta\sigma_t^{FX} = \frac{1}{12} \ln\left(\frac{\Delta\sigma_t^{FX}}{\Delta\sigma_{t-11}^{FX}}\right) \tag{4.25}$$

The rationale for using a volatility-based predictor is that Menkhoff et al. (2012a) have shown that the profitability of carry trades should be inversely related to changes in aggregate global FX volatility (see Section 4.3.3). This predictor is essentially the same as the one used by Bakshi and Panayotov (2013), with the exception that we calculate the weekly average of the daily cross-sectional averages of the absolute rather than the squares of the daily log changes in the spot rate.

The sixth predictor is a measure of global FX liquidity, computed as in Menkhoff et al. (2012a) as a measure of a global bid-ask spread, which is subject to the same aggregation scheme as global FX volatility. This means that we first calculate the weekly average of the daily cross-sectional averages of the percentage bid-ask spread of each currency on each day within each week t. We then compute the average log change in the level of aggregated global FX liquidity in the 12-week period prior to the prediction of the pricing regime at the end of week t:

$$\Delta\sigma_t^{LIQ} = \frac{1}{12}\ln\left(\frac{\Delta\sigma_t^{LIQ}}{\Delta\sigma_{t-11}^{LIQ}}\right) \tag{4.26}$$

The rationale for using a liquidity-based predictor is that higher liquidity, as indicated by a decline in bid-ask spreads, leads to lower transaction costs. This, in turn, may lead to increased activity in carry trades, leading to higher carry trade excess returns (Bakshi & Panayotov, 2013). Brunnermeier et al. (2009) provide a theoretical basis for this relationship and show how favourable (tighter) liquidity conditions can reduce (increase) borrowing costs and induce traders to open (close) carry trade positions, thereby positively (negatively) affecting excess returns.

4.5.3.2 Predictability of excess return reversals

In this section, we regress the next week's excess return of the carry risk factor HML^{FX} on the six predictor variables described in Section 4.5.3.1 using the difference-in-difference regression approach to test whether contrarian pricing regimes exhibit a predictable reversal component. For clarity, Scenario two is used as the reference category in all regression models.

Table 4.5 presents the coefficient estimates, which show that the slope estimates for $iMOM^{FX}$ (CT^{FX}) in scenario two are uniformly negative (positive) across all three specifications. These slope estimates are consistent with the interpretation that $iMOM^{FX}$ (CT^{FX}) predicts negative (positive) short-term excess returns of the carry risk factor HML^{FX} in contrarian pricing regimes, which are periods of low global FX volatility innovation. Furthermore, these coefficients are statistically significant, the only exception being the coefficient 0.43 of CT^{FX} in specification 3, where the addition of $\Delta\sigma^{FX}$ slightly reduces the predictive power of CT^{FX}. Nevertheless, these slope estimates do indeed imply the existence of information about impending excess return reversals of the carry risk factor. That is, the low average excess returns in contrarian pricing regimes, which are periods of low global FX volatility innovation of both funding and investment currencies, as documented in Table 4.3, ultimately provide both the increase in CVaR and the required discount, which then leads to a lower (higher) expected future excess return on the strategy of shorting the funding currency (buying the investment currency), which is necessary to restore the second core prediction, i.e. the 'in equilibrium' condition of Menkhoff et al.'s (2012a) currency pricing model.

For scenario four, we find negative slope estimates for both $iMOM^{FX}$ and CT^{FX}. The change in sign for CT^{FX} can be rationalised with the intuition that the excess returns of HML^{FX} are low following an unexpected increase in global FX volatility.

Table 4.5
Predictability of excess returns of the carry risk factor HML^{FX}

	(1)	(2)	(3)
Intercept	0.05	0.04	0.03
ΔGSCI		-0.26**	-0.27**
$\Delta\sigma^{FX}$			0.02
$\Delta\sigma^{LIQ}$		-0.05	-0.06
$iMOM^{FX}$	-0.54*	-0.65**	-0.66**
$sMOM^{FX}$	0.00	0.01	0.01
CT^{FX}	0.72**	0.53*	0.44
Conformity	0.23***	0.24***	0.25***
HighVOL	-0.67***	-0.66***	-0.80***
Conformity × HighVOL	0.02	0.01	0.02
ΔGSCI × Conformity		0.21	0.21
$\Delta\sigma^{FX}$ × Conformity			-0.01
$\Delta\sigma^{LIQ}$ × Conformity		0.04	0.05
$iMOM^{FX}$ × Conformity	0.31	0.42	0.43
$sMOM^{FX}$ × Conformity	-0.01	-0.02	-0.02
CT^{FX} × Conformity	-0.66*	-0.50	-0.44
ΔGSCI × HighVOL		0.02	0.12
$\Delta\sigma^{FX}$ × HighVOL			-0.15**
$\Delta\sigma^{LIQ}$ × HighVOL		0.21	0.18
$iMOM^{FX}$ × HighVOL	-0.82	-0.92	-0.51
$sMOM^{FX}$ × HighVOL	-0.15***	-0.16***	-0.16***
CT^{FX} × HighVOL	-3.99***	-4.43***	-3.28***
ΔGSCI × Conformity × HighVOL		0.26	0.18
$\Delta\sigma^{FX}$ × Conformity × HighVOL			0.05
$\Delta\sigma^{LIQ}$ × Conformity × HighVOL		-0.18	-0.15
$iMOM^{FX}$ × Conformity × HighVOL	1.58	1.66	1.19
$sMOM^{FX}$ × Conformity × HighVOL	0.18***	0.15**	0.16**
CT^{FX} × Conformity × HighVOL	2.80**	3.60**	2.85**
Adj. R^2	0.06	0.06	0.07
n	1263	1263	1263

Note: Table 4.5 reports the coefficient estimates from a predictive OLS difference-in-difference regression of the log HML^{FX} excess returns at the end of week t+1 on the values of the six predictor variables at the end of week t, as described in Section 4.5.3.1, and on the interaction terms of the predictors with the Conformity and HighVOL dummy variables, as well as on the interaction term Conformity × HighVOL. *, ** and *** indicate significance according to Newey-West (1994) HAC standard errors at the 10%, 5% and 1% levels, respectively. The sample period is January 1999 to March 2023.

That is, a significant shock increase in global FX volatility will naturally lead to both low excess returns and an increase in the cross-sectional average level of CVaR in week t+1. However, given the much higher persistence of CVaR relative to global FX volatility innovations, a high level of CT^{FX} may lead to even larger reversal effects once volatility spikes have subsided. At least the lower size of $iMOM^{FX}$ seems to imply this conclusion.

Turning to the $sMOM^{FX}$ estimates, we find that the treatment effect, i.e. the difference-in-difference estimator, is significantly positive in all three specifications. This implies that systematic excess returns contain momentum, consistent with Zhang (2022), in conformity pricing regimes rather than in contrarian pricing regimes. Presumably, it is precisely this strength of factor momentum that explains why systematic excess returns in contrarian pricing regimes do not negatively predict short-term excess returns for the carry risk factor HML^{FX} and thus do not seem to contribute to realigning prices with the equilibrium condition of Menkhoff et al.'s (2012a) currency pricing model.

We note that while the coefficients of the control predictors mostly have signs consistent with those reported in the literature (e.g., Bakshi & Panayotov, 2013), they are mostly insignificant. Thus, with respect to $\Delta\sigma^{LIQ}$, our results support the notion of Bakshi and Panayotov (2013) that global FX liquidity may be of secondary importance at short frequencies, i.e. weekly or even monthly. The lower predictive power of $\Delta\sigma^{FX}$ is most likely due to the simultaneous use of CT^{FX}, as these two predictors have a Spearman rank correlation of 0.36, which is highly significant.

The only surprise is the significance of the negative coefficients on ΔGSCI in contrarian pricing regimes, which turn out to be periods of low global FX volatility. Given that ΔGSCI is significantly and highly positively correlated with $sMOM^{FX}$ but essentially uncorrelated with $iMOM^{FX}$, this result suggest that commodity currencies may play a role in explaining why systematic excess returns do not contribute to restoring the second core prediction, i.e.

the ‘in equilibrium’ condition of Menkhoff et al.'s (2012a) currency pricing model. This relationship may be fruitful, but we leave it for future research.

4.5.3.3 CVaR-Trend and idiosyncratic momentum

The Spearman rank correlation between CT and iMOM is -0.05, which is slightly but statistically significantly negative. The negative correlation suggests that a reversal strategy may benefit from sorting dependently on CVaR-Trend as the control variable (the first sorting variable) and on idiosyncratic momentum as the risk dimension to be priced (the second sorting variable). This is because a univariate sort on idiosyncratic momentum yields a low (high) iMOM portfolio that is distorted by currencies that have not experienced an increase (decrease) in CVaR. A reversal strategy that avoids holding unprofitable but not unexpectedly riskier currencies and avoids selling profitable but not unexpectedly less risky currencies should therefore better capitalise on the cross-sectional information about the ongoing price adjustment that reconciles prices with the risk-based explanatory approach of the Menkhoff et al. (2012a) currency pricing model.

To test these predictions, at the end of each week in the period from 6 January 1999 to 15 February 2023, all currencies are allocated into three groups based on an ascending sort of CVaR-Trend as the control variable. Within each control variable group, the three currencies are then sorted into three portfolios based on an ascending sort of idiosyncratic momentum. A currency is classified as ‘low iMOM’ (‘high iMOM’) if it has an iMOM lower (higher) than two-thirds of the currencies in the same CVaR-Trend tertile. We choose a tertile sort on $iMOM_t$ within CT_t tertiles as this breakpoint selection is consistent with the suggestions of Lambert et al. (2020) and the recent literature (e.g., Cespa et al., 2022).

We then regress the risk-adjusted excess returns relative to the risk factors DOL, HML^{FX} and VOL of the nine portfolios formed from the conditional double sorting on the two pricing regime dummy variables with no intercept to test whether the alphas are equal to zero in each pricing regime. Panel A of Table 4.6 shows that in contrarian pricing regimes, currencies in the high (low) CVaR-Trend tertile appear to perform particularly well (poorly) precisely when they exhibit lower (higher) levels of idiosyncratic momentum.

Table 4.6
Pricing classifier and double sorts on CVaR-Trend and idiosyncratic momentum

Panel A: Excess returns of portfolios sorted by CVaR-Trend and iMOM

Conformity pricing regimes

		CVaR-Trend						CVaR-Trend			
	rx	1	2	3	HML		α	1	2	3	HML
iMOM	1	0.02	0.03	0.07	0.05	iMOM	1	0.00	0.00	0.04	0.04
	2	0.07	0.03	-0.01	-0.08		2	0.04	0.01	-0.03	-0.07
	3	0.01	-0.01	0.01	0.00		3	-0.01	-0.04	0.01	0.02
	HML	-0.01	-0.04	-0.06			HML	-0.01	-0.04	-0.03	

Contrarian pricing regimes

		CVaR-Trend						CVaR-Trend			
	rx	1	2	3	HML		α	1	2	3	HML
iMOM	1	-0.08	-0.05	0.10	0.18**	iMOM	1	-0.03	0.00	0.16***	0.19***
	2	-0.07	-0.04	-0.12	-0.05		2	-0.03	0.01	-0.06	-0.03
	3	-0.19***	0.01	-0.05	0.14*		3	-0.13***	0.06	0.01	0.14*
	HML	-0.11	0.06	-0.15*			HML	-0.10	0.06	-0.15**	

Panel B: Excess returns of a cross-sectional currency reversal strategy

	Conformity pricing regimes	Contrarian pricing regimes
rx	0.06	0.29***
α	0.05	0.29***

Note: Panel A of Table 4.6 shows the average excess return (rx) and the average risk-adjusted excess return (α) in percent per week for portfolios dependent sorted by CVaR-Trend and iMOM, as well as for the long-short difference portfolios HML in each tertile of CVaR-Trend and iMOM, following conformity and contrarian pricing regimes. Panel B shows equivalent information for a cross-sectional currency reversal strategy that is long (short) in the low (high) iMOM portfolio within the high (low) CVaR-Trend tertile following conformity and contrarian pricing regimes. *, ** and *** indicate significance according to Newey-West (1994) HAC standard errors at the 10, 5 and 1% level, respectively. The sample period is January 1999 to March 2023.

This is because the average risk-adjusted excess return of 0.16% (-0.13%) per week is both economically and statistically highly significant with a t-statistic of 3.80 (2.60). These results confirm the prediction that controlling for CVaR-Trend improves the performance of reversal strategies based on idiosyncratic momentum.

Consequently, as shown in Panel B of Table 4.6, the average risk-adjusted excess return of a cross-sectional currency reversal strategy that is long in the high CT and low iMOM portfolio, i.e. in 'high-risk loser' currencies, and short in the low CT and high iMOM portfolio, i.e. in 'low-risk winner' currencies, is 0.29% per week, which is both economically very large and highly statistically significant with a t-statistic of 4.30.

4.6 Conclusion

The objective of this study is to investigate the value of forward-looking information about future violations of the equilibrium expectation of the two-factor currency pricing model of Menkhoff et al. (2012a). The main contribution of our paper to the literature is the construction of a predictive indicator, called the 'pricing classifier', which defines a minimum requirement for the contribution of the long position in the investment currency to the expected risk-adjusted performance of the carry trade. The pricing classifier predicts 'conformity' ('contrarian') pricing regimes when it predicts that the performance of the investment currencies will be too poor to be consistent with the underlying risk-based explanation of the two-factor currency pricing model of Menkhoff et al. (2012a).

The second result is that for the funding and investment currencies that together form the carry trade strategy, the difference in excess returns between periods of high and low global FX volatility innovation is significantly larger, i.e. more positive for funding currencies and less negative for investment currencies, in contrarian than in conformity pricing regimes. We refer to this phenomenon as 'contrarian currency pricing' when both the negative impact of high global FX volatility innovations on currency excess returns and thus the relevance of systematic volatility risk, i.e. the negative exposure of investment currencies to volatility risk, diminish in contrarian pricing regimes. Third, we find clear implications for a reduced equilibrium model in contrarian pricing regimes, where one would favour omitting the systematic HML^{FX} risk factor, as it appears to have little power to price the cross-section of G10 currency excess returns in these periods. As a direct consequence of this result, an investor would prefer not to enter into a carry trade in contrarian pricing regimes because the carry trade is a priori expected to perform too poorly and it is therefore undesirable to expose investment capital to the negative systematic volatility risk of the carry trade.

Finally, we provide empirical evidence that contrarian pricing regimes reveal a predictable reversal component in currency excess returns. We find that idiosyncratic momentum (changes in risk) negatively (positively) predicts short-term excess returns for the carry risk factor HML^{FX}. Consequently, a reversal strategy that avoids holding unprofitable but not unexpectedly riskier currencies and avoids selling profitable but not unexpectedly less risky currencies is very successful in exploiting the cross-sectional information about this adjustment, which in turn aligns prices more closely with the risk-based explanatory approach of the Menkhoff et al. (2012a) currency pricing model.

Our findings have important implications for the management of portfolios invested in G10 currencies. Since we find that the pricing classifier predicts a contrarian pricing regime in almost a quarter of the entire period under consideration, it allows to better time the construction of a portfolio strategy according to the conventional carry trade investment rule and to better assess the prospects of success. Moreover, our contribution to the understanding of pricing in contrarian pricing regimes contributes to a unified explanation of the cross-section of G10 currency excess returns.

5 Diversification Benefits of the Contrarian Pricing Trade

5.1 Introduction

Solnik (1974) showed that investing in global equities allows investors to benefit from international portfolio diversification, which is a natural consequence of Markowitz's (1952) mean-variance portfolio optimisation. The benefit of international diversification comes from the fact that monetary policies and business cycles are not perfectly correlated across countries. This allows investors to reduce the systematic risk arising from purely domestic sources that affect companies' cash flow prospects and the discount rates used to value those cash flows (Bekaert & Hodrick, 2018). However, exchange rate risk can have a significant impact on the overall risk-return profile of foreign currency investments when converted into domestic currency, so investors need to decide to what extent they want to hedge. That is, they need to find an optimal currency overlay, i.e. a currency strategy that optimally complements a predetermined long position in a foreign equity portfolio (Barroso et al., 2021; Opie & Riddiough, 2020).

However, there is still no consensus in the literature on how to optimally hedge foreign exchange risk, although the prevailing view since Solnik (1993) has been that the highest benefits can be achieved through a hedging strategy that is neither fully hedged nor unhedged. In particular, there is a growing body of literature suggesting that investors can effectively diversify their existing international equity portfolio with specific FX investment styles. Such a ‘separate’ currency investment approach requires the construction of an independent currency portfolio, which is then combined with a global equity portfolio (Opie & Riddiough, 2020). Previous research has shown that overall portfolio performance can be significantly improved if investors are not restricted to hedging only existing currency exposures, but also establish strategic currency positions to profitably participate in speculative currency movements (e.g., Barroso & Santa-Clara, 2015; Barroso et al., 2021; Dupuy, 2021; Kroencke et al., 2014; Mulder & Tims, 2018; Opie & Riddiough, 2020).

