Currency Carry Trade Performance Across Market Conditions: An Empirical Study of the G10 Currency

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CURRENCY CARRY TRADE PERFORMANCE ACROSS MARKET CONDITIONS:

An Empirical Study of the G10 Currency

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List of Abbreviations

BAS	Bid-Ask Spread (Spot)
BAF	Bid-Ask Spread (Forward)
CIP	Covered Interest Parity
CP	Commercial Paper
CPI	Consumer Price Index
FX	Foreign Exchange
GFC	Global Financial Crisis
HML	High Minus Low
OTC	Over-the-counter
UIP	Uncovered Interest Parity
VIX	Chicago Board Options Exchange Volatility Index
VXY	JPMorgan G7 FX Volatility Index
TB	Treasury Bill

1. Introduction

The Foreign Exchange (FX) market is known to be the largest and most liquid financial market, facilitating the exchange of currencies, enabling international trade and investment. To illustrate the size of the FX market, according to the Bank of International Settlement, the daily turnover of the OTC (Over-the-counter) FX market has reached USD 7.5 billion (BIS, 2022). Among the broad set of strategies that are used in this market, the currency carry trade has emerged as a particularly prominent and widely studied trading strategy. The FX carry trade involves borrowing a low-yielding currency (also called as the funding currency) and consequently investing the borrowed amount in a high yielding currency (the investment currency), this way profiting from the interest rate differential.

The profitability of the carry trade is an anomaly that is contradicting the expectations of international finance theory. According to the Uncovered Interest Parity (UIP) condition, differences in interest rates between countries should be offset by corresponding exchange rate movements, such that the expected returns from currency speculations is zero, leaving no space for arbitrage. However, a large body of academic literature, starting with Fama (1984), has rejected the UIP empirically, shedding light to systematic deviations from the theory that makes the carry trade profitable in practice. This inconsistency is referred to by researchers as the forward premium puzzle and raises a multitude of important questions widely studied in the past 40 years.

One of the most broadly accepted explanations for existence of carry trade profits is the time-varying risk premia. Several studies argued that the revenues realized from the currency carry trade strategy are compensation for bearing risks and exposures, indicating that investors demand a premium for holding carry positions. Understanding the drivers and sensitivity of carry trade returns has become crucially important for both investors and financial theory.

The motivation for this study is to further investigate the profitability of FX carry trades. Recent years have been characterised by considerable volatility, persistent inflation, and rising geopolitical risk. These developments have likely altered the risk-return profile of the carry trade, making it necessary to reassess their performance. This is going to be done by constructing several macro-financial “high and low” regimes – including inflation, economic cycles, investor sentiment, and liquidity conditions – to assess their effects on the revenues generated by a carry trade portfolio. These questions are addressed through a comprehensive empirical framework, using monthly spot and forward exchange rate data of the G10 currencies and other indicators between January 2000 and January 2025.

The thesis makes several contributions to existing literature. It integrates a regime-based approach, using binary dummy variables as well as continuous indicators to assess the behaviour of carry trade returns under different market conditions. Subsample analysis is also conducted across four key periods differentiated over the 25-year sample period. The analysis works with both contemporaneous and lagged regime variables in order to further enhance the understanding of the link between carry trade performance and market conditions.

The methodology of the thesis begins with the construction of carry trade portfolios from spot and forward exchange rates of the G10 currencies against the USD, using a tercile-based sorting approach to create a “High minus Low” (HML) portfolio. Transaction costs are accounted for using the bid-ask spreads on both spot and forward transactions. The analysis then proceeds by estimating dummy and continuous variable regressions, with contemporaneous and lagged variables. This is repeated for four subsamples in the 25-year full sample period that were chosen to explore how the effect of the different market conditions on carry trade returns changed over time. Finally, a subsample mean- and t-test is included to compare mean returns across different states.

The empirical results reveal that carry trade excess returns show limited and inconsistent sensitivity to the examined high and low regimes, with most effects lacking statistical significance and results varying across periods and model specifications. While indicators occasionally display significant coefficients in line with expectations, these effects remain modest and not robust, highlighting the complex nature of carry trade performance.