In particular, our paper contributes to the literature studying this specific type of currency hedging by extending recent findings on the predictability of contrarian pricing regimes. These are periods in which the negative effect of high global FX volatility innovations on currency excess returns documented in Menkhoff et al. (2012a) seems to be absent and the specific carry trade strategy using two currencies on both the investment and funding legs, i.e. Lustig et al.'s (2011) currency risk factor HML^{FX}, is found to be unable to explain the cross-section of G10 currency excess returns (Hertrich, 2024).

Given that the carry trade is well established as a popular FX strategy among institutional currency fund managers and accounts for a large share of trading volume in FX markets (e.g., Aloosh & Bekaert, 2022; Galati et al., 2007; Pojarliev & Levich, 2008), we expect that this ex ante available information on the profitability of carry trades should be relevant for the construction of an augmented carry trade strategy, i.e. a novel FX investment style that we call the 'contrarian pricing trade'. We then ask whether adding the contrarian pricing trade to a benchmark portfolio of a US investor internationally invested in the G10 currency economies significantly improves the overall performance of the portfolio.

The remainder of the paper is structured as follows. Section 5.2 presents the literature review and discusses how this paper contributes to the relevant literature. Section 5.3 provides an overview of our methodology for assessing the diversification benefits of FX investment styles, presents the data and explains the calculation of the benchmark portfolio return without and with adjustment for FX investment styles. We also describe the inclusion of FX transaction costs, equity rebalancing costs and margin requirements. Section 5.4 explains the three FX investment styles, carry, momentum and value, which we use as a benchmark for the diversification benefits of the contrarian pricing trade, the construction of which is also explained in this section. Section 5.5 then presents the empirical results, while section 5.6 summarises the key findings and their main implications.

5.2 Literature review

There is an ongoing debate in the literature on how to optimally hedge currency risk. Initial approaches include the extreme of full hedging (e.g., Perold & Schulman, 1988; Solnik, 1974) or leaving currency exposure unhedged (e.g., Froot, 1993). Perhaps even more extreme, Black (1989) suggests that a universal hedging strategy is optimal for all investors, regardless of portfolio composition and reference currency. Campbell et al. (2010) argue that holding unhedged equity positions in currencies that are negatively correlated with international equity markets is a natural hedge because an appreciation of the foreign currency will partially offset low foreign currency equity returns, thereby obviating the need for further hedging. However, De Roon et al. (2012) argue for unhedged foreign equity positions, as natural hedging typically involves selling currencies with the highest returns and buying safe haven currencies with the lowest returns, thereby negatively affecting overall portfolio performance. Solnik (1993) showed that the optimal hedging strategy depends on the individual portfolio composition due to cross-correlations between different currencies and asset classes, as well as on investor preferences. This implies that neither fully hedged nor unhedged can be optimal and that, contrary to Black (1989), there is no universal hedging ratio. These findings are strongly supported by Glen and Jorion (1993), who find that adding currency hedging strategies that exploit the predictability of currency excess returns from forward discounts to a portfolio of stocks and bonds statistically significantly improves portfolio performance. Similarly, Campbell et al. (2010) suggests that timing the tilt of the currency overlay towards higher-yielding currencies improves overall portfolio performance.

In this respect, research on optimal currency hedging has benefited immensely from recent advances in the predictability of excess returns from the information contained in currency characteristics and risk premia (e.g., Della Corte et al., 2016a; Dupuy, 2015; Fan et al., 2022; Gao et al., 2019; Lettau et al., 2014; Lustig et al., 2011; Menkhoff et al., 2012a; Verdelhan, 2018; Zhang, 2022). For example, Opie and Riddiough (2020) develop an approach that exploits information from a predictable component in the two global risk factors of the Lustig et al. (2011) currency pricing model. Filipozzi and Harkmann (2020) show that carry trades play a crucial role in the optimal hedging of currency risk. Barroso et al. (2021) propose a currency hedging strategy that incorporates the predictive information contained in several currency characteristics such as interest rates, value, carry and momentum. Most relevant to our study, Hertrich (2023) shows that a variable capturing the magnitude of the recent change in risk, called CVaR-Trend, predicts the cross-section of G10 currency excess returns, and Hertrich (2024) shows that forecasts of mean spot returns of currencies and their conditional value at risk allow to predict violations of the 'in equilibrium' condition of Menkhoff et al.'s (2012a) currency pricing model, and that there is information about reversals necessary to restore this condition. We contribute to this strand of the literature by showing that this predictable component of violations of the Menkhoff et al. (2012a) currency pricing model allows to augment the carry trade strategy, which is then a strong diversification instrument for US investors holding a portfolio of global equities, as it significantly improves the overall portfolio performance, which was not investigated by Hertrich (2023, 2024).

In addition, the success of currency overlay strategies appears to increase with the complexity of the econometric models used, as these models appear to capture the multivariate distribution of asset and currency returns more effectively (e.g., Boudoukh et al., 2019; Christensen & Varneskov, 2021; Cho et al., 2019; De Roon et al., 2003; Hsu et al., 2008; Polak & Ulrych, 2024). Furthermore, there is growing evidence in the literature that hedge effectiveness and portfolio performance can be improved by using tail risk measures such as Value at Risk or Expected Shortfall instead of variance, especially in combination with dynamic estimation techniques (e.g., Álvarez-Díez et al., 2016; Guo & Ryan, 2018; Harris & Shen, 2006; Topaloglou et al., 2002). We contribute to these two strands of literature by showing that the information embedded in changes in the level of the conditional value at risk of currencies provides valuable predictive information for effectively diversifying a global equity portfolio.

Finally, our paper contributes in three aspects to the strand of research that examines whether overall investment performance is improved when the objective is to add strategic currency positions to a portfolio rather than to hedge existing currency exposures. Kroencke et al. (2014) and Opie and Riddiough (2020) find evidence that the FX investment styles carry trade, momentum and value offer economically large and significant diversification benefits beyond those of hedging currency risk. Das et al. (2013), Barroso and Santa-Clara (2015), Mulder and Tims (2018) and Reichenecker (2019) also show that strategic currency positions can improve the risk-return profile of a benchmark equity portfolio. First, we provide evidence that the suitability of conventional carry trades as a diversification instrument for a global equity portfolio declined significantly after the global financial crisis, a finding that is not reflected in Kroencke et al. (2014) or in subsequent studies. However, this finding is consistent with evidence showing that the performance of conventional carry trade strategies declined sharply after the global financial crisis (Fan et al., 2022). Second, we show that the contrarian pricing trade is highly profitable in its own right and competes very successfully with carry, momentum and value, especially in the post global financial crisis era. Third, we show that the contrarian pricing trade has safe haven characteristics as defined by Baur and McDermott (2010), as it significantly improves the risk-return profile of a global equity portfolio during periods of market turmoil. Ranaldo and Söderlind (2010) also examine the safe haven characteristics of currencies, and Habib and Stracca (2012) examine the factors that determine the safe haven characteristics of a currency. However, they examine individual currencies rather than FX investment styles, so they do not take into account the predictive information contained in the risk premia in the cross-section of currency excess returns.

5.3 Empirical research design

5.3.1 Methodology

To analyse the diversification benefits of the contrarian pricing trade and competing FX investment styles, we take the perspective of a US investor holding a predetermined GDP-weighted global equity portfolio of developed economies. We focus on the economies with the most liquid currencies, the G10 currencies, to avoid selection bias and to make our study comparable to previous literature that has examined the diversification potential of FX investment styles (e.g., Barroso et al., 2021; Campbell et al., 2010; Kroencke et al., 2014; Opie & Riddiough, 2020). Moreover, the contrarian pricing trade exploits violations of the Menkhoff et al. (2012a) currency pricing model when applied to G10 currencies, and may not be applicable to emerging market currencies without adjustment, as these currencies are intertwined with their sovereign credit risk and have a different composition of currency risk premia than G10 currencies (Daniel et al., 2017).

We choose to weight global equities according to their relative share of GDP based on purchasing power parity, as this is consistent with DeMiguel et al. (2009), who show that more sophisticated approaches, such as mean-variance optimisation, do not outperform a naive strategy in terms of Sharpe ratio. Since a simple benchmark portfolio also facilitates the attribution of diversification benefits, the literature typically uses benchmark portfolios that are equal-weighted (e.g., Campbell et al., 2010; Filipozzi & Harkmann, 2020; Opie & Riddiough, 2020; Reichenecker, 2019), value-weighted (e.g., Barroso et al., 2021) or GDP-weighted (e.g., Kroencke et al., 2014; Opie & Riddiough, 2020). Section 5.3.3 describes the calculation of the benchmark portfolio return in more detail.

We then add one of four different FX investment styles, either carry, momentum, value or contrarian pricing, to the GDP-weighted global equity portfolio to test their diversification benefits. Section 5.3.4 details the calculation of the FX investment style augmented benchmark portfolio. As fund managers are typically mandated to hedge only existing FX exposures, we acknowledge that this strategy is not always feasible. However, with a less restrictive mandate, this strategy provides diversification benefits by relaxing the constraint on currency weights (e.g., Kroencke et al., 2014; Opie & Riddiough, 2020).

Following the literature (e.g., Barroso et al., 2021; Kroencke et al., 2014; Opie & Riddiough, 2020), we measure the diversification benefits of FX investment styles mainly as the increase in the Sharpe ratio of the benchmark portfolio when they are added. We choose this approach because Sharpe ratios can be formally compared to assess whether one ratio is statistically higher than another, even in the presence of non-normal return distributions and serial correlation, using the studentized time series bootstrap test of Ledoit and Wolf (2008). Following Ledoit and Wolf (2008), we approximate the unknown distribution function of the studentized difference between two Sharpe ratios by a distribution obtained from bootstrap resamples generated using the circular block bootstrap of Politis and Romano (1992) to account for serial correlation. This involves resampling 5000 bootstrapped sequences of pairs from the observed excess return pairs with replacement. We use their calibration procedure to determine the data-dependent optimal block size. The standard error of the estimated difference between two Sharpe ratios is then computed from the bootstrapped data and used to construct a t-test for the difference between the two Sharpe ratios.

In assessing performance, we take into account rebalancing costs for equities, transaction costs for currencies and margin requirements for forward contracts, as frictions have a non-negligible impact on the performance of currency trading strategies (e.g., Barroso et al., 2021; Menkhoff et al., 2012b). Section 5.3.5 describes in more detail how we incorporate currency transaction costs and equity rebalancing costs.

In order to assess the effective diversification benefits of the FX investment styles as comprehensively as possible, we look beyond the full observation period to include the two periods before and after the global financial crisis, as well as alternating periods of low and high market stress, to analyse the risk-return profile of the strategies in extreme market conditions. We also distinguish between conformity and contrarian pricing regimes to test whether the contrarian pricing trade is able to improve the performance of the benchmark portfolio in the two periods on which its construction is based.

5.3.2 Data and investigation period

The US investor is assumed to be exposed to currency risk against the Australian dollar (AUD), British pound (GBP), Canadian dollar (CAD), euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), Swedish krona (SEK) and Swiss franc (CHF). Each equity market in the ten economies is represented by the corresponding Morgan Stanley Capital International (MSCI) Total Return stock market indices. Consumer Price Index (CPI) and Gross Domestic Product (GDP) based on purchasing power parity are from national statistical offices and have been standardised by Refinitiv for comparability. Foreign exchange data on forward rates and corresponding spot rates are from WM/Refinitiv. We follow Burnside et al. (2011a) and multiply GBP/FCU quotes by USD/GBP quotes to obtain the longer sample of spot rates against the dollar. Interest rates are implied rates derived from forward rates quoted against the US dollar, where the US dollar rate is equal to the 3-month Treasury bill rate, converted to a weekly frequency (e.g., Barroso et al., 2021). We use the Office of Financial Research's Financial Stress Index (OFR FSI) to assess the level of market stress in global financial markets. The OFR FSI aggregates information from 33 financial market variables to provide a daily measure of systemic financial stress.

We choose a weekly data frequency, consistent with Hertrich (2024), to efficiently forecast the distribution of G10 currency excess returns. All data refer to Wednesdays because Dao et al. (2016) find evidence of a weekend overreaction in the exchange rates of seven major currency pairs, all of which are G10 currencies. Consequently, we follow the suggestion of Chong and Miffre (2010) not to use Friday's closing or Monday's opening prices in order to avoid distorting excess returns caused by unusually high or low weekend price gaps and subsequent price reversals. As the currency dataset includes the euro, the first portfolio formation takes place on 6 January 1999, the first business Wednesday of the euro, to avoid a look-ahead bias, resulting in a study period of 13 January 1999 to 21 June 2023. The holding period is one week, so portfolios are rebalanced at the end of each week. The last portfolio rebalancing takes place on 14 June 2023, so there are 1276 weekly returns of the FX investment styles and the equity benchmark portfolio available for empirical analysis.

Since the OFR FSI only goes back to January 2000, we extend its time series of financial stress signals back to January 1999 using the Federal Reserve Bank of St. Louis Financial Stress Index. In addition, since we need weekly data to construct the value strategy, but CPI data are only available at monthly frequency, we follow the literature (e.g., Barroso & Santa-Clara, 2015) and carry forward the most recent value to the intervening weeks until the next update. While we can construct the carry trade strategy for the first time using forward and spot rates available on 6 January 1999, for the momentum (value) strategy we use currency excess return (CPI) data going back to 21 October 1998 (21 July 1993). In order to construct the contrarian pricing trade on 6 January 1999, we need to estimate the joint distribution of spot returns of the G10 currencies for the first time on 25 March 1998, as we need 42 initial weekly CVaR forecasts over the period 25 March 1998 to 6 January 1999 to calculate the variable CVaR-Trend. To this end, we use a time-varying t-copula with skewed t-GJR-GARCH margins as proposed by Hertrich (2024), using spot price data from 6 June 1990 to 25 March 1998. Note that all one-week-ahead forecasts used to construct the pricing classifier and the contrarian pricing trade are made in an out-of-sample framework with increasing window length to avoid look-ahead bias.

5.3.3 Benchmark portfolio return

Suppose that at the end of week t, a share $\omega_{j,t}$ of a dollar is used to buy an asset in the foreign equity market of country j. To this end, $\omega_{j,t}$ DCU must first be exchanged for $\omega_{j,t} \cdot S_{j,t}$ FCU. The asset has a discrete return of $R_{j,t+1} = (P_{j,t+1}/P_{j,t} - 1)$, so that at the end of week t+1 the return is $\omega_{j,t} \cdot S_{j,t} \cdot (1 + R_{j,t+1})$ (e.g., Campbell et al., 2010). We assume full investment, so that the sum of the shares invested in all ten countries equals one. Furthermore, let F_t denote the one-week forward rate in units of foreign currency per US dollar at time t and maturity at t+1, and S_t denote the corresponding spot rate at time t. Following Menkhoff et al. (2012a), we denote discrete (logarithmic) rates by uppercase (lowercase) letters. To keep the notation consistent, we refer to the US dollar (USD) as the domestic currency (DCU) and assign it the index ‘d’, so that the index numbers j = 1,...,n denote the foreign currencies (FCU) in the sample. Since the domestic forward and spot exchange rates are constant over time and equal to one, the gross return of the unhedged benchmark portfolio, converted into US dollars, is as follows (Campbell et al., 2010):

$$R_{B,t+1}^{unhedged} = -1 + \omega_{d,t} \cdot (1 + R_{d,t+1}) + \sum_{j=1}^{n} \omega_{j,t} \cdot \frac{S_{j,t}}{S_{j,t+1}} \cdot (1 + R_{j,t+1}) \tag{5.1}$$

If an unhedged portfolio is now combined with a style-based FX strategy, the problem is that the performance contribution of the FX strategy is based on a hedging contribution and a speculative contribution, which means that the diversification benefits cannot be assessed without bias (e.g., Kroencke et al., 2014). This is because short positions in the foreign currency correspond to hedging positions until the full hedge is reached, while long positions and additional short positions exceeding the full hedge serve to benefit from the appreciation or depreciation of the foreign currency. To properly assess the diversification benefits of FX investment styles, we need to disentangle the hedging contribution from the speculative contribution of their return contribution to the benchmark portfolio. In particular, we aim to avoid alternative hedging styles that cause deviations from a full hedge that are consistent with FX investment styles and thus more speculative, and thus follow the literature (e.g., Barroso et al., 2021; Campbell et al., 2010; Opie & Riddiough, 2020) and use a full hedge to determine the benchmark portfolio return. That is, we implement a full hedge at the end of week t by entering into forward contracts to sell $\omega_{j,t} \cdot S_{j,t}$ units of FCU at the end of week t+1 at a forward price of $F_{j,t}$. The amount $\omega_{j,t} \cdot S_{j,t}$ can be exchanged at the forward price $F_{j,t}$, while the realised return $\omega_{j,t} \cdot S_{j,t} \cdot (1 + R_{j,t+1}) - \omega_{j,t} \cdot S_{j,t}$ must be converted at the spot rate $S_{j,t+1}$. This gives the following return denominated in DCU at the end of week t+1 (Campbell et al., 2010):

$$R_{B,t+1}^{hedged} = -1 + \omega_{d,t} \cdot (1 + R_{d,t+1}) + \sum_{j=1}^{n} \frac{\omega_{j,t} \cdot S_{j,t} \cdot (1 + R_{j,t+1})}{S_{j,t+1}} - \frac{\omega_{j,t} \cdot S_{j,t}}{S_{j,t+1}} + \frac{\omega_{j,t} \cdot S_{j,t}}{F_{j,t}} \quad (5.2)$$

In line with the idea of taking a short position in the foreign currency to hedge the currency risk of a foreign investment, the return can also be written as follows:

$$R_{B,t+1}^{hedged} = -1 + \omega_{d,t} \cdot (1 + R_{d,t+1}) + \sum_{j=1}^{n} \frac{\omega_{j,t} \cdot S_{j,t} \cdot (1 + R_{j,t+1})}{S_{j,t+1}} + \omega_{j,t} \cdot S_{j,t} \cdot \left(\frac{S_{j,t+1} - F_{j,t}}{F_{j,t}}\right)$$

$$= -1 + \omega_{d,t} \cdot (1 + R_{d,t+1}) + \sum_{j=1}^{n} \frac{\omega_{j,t} \cdot S_{j,t}}{S_{j,t+1}} \left(1 + R_{j,t+1} + RX_{j,t+1}^{S}\right) \quad (5.3)$$

Thereby, we calculate the log excess return of buying (selling) the foreign currency at time t in the forward market and selling (buying) it one week later at time t+1 in the spot market as follows (Lustig et al., 2011):

$$rx_{j,t+1}^{L} = \ln\left(\frac{F_{j,t} - S_{j,t+1}}{S_{j,t+1}}\right) = f_{j,t} - s_{j,t+1} \quad (5.4)$$

$$rx_{j,t+1}^{S} = \ln\left(\frac{S_{j,t+1} - F_{j,t}}{F_{j,t}}\right) = s_{j,t+1} - f_{j,t} \quad (5.5)$$

If a portfolio is fully hedged against foreign exchange risk, forward contracts must be entered into, for which a margin must be deposited, resulting in a return on the collateral and a reduction in the capital available for equity investments. Often, research simply assumes that margin requirements for forward contracts are zero (e.g., Campbell et al., 2010; Kroencke et al., 2014). However, as the margin must be provided from the available investment capital, there is a trade-off between investments in domestic equities, foreign equities and currencies. This is because the required margin reduces the investment capital available for foreign equity investments. Ignoring margin requirements would therefore result in higher portfolio weights for both equity and FX investment styles than is actually possible, thereby overstating their performance contribution to a fully hedged or FX style augmented global equity portfolio (Barroso et al., 2021).

Consequently, the actual invested share $\omega^*_{d,t}$ is equal to the intended share $\omega_{d,t}$, since the domestic investment does not need to be hedged against exchange rate risk. However, in the case of foreign investment, the intended share $\omega_{j,t}$ must be scaled by 1 + c, where c corresponds to the required margin, in order to obtain the share $\omega^*_{j,t}$ actually invested. Since the margin for institutional investors is between 5% and 15% of the forward contract volume for liquid G10 currencies, we assume a margin requirement for forward contracts of 10%, i.e. c = 0.10. The deposited collateral $c \cdot \omega^*_{j,t}$ is then 'only' invested at a 'risk-free' interest rate and does not earn the equity return $R_{j,t+1}$, but $R^f_{j,t+1}$, which is equal to the return on an investment at the implied foreign interest rate. The gross return of the benchmark portfolio fully hedged against foreign currency risk using the excess return of a short currency position is thus (Barroso et al., 2021; Campbell et al., 2010):

$$R^{hedged}_{B,t+1} = -1 + \omega^*_{d,t} \cdot (1 + R_{d,t+1}) + \sum_{j=1}^{n} \left[\omega^*_{j,t} \cdot \frac{S_{j,t}}{S_{j,t+1}} \cdot (1 + R_{j,t+1} + RX^S_{j,t+1}) + c \cdot \omega^*_{j,t} \cdot \frac{S_{j,t}}{S_{j,t+1}} \left(1 + R^f_{j,t+1}\right) \right] \quad (5.6)$$

5.3.4 FX investment style-adjusted benchmark portfolio return

Following Bakshi and Panayotov (2013), we do not use leverage, which means that we limit the strategic short (Ψ_t^S) and long (Ψ_t^L) currency positions of the FX investment styles to an absolute demand for forward contracts of half a dollar each. Therefore, at the end of each week, the net forward demand of an FX investment style invested in two currencies across all G10 foreign currencies accumulates to 1:

$$\sum_{j=1}^{n} \psi_{j,t} = \sum_{j=1}^{n} \psi_{j,t}^{S} + \psi_{j,t}^{L} \tag{5.7}$$

However, as the collateral for the demand for forward contracts of these separate currency positions in the FX investment styles must be provided by initially available investment capital, the predetermined shares $\omega_{j,t}$ and $\omega_{d,t}$ cannot be achieved but must be adjusted in advance (Barroso et al., 2021):

$$\omega_{j,t}^{'} = \left(1 - c \cdot \sum_{j=1}^{n} \psi_{j,t}\right) \cdot \omega_{j,t} \quad \text{and} \quad \omega_{d,t}^{'} = \left(1 - c \cdot \sum_{j=1}^{n} \psi_{j,t}\right) \cdot \omega_{d,t} \tag{5.8}$$

Again, the share $\omega_{d,t}^{*}$ actually invested at the end of week t is equal to $\omega_{d,t}^{'}$, since there is no need to hedge domestic investments against currency risks. However, for foreign investments, $\omega_{j,t}^{*}$ is obtained by scaling $\omega_{j,t}^{'}$ by 1 + c. The share that bears interest at the risk-free rate is thus $c \cdot \sum_{j=1}^{n} \left(\psi_{j,t} + \omega_{j,t}^{*}\right)$. Therefore, the gross return of the FX investment style-adjusted benchmark portfolio is:

$$\begin{aligned} R_{B,t+1}^{FX\text{-}adj} = & -1 + \omega_{d,t}^{*} \cdot (1 + R_{d,t+1}) \\ & + \sum_{j=1}^{n} \left[\omega_{j,t}^{*} \cdot \frac{S_{j,t}}{S_{j,t+1}} \cdot (1 + R_{j,t+1} + RX_{j,t+1}^{S}) + c \cdot \omega_{j,t}^{*} \cdot \frac{S_{j,t}}{S_{j,t+1}} \left(1 + R_{j,t+1}^{f}\right) \right] \\ & + \psi_{j,t}^{L} \cdot RX_{j,t+1}^{L} + \psi_{j,t}^{S} \cdot RX_{j,t+1}^{S} + \sum_{j=1}^{n} c \cdot \psi_{j,t} \cdot \frac{S_{j,t}}{S_{j,t+1}} \left(1 + R_{j,t+1}^{f}\right) \end{aligned} \tag{5.9}$$

5.3.5 Currency transaction costs and equity rebalancing costs

We calculate currency excess returns adjusted for transaction costs using bid-ask quotes for spot and forward rates to avoid overstating the performance of FX investment styles. However, Lyons (2001) has shown that the indicative spreads reported by WM/Refinitiv are much higher than the spreads actually paid by retail and institutional investors. We follow the literature and apply a scaling of 50% of the bid-ask spread (e.g., Menkhoff et al., 2012b). However, especially for recent years, even halving the bid-ask spread can significantly underestimate the returns of a foreign exchange trading strategy, which is why even a 25% scaling is recommended (e.g., Cespa et al., 2022; Gilmore & Hayashi, 2011).

In addition, some studies assume full portfolio turnover in each period (e.g., Barroso et al., 2021; Lustig et al., 2011), but this biases the results in favour of the most static strategy. In recent years, the literature has recognised that forward contracts can be rolled over at a much lower cost using FX swaps to extend currency positions, but often assumes that rollover costs are negligible, so that bid-ask spreads are only applied to volumes where there has actually been a change in the overall portfolio position (e.g., Della Corte et al., 2016b; Kroencke et al., 2014; Menkhoff et al., 2012a). However, as Darvas (2009) shows, neglecting rollover costs can also bias the results. Therefore, we charge a cost equal to half the bid-ask spread of the swap points to roll over the forward contract. To open a new position, we charge half the spot spread plus half the swap point spread. To close an existing position, we charge half of the previously unsettled spot spread. In total, the transaction costs for opening and closing a new position are the full spot spread and half the swap point spread. Table 5.1 shows how we calculate currency excess returns at the end of each week, following Darvas (2009).

In order to take into account the transaction costs associated with the currency transactions of the FX style-adjusted benchmark portfolio, we proceed as follows. First, at the end of each week, for each FX investment style, we calculate the difference between the excess return excluding transaction costs and the excess return net of bid-ask spreads, taking into account changes in the strategy composition and charging transaction costs depending on whether a currency enters, remains in or exits the FX investment style portfolio, as shown in Table 5.1.

Table 5.1
Currency excess returns net of bid-ask spreads

	Exits in t+1	Remains in t+1
Long position		
Enters in t	$\frac{F^b_{j,t}}{S^a_{j,t+1}}-1$	$\frac{F^b_{j,t}}{S_{j,t+1}}-1$
Remains in t	$\frac{F_{j,t}}{S^a_{j,t+1}}-1$	$\frac{F_{j,t}}{S_{j,t+1}+0.5[F^a_{j,t}-F^b_{j,t}-S^a_{j,t}+S^b_{j,t}]}-1$
Short position		
Enters in t	$\frac{S^b_{j,t+1}}{F^a_{j,t}}-1$	$\frac{S_{j,t+1}}{F^a_{j,t}}-1$
Remains in t	$\frac{S^b_{j,t+1}}{F_{j,t}}-1$	$\frac{S_{j,t+1}}{F_{j,t}+0.5[F^a_{j,t}-F^b_{j,t}-S^a_{j,t}+S^b_{j,t}]}-1$

Note: Table 5.1 provides an overview of the calculation of the currency excess return net of bid-ask spreads.

We then subtract this excess return difference, i.e. the transaction costs of the FX investment style, from the gross return $R^{FX\text{-}adj}_{B,t+1}$. Second, we proceed in the same way to account for changes in the full currency hedge positions that occur when the GDP-weighted actual share $\omega^*_{j,t}$ invested in foreign equity markets changes. That is, if $\omega^*_{j,t}$ remains unchanged, we maintain the corresponding short position in the foreign currency, but subtract the rollover costs from $R^{FX\text{-}adj}_{B,t+1}$. If $\omega^*_{j,t}$ increases (decreases), the transaction costs for the opened (closed) short position in the foreign currency are deducted from $R^{FX\text{-}adj}_{B,t+1}$. Third, due to price fluctuations, a portfolio rebalancing of the equity positions is required to adjust the actual value shares $\omega_{j,t}^{(*)}$ and $\omega_{d,t}^{(*)}$ of the current holdings at the end of each week to their strategic target weighting $\omega_{j,t}^{*}$ and $\omega_{d,t}^{*}$ for the following week's holding period. $\omega_{j,t}^{(*)}$ and $\omega_{d,t}^{(*)}$ are calculated as the quotient of the values actually held in the equity positions and the total value of the portfolio at the end of each week t. We follow the literature and assume rebalancing costs of 50 basis points relative to the volume to be reallocated, so that the rebalancing costs to be deducted from $R_{B,t+1}^{FX\text{-}adj}$ at the end of each week are then calculated as follows (e.g., Barroso et al., 2021; DeMiguel et al., 2009):

$$RBC_t = \frac{50}{10000} \cdot \left[\left| \omega_{d,t}^{(*)} - \omega_{d,t}^{*} \right| + \sum_{j=1}^{n} \left| \omega_{j,t}^{(*)} - \omega_{j,t}^{*} \right| \right] \tag{5.10}$$

5.4 Foreign exchange investment styles

5.4.1 Carry trade

The carry trade strategy is based on the empirically well-documented 'forward premium puzzle' (Fama, 1984), which states that, contrary to uncovered interest parity (UIP), currencies with high (low) interest rates tend to appreciate (depreciate) rather than depreciate (appreciate), resulting in the interest rate differential between the two currencies not being offset by exchange rate changes in the same period. There is evidence that a carry trade, which involves borrowing in (funding) currencies with the lowest interest rate differential relative to the US money market and investing the amount in (investment) currencies with the highest interest rate differential relative to the US money market, is highly profitable (e.g., Burnside et al., 2011a; Galati et al., 2007). Assuming that covered interest parity (CIP) holds, which is empirically supported by Akram et al. (2008), we derive interest rate differentials from FX forward discounts (e.g., Lustig et al., 2011):

$$fd_{j,t} = \ln\left(\frac{F_{j,t} - S_{j,t}}{S_{j,t}}\right) = f_{j,t} - s_{j,t} \tag{5.11}$$

Following the literature, we then create a carry trade by first sorting all foreign currencies into nine portfolios according to increasing forward discounts and then going long in portfolio nine with the highest forward discount currencies and short in portfolio one with the lowest forward discount currencies (e.g., Lustig et al., 2011; Menkhoff et al., 2012a).

5.4.2 Momentum trade

Since Jegadeesh and Titman (1993) empirically documented the momentum effect in equity markets, evidence of the momentum phenomenon has also emerged in foreign exchange markets (e.g., Menkhoff et al., 2012b; Okunev & White, 2003). A momentum strategy is a long-short portfolio constructed by buying 'winner' currencies, defined as currencies with high past cumulative excess returns, and selling 'loser' currencies, defined as currencies with low past cumulative excess returns. Since currencies are less affected by liquidity problems and momentum returns are indeed higher when the last month is not skipped (Asness et al., 2013), we use the average log excess return of a long position in the foreign currency over the last three months (or 12 weeks) as the conditioning variable for the momentum strategies (Kroencke et al., 2014):

$$MOM_{j,t} = \frac{1}{12}\sum_{\tau=11}^{0} rx^{L}_{j,t-\tau} \qquad (5.12)$$

Similar to the carry trade, we sort the foreign currencies into nine portfolios based on an ascending sort of momentum. We then create the momentum trade by going long the ninth portfolio and short the first portfolio, using the recent winner currencies for the investment and the recent loser currencies for the funding leg (e.g., Menkhoff et al., 2012b).

5.4.3 Value trade

Following Asness et al. (2013), we define the value of a foreign currency relative to the domestic currency at the end of week t as the 5-year change in purchasing power parity. This is the negative of the 5-year return on the exchange rate, which is measured as the log difference between the spot exchange rate today and the average spot exchange rate from 4.5-5.5 years ago, plus the log difference in the rates of change between the domestic and the foreign CPI over the same period. Consequently, we calculate the FX value for a foreign currency as follows (Asness et al., 2013)

$$\Delta PPP_{j,t} = - \left[\ln\left(S_{j,t}\right) - \ln\left(\bar{S}_{j,t}\right)\right] + \left(\left[\ln\left(CPI_{d,t}\right) - \ln\left(\overline{CPI}_{d,t}\right)\right] - \left[\ln\left(CPI_{j,t}\right) - \ln\left(\overline{CPI}_{j,t}\right)\right]\right) \quad (5.13)$$

where the average spot exchange rate from 4.5-5.5 years ago is calculated as follows

$$\bar{S}_{j,t} = \frac{1}{52} \sum_{\tau = 286}^{235} S_{j,t-\tau} \quad (5.14)$$

and the average consumer price index from 4.5-5.5 years ago is calculated in the same way for all countries, i.e. also for the domestic country, as follows:

$$\overline{CPI}_t = \frac{1}{52} \sum_{\tau = 286}^{235} CPI_{t-\tau} \quad (5.15)$$

A real appreciation (depreciation) of an FCU against the DCU from the average point in time five years ago until today has occurred if $\Delta PPP_{t,j} > 0$ (< 0). In this context, $\Delta PPP_{t,j}$ increases (decreases) both in the case of a nominal appreciation (depreciation) of an FCU against the DCU and in the case of a smaller (larger) change in the price level in the foreign country than in the domestic country. Since foreign currencies where $\Delta PPP_{t,j}$ is below (above) zero can be considered 'undervalued' ('overvalued'), we sort the currencies into nine portfolios based on a descending sort by value. Again, we construct the value trade by going long the ninth portfolio and short the first portfolio (e.g., Asness et al., 2013; Opie & Riddiough, 2020).

5.4.4 Contrarian pricing trade

We propose an augmented carry trade, which we call the contrarian pricing trade (CPT). We construct this currency strategy by first determining whether the pricing classifier of Hertrich (2024) predicts a conformity or a contrarian pricing regime for the following week. Second, if a contrarian pricing regime is predicted, we conditionally double-sort on a variable that captures a recent change in conditional value at risk (CVaR), called CVaR-Trend (CT), and on idiosyncratic excess return momentum (iMOM). Following Hertrich (2024), we apply a tertile sort on $iMOM_t$ within CT_t tertiles. We then construct the CPT strategy by buying (selling) the low (high) idiosyncratic momentum currencies in the high (low) CVaR-Trend tertile. Third, if a conformity pricing regime is predicted, we conditionally double-sort on forward discount and CVaR-Trend. Following Hertrich (2023), we apply a tertile sort on CT_t tertiles within fd_t tertiles. We then construct the CPT strategy by buying (selling) the high CVaR-Trend currencies in the high (low) forward discount tertile.