The rest of the thesis is structured as follows. Chapter 2 presents the theoretical background that is necessary to understand prior to the analysis of carry trade returns. Exchange rate mechanisms, interest parity conditions, and the details of the carry trade strategy is described. Chapter 3 reviews the relevant literature on carry trade performance. Chapter 4 describes the data, including sources, descriptive statistics, plots, and the construction of key variables. Chapter 5 outlines the empirical methodology, the construction of portfolios, regression models and statistical tests. Chapter 6 presents the empirical results obtained by implementing the models described in the previous chapter. Interpretation of the findings are also included. Finally, Chapter 7 concludes the thesis with a summary of the findings and limitations to the research.

2. Theoretical background

This chapter aims to introduce some theoretical principles to support the understanding of the central theme of this thesis and lay down the foundations to the context of currency carry trades. It begins with a basic overview of the functioning of exchange rates and the foreign exchange market, followed by the introduction of international finance theory concepts – such as the parity conditions. This section will also highlight the carry trades mechanism and the empirical puzzles surrounding carry trade returns to set the stage for further analysis.

2.1. Exchange rates

An exchange rate is the price of one currency expressed in terms of another. Exchange rates allow comparison between prices expressed in different currencies. There are two ways to quote an exchange rate: direct and indirect. A direct (or American) quotation expresses the price of one unit of foreign currency in terms of the domestic currency. For example, as of April 4, 2025, the EUR/USD is 1.0963, meaning that 1 EUR equals 1.0963 USD (Financial Times, 2025). In contrast, an indirect (or European) quotation shows how many units of foreign currency is needed to buy one unit of domestic currency. This would be the opposite: USD/EUR is 0.9122, meaning that 1 USD equals 0.9112 EUR. The direct and indirect exchange rates are reciprocals of each other. Exchange rates are used by economic players to translate the price of foreign goods and services into domestic currency and enables international trade (Krugman et al., 2012). For example, if a US consumer would like to know the price of a foreign good, that costs EUR 1000 in USD, they can simply take the current EUR/USD exchange rate and multiply by the price indicated. This way, the US consumer could understand, that the foreign good costs:

$$EUR\ 1000\ \times\ 1.0963\frac{EUR}{USD} = USD\ 1096.3. \tag{1}$$

Exchange rates are constantly moving depending on the supply and demand for individual currencies. When the price of a currency falls in terms of another, it said to have depreciated. For example, the EUR/USD exchange rate moving from 1.0963 to 1.1024 would mean that the USD had depreciated (or weakened) against the EUR. After this move, 1 EUR would buy slightly more USD, the USD would worth slightly less. A depreciation in one currency simultaneously always means the appreciation of another. An appreciation is the rise in the price of a currency in terms of another (Krugman et al., 2012). In this example, the EUR had appreciated (or strengthened) against the USD. To illustrate, buying the same EUR 1000 good would cost a US consumer a bit more,

$$EUR\ 1000\ \times\ 1.1024\frac{EUR}{USD} = USD\ 1102.4. \tag{2}$$

Shifts in demand for assets denominated in currency A causes changes in the exchange rate. When expected return of assets denominated in currency A increases, demand increases, and the exchange rate rises (currency A appreciates). Conversely, if expected returns fall, demand decreases, and the exchange rate falls as well (currency A depreciates). Factors affecting the expected return on assets can be: domestic interest rates, foreign interest rates, price level, trade barriers, import and export demand, and productivity (Mishkin & Serletis, 2011). Table 1 summarizes the direction of the effect these factors create, assuming the USD as domestic currency.

Table 1: Factors influencing exchange rates

Factors Influencing Exchange Rates

Factor	Effect on Expected Return (USD assets)	Exchange Rate Effect
Domestic interest rate ↑	Increases	USD appreciates
Foreign interest rate ↑	Decreases	USD depreciates
Expected domestic price level ↑	Decreases (dollar expected to weaken)	USD depreciates
Expected trade barriers ↑	Increases (stronger dollar expected)	USD appreciates
Expected import demand ↑	Decreases (more outflow expected)	USD depreciates
Expected export demand ↑	Increases (stronger dollar expected)	USD appreciates
Expected domestic productivity ↑	Increases (more competitive economy)	USD appreciates

Source: Mishkin & Serletis (2011)