We refer to Hertrich (2023, 2024) for more details on the construction of the pricing classifier, the CVaR-Trend variable and the rationale for the two double-sorting approaches. However, we outline the main arguments on which we base our contrarian pricing trade.

The pricing classifier is an ex-ante indicator that predicts violations of the ‘in equilibrium’ prediction of the Menkhoff et al. (2012a) currency pricing model, which is that during periods of low global FX volatility, the carry trade must generate a higher positive excess return per unit of systematic risk (i.e. volatility risk) taken than the strategy of shorting the funding currencies in order to generate a positive risk premium for the negative covariation of the investment currencies with global FX volatility innovations. To construct the pricing classifier at the end of each week t, we need the one-step-ahead forecasts of the mean excess return and the CVaR of the spot returns for the three strategies: the carry trade and a short (long) position in the lowest (highest) forward discount, i.e. in the funding (investment) currencies. We refer to these variables as $\widehat{rx}_t^{CT}$, $\widehat{rx}_{F,t}^{S}$, $\widehat{rx}_{I,t}^{L}$ and $\widehat{CVaR}_\alpha(Y_t^{CT})$, $\widehat{CVaR}_\alpha(Y_{F,t}^{S})$, $\widehat{CVaR}_\alpha(Y_{I,t}^{L})$. Furthermore, we require the betas of the carry trade and the short position in the funding currency with global FX volatility innovations, denoted as $\hat{\beta}_t^{CT}$ and $\hat{\beta}_t^{S}$. The pricing classifier is then constructed at the end of week t as a four-week moving average as follows (Hertrich, 2024):

$$\frac{1}{4}\sum_{\tau=-3}^{0}\frac{\widehat{CVaR}_\alpha(Y_{I,t+\tau}^{L})}{\widehat{CVaR}_\alpha(Y_{t+\tau}^{CT})}\frac{\widehat{rx}_{I,t+\tau}^{L}}{\widehat{CVaR}_\alpha(Y_{I,t+\tau}^{L})}-\left(\frac{2\hat{\beta}_{t+\tau}^{CT}}{\hat{\beta}_{t+\tau}^{S}}-\frac{\widehat{CVaR}_\alpha(Y_{F,t+\tau}^{S})}{\widehat{CVaR}_\alpha(Y_{t+\tau}^{CT})}\right)\frac{\widehat{rx}_{F,t+\tau}^{S}}{\widehat{CVaR}_\alpha(Y_{F,t+\tau}^{S})} \tag{5.16}$$

The pricing classifier takes a (positive) negative value, indicating a conformity (contrarian) pricing regime, when the investment currencies are likely to perform well (poorly), thus making it more attractive to engage in a carry trade (short only the funding currencies), which is consistent (contrary) to the in equilibrium prediction of Menkhoff et al.'s (2012a) currency pricing model. Hertrich (2024) shows that the carry risk factor HML^{FX} actually performs poorly in contrarian pricing regimes and cannot explain the cross-section of G10 currency excess returns. Furthermore, he shows that there are excess return reversals in contrarian pricing regimes, bringing prices in line with the risk-based explanation of Menkhoff et al. (2012a), as the cross-sectional average level of idiosyncratic momentum (CVaR-Trend) negatively (positively) predicts short-term excess returns of the carry risk factor HML^{FX}.

This CVaR-Trend predictor was introduced in Hertrich (2023). Merton's (1987) model of capital market equilibrium suggests that when investors are under-diversified with respect to higher-order moments of the excess return distribution, currencies with higher left-tail risk should be priced lower to compensate for the higher probability and magnitude of large losses associated with them (e.g., Atilgan et al., 2020). Consequently, an increase (decrease) in the predicted conditional value at risk (CVaR) should be associated with an instantaneous depreciation (appreciation) of the quoted currency, providing the necessary discount (premium) in spot prices, as investors demand (accept) a higher (lower) risk premium, i.e. a higher (lower) expected excess return, to be willing to hold the quoted currency with high (low) left-tail risk (e.g., Fama, 1970; Hertrich, 2023).

However, if investors underreact to persistent changes in the level of CVaR, a discount (premium) to account for an increase (decrease) in CVaR will not be immediately reflected in spot prices through the sale (purchase) of the quote currency, but will only materialise over time as information about a persistent change in CVaR gradually diffuses through the market (e.g., Atilgan et al., 2020; Hertrich, 2023). For this reason, those currencies that have experienced the largest increase (decrease) in CVaR and, at the same time, the largest discounts (premiums) in spot prices due to the concomitant depreciation (appreciation) of the quote currency are most likely to have, and, as the empirical evidence in Hertrich (2023) shows, will ultimately have, high (low) risk premiums to compensate for their high (low) CVaR levels. Hertrich (2023, 2024) calculates this variable CVaR-Trend by first subtracting the moving average of the L previous CVaR forecasts from the CVaR forecasts at the end of week t to obtain the trend signal $CS_{t,L}$ with a window length of L:

$$CS_{j,t,L} = \widehat{CVaR}_{\alpha}(Y_{j,t}) - \frac{\widehat{CVaR}_{\alpha}(Y_{j,t-L}) + \ldots + \widehat{CVaR}_{\alpha}(Y_{j,t-1})}{L} \tag{5.17}$$

Second, following the suggestion of Han et al. (2016), he averages over all trend signals at lag lengths of 1-, 2-, 4-, 10-, 21-, 31-, and 41-weeks, corresponding to 5-, 10-, 20-, 50-, 100-, 150-, and 200-days, to obtain the indicator $CT_{j,t}$, named CVaR-Trend.

Consequently, the prediction of a contrarian pricing regime suggests that an investor should avoid engaging in a carry trade. Instead of a forward discount sort, a tertile sort on $iMOM_t$ within CT_t tertiles is appropriate as it allows for a currency reversal strategy in contrarian pricing regimes that buys (sells) those currencies that have become unexpectedly riskier (less risky) while they have experienced low (high) average idiosyncratic excess returns in the past, providing the discount (premium) to allow for higher (lower) excess returns in the future. As a result, this double sort allows the contrarian pricing trade to avoid buying unprofitable but not unexpectedly riskier currencies and to avoid selling profitable but not unexpectedly less risky currencies in contrarian pricing regimes.

To calculate the idiosyncratic excess return momentum, we first regress the excess returns on the systematic risk factors DOL and HML^{FX} from Lustig et al. (2011) and VOL from Menkhoff et al. (2012a) at the end of each week, as in Zhang (2022) and Hertrich (2024):

$$rx^{L}_{j,t} = [\text{systematic excess return}] + [\text{idiosyncratic excess return}]$$

$$= \left[\hat{\beta}_j^{DOL} \cdot DOL_t + \hat{\beta}_j^{VOL} \cdot VOL_t + \hat{\beta}_j^{HML^{FX}} \cdot HML_t^{FX}\right] + \left[\hat{\alpha}_j + \hat{\varepsilon}_{j,t}\right] \quad (5.18)$$

We standardise the residual excess returns by their standard deviation over the three-year estimation period before adding the alpha (Gutierrez & Prinsky, 2007) and then obtain the idiosyncratic momentum as the average of the volatility-scaled idiosyncratic log excess returns in the 12-week period preceding the end of week t, as in Hertrich (2024):

$$iMOM_{j,t} = \frac{1}{12}\sum_{\tau=11}^{0} rx_{j,t-\tau}^{L,idiosyncratic} \quad (5.19)$$

Furthermore, Hertrich (2023) shows that funding currencies tend to experience an increase (decrease) in CVaR when they appreciate (depreciate) and subsequently have low (high) future excess returns. However, this phenomenon only occurs when the HML^{FX} risk factor is a significant driver of the cross-section of G10 currency excess returns. Although this inverse asymmetric volatility effect seems counterintuitive at first sight (e.g., Bekaert & Wu, 2000; Glosten et al., 1993; Wang & Yang, 2009), we expect it to occur in conformity pricing regimes because it can be fully rationalised with the Menkhoff et al. (2012a) currency pricing model. Periods of high global FX volatility are likely to be periods in which funding currencies experience an increase in CVaR.

This is almost certainly a consequence of the construction of the global FX volatility risk factor (Menkhoff et al., 2012a). Low future excess returns following periods of increasing CVaR may therefore simply reflect the fact that funding currencies have appreciated during periods of market turmoil, providing a hedge against volatility risk, and investors are then willing to pay a premium, i.e. accept low risk premia, for insurance against future systematic volatility risk.

Thus, a tertile sort on CT_t tertiles within fd_t tertiles allows the contrarian pricing trade in conformity pricing regimes to avoid buying investment currencies that offer a discount that is insufficient to compensate for the higher probability and magnitude of large losses associated with their higher CVaR level, and to avoid selling funding currencies that do not command a premium sufficient for the insurance provided, i.e. that do not sufficiently compensate for the higher probability and magnitude of large gains associated with their higher CVaR level.

5.5 Empirical results

5.5.1 Performance of FX investment styles

Panel A of Table 5.2 shows that the fully hedged global equity portfolio has an annual excess return of 5.38% and a Sharpe ratio of 0.37, which is very similar to previous evidence (e.g., Barroso et al., 2021; Opie & Riddiough, 2020). Furthermore, Panel A of Table 5.2 shows that the carry (value) trade has an average annual excess return of 2.62% (2.76%), which is slightly lower than that documented in Asness et al. (2013) for the period 1979-2011. Figure 5.1 shows that this discrepancy is due to the near-zero excess returns of the two trades in the period following the global financial crisis. This phenomenon of performance loss is well documented in the literature (e.g., Fan et al., 2022; Opie & Riddiough, 2020). Moreover, Panel A of Table 5.1 confirms the evidence (e.g., Brunnermeier et al., 2008; Kroencke et al., 2014) that the carry trade has a highly negatively skewed return distribution and a high positive kurtosis, suggesting that it is susceptible to crash risk (e.g., Farhi & Gabaix, 2016), which is also reflected in its significantly higher maximum drawdown compared to the value trade and the contrarian pricing trade. As the carry trade also has the highest correlation with the benchmark portfolio of the four FX investment styles, it may be significantly less suitable as an effective diversification instrument after the global financial crisis than before. In contrast, the return distribution of the value trade is almost symmetrical and has a much lower kurtosis.

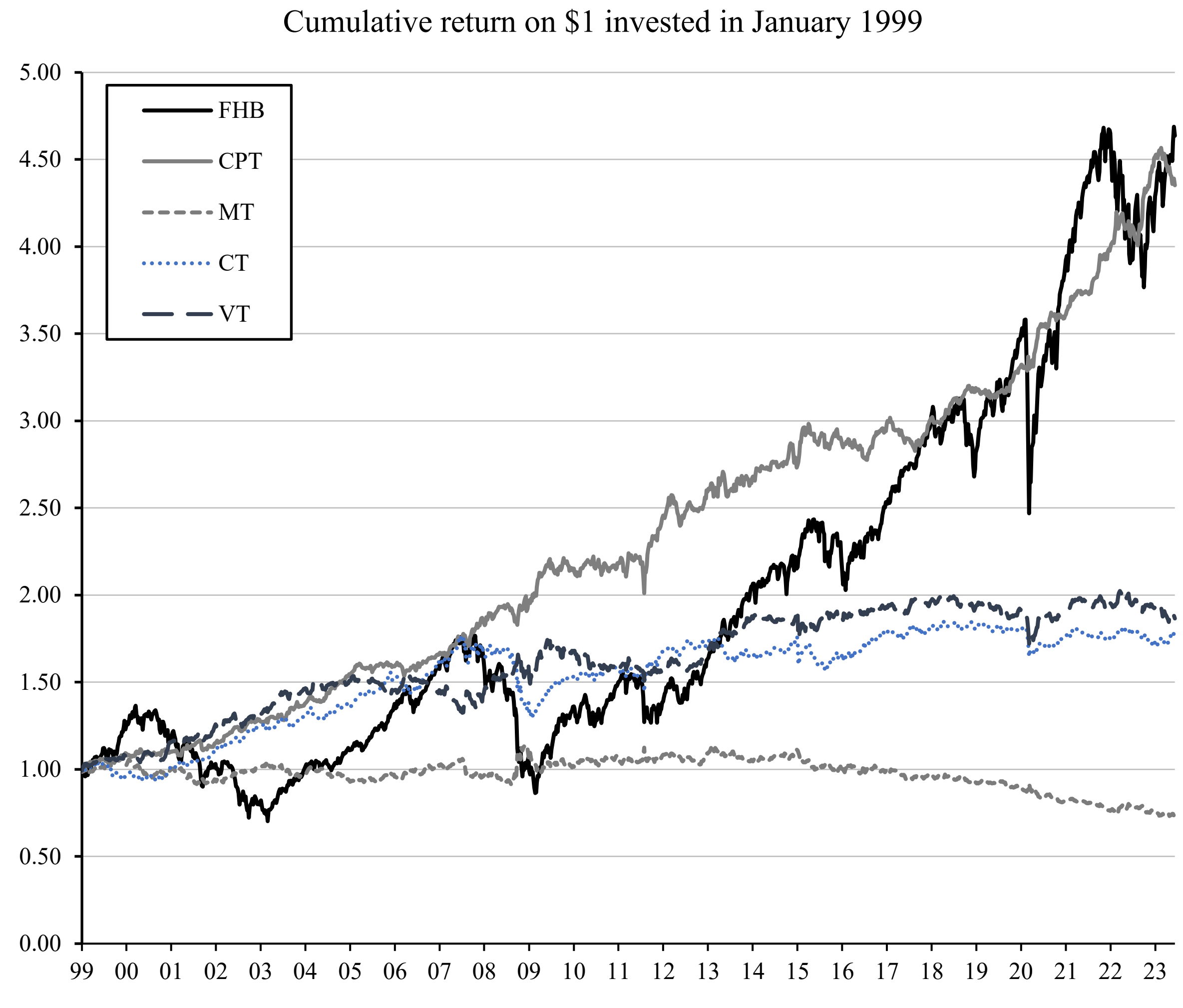

Figure 5.1. The figure presents the cumulative return on $1 invested in the benchmark, i.e. the fully hedged global equity portfolio (FHB), and the four FX investment styles, contrarian pricing trade (CPT), momentum trade (MT), carry trade (CT) and value trade (VT), as described in Section 5.4. Geometric cumulative returns use discrete excess returns over the US Treasury rate, net of rebalancing and transaction costs. The sample period is January 1999 to June 2023.

This results in a lower maximum drawdown, which together with a higher Sharpe ratio and a lower correlation to the benchmark portfolio suggests that the value trade could be more attractive as a diversification instrument than the carry trade, especially in the post global financial crisis period. For the momentum trade, however, we find in Panel A of Table 5.2 and Figure 5.1 that it does not perform very well at any point in our data sample, with an average annual excess return of -0.96%.

Table 5.2
Performance of FX investment styles

Panel A: Descriptive statistics					
	FHB	CPT	MT	CT	VT
Mean	5.84	6.17	-0.96	2.62	2.76
Std	15.83	5.84	7.12	6.86	6.57
SR	0.37	1.06	-0.14	0.38	0.42
Skew	-0.68	0.48	1.32	-1.28	-0.05
Kurt	4.56	5.72	20.12	12.35	7.86
MDD	53.12	10.29	35.31	26.76	13.94
COR		0.32	-0.18	0.41	0.31
Panel B: Sharpe ratio differences					
FHB		0.01	0.09	0.95	0.81
CPT			0.00	0.01	0.01
MT				0.09	0.02
CT					0.89

Note: Panel A reports summary statistics for the benchmark, i.e. the fully hedged global equity portfolio (FHB), and the four FX investment styles, contrarian pricing trade (CPT), momentum trade (MT), carry trade (CT) and value trade (VT), as described in Section 5.4. Mean refers to the average annual excess return. Std is the annualised volatility. SR is the annualised Sharpe ratio. Skew and Kurt are the skewness and kurtosis of the weekly excess returns. MDD is the maximum drawdown, calculated as the maximum percentage decline below the local maximum cumulative return using geometric chaining. COR refers to the sample correlation between the benchmark FHB and FX investment styles. Panel B reports p-values (following Ledoit & Wolf, 2008) testing the differences in the Sharpe ratio between all combinations of the five strategies. The statistics refer to excess returns over the US Treasury rate, net of rebalancing and transaction costs. A margin requirement of 10% is assumed for forward contracts. The sample period is January 1999 to June 2023.

However, this is consistent with the earlier findings of Menkhoff et al. (2012b) and Asness et al. (2013), as the higher average excess returns of momentum trades they find were mainly generated in the 1970s to 1990s. Indeed, Zhang (2022) and Opie and Riddiough (2020) also find evidence that the performance loss of momentum trades after the turn of the millennium and especially after the global financial crisis is substantial.

At first glance, the high positive skewness of the momentum trade might suggest that its downside risk should be limited, as negative excess returns are relatively close to the mean. However, its high excess kurtosis and the fact that it has the largest maximum drawdown of the four FX investment styles indicate that the compensation for very high negative excess returns, and hence the recovery from large drawdowns by sufficiently high positive excess returns, has apparently not materialised, resulting in the lowest average excess return and Sharpe ratio of the four FX investment styles. These results are broadly consistent with evidence that momentum trades are subject to considerable crash risk (Daniel & Moskowitz, 2016), suggesting that despite being negatively correlated with the benchmark portfolio, the momentum trade may perform too poorly on average to ultimately be an effective diversification instrument.

Notably, the contrarian pricing trade offers an average annual excess return of 6.17%, which is more than double that of the carry and value trades and even higher than the benchmark portfolio. Furthermore, because CPT's high excess returns are positively skewed and have a positive excess kurtosis, large positive excess returns are likely to occur much more frequently with CPT than with the other FX investment styles. As a result, CPT has the lowest maximum drawdown, which, given its high excess returns, results in the fastest expected recovery from maximum drawdown. Figure 5.1 supports the view that the contrarian pricing trade has significantly outperformed the other three FX investment styles for most of the sample period, and also generated substantial positive cumulative excess returns during and after the global financial crisis and during the Corona pandemic.

Finally, Panel B of Table 5.2 shows that the Sharpe ratio of CPT of 1.06 is fairly large and statistically significantly higher than the Sharpe ratio of the benchmark portfolio and the other three FX investment styles. Notably, the higher Sharpe ratio is the result not only of a higher average excess return, but also of lower volatility, suggesting that managing the conventional carry trade construction by taking into account CVaR forecasts is not only supported by theory, but actually leads to a significant increase in efficiency. This is also reflected in Figure 5.1, which shows that the trajectory of CPT's cumulative excess return is much smoother than that of the other strategies.

5.5.2 Diversification effects

This section presents the results of the investigation into the diversification benefits of FX investment styles for a US investor holding a global portfolio of equities from the economies of the G10 currencies. Table 5.3 shows that we do not find an economically or statistically significant diversification benefit for the momentum trade, a result that is in line with the literature, as Kroencke et al. (2014) and Opie and Riddiough (2020) already document that this FX investment style does not provide any diversification benefit if only developed market equities and currencies are considered, and Barroso et al. (2021) also reject the null hypothesis of a difference in Sharpe ratios of the Sharpe ratio test of Ledoit and Wolf (2008) for the momentum trade, interestingly with the same p-value of 0.40. In addition, Table 5.3 shows that adding the contrarian pricing trade, the carry trade and the value trade to the benchmark portfolio provides economically significant diversification benefits to the global equity investor, as the average annual excess return increases from 5.84% to 11.48%, 8.01% and 7.99% respectively. However, the annualised standard deviation of the benchmark portfolio also increases when combined with these three FX investment styles, with the result that although the Sharpe ratio is higher over the entire sample period, the diversification benefits for the global equity investor are only statistically significant for the contrarian pricing trade, where the Sharpe ratio increases from 0.37 to 0.66 (p-value less than 1%).

Table 5.3
Diversification benefits of FX investment styles

Benchmark portfolio augmented by FX investment styles					
	FHB	CPT	MT	CT	VT
Mean	5.84	11.48	4.30	8.01	7.99
Std	15.83	17.36	14.91	18.41	17.57
SR	0.37	0.66	0.29	0.43	0.45
p-value		(0.00)	(0.40)	(0.36)	(0.31)
Skew	-0.68	-0.41	-0.48	-1.03	-0.63
Kurt	4.56	4.52	2.31	8.33	6.05
MDD	53.12	44.21	49.39	62.84	41.93

Note: Table 5.3 reports the average excess return (Mean), standard deviation (Std), Sharpe ratio (SR) in percentage points (p.a.) as well as skewness (Skew), kurtosis (Kurt) and maximum Drawdown (in percentage points) of the fully hedged global equity portfolio (FHB) without and with supplementation by contrarian pricing trade (CPT), momentum trade (MT), carry trade (CT) and value trade (VT). P-values (according to Ledoit & Wolf, 2008), testing the differences in the Sharpe ratio to FHB, are reported in parentheses. The statistics refer to excess returns over the US Treasury rate, net of rebalancing and transaction costs. A margin requirement of 10% is assumed for forward contracts. The sample period is January 1999 to June 2023.

This finding contrasts with the literature (e.g., Barroso et al., 2021; Kroencke et al., 2014; Opie & Riddiough, 2020), which documents significant diversification benefits from adding carry and value trades to an existing international equity portfolio. Specifically, we find that the carry trade significantly worsens the skewness and inflates the kurtosis of the benchmark portfolio, which on average limits the upside potential and increases the downside risk, as evidenced by an 18% increase in the maximum drawdown. Strikingly, although the return distribution of the value trade is almost symmetrical, this advantage cannot be sufficiently exploited when added to the benchmark portfolio to generate a significant performance gain or reduce the overall portfolio skewness.

To better understand this contradiction, we consider the two subperiods 01/1999 to 12/2009 and 01/2010 to 06/2023 in Panel A of Table 5.4. We choose this sample split because the diversification benefits of FX investment styles have not been specifically studied in the post global financial crisis period, although it is well known in the literature that the performance of these three FX investment styles declined significantly after the global financial crisis (e.g., Fan et al., 2022; Opie & Riddiough, 2020; Zhang, 2022). Panel A of Table 5.4 clearly shows that the first subperiod, 01/1999 to 12/2009, which is characterised by the dotcom bubble and the global financial crisis, represents a rather difficult environment for global equities, as reflected in the much lower Sharpe ratio of 0.07 for the benchmark portfolio. In contrast, the second subperiod, 01/2010 to 06/2023, is characterised by a very strong performance of the global equity benchmark portfolio, reflected in a higher Sharpe ratio, driven by both higher annual excess returns and a lower annualised standard deviation.

Panel A of Table 5.4 also shows that carry and value trades statistically significantly improve the Sharpe ratio of the benchmark portfolio only in the first subperiod, but not in the second subperiod. In fact, the results indicate that the individual performance of the two FX investment styles must be too low to successfully diversify the benchmark portfolio, as they even tend to worsen its Sharpe ratio in the second subperiod due to an increase in volatility, although this decrease is not significant. The momentum trade again shows no effective diversification benefit for both subperiods. This is striking because our results suggest that there has been no economically or statistically significant effective diversification benefit from carry, value and momentum trades for a US global equity investor since the global financial crisis. Since the significant and large diversification benefits of carry and value trades have been shown by Kroencke et al. (2014) for the period 02/1981 to 12/2011, by Opie and Riddiough (2020) for the period 01/1987 to 07/2017, and by Barroso et al. (2021) for the period 01/1986 to 12/2016, we conclude that their overall results must be largely driven by the high performance of FX investment styles in the period before the global financial crisis, but do not hold for the period after the global financial crisis.

Table 5.4
Diversification benefits of FX investment styles in subperiods

Panel A: Performance after the global financial crisis

	January 1999 – December 2009					January 2010 – June 2023				
	FHB	+CPT	+MT	+CT	+VT	FHB	+CPT	+MT	+CT	+VT
Mean	1.26	8.57	1.91	5.52	6.23	9.57	13.85	6.25	10.03	9.42
Std	16.91	17.78	16.44	19.44	17.79	14.88	17.01	13.53	17.54	17.41
SR	0.07	0.48	0.12	0.28	0.35	0.64	0.81	0.46	0.57	0.54
p-value		(0.00)	(0.78)	(0.06)	(0.03)		(0.08)	(0.15)	(0.34)	(0.21)

Panel B: Performance in conformity and contrarian pricing regimes

	Conformity pricing regimes					Contrarian pricing regimes				
	FHB	+CPT	+MT	+CT	+VT	FHB	+CPT	+MT	+CT	+VT
Mean	9.39	14.75	7.97	11.98	12.54	-4.63	1.82	-6.52	-3.73	-5.44
Std	15.84	17.86	15.09	18.62	17.62	15.72	15.75	14.26	17.71	17.34
SR	0.59	0.83	0.53	0.64	0.71	-0.29	0.12	-0.46	-0.21	-0.31
p-value		(0.00)	(0.58)	(0.57)	(0.21)		(0.00)	(0.28)	(0.51)	(0.90)

Note: Table 5.4 reports the average excess return (Mean), standard deviation (Std) and Sharpe ratio (SR) in percentage points (p.a.) of the fully hedged global equity portfolio (FHB) without and with supplementation by contrarian pricing trade (CPT), momentum trade (MT), carry trade (CT) and value trade (VT). P-values (according to Ledoit & Wolf, 2008), testing the differences in the Sharpe ratio to FHB, are reported in parentheses. The statistics refer to excess returns over the US Treasury rate, net of rebalancing and transaction costs. A margin requirement of 10% is assumed for forward contracts. Panel A provides information on the diversification benefits within the two subsamples January 1999 – December 2009 and January 2010 – June 2023. Panel B distinguishes between the periods identified by the pricing classifier as conformity or contrarian pricing regimes within the entire sample period from January 1999 to June 2023.

On the contrary, the contrarian pricing trade, when added to the benchmark portfolio, achieves a statistically significant improvement in the Sharpe ratio in both subperiods, as shown in Panel A of Table 5.4, and thus over the entire sample period, as shown in Table 5.3. These performance gains are mainly achieved through a higher average excess return, with volatility comparable to the other three FX investment styles. In particular, Table 5.3 shows that the contrarian pricing trade is able to contribute its high performance to the benchmark portfolio in such a way that a desirable combination of reduced skewness and reduced kurtosis is achieved, which increases the upside potential and limits the downside risk.

In Panel B of Table 5.4, we find that the two double sorting procedures which are required to construct the contrarian pricing trade depending on the pricing regime perform well, as it is possible to statistically significantly improve the Sharpe ratio of the benchmark portfolio in both conformity and contrarian pricing regimes. In contrast, the other three FX investment styles do not significantly improve the Sharpe ratio of the benchmark portfolio when added, either in contrarian or in conformity pricing regimes. Notably, the global equity portfolio appears to significantly underperform in contrarian pricing regimes. According to the pricing classifier, contrarian pricing regimes are periods when investment currencies are likely to underperform, which typically occurs during periods of market turmoil (e.g., Menkhoff et al., 2012a). Since equity returns are known to be inversely related to innovations in aggregated volatility (e.g., Ang et al., 2006), this raises the question of whether the pricing classifier simply repackages the global FX volatility innovation risk factor of Menkhoff et al. (2012a) or some other financial stress indicator. We address these concerns empirically in the following section.

From a theoretical perspective, however, there are several arguments against this view. First, the pricing classifier is an ex-ante indicator, while financial stress indicators typically measure the level of market turmoil ex-post. As Hertrich (2024) points out, since predicting future periods of high or low global FX volatility innovations is inherently difficult, if not unpredictable, it is unlikely that the pricing classifier captures information that will be measured by financial stress indicators in the future. Second, as shown in Panel B of Table 5.4, the annualised volatilities of conformity and contrarian pricing regimes are quite similar and, if anything, suggest that contrarian pricing regimes are periods of lower volatility, contradicting the view that contrarian pricing regimes are periods of market turmoil. Third, the pricing classifier also predicts contrarian pricing regimes when the predicted performance of funding currencies appears to be so poor that shorting them appears to be profitable. However, the first core prediction of the two-factor currency pricing model of Menkhoff et al. (2012a) is that funding currencies would be expected to generate rather low positive excess returns in periods of market turmoil, as they are supposed to be hedges. This also contradicts the view that contrarian pricing regimes may simply be periods of market turmoil.

5.5.3 Are FX investment styles safe havens?

Baur and McDermott (2010) argue that it is important to distinguish between assets that provide diversification benefits on average, but not necessarily when they are most needed, i.e. in times of market stress or turmoil, and so-called ‘safe havens’ that provide positive returns and performance enhancement in adverse market conditions, while the rest of the portfolio delivers negative returns. In order to assess the state of the global financial market in terms of market turmoil, at the end of each week t, i.e. at the end of the strategies' holding period, we determine whether the OFR Financial Stress Index is positive (negative) and thus the level of financial market stress is above (below) the average level. We first present a graphical analysis to assess whether it is likely that the prediction of contrarian pricing regimes by the pricing classifier is simply driven by adverse market conditions. In doing so, we also consider global FX volatility, as suggested by Menkhoff et al. (2012a), since the construction of both the pricing classifier and global FX volatility is based on their currency pricing model, and therefore the two may capture similar information.

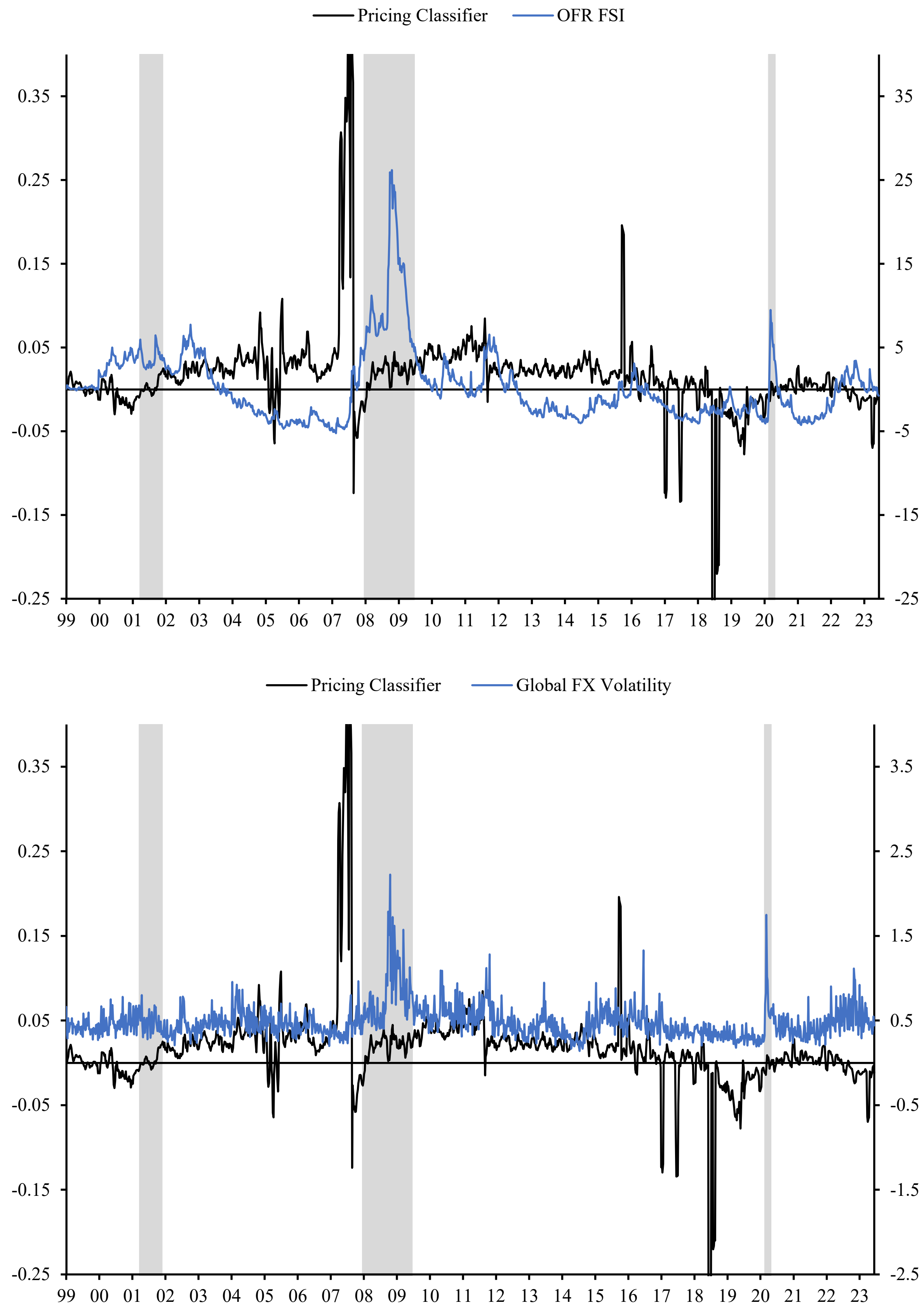

Figure 5.2. The top panel of this figure shows a time series plot of the Office of Financial Research's Financial Stress Index on the right y-axis and the pricing classifier on the left y-axis. The bottom panel shows a time series plot of global FX volatility on the right y-axis and the pricing classifier on the left y-axis. Shaded areas in the figure correspond to NBER recessions. The sample period is January 1999 to June 2023.

Figure 5.2 shows several spikes in the pricing classifier, with positive (negative) values of the pricing classifier indicating periods when the performance of the investment currencies is expected to be consistent (inconsistent) with the second core prediction of the two-factor currency pricing model of Menkhoff et al. (2012a). Interestingly, the pricing classifier seems to suggest that an investor prefers to enter into a carry trade during periods of market turbulence, as it shows positive values during the dotcom bubble or the Corana pandemic, but especially during the global financial crisis.