2.2. The foreign exchange market

The buying and selling of currencies takes place on the foreign exchange market. The FX market is the world's largest and most liquid financial market, mostly decentralized, running 24 hours a day (Krugman et al., 2012). According to the Triennial Central Bank Survey, conducted by the Bank for International Settlements in 2022, the daily turnover of the FX market is around USD 7.5 trillion and 78% of all FX trading takes place in one of the following five places: London, New York, Hong Kong, Singapore, and Tokyo (BIS, 2022). The main participants of the foreign exchange market are commercial banks, corporations, central banks, and other financial institutions (hedge funds, asset managers, insurance companies, etc.). The infrastructure of the market consists of two tiers: the interbank market and the retail market. The FX market facilitates international trade and investment and serves as a platform for speculation (seeking a profit from the moves in exchange rates) and hedging against exchange rate exposure. (King et al., 2012). The FX market has two major segments: the spot and the forward market. On the spot market, exchange happens immediately at the current exchange rate (also called the spot rate) and is typically settled in two business days. On the other hand, on the forward market, exchange happens at a predetermined rate on a future date, so delivery and payment is delayed (Secru, 2009). In addition to spot and forward transactions, several other types of financial instruments are traded on the FX market. A FX swap involves spot transaction and a simultaneous reversed forward transaction. FX futures are similar to forward contracts, only the terms of the contract (such as size, settlement date, etc.) are standardized and traded on organized exchanges, while forwards are traded over-the-counter (OTC) and can be entirely customized. FX options give the owner the right but not the obligation exchange currency at a future date and rate. The large majority of transaction on the FX market involve the USD, for this reason it is also called a vehicle currency (Krugman et al., 2012). An exchange rate between two currencies, neither of which is the USD, is called a cross-exchange rate (Copeland, 2005). Besides the USD, the most widely traded currencies are the EUR, GBP, JPY, CHF, AUD, CAD, NZD, NOK, KRW, and the HKD (King et al., 2012).

2.3. Parity conditions

In an open economy with integrated financial markets, the pricing of foreign exchange and interest-bearing assets across borders is governed by equilibrium conditions known as Interest Rate Parity (IRP) conditions. Among these, the two most important are the Covered Interest Parity (CIP) and the

Uncovered Interest Parity (UIP). These equilibrium conditions theorise the relationship between interest rates and exchange rates. According to the IRP conditions, an investor should be indifferent between holding asset denominated in the domestic currency at the domestic interest rate and holding a foreign asset at a foreign interest rate, since the returns should compare (Isard, 2006).

Covered Interest Parity (CIP)

The Covered Interest Parity theory states that the returns on interest-bearing assets denominated in the domestic currency and a foreign currency should be equal, when exchange rate risk is fully hedged through a forward contract. In other words, the interest rate differential between the domestic and foreign country is exactly offset by the forward premium or discount, implying that there are no arbitrage opportunities (Burnside, 2019). The forward premium is the defined as the proportion by which the forward exchange rate exceeds the spot rate (Copeland, 2005). Mathematically, this relationship is expressed as:

$$1 + i_t = (1 + i_t^*)\frac{F_t}{S_t}, \tag{3}$$

where i_t is the interest rate on a deposit denominated in the domestic currency, i_t^* is the interest rate on a deposit denominated in the foreign currency, F_t is the forward rate and S_t is the spot rate. The left-hand side of this equation represents the return earned on a domestic investment at i_t. The right-hand side of the formula represents the return earned by exchanging the same amount of domestic currency for foreign currency at S_t, investing the amount in foreign currency at i_t^*, and locking in the future conversion back to domestic currency through a forward contract at of F_t (Bertolini, 2011). CIP assumes, if the domestic and foreign assets differ only in their currency of denomination and the investor can *cover* the interest rate risk by entering into a forward contract to convert back to domestic currency (Isard, 2006). The Covered Interest Parity holds, if the returns on comparable domestic and foreign financial assets are equal. This implies a no-arbitrage environment, where investors cannot profit from exploiting differences in interest rates and exchange rates (Kaushala & Rajapakse, 2016).