Consequently, despite Menkhoff et al. (2012a) finding that periods of high global FX volatility innovation are periods of poor carry trade performance, the pricing classifier suggests that the carry trade still performs well enough to expose investment capital to the negative systematic volatility risk of the carry trade. Overall, however, Figure 5.2 suggests that contrarian pricing regimes tend not to be periods of high financial market stress. This is also supported by the fact that the time series of the pricing classifier has a Spearman rank correlation with the time series of the OFR Financial Stress Index (global FX volatility) of -0.05 (0.17), while the two indicators of market turbulence have a correlation of 0.47.

Panel A of Table 5.5 shows that the three FX investment styles carry, contrarian pricing and value trade lead to a statistically significant improvement in the Sharpe ratio of the benchmark portfolio during market turmoil. In particular, contrarian pricing and value trade improve the negative average excess return of the global equity portfolio from -7.91% to -1.64% and -3.43% respectively, providing economically significant diversification benefits. However, while the momentum trade slightly improves the negative excess return and reduces volatility, which leads to an improvement in the Sharpe ratio of the benchmark portfolio when added, as shown by the modified Sharpe ratio of Israelsen (2004), the improvement is ultimately too small so that the momentum trade fails to provide statistically significant diversification benefits during periods of above-average financial market stress.

Table 5.5
Safe haven characteristics of FX investment styles

Panel A: Performance of benchmark supplemented by FX investment styles

	Above-average financial stress					Below-average financial stress				
	FHB	+CPT	+MT	+CT	+VT	FHB	+CPT	+MT	+CT	+VT
Mean	-7.91	-1.64	-7.17	-5.31	-3.43	16.53	21.67	13.22	18.36	16.86
Std	20.71	22.62	18.65	24.09	23.03	10.34	11.56	11.01	12.14	11.56
$SR^{modified}$	-163.8	-37.1	-133.7	-127.9	-79	1.60	1.87	1.20	1.51	1.46
SR	-0.38	-0.07	-0.38	-0.22	-0.15	1.60	1.87	1.20	1.51	1.46
p-value		(0.00)	(0.99)	(0.08)	(0.02)		(0.02)	(0.01)	(0.54)	(0.30)

Panel B: Performance of FX investment styles

	Above-average financial stress					Below-average financial stress				
	FHB	CPT	MT	CT	VT	FHB	CPT	MT	CT	VT
Mean	-7.91	5.25	-0.32	1.67	3.59	16.53	6.88	-1.47	3.36	2.11
Std	20.71	6.99	8.97	8.19	6.09	10.34	4.76	5.26	5.60	5.33
$SR^{modified}$	-163.8	0.75	-2.87	0.20	0.45	1.60	1.44	-7.73	0.60	0.40
SR	-0.38	0.75	-0.04	0.20	0.45	1.60	1.44	-0.28	0.60	0.40
p-value										
FHB		0.00	0.44	0.05	0.02		0.70	0.00	0.02	0.00
CPT			0.08	0.09	0.47			0.00	0.03	0.01
MT				0.60	0.25				0.02	0.09
CT					0.50					0.59

Note: Panel A of Table 5.5 reports the average excess return (Mean), standard deviation (Std) and Sharpe ratio (SR) in percentage points (p.a.) of the fully hedged global equity portfolio (FHB) without and with supplementation by contrarian pricing trade (CPT), momentum trade (MT), carry trade (CT) and value trade (VT) for periods of above-average and below-average financial stress. Periods of above (below) average financial market stress are identified by positive (negative) values of the OFR Financial Stress Index. P-values (according to Ledoit & Wolf, 2008), testing the differences in the Sharpe ratio to FHB, are reported in parentheses. Panel A also shows the modified Sharpe ratio of Israelsen (2004) in order to correctly assess performance rankings during periods of negative excess returns. Panel B shows equivalent information, but for the individual FX investment styles. P-values (according to Ledoit & Wolf, 2008), testing the differences in the Sharpe ratio between all combinations of the five strategies are reported in the last section of Panel B. The statistics refer to excess returns over the US Treasury rate, net of rebalancing and transaction costs. A margin requirement of 10% is assumed for forward contracts. The sample period is January 1999 to June 2023.

Panel B of Table 5.5 confirms that the three FX investment styles, carry, contrarian pricing and value, but not momentum, provide diversification benefits during periods of above-average financial market stress, as the Sharpe ratio tests show that their performance is indeed statistically significantly better than that of the benchmark portfolio. As a result, these three FX investment styles, but not the momentum trade, possess the characteristics of safe havens as defined by Baur and McDermott (2010), as they provide positive excess returns to investors during periods of market turmoil when global equity prices are falling.

It is worth noting, however, that although the contrarian pricing trade is often simply the extension of the carry trade by a second sort on CVaR-Trend in periods of market turmoil, this extension leads to significant outperformance of the standard carry trade investment rule, as the contrarian pricing trade achieves a Sharpe ratio of 0.75, almost four times that of the carry trade (0.20). It is also noteworthy that Panel A of Table 5.5 shows that in periods of below-average financial stress, the high Sharpe ratio of the benchmark portfolio of 1.60 can be statistically significantly improved to 1.87 by adding the contrarian pricing trade, while adding the carry or value trade slightly reduces the Sharpe ratio to 1.51 and 1.46 respectively, and adding the momentum trade actually leads to a deterioration of the Sharpe ratio to 1.20.

In addition, Panel B of Table 5.5 shows that the Sharpe ratio of the benchmark portfolio is similar to that of the contrarian pricing trade, but statistically significantly higher than that of the other three FX investment styles during periods of below-average financial stress. This implies that the carry and value trades tend to provide diversification benefits not so much because of their average performance, but rather because they are safe havens, i.e. they move on average in the opposite direction to global equities in times of market turmoil. However, the momentum trade is not a safe haven in times of market turmoil, nor does it perform well during periods of below-average financial stress, making the currency momentum trade a poor diversifier for a global equity portfolio.

In contrast, Table 5.5 shows that the contrarian pricing trade acts as a safe haven for investors in times of market turmoil and is also able to statistically significantly improve the risk-return profile of the benchmark portfolio in times of below-average financial market stress. This gives the contrarian pricing trade a significant advantage as a diversification instrument over the carry and value trades for global equity investors, as we cannot determine in advance the future level of financial market stress and thus the optimal entry point to take advantage of the safe haven characteristics of these two FX investment styles.

5.6 Conclusion

We propose an extended carry trade, which we call the contrarian pricing trade, that exploits the predictability of conformity and contrarian pricing regimes. A conformity (contrarian) pricing regime is a period in which the carry trade offers a (higher) lower expected reward to risk ratio per unit of systematic volatility risk taken than the strategy of only shorting the funding currencies, and in which it is thus more (less) attractive to engage in a carry trade instead of only shorting the funding currencies, consistent with (contrary to) the equilibrium prediction of the Menkhoff et al. (2012a) currency pricing model (Hertrich, 2024).

The contrarian pricing trade is constructed in conformity pricing regimes by extending the standard carry trade investment rule with a conditional double-sort on forward discount and a variable that captures a recent change in the conditional value at risk, called CVaR-Trend (Hertrich, 2023). In this way, the contrarian pricing trade only buys investment currencies that offer a discount sufficient to compensate for the higher probability and magnitude of large losses associated with their higher level of risk, and only sells funding currencies that offer a premium sufficient to compensate for the higher probability and magnitude of large gains, or insurance against volatility risk, associated with their higher level of CVaR. For contrarian pricing regimes, however, the forward discount sorting is omitted and replaced by a conditional double-sort on CVaR-Trend and idiosyncratic excess return momentum. In this way, the contrarian pricing trade avoids buying unprofitable but not unexpectedly risky currencies, and avoids selling profitable but not unexpectedly less risky currencies in contrarian pricing regimes.

The main objective of this paper is to analyse whether the contrarian pricing trade offers diversification benefits to a US investor who is internationally invested in the equities of the G10 currency economies. As benchmarks, we include in our analyses three conventional FX investment styles, namely the carry, momentum and value trades, which are known to be profitable in their own right (e.g., Asness et al., 2013; Lustig et al., 2011; Menkhoff et al., 2012b) and to provide diversification benefits for a global equity portfolio (e.g., Kroencke et al., 2014; Opie & Riddiough, 2020).

Our results show that the contrarian pricing trade economically and statistically increases the Sharpe ratio of the benchmark equity portfolio when added, not only over the entire sample period from January 1999 to June 2023 and for both conformity and contrarian pricing regimes, but also during periods of above- and below-average financial market stress and for the periods before and after the global financial crisis. In contrast, carry and value trades only show diversification benefits in the period prior to the global financial crisis, not so much because of their average performance, but rather because they are safe havens, i.e. they provide positive excess returns to investors during periods of market turmoil when global equity prices are falling. Notably, the carry and value trades actually tend to worsen the performance of the benchmark portfolio during periods of below-average financial market stress and in the aftermath of the global financial crisis. For the momentum trade, however, we find no diversification benefits, regardless of the time period or market conditions considered. These results show that the performance loss experienced by the three traditional FX investment styles, carry, momentum and value, since the global financial crisis (e.g., Fan et al., 2022; Opie & Riddiough, 2020; Zhang, 2022) has also significantly impaired their ability to be good diversifiers.

These results have two main implications. First, for investors planning to establish strategic currency positions to diversify their existing portfolios, our study provides insight into how information about the risk factors driving currency excess returns can be a fruitful source for constructing currency overlays. Second, the performance of future currency overlay strategies should also be measured against the contrarian pricing trade, as beating a fully hedged benchmark is not enough to claim success.

6 Conclusion

This dissertation began with the question of whether changes in individual foreign exchange rate risk affect the pricing of G10 currencies. It has been quite a journey to find initial answers to this question, as there is very little in the empirical asset pricing literature on the subject, particularly for foreign exchange markets, where the implications of equilibrium pricing models are not yet sufficiently clear. To get closer to an answer, this initial question is essentially broken down into four central research hypotheses to understand under what conditions and in what way changes in exchange rate risk affect currency pricing.

The second chapter begins by explaining that, according to the unbiasedness hypothesis, non-zero currency excess returns should not exist. Consequently, a relationship between changes in currency risk and expected excess returns requires forward rates to be biased predictors of future spot rates. However, the large body of empirical literature on the success of carry trades suggests that this condition is likely to be met. After discussing common explanations, section 2.2 focuses on the most important approach according to the current state of the literature, which argues that the unbiasedness hypothesis fails because investors demand a risk premium as compensation for being exposed to systematic volatility risk. That is, consistent with the fundamental financial principle that a risk-averse investor will demand higher (lower) future excess returns to hold currencies with higher (lower) future risk, low (high) interest rate currencies must in equilibrium offer a low (high) risk premium because they perform particularly well (poorly) in periods of market turbulence.

As discussed in sections 2.3.1 and 2.3.2, both its theoretical basis in Merton's ICAPM and its empirical support from the ‘on average’ perspective of currency pricing suggest that the power of systematic volatility risk to drive prices is likely to set the framework for changes in idiosyncratic currency risk to affect currency prices. Thus, the ‘first’ central research hypothesis asks whether there are periods when this risk-based explanation fails to explain the cross-section of currency excess returns. The answer provides an indicator in section 4.3 we call the ‘pricing classifier’, which predicts conformity (contrarian) pricing regimes when the carry trade offers a higher (lower) expected excess return per unit of systematic volatility risk taken than the strategy of shorting the funding currencies, implying that the relevance of systematic volatility risk for currency pricing is high (low), consistent with (contrary to) the ‘in equilibrium’ prediction of the Menkhoff et al. (2012a) currency pricing model.

The theoretical justification for the role of changes in idiosyncratic risk in currency pricing, as discussed in section 2.3. 3, comes from Fama's (1991) remark on the joint hypothesis problem, since the failure of the carry trade risk factor to price the cross-section of G10 currency excess returns may reflect both a misspecification of the market equilibrium model due to the omission of idiosyncratic risk (the ‘second’ central research hypothesis) and market inefficiencies affecting price adjustment (the ‘third’ central research hypothesis).

The third chapter then focuses simultaneously on the second and third central research hypotheses by testing whether a variable we call ‘CVaR-Trend’, which captures changes in a currency's individual CVaR, can price the cross-section of G10 currency excess returns in periods when the carry trade cannot. Idiosyncratic CVaR, as a proxy for idiosyncratic risk, may have pricing power because, as explained in sections 2.3.4 and 2.3.5, Merton's (1987) model of capital market equilibrium assumes that, if investors are under-diversified with respect to higher-order moments of the excess return distribution, currencies with higher left-tail risk should, in equilibrium, offer higher excess returns to compensate for the higher probability and magnitude of large losses associated with them. Changes in CVaR become relevant when information about a persistent change in CVaR diffuses only gradually through the market and, as a result, investors underreact to persistent changes in the level of CVaR, implying that an appropriate discount (premium) to account for an increase (decrease) in CVaR is not immediately reflected in spot prices but only materialises over time.

The empirical findings in chapter three confirm the interplay between these two theoretical frameworks, as those currencies that have experienced the greatest increase (decrease) in CVaR and, at the same time, the greatest discounts (premiums) in spot prices due to the concomitant depreciation (appreciation) of the quote currency will ultimately have high (low) risk premiums to compensate for their high (low) CVaR levels.

The fourth chapter then links the first to the second and third central research hypotheses. The results show that, first, these idiosyncratic price adjustments drive currency pricing in contrarian pricing regimes, as a dependent double sort on CVaR-Trend and idiosyncratic momentum explains the cross-section of G10 currency excess returns. Second, idiosyncratic momentum (CVaR-Trend) negatively (positively) predicts short-term excess returns of the carry trade risk factor. This implies that there are contrarian pricing regimes, as both funding and investment currencies are among those that have experienced an increase in CVaR and where prices are still adjusting due to an underreaction to the persistence of CVaR. It is only when the discount built into spot prices through low idiosyncratic excess returns is sufficient that both investment and funding currencies again have higher expected future excess returns, which then leads to a lower (higher) expected future excess return on the strategy of shorting the funding currency (buying the investment currency), which then restores the 'in equilibrium' condition of Menkhoff et al.'s (2012a) currency pricing model.

The initial results in Section 3.4.3, and then in more detail in sections 5.4.4 and 5.5, also provide evidence that changes in CVaR affect currency pricing in conformity pricing regimes, albeit the causal mechanism that links the first to the second and third central research hypotheses is somewhat different. In periods when the carry trade risk factor is a significant driver of the cross-section of G10 currency excess returns, investment currencies behave as expected when Merton's (1987) model is combined with the possibility of underreaction to the persistence of CVaR. That is, the mechanism outlined above applies here as well, as investment currencies price in a discount (premium) through low (high) excess returns over time, while experiencing an increase (decrease) in CVaR to provide the required higher (lower) risk premium. However, funding currencies experience an increase (decrease) in CVaR when they appreciate (depreciate) and subsequently have low (high) future excess returns. This is initially counterintuitive as it represents an inverse asymmetric volatility effect. One interpretation is that the asymmetric investment preferences associated with high and low forward discounts are likely to cause this phenomenon. If investors tend to go short rather than long in currencies with low forward discounts in order to use the negative interest rate differential to fund their long position, they are likely to perceive an appreciation of a funding currency as riskier than a depreciation. A second interpretation relates this phenomenon to the currency pricing model of Menkhoff et al. (2012a). Low future excess returns on funding currencies following periods of increasing CVaR may reflect the fact that they have appreciated during periods of market turbulence, providing a hedge against systematic volatility risk, and that investors are then willing to pay a premium, i.e. accept low risk premia, for insurance against future systematic volatility risk.

As explained in section 2.3.6, the ‘fourth’ central research hypothesis of this dissertation then asks in chapter five whether the theoretical implications and empirical findings of the previous two chapters can be used to construct a new currency trading strategy that not only survives the impact of transaction costs and margin requirements, but also provides diversification benefits to a global equity investor. The resulting FX investment style, which we call the ‘contrarian pricing trade’, is an extension of the conventional carry trade investment rule. In contrarian pricing regimes, we remove the forward discount sorting and replace it with a conditional double-sorting on CVaR-Trend and idiosyncratic excess return momentum. The contrarian pricing trade then buys (sells) the low (high) idiosyncratic momentum currencies in the high (low) CVaR-Trend tertile, which allows it to avoid holding unprofitable but not unexpectedly riskier currencies and to avoid selling profitable but not unexpectedly less risky currencies in order to benefit from excess return reversals that bring prices in line with the risk-based explanation of Menkhoff et al. (2012a). In contrast, in conformity pricing regimes, the contrarian pricing trade is based on the first sort on forward discount and then applies a dependent second sort on CVaR-Trend to buy (sell) the high CVaR-Trend currencies in the high (low) forward discount tertile. This allows the contrarian pricing trade to avoid buying (selling) investment (funding) currencies that offer (command) a discount (premium) that is insufficient to compensate for the higher probability and magnitude of large losses (gains) associated with their higher CVaR level.

The results in chapter five show that the contrarian pricing trade economically and statistically increases the Sharpe ratio of the benchmark equity portfolio when added, not only over the entire sample period from January 1999 to June 2023 and for both conformity and contrarian pricing regimes, but also during periods of above- and below-average financial market stress and for the periods before and after the global financial crisis. In addition, the contrarian pricing trade outperforms the conventional FX investment styles carry, momentum and value, both in terms of individual performance and as a diversification instrument for global equity investors. Since the contrarian pricing trade essentially evolves the conventional carry trade investment rule, we conclude this dissertation as follows.

The three key findings, first, the pricing classifier as a mispricing indicator that signals when to avoid carry trades, second, the sorting variable CVaR-Trend that highlights the relevance of changes in individual risk for currency pricing, and third, the predictability of excess return reversals in contrarian pricing regimes that reveals price adjustments towards equilibrium, improve our understanding to explain the cross-section of G10 currency excess returns and exploiting their implications helps to mitigate the shortcomings of the carry trade strategy following the global financial crisis.

Bibliography

Ackermann, F., Pohl, W., & Schmedders, K. (2017). Optimal and naive diversification in currency markets. *Management Science, 63*(10), 3347–3360.

Akram, Q. F., Rime, D., & Sarno, L. (2008). Arbitrage in the foreign exchange market: Turning on the microscope. *Journal of International Economics, 76*(2), 237–253.

Al-Zoubi, H. A. (2011). A new look at the forward premium 'puzzle'. *Journal of Futures Markets, 31*(7), 599–628.

Aloosh, A., & Bekaert, G. (2022). Currency factors. *Management Science, 68*(6), 4042–4064.

Álvarez-Díez, S., Alfaro-Cid, E., & Fernández-Blanco, M. O. (2016). Hedging foreign exchange rate risk: Multi-currency diversification. *European Journal of Management and Business Economics, 25*(1), 2–7.

Ang, A., Hodrick, R., Xing, Y., & Zhang, X. (2006). The cross section of volatility and expected returns. *Journal of Finance, 61*(1), 259–299.

Artzner, P., Delbaen, F., Eber, J., & Heath, D. (1999). Coherent measures of risk. *Mathematical Finance, 9*(3), 203–228.

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and momentum everywhere. *The Journal of Finance, 68*(3), 929–985.

Atilgan, Y., Bali, T. G., Demirtas, K. O., & Gunaydin, A. D. (2020). Left-tail momentum: Underreaction to bad news, costly arbitrage and equity returns. *Journal of Financial Economics, 135*(3), 725–753.

Ausin, M. C., & Lopes, H. F. (2010). Time-varying joint distribution through copulas. *Computational Statistics and Data Analysis, 54*(11), 2383–2399.

Baker, A. C., Larcker, D. F., & Wang, C. C. Y. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics, 144*(2), 370–395.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics, 131*(4), 1593–1636.

Bakshi, G., & Panayotov, G. (2013). Predictability of currency carry trades and asset pricing implications. *Journal of Financial Economics, 110*(1), 139–163.

Bali, T. G., Engle, R. F., & Murray, S. (2016). Empirical asset pricing – The cross section of stock returns. Hoboken, NJ: Wiley.

Bank for International Settlements (BIS). (2022a). Triennial Central Bank Survey on OTC foreign exchange turnover in April 2022. Monetary and Economic Department.

Bank for International Settlements (BIS). (2022b). Quarterly review on international banking and financial market developments. Monetary and Economic Department.

Barber, B., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *Quarterly Journal of Economics, 116*(1), 261–292.

Barberis, N., Shleifer, A., & Vishny, R. W. (1998). A model of investor sentiment. *Journal of Financial Economics, 49*(1), 307–343.

Barroso, P., & Santa-Clara, P. (2015). Beyond the carry trade: Optimal currency portfolios. *Journal of Financial and Quantitative Analysis, 50*(5), 1037–1056.

Barroso, P., Reichenecker, J.-A., & Menichetti, M. J. (2021). Hedging with an edge: Parametric currency overlay. *Management Science, 68*(1), 669–689.

Basel Committee on Banking Supervision. (2019). Minimum capital requirements for market risk. Bank for International Settlements.

Baur, D. G., & McDermott, T. K. (2010). Is gold a safe haven? International evidence. *Journal of Banking and Finance, 34*, 1886–1898.

Bayer, S., & Dimitriadis, T. (2020). Regression-based expected shortfall backtesting. *Journal of Financial Econometrics, 20*(3), 437–471.

Bekaert, G., & Panayotov, G. (2020). Good carry, bad carry. *Journal of Financial and Quantitative Analysis, 55*(4), 1063–1094.

Bekaert, G., & Hodrick, R. (2018). International financial management (3rd ed.). Cambridge University Press.

Bekaert, G., & Wu, G. (2000). Asymmetric volatility and risk in equity markets. *The Review of Financial Studies, 13*(1), 1–42.

Bekaert, G. (1996). The time-variation of risk and return in foreign exchange markets: A general equilibrium perspective. *The Review of Financial Studies, 9*(2), 427–470.

Bilson, J. (1981). The "speculative efficiency" hypothesis. *Journal of Business, 54*(3), 435–451.

Black, F. (1989). Universal hedging: Optimizing currency risk and reward in international equity portfolios. *Financial Analysts Journal, 45*(4), 16–22.

Blitz, D., van Vliet, P., & Baltussen, G. (2020). The volatility effect revisited. *The Journal of Portfolio Management, Quantitative Special Issue, 46*(2), 45–63.

Boudoukh, J., Richardson, M., Thapar, A., & Wang, F. (2019). Optimal currency hedging for international equity portfolios. *Financial Analysts Journal, 75*(4), 65–83.

Breedon, F. (2001). Market liquidity under stress: Observations from the FX market. In *Proceedings of a workshop on market liquidity* (Bank for International Settlements Papers No. 2, pp. 149–151).

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *The Journal of Finance, 47*(5), 1731–1764.

Brunnermeier, M., Farhi, E., Koijen, R. S. J., Krishnamurthy, A., Ludvigson, S. C., Lustig, H., Nagel, S., Piazzesi, M. (2021). Review article: Perspectives on the future of asset pricing. *The Review of Financial Studies, 34*(4), 2126–2160.

Brunnermeier, M. K., Nagel, S., & Pedersen, L. H. (2009). Market liquidity and funding liquidity. *The Review of Financial Studies, 22*(6), 2201–2238.

Brunnermeier, M. K., Nagel, S., & Pedersen, L. H. (2008). Carry trades and currency crashes. *NBER Macroeconomics Annual, 23*, 313–347.

Bruno, V., & Shin, H. S. (2017). Global dollar credit and carry trades: A firm-level analysis. *The Review of Financial Studies, 30*(3), 703–749.

Burnside, C. (2012). Carry trades and risk. In J. James, L. Sarno, & I. W. Marsh (Eds.), *Handbook of exchange rates* (pp. 283–312). Wiley.

Burnside, C., Eichenbaum, M., Kleshchelski, I., & Rebelo, S. (2011a). Do peso problems explain the returns to the carry trade? *The Review of Financial Studies, 24*(3), 853–891.

Burnside, G., Han, B., Hirshleifer, D., & Wang, T. Y. (2011b). Investor overconfidence and the forward premium puzzle. *The Review of Economic Studies, 78*(2), 523–558.

Caballero, R. J., Farhi, E., & Gourinchas, P.-O. (2017). The safe assets shortage conundrum. *Journal of Economic Perspectives, 31*(3), 29–46.

Caballero, R. J., & Krishnamurthy, A. (2009). Global imbalances and financial fragility. *American Economic Review, 99*(2), 584–588.

Campbell, J. Y., Lettau, M., Malkiel, B. G., & Xu, Y. (2023). Idiosyncratic equity risk two decades later. *Critical Finance Review, 12*(1-4), 203–223.

Campbell, J. Y., de Medeiros, K. S., & Viceira, L. M. (2010). Global currency hedging. *Journal of Finance, 65*(1), 87–121.

Campbell, J. Y., Lettau, M., Malkiel, B. G., & Xu, Y. (2001). Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *Journal of Finance, 56*(1), 1–43.

Campbell, B., & Dufour, J.-M. (1997). Exact nonparametric tests of orthogonality and random walk in the presence of a drift parameter. *International Economic Review, 38*(1), 151–173.

Cenedese, G., Sarno, L., & Tsiakas, I. (2014). Foreign exchange risk and the predictability of carry trade returns. *Journal of Banking & Finance, 42*, 302–313.

Cespa, G., Gargano, A., Riddiough, S. J., & Sarno, L. (2022). Foreign exchange volume. *The Review of Financial Studies, 35*(5), 2386–2427.

Chan, W. S. (2003). Stock price reaction to news and no-news: drift and reversal after headlines. *Journal of Financial Economics, 70*(2), 223–260.

Chen, Y. C., & Rogoff, K. (2003). Commodity currencies. *Journal of International Economics, 60*(1), 133–160.

Cheng, S., Hameed, A., Subrahmanyam, A., & Titman, S. (2017). Short-term reversals: The effects of past returns and institutional exits. *The Journal of Financial and Quantitative Analysis, 52*(1), 143–173.

Chernov, M., Dahlquist, M., & Lochstoer, L. A. (2023). Pricing currency risks. *Journal of Finance, 78*(2), 693–730.

Cho, J. B., Min, H. G., & McDonald, J. (2019). Volatility and dynamic currency hedging. *Journal of International Financial Markets, Institutions and Money, 64*(3), 609–621.

Choi, N., Fedenia, M., Skiba, H., & Sokolyk, T. (2017). Portfolio concentration and performance of institutional investors worldwide. *Journal of Financial Economics, 123*(1), 189–209.

Chong, J., & Miffre, J. (2010). Conditional correlation and volatility in commodity futures and traditional asset markets. *Journal of Alternative Investments, 12*(3), 61–75.

Christensen, B. J., & Varneskov, R. T. (2021). Dynamic global currency hedging. *Journal of Financial Econometrics, 19*(1), 97–127.

Clarida, R., Davis, J., & Pedersen, N. (2009). Currency carry trade regimes: beyond the Fama regression. *Journal of International Money and Finance, 28*(8), 1375–1389.

Cochrane, J. H. (2011). Presidential address: Discount rates. *Journal of Finance, 66*(4), 1047–1108.

Cochrane, J. H. (2005). Asset pricing. Princeton University Press.

Cont, R. (2001). Empirical properties of asset returns: stylized facts and statistical issues. *Quantitative Finance, 1*(2), 223–236.

Cooper, M. J., Gutierrez, R. C., & Hameed, A. (2005). Market states and momentum. *The Journal of Finance, 59*(3), 1345–1365.

Cornell, B. (1989). The impact of data errors on measurement of the foreign exchange risk premium. *Journal of International Money and Finance, 8*(1), 147–157.

Cornell, B. (1977). Spot rates, forward rates and exchange market efficiency. *Journal of Financial Economics, 5*(1), 55–65.

Croissant, Y., & Millo, G. (2019). Panel data econometrics with R. John Wiley & Sons, Inc.

Dahlquist, M., & Hasseltoft, H. (2020). Economic momentum and currency returns. *Journal of Financial Economics, 136*(1), 152–167.

Daniel, K., Hirshleifer, D., & Sun, L. (2020). Short- and long-horizon behavioral factors. *Review of Financial Studies, 33*, 1673–1736.

Daniel, K., Hodrick, R. J., & Lu, Z. (2017). The carry trade: Risks and drawdowns. *Critical Finance Review, 6*, 211–262.

Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. *Journal of Financial Economics, 122*(2), 221–247.

Daniel, K., & Titman, S. (2006). Market reactions to tangible and intangible information. *Journal of Finance, 61*(4), 1605–1643.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and over-reaction. *Journal of Finance, 53*(6), 1839–1885.

Dao, T. M., McGroarty, F., & Urquhart, A. (2016). A calendar effect: Weekend overreaction (and subsequent reversal) in spot FX rates. *Journal of Multinational Financial Management, 37-38*, 158–167.

Darvas, Z. (2009). Leveraged carry trade portfolios. *Journal of Banking and Finance, 33*(5), 944–957.

Das, S., Kadapakkam, P.-R., & Tse, Y. (2013). Is carry-trade a viable alternative asset class? *Journal of International Financial Markets, Institutions and Money, 24*(1), 247–257.

Della Corte, P., Riddiough, S. J., & Sarno, L. (2016a). Currency premia and global imbalances. *The Review of Financial Studies, 29*(8), 2161–2193.

Della Corte, P., Ramadorai, T., & Sarno, L. (2016b). Volatility risk premia and exchange rate predictability. *Journal of Financial Economics, 120*(1), 21–40.

Della Corte, P., Sarno, L., & Tsiakas, I. (2009). An economic evaluation of empirical exchange rate models. *The Review of Financial Studies, 22*(9), 3491–3530.

DeMiguel, V., Garlappi, L., & Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *Review of Financial Studies, 22*, 1915–1953.

De Roon, F. A., Eiling, E., Gerard, B., & Hillion, P. (2012). Currency risk hedging: No free lunch. Working paper, Tilburg University.

De Roon, F. A., Nijman, T. E., & Werker, B. J. M. (2003). Currency hedging for international stock portfolios: The usefulness of mean-variance analysis. *Journal of Banking & Finance, 27*(2), 327–349.

Dimmock, S. G., Kouwenberg, R., Mitchell, O. S., & Peijnenburg, K. (2021). Household portfolio underdiversification and probability weighting: Evidence from the field. *Review of Financial Studies, 34*(9), 4524–4563.

Dimmock, S. G., Kouwenberg, R., Mitchell, O. S., & Peijnenburg, K. (2016). Ambiguity aversion and household portfolio choice puzzles: Empirical evidence. *Journal of Financial Economics, 119*(3), 559–577.

Dobrynskaya, V. (2015). Currency exposure to downside risk: Which fundamentals matter? *Review of International Economics, 23*(2), 345–360.

Dobrynskaya, V. (2014). Downside market risk of carry trades. *Review of Finance, 18*(5), 1885–1913.

Dorn, D., & Huberman, G. (2010). Preferred risk habitat of individual investors. *Journal of Financial Economics, 97*(1), 155–173.

Dorn, D., & Huberman, G. (2005). Talk and action: What individual investors say and what they do. *Review of Finance, 9*(4), 437–481.

Dovern, J., & Manner, H. (2020). Order-invariant tests for proper calibration of multivariate density forecasts. *Journal of Applied Econometrics, 35*(4), 440–456.

Duarte, J., Kamara, A., Siegel, S., & Sun, C. (2014). The systematic risk of idiosyncratic volatility. Unpublished working paper. Social Science Research Network.

Dupuy, P. (2021). Risk-adjusted return managed carry trade. *Journal of Banking & Finance, 129*.

Dupuy, P. (2015). The tail risk premia of the carry trades. *Journal of International Money and Finance, 59*, 123–145.

Embrechts, P., McNeil, A., & Straumann, D. (1999a). Correlation: Pitfalls and alternatives. *Risk, 5*(12), 69–71.

Embrechts, P., Resnick, S., & Samorodnitsky, G. (1999b). Extreme value theory as a risk management tool. *North American Actuarial Journal, 3*(2), 30–41.

Engel, C., Kazakova, K., Wang, M., & Xiang, N. (2022). A reconsideration of the failure of uncovered interest parity for the U.S. dollar. *Journal of International Economics, 136*, 103602.

Engel, C., Lee, D., Liu, C., Liu, C., & Wu, S. P. Y. (2019). The uncovered interest rate parity puzzle, exchange rate forecasting, and Taylor rules. *Journal of International Money and Finance, 95*, 317–331.

Engle, R. F. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroscedasticity models. *Journal of Business & Economic Statistics, 20*(3), 339–350.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50*(4), 987–1008.

Eren, E., & Malamud, S. (2022). Dominant currency debt. *Journal of Financial Economics, 144*(2), 571–589.

Eun, C. S., & Resnick, B. G. (2004). *International financial management* (3rd ed.). McGraw-Hill-Irwin.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics, 116*(1), 1–22.

Fama, E. F. (1991). Efficient capital markets: II. *The Journal of Finance, 46*(5), 1575–1617.

Fama, E. F. (1984). Forward and spot exchange rates. *Journal of Monetary Economics, 14*, 319–338.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25*(2), 383–417.

Fan, Z., Londono, J. M., & Xiao, X. (2022). Equity tail risk and currency risk premiums. *Journal of Financial Economics, 143*(1), 484–503.

Farhi, E., & Gabaix, X. (2016). Rare disasters and exchange rates. *Quarterly Journal of Economics, 131*(1), 1–52.

Federal Open Market Committee. (FOMC) (2015). Transcript of Chair Yellen's press conference, December 16, 2015.

Fernandez, C., & Steel, M. F. J. (1998). On Bayesian modeling of fat tails and skewness. *Journal of the American Statistical Association, 93*(441), 359–371.

Filipozzi, F., & Harkmann, K. (2020). Optimal currency hedge and the carry trade. *Review of Accounting and Finance, 19*(3), 411–427.

Frankel, J., & Froot, K. (1987). Using survey data to test standard propositions regarding exchange rate expectations. *American Economic Review, 77*(1), 133–153.