The Covered Interest Parity condition has been previously empirically verified; however, especially in recent years some empirical studies have identified deviations from the theory. For example, Du et al. (2017) found proof for systematic and persistent deviations from the CIP since the 2008 financial crisis that are not explained by credit risk or transaction costs. Bräuning & Puria (2017) concluded that recent deviations from the CIP were cause by tighter post-crisis bank capital requirements. Similarly, Cerutti et al. (2019) also stated that CIP has been eliminated since the global financial crisis and explained the divergences by macro financial factors such as FX market liquidity, the strength of the USD, and monetary policy changes.

Uncovered Interest Parity (UIP)

The Uncovered Interest Parity theory differs slightly from the CIP. Investors can choose to leave their foreign exchange exposure *uncovered* by not entering into a forward contract and wait until *t+k* to reconvert at the spot rate S_{t+k} (Isard, 2006). According to the UIP, the interest rate differential between two countries should be offset by the appreciation of the lower yielding currency and the depreciation of the higher yielding currency (Bertolini, 2011). In other words, the adjustments in the spot exchange rate is expected to be offset the excess returns an investor could earn from the interest rate differential. This condition can be stated mathematically as:

$$1 + i_t = (1 + i_t^*)\frac{E(S_{t+k})}{S_t}, \tag{4}$$

where $E(S_{t+k})$ is the expected spot rate at *t+k*. Contrary to the CIP, where the forward market is used to hedge against exchange rate risk, under the UIP, transactions happen on the spot market (Kaushala & Rajapakse, 2016) UIP implies that the interest rate of the domestic and foreign countries determine the changes in the exchange rate of their currencies.

The UIP theory contains an additional element compared to the CIP, which is that the expected spot exchange rate at time *t+k* (Isard, 2006). If both UIP and CIP were to hold at the same time, the current forward rate should equal the expected spot rate, meaning that the current forward exchange rate is an unbiased predictor of the future spot exchange rate (Zivot, 2000). This relationship is called the forward rate unbiasedness hypothesis (FRUH), and it makes the assumption that prices fully reflect all available information (efficient markets hypothesis) (Fama, 1970). The forward rate unbiasedness hypothesis can be expressed mathematically as:

$$F_t = E(S_{t+k}). \tag{5}$$

However, the UIP has been found not to hold empirically. One of the most influential early empirical tests of the UIP was performed by Fama (1984), who found that forward rates have little, if any power predicting future spot rates. The study concludes that forward exchange rates primarily reflect a time-varying risk premium, which is negatively correlated with the expected future spot rate - hence often moving in the opposite direction. Similarly, Hansen & Hodrick (1980) also found consistent evidence that forward rates were not efficient predictors of future spot rates. According to Froot & Thaler (1990) deviations from the UIP occur at frequencies shorter than one year, but holds on long-horizons. This view is supported by Chinn & Meredith (2004), who empirically reject short-run UIP, but found greater support for the theory on the long run. More recent studies, such as Bekaert et al. (2007) found that the statistical evidence against UIP is mixed and depends on the currency pair, rather than the time horizon.

To conclude, researchers testing the Uncovered Interest Rate parity overwhelmingly rejected the hypothesis and concluded that the UIP conditions do not hold in real life. On the contrary, numerous studies documented an empirical phenomenon, called the forward discount bias (or forward-premium puzzle), which contradicts the UIP theory. The forward discount bias refers to the tendency of high yielding currencies to appreciate or not depreciate as much as UIP would predict, and low-interest-rate currencies to depreciate less than what UIP would predict. This is an systematic deviation from the UIP is documented by several studies, including Fama (1984) and Engel (1996). Regressions of exchange rate changes on interest rate differentials produced low or negative coefficients, implying that when a forward rate suggests a currency will appreciate, it often weakens instead. This empirical regularity is known as the forward discount bias, where high yielding currencies are often priced at a forward discount, yet do not depreciate as expected. The anomaly of the forward discount bias enables arbitrage, referred to as the currency carry trade.

2.4. The currency carry trade

The speculative trading strategy that exploits the arbitrage opportunity stemming from the systematic failure of the Uncovered Interest Parity is called the currency carry trade. Under a currency carry trade, an investor borrows funds in a low interest rate currency (funding currency) and lends them in a high interest rate currency (investment currency), *carrying* home the profits (Burnside, 2019). The payoff of the currency carry trade depends on two things: the interest rate differential and the exchange rate movements. If, in line with the forward-premium puzzle, the high yielding currency appreciates, the return increases. However, if the investment currency depreciates, the return decreases, it can even wipe out the profits gained from the interest rate differential (Menkhoff et al., 2012). Hence, the return can be expressed as

$$x_{t+k} = (1+i_t^*)\frac{S_{t+k}}{S_t} - (1+i_t). \tag{6}$$

In practice, these trades do not involve borrowing and lending, only buying high yielding currencies and simultaneously selling low yielding currencies on the forward market. As such, the investor enters into a forward contract to buy a high-yielding currency using a low-yielding currency, avoiding capital movement. Since the high-yielding currency trades at a forward discount, the investor is able lock in a lower price to buy in the future (Bertolini, 2011). Forward discounts are commonly used as a proxy for interest rate differentials, in line with the principle of CIP (Menkhoff et al., 2012). Therefore, excess returns can be calculated as

$$x_{t+k} = i_t^* - i_t - \Delta s_{t+k} \approx f_t - s_t - \Delta s_{t+k} \tag{7}$$

$$\Delta s_{t+k} = s_{t+k} - s_t$$

$$x_{t+k} = f_t - s_t - (s_{t+k} - s_t)$$

$$x_{t+k} = f_t - s_{t+k}\,.$$

Historically, FX carry trades were proved to be profitable. Burnside (2019) tested three carry portfolios: and equal-weighted carry trade (EWC) portfolio, a portfolio mimicking the Deutsche Bank G10 Currency Future Harvest (DBM) index, and a High minus Low (HML) portfolio that takes long positions in high-yield currencies and short positions in low-yield currencies. The average annual return on these portfolios were 4.1%, 5.5%, and 4.3% respectively. The author also looked at the Sharpe ratios of these carry strategies, which is a measurement of excess returns per unit of risk. The carry portfolios performed better than US equities, they scored 0.82, 0.62, 0.69, while US stocks scored 0.51. According to Menkhoff et al. (2012) carry trade yields a high and significant unconditional excess return, the HML portfolio producing 7.99%. returns with a Sharpe ratio of 0.82. The study notes, that carry trades have suffered significant losses since the 2008 financial crisis, but the cumulative returns over the previous 20 years significantly outweigh these losses. Lustig et al. (2011) also found empirical evidence for the profitability of carry trades. A HML portfolio produced annualized excess return of 454 basis points with a Sharpe ratio of 0.50.

The literature mentions certain historically low-yielding currencies that are predominantly used as funding currencies in carry strategies, such as the JPY and the CHF. Conversely, the AUD, NZD, and the ZAR are often used as investment currencies due to the higher yield associated.

As established, the FX carry trade has been found to yield excess returns and occasionally even outperformed US equities. The persistent profitability and risk characteristics of currency carry trade have motivated extensive academic inquiry, discussed in the following section.

3. Literature review

This section focuses on reviewing the existing literature dedicated to exploring various factors believed to have an impact on carry trade returns with the objective of spotting patterns, finding an explanation for the empirical deviations from the UIP theory, and making the carry strategy more predictable and a more attractive investment strategy.

3.1. Volatility

A large number of studies looked at market volatility as a potential determinant of carry trade profitability. One of the most likely explanations for the deviations from the UIP theory and the existence of carry profits is a time-varying risk premium. Volatility and other market conditions could play an important factor in the changes of this risk premium. The most commonly used measurement for volatility is the VIX index, which was developed by the Chicago Board Options Exchange (CBOE). Several studies proved, that carry trades earn positive excess returns when volatility is low.

A detailed examination of time varying systematic risk by Christiansen et al. (2011) showed that not only volatility is a strong predictor of shifts in carry trade behaviour, but when volatility increases, carry trade and stock market returns start to move together. The authors use, besides the CBOE VIX, another measure of volatility. They construct a FX volatility variable using 1-month FX options data on selected currencies, which turned out to be more relevant, than the VIX, which measures equity market volatility. Menkhoff et al. (2012) also concluded that volatility is a key driver of carry profits and that high returns to currency speculation can be understood as compensation risk-averse investors demand for taking on extra risks. The variable they use to describe FX volatility is a simple indicator that averages the absolute value of daily exchange rate changes for each currency. The study finds that high-yielding currencies are negatively correlated with changes in global FX volatility, meaning they provide low returns during periods of unexpectedly high volatility. On the other hand, low-yielding currencies continue to provide positive excess returns during periods of high volatility, thereby acting as safe havens and providing a hedge. Hoffmann (2011) looked at determinants of carry trades in Central Eastern Europe. Carry trades were popular in the region, since CEE countries offered higher interest rates than the eurozone and CHF. The author used the VIX index as an indicator for risk aversion and estimated that an increase in the VIX index negatively affected the returns of carry trades. Vistesen (2009) explored what the 2007 financial crisis revealed about carry trades. The findings showed that low-yielding currencies (such as JPY and CHF, most often used as funding currencies in carry trades) exhibit positive correlation to market volatility, measured by the VIX. This is in line with the idea that carry trades are sensitive to volatility. The study also adds that the financial crisis amplified the connection between carry trade currencies and volatility. Dunis & Miao (2007) applied two types of volatility filters (no trade filter and reverse filter) to a carry model. The results show that both of the filters improved the models tested, proving that the performance of carry strategies are negatively impacted by rising market volatility and proactively adapting to the changes in volatility can improve returns. A similar point has been made by Copeland & Lu (2016), who found that excess returns of carry trades are a low-volatility phenomenon and that a simple volatility-driven switching strategy can outperform pure trading strategies. A recent study, performed by (Asano et al., 2024) extended the literature by distinguishing between volatility (measurable uncertainty) and ambiguity (unmeasurable uncertainty). The paper categorizes FX market regimes into four types: high/low volatility combined with high/low ambiguity and examines carry trade performance across these regimes. They find that carry trade returns are not uniformly low during high-volatility regimes. Instead, returns increase when both volatility and ambiguity are high due to investors' hesitation that prevents the typical unwinding of carry trades.

3.2. Correlation with stock and bond markets

Several papers made a connection between carry trade profitability and the global equity and debt markets. The main rationale behind researching this connection was to understand whether carry trades could be used for diversification purposes to make optimal portfolio decisions. Another motivation was to further shed light on the risk-return profile of carry trades and develop more accurate asset pricing models (Christiansen et al., 2011).

Kohler (2007) measured correlation between the returns on the carry trade and on the global stock market and concludes that carry trade positions are subject to significant correlation risk to global equity markets. Additionally, currencies that tend to offer higher average returns (high-yielding currencies, such as: AUD, CAD, etc.) often have a higher correlation with stock markets and this correlation spikes during economic downturns. This can be interpreted as currencies that tend to move with the market offer higher average returns to compensate for added risk. Of course, it also means that investors using carry trades for diversification purposes can experience that they do not offer downside protection, amplifying losses. On the other hand, low-yielding currencies, such as the CHF act as safe havens, as they have a slightly negative correlation with returns on global equity. Christiansen et al. (2011) also mentions the exposure of currencies to equity and bond markets. To introduce stock and bond markets into the research, the authors use the use the log-returns on the futures contract on the S&P 500 index and on the 10-year U.S. T-notes. They report, that carry trade returns are positively correlated with stock market movements. In other words, when the stock market booms, investment currencies tend to strengthen and carry traders long on these currencies can realize extra profits, while funding currencies showcase a safe haven function. On the other hand, there is a slight negative correlation between bond markets and carry returns. When bond prices increase, investment currencies tend to lose value against funding currencies. Along the same lines, Vistesen (2009) identifies negative correlation between stock markets and funding currencies. The author highlights that due to this relationship, in economic turbulent times, funding currencies, such as JPY and CHF, are considered safe investments. The surge in appreciation can cause losses for traders using them to fund carry strategies. A broader perspective has been adopted by Schulze (2021) who found no clear link between market volatility and risk aversion differences between countries. This implies, that risk pricing may be segmented between the stock market and interest rate markets. This view is supported by Byrne et al. (2016) who extracted common information from nine often used currency and non-currency carry trade risk factors and concluded that it results in smaller pricing errors. The empirical results also suggest that there are risk characteristics of carry trades that are not captured in stock market risk. In other words, capital market risk is to some extent separated from foreign exchange market risk.

3.3. Liquidity

Previous research has investigated the impact of market liquidity on carry trade performance. Liquidity is an important factor that cannot be ignored, since assuming a frictionless market may result in misleading results and liquidity as a risk factor may explain excess carry returns (Abankwa & Blenman, 2015). Additionally, liquidity stress can cause sudden unwinding of carry trades (Brunnermeier et al., 2009). Carry trades also rely on funding liquidity, as they consist of borrowing and lending in foreign currencies (Burnside et al., 2008).

Orlov (2016) aimed to uncover any relationship between equity market illiquidity and currency momentum and carry trade strategy returns. Although there was a significant connection between momentum strategy excess returns and the level of stock market illiquidity, the effect of stock market illiquidity on carry trades were less clear and robust. Instead, the author confirmed, that carry trade returns are much more dominated by foreign exchange market liquidity. To measure stock market illiquidity, the author used the Amihud (2002) illiquidity estimator which expresses the price impact of trading volume. To FX market illiquidity, an adjusted bid-ask spread estimator was used. Christiansen et al. (2011) also examined how carry trade returns are impacted by illiquidity. Two variables were introduced. Firstly, to measure funding liquidity the TED spread was applied, which is the difference between the 3-month LIBOR and the 3-month US Treasury bill yield. A widening TED spread signals tighter liquidity. Secondly, to capture market liquidity, the JPY/USD bid-ask spreads were used. The study reported a significant impact of both funding and market liquidity on the potential return of carry trade strategies. In times of higher illiquidity, carry trade returns were negatively impacted. Bertolini (2011) looked at liquidity indicators, namely the TED spread, and the 2-year US swap spread, as a potential market-timing signals. The empirical results showed that market timing signals based on liquidity indicators achieved the best carry trading performance. Abankwa & Blenman (2015) took a slightly different approach to study the impact of FX liquidity risk on carry trade returns. The study defined liquidity risk, as the risk that a security's illiquidity will make it more difficult for its holder to sell. The authors highlighted that different currencies react differently to FX market liquidity changes. Low-yielding currencies (such as the JPY and CHF) are less sensitive to liquidity risk; hence they provide a liquidity hedge or liquidity coverage to investors. The opposite is true for high-yielding currencies (such as the AUD and the NZD). This can be interpreted as investors demand a premium for holding currencies with higher liquidity risk, which means liquidity risk is priced in. The liquidity risk factor explains a considerable part in carry trade returns. This was apparent when the authors constructed a portfolio that is long on the illiquid currencies, and short on the stable ones. The study deployed various liquidity indicators, such as the Roll (1984) bid-ask spread estimate or the Corwin-Schultz (2012) liquidity measure. To better understand what risks drive carry profits, Menkhoff et al. (2012) assessed the role of liquidity in the risk profile of carry trade strategies. To do so, the study introduced three liquidity indicators: global bid-ask spread, the TED spread, and a liquidity measure constructed by Pastor & Stambaugh (2001) for the US stock market based on price reversals. The study confirmed some relevance of illiquidity as risk factor, however concluded that volatility, as a more comprehensive indicator, emerged as the dominant risk factor responsible for carry trade returns. Filipe & Suominen (2012) focused on the JPY funding risk which they measured by combining option implied Japanese stock market volatility and crash risk. They found that funding risk had a strong explanatory power for FX carry trade returns, better than US-derived measures, such as the TED spread.

3.4. Macroeconomic and monetary variables

A large body of literature has investigated the relationship between carry trade returns and various macroeconomic indicators. As all the previous examples before, these studies also aimed to provide some explanation to the empirical deviation from UIP and help identify underlying drivers of profitability and risk dynamics.

One study by Hutchison & Sushko (2013) investigated how and to what extent macroeconomic surprises (such as news or policy announcements) have an impact on FX market speculation and are responsible for pricing downside risk for carry trade activity. By doing so, the authors wanted to focus on the market expectations of crash risk and how traders price this risk using risk reversal options. They found that certain macroeconomic news play a role in FX market risk assessment. For example, news on trade balance, GDP and consumer credit growth, consumer confidence, and household spending produced relevant results. According to Kim (2016), the role of macro news in carry trade decisions is complex and time-varying, with different effects across currencies and in the pre- and post-global financial crisis environment. Among others, news on CPI, current account balance, GDP, and unemployment rates were used in the analysis. Anzuini & Fornari (2011) performed a VAR analysis to examine macroeconomic determinants of carry trade activity. They conclude that demand and confidence