Frenkel, J. (1976). A monetary approach to the exchange rate: Doctrinal aspects and empirical evidence. *Scandinavian Journal of Economics, 78*(2), 200–224.

Froot, K. A. (1993). Currency hedging over long horizons. Unpublished working paper. NBER paper No. 4355.

Froot, K. A., & Thaler, R. H. (1990). Anomalies: Foreign exchange. *Journal of Economic Perspectives, 4*(3), 179–192.

Froot, K. A., & Frankel, J. (1989). Forward discount bias: Is it an exchange risk premium? *Quarterly Journal of Economics, 104*(1), 139–161.

Fu, H., & Ruger, L. (2022). Multiple testing of the forward rate unbiasedness hypothesis across currencies. *Journal of Empirical Finance, 68*, 232–245.

Galati, G., Heath, A., & McGuire, P. (2007). Evidence of carry trade activity. *BIS Quarterly Review, 3*, 27–41.

Gao, G. P., Lu, X., & Song, Z. (2019). Tail risk concerns everywhere. *Management Science, 65*(7), 3111–3130.

Geweke, J., & Feige, E. (1979). Some joint tests of the efficiency of markets for forward foreign exchange. *Review of Economics and Statistics, 61*(3), 334–341.

Gilmore, S., & Hayashi, F. (2011). Emerging market currency excess returns. *American Economic Journal: Macroeconomics, 3*(4), 85–111.

Glen, J., & Jorion, P. (1993). Currency hedging for international portfolios. *Journal of Finance, 48*(5), 1865–1886.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relationship between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance, 48*(5), 1779–1801.

Goetzmann, W. N., & Kumar, A. (2008). Equity portfolio diversification. *Review of Finance, 12*(3), 433–463.

Goldberg, L. S., & Tille, C. (2008). Vehicle currency use in international trade. *Journal of International Economics, 76*(2), 177–192.

Gopinath, G., & Stein, J. C. (2020). Banking, trade, and the making of a dominant currency. *The Quarterly Journal of Economics, 136*(2), 783–830.

Gourinchas, P.-O., Rey, H., & Sauzet, M. (2019). The international monetary and financial system. *Annual Review of Economics, 11*(1), 859–893.

Gourinchas, P.-O., & Rey, H. (2007). From world banker to world venture capitalist: US external adjustment and the exorbitant privilege. In *G7 current account imbalances: Sustainability and adjustment* (pp. 11–66). University of Chicago Press.

Guo, H., & Ryan, L. (2018). Currency-hedging optimization for multi-asset portfolios. *The Journal of Portfolio Management, 44*(2), 100–113.

Gutierrez, R. C., & Prinsky, C. A. (2007). Momentum, reversal, and the trading behaviors of institutions. *Journal of Financial Markets, 10*(1), 48–75.

Habib, M. M., & Stracca, L. (2012). Getting beyond carry trade: What makes a safe haven currency? *Journal of International Economics, 87*(1), 50–64.

Han, Y., Zhou, G., & Zhu, Y. (2016). A trend factor: Any economic gains from using information over investment horizons? *Journal of Financial Economics, 122*(2), 352–375.

Hansen, L., & Hodrick, R. (1980). Forward exchange rates as optimal predictors of future spot rates: An econometric analysis. *Journal of Political Economy, 88*(5), 829–853.

Harris, M., & Raviv, A. (1993). Differences of opinion make a horse race. *The Review of Financial Studies, 6*(3), 473–506.

Harris, R. D. F., & Shen, J. (2006). Hedging and value at risk. *The Journal of Futures Markets, 26*(4), 369–390.

Hassan, T. A., & Mano, R. C. (2019). Forward and spot exchange rates in a multi-currency world. *The Quarterly Journal of Economics, 134*(1), 397–450.

Hassan, T. A. (2013). Country size, currency unions, and international asset returns. *Journal of Finance, 68*(6), 2269–2308.

Harvey, C. R., Liu, Y., & Zhu, H. (2021). Lucky factors. *Journal of Financial Economics, 141*(2), 413–435.

Harvey, C. R., Liu, Y., & Zhu, H. (2016). ... and the cross-section of expected returns. *Review of Financial Studies, 29*(1), 5–68.

Herskovic, B., Kelly, B., Lustig, H., & Van Nieuwerburgh, S. (2016). The common factor in idiosyncratic volatility: Quantitative asset pricing implications. *Journal of Financial Economics, 119*(2), 249–283.

Hertrich, D. (2024). Contrarian currency pricing: When risk tells you to expect mispricing. Unpublished working paper. Social Science Research Network.

Hertrich, D. (2023). Carry and conditional value at risk trend: Capturing the short-, intermediate-, and long-term trends of left-tail risk forecasts. *Journal of International Financial Markets, Institutions and Money, 82*, 101710.

Hochberg, Y., & Tamhane, A. (1987). *Multiple comparison procedures*. John Wiley & Sons.

Hodgson, D., Linton, O., & Vorkink, K. (2004). Testing forward exchange rate unbiasedness efficiency: A semiparametric approach. *Journal of Applied Economics, 7*(1), 325–353.

Hong, H., Lim, T., & Stein, J. (2000). Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance, 55*(1), 265–295.

Hong, H., & Stein, J. (1999). A unified theory of underreaction, momentum trading and overreaction in assets markets. *Journal of Finance, 54*(6), 2143–2184.

Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *Review of Financial Studies, 28*(3), 650–705.

Hsu, C. C., Tseng, C. P., & Wang, Y. H. (2008). Dynamic hedging with futures: A copula-based GARCH model. *The Journal of Futures Markets, 28*(11), 1095–1116.

Israelsen, C. L. (2004). A refinement to the Sharpe ratio and information ratio. *Journal of Asset Management, 5*(6), 423–427.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance, 48*(1), 65–91.

Jiang, Z., Krishnamurthy, A., & Lustig, H. (2021). Foreign safe asset demand and the dollar exchange rate. *The Journal of Finance, 76*(3), 1049–1089.

Joe, H., & Xu, J. (1996). The estimation method of inference functions for margins for multivariate models (Technical Report No. 166). Department of Statistics, University of British Columbia.

Jurek, J. W. (2014). Crash-neutral currency carry trades. *Journal of Financial Economics, 113*(3), 325–347.

Karnaukh, N., Ranaldo, A., & Söderlind, P. (2015). Understanding FX liquidity. *The Review of Financial Studies, 28*(11), 3073–3108.

Kim, M., Yang, J., Song, P., & Zhao, Y. (2021). The dependence structure between equity and foreign exchange markets and tail risk forecasts of foreign investments. *Quantitative Finance, 21*(5), 815–835.

Koijen, R. S. J., Moskowitz, T. J., Pedersen, L. H., & Vrugt, E. B. (2018). Carry. *Journal of Financial Economics, 127*(2), 197–225.

Kroencke, T. A., Schindler, F., & Schrimpf, A. (2014). International diversification benefits with foreign exchange investment styles. *Review of Finance, 18*(5), 1847–1883.

Lambert, M., Fays, B., & Hübner, G. (2020). Factoring characteristics into returns: A clinical study on the SMB and HML portfolio construction methods. *Journal of Banking & Finance, 114*.

Laurent, S. (2002). Asymmetry and fat-tails in financial time series. Maastricht.

Ledoit, O., & Wolf, M. (2008). Robust performance hypothesis testing with the Sharpe ratio. *Journal of Empirical Finance, 15*(5), 850–859.

Lehavy, R., & Sloan, R. G. (2008). Investor recognition and stock returns. *Review of Accounting Studies, 13*, 327–361.

Lettau, M., Maggiori, M., & Weber, M. (2014). Conditional risk premia in currency markets and other asset classes. *Journal of Financial Economics, 114*(2), 197–225.

Levich, R. M. (1979). Further results on the efficiency of markets for foreign exchange. In R. Dornbusch & J. Frenkel (Eds.), *International Economic Policy: Theory and Evidence* (pp. 246–267). Johns Hopkins University Press.

Lewis, K. (2011). Global asset pricing. *Annual Review of Financial Economics, 3*, 435–466.

Lewis, K. (1989). Can learning affect exchange-rate behavior? The case of the dollar in the early 1980's. *Journal of Monetary Economics, 23*(1), 79–100.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics, 47*(1), 13–37.

Lustig, H., Roussanov, N., & Verdelhan, A. (2014). Countercyclical currency risk premia. *Journal of Financial Economics, 111*(3), 527–553.

Lustig, H., Roussanov, N., & Verdelhan, A. (2011). Common risk factors in currency markets. *The Review of Financial Studies, 24*(11), 3731–3777.

Lustig, H., & Verdelhan, A. (2007). The cross section of foreign currency risk premia and consumption growth risk. *American Economic Review, 97*(1), 89–117.

Lyons, R. K. (2001). *The microstructure approach to exchange rates*. MIT Press.

Maio, P., & Santa-Clara, P. (2012). Multifactor models and their consistency with the ICAPM. *Journal of Financial Economics, 106*(3), 586–613.

Mancini, L., Ranaldo, A., & Wrampelmeyer, J. (2013). Liquidity in the foreign exchange market: Measurement, commonality, and risk premiums. *The Journal of Finance, 68*(5), 1805–1841.

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance, 7*(1), 77–91.

Marshall, B. R., Nguyen, N. H., & Visaltanachoti, N. (2017). Time series momentum and moving average trading rules. *Quantitative Finance, 17*(3), 405–421.

Maurer, T., Thuy-Duong, T., & Ngoc-Khanh, T. (2023). Market timing and predictability in FX markets. *Review of Finance, 27*(1), 223–246.

Maurer, T., Thuy-Duong, T., & Ngoc-Khanh, T. (2022). Pricing implications of covariances and spreads in currency markets. *Review of Asset Pricing Studies, 12*(1), 336–388.

Menkhoff, L., Sarno, L., Schmeling, M., & Schrimpf, A. (2012a). Carry trades and global foreign exchange volatility. *The Journal of Finance, 67*(2), 681–718.

Menkhoff, L., Sarno, L., Schmeling, M., & Schrimpf, A. (2012b). Currency momentum strategies. *Journal of Financial Economics, 106*(3), 660–684.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *Journal of Finance, 42*(3), 483–510.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica, 41*(5), 867–887.

Merton, R. C. (1971). Optimum consumption and portfolio rules in a continuous-time model. *Journal of Economic Theory, 3*(4), 373–413.

Merton, R. C. (1969). Lifetime portfolio selection under uncertainty: The continuous-time case. *The Review of Economics and Statistics, 51*(3), 247–257.

Meese, R. (1989). Empirical assessment of foreign currency risk premiums. In C. Stone (Ed.), *Financial Risk: Theory, Evidence and Implications* (pp. 157–180). Springer.

Meese, R., & Singleton, K. (1982). On unit roots and the empirical modeling of exchange rates. *Journal of Finance, 37*(4), 1029–1035.

Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time-series momentum. *Journal of Financial Economics, 104*(2), 228–250.

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica, 34*(4), 768–783.

Mulder, A., & Tims, B. (2018). Conditioning carry trades: less risk, more return. *Journal of International Money and Finance, 85*, 1–19.

Newey, W. K., & West, K. D. (1994). Automatic lag selection in covariance matrix estimation. *Review of Economic Studies, 61*(4), 631–653.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics, 108*(1), 1–28.

Nucera, F., Sarno, L., & Zinna, G. (2023). Currency risk premiums redux. *The Review of Financial Studies, 37*(2), 356–408.

Odean, T. (1999). Do investors trade too much? *American Economic Review, 89*(5), 1279–1298.

Okunev, J., & White, D. (2003). Do momentum-based strategies still work in foreign currency markets? *Journal of Financial and Quantitative Analysis, 38*(2), 425–447.

Opie, W., & Riddiough, S. J. (2020). Global currency hedging with common risk factors. *Journal of Financial Economics, 136*(3), 780–805.

Patton, A. J. (2006). Modelling asymmetric exchange rate dependence. *International Economic Review, 47*(2), 527–556.

Pennacchi, G. (2008). *Theory of asset pricing*. Pearson/Addison Wesley.

Perold, A. F., & Schulman, E. C. (1988). The free lunch in currency hedging: Implications for investment policy and performance standards. *Financial Analysts Journal, 44*(3), 45–50.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies, 22*(1), 435–480.

Pojarliev, M., & Levich, R. M. (2008). Do professional currency managers beat the benchmark? *Financial Analysts Journal, 64*(5), 18–32.

Polak, P., & Ulrych, U. (2024). Dynamic currency hedging with non-Gaussianity and ambiguity. *Quantitative Finance, 24*(2), 305–327.

Politis, D. N., & Romano, J. P. (1992). A circular block-resampling procedure for stationary data. In R. LePage & L. Billard (Eds.), *Exploring the Limits of Bootstrap* (pp. 263–270). John Wiley.

Polkovnichenko, V. (2005). Household portfolio diversification: A case for rank-dependent preferences. *Review of Financial Studies, 18*(4), 1467–1502.

Rachev, S. T., Jašić, T., Stoyanov, S., & Fabozzi, F. J. (2007). Momentum strategies based on reward-risk stock selection criteria. *Journal of Banking & Finance, 31*(8), 2325–2346.

Rafferty, B. (2012). Currency returns, skewness and crash risk. Unpublished working paper, Duke University.

Ranaldo, A., & de Magistris, P. S. (2022). Liquidity in the global currency market. *Journal of Financial Economics, 146*(3), 859–883.

Ranaldo, A., & Söderlind, P. (2010). Safe haven currencies. *Review of Finance, 14*(3), 385–407.

Raza, A., Marshall, B. R., & Visaltanachoti, N. (2014). Is there momentum or reversal in weekly currency returns? *Journal of International Money and Finance, 45*, 38–60.

Ready, R., Roussanov, N., & Ward, C. (2017). Commodity trade and the carry trade: A tale of two countries. *Journal of Finance, 72*(6), 2629–2684.

Reichenecker, J.-A. (2019). Diversification effect of standard and optimized carry trades. *The European Journal of Finance, 25*(8), 745–761.

Rockafellar, R., Uryasev, S., & Zabarankin, M. (2006). Generalized deviations in risk analysis. *Finance and Stochastics, 10*(1), 51–74.

Rockafellar, R., & Uryasev, S. (2000). Optimization of conditional value-at-risk. *Journal of Risk, 2*, 21–42.

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory, 13*(3), 341–360.

Rossi, B. (2013). Exchange rate predictability. *Journal of Economic Literature, 51*(4), 1063–1119.

Rossi, B. (2006). Are exchange rates really random walks? Some evidence robust to parameter instability. *Macroeconomic Dynamics, 10*(1), 20–38.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance, 19*(3), 425–442.

Sklar, A. (1959). Fonctions de répartition à n dimensions et leurs marges. *Publications de l'Institut Statistique de l'Université de Paris, 8*, 229–231.

Solnik, B. H. (1993). Currency hedging and Siegel's paradox: On Black's universal hedging rule. *Review of International Economics, 1*(2), 180–187.

Solnik, B. H. (1974). The international pricing of risk: An empirical investigation of the world capital market structure. *The Journal of Finance, 29*(2), 365–378.

Stambaugh, R. F., & Yuan, Y. (2017). Mispricing factors. *The Review of Financial Studies, 30*(4), 1270–1315.

Stoyanov, S. V., Rachev, S. T., & Fabozzi, F. J. (2007). Optimal financial portfolios. *Applied Mathematical Finance, 14*(5), 401–436.

Tessari, C. (2020). Common idiosyncratic volatility and carry trade returns. Unpublished working paper. Social Science Research Network.

The Economist. (2007). Carry on speculating: How traders have been triumphing over economic theory. *The Economist*, February 22, p. 80.

Thompson, S. B. (2011). Simple formulas for standard errors that cluster by both firm and time. *Journal of Financial Economics, 99*(1), 1–10.

Topaloglou, N., Vladimirou, H., & Zenios, S. A. (2002). CVaR models with selective hedging for international asset allocation. *Journal of Banking & Finance, 26*(7), 1535–1561.

Tryon, R. (1979). Testing for rational expectations in foreign exchange markets. Federal Reserve Board International Finance Discussion Paper 139.

Van Nieuwerburgh, S., & Veldkamp, L. (2010). Information acquisition and portfolio under-diversification. *Review of Economic Studies, 77*(2), 779–805.

Van Nieuwerburgh, S., & Veldkamp, L. (2009). Information immobility and the home bias puzzle. *Journal of Finance, 64*(3), 1187–1215.

Verdelhan, A. (2018). The share of systematic variation in bilateral exchange rates. *The Journal of Finance, 73*(1), 375–418.

Wang, J., & Yang, M. (2009). Asymmetric volatility in the foreign exchange markets. *Journal of International Financial Markets, Institutions and Money, 19*(4), 597–615.

Westerlund, J. (2007). Estimating cointegrated panels with common factors and the forward rate unbiasedness hypothesis. *Journal of Financial Econometrics, 5*(3), 491–522.

Zhang, S. (2022). Dissecting currency momentum. *Journal of Financial Economics, 144*(1), 154–173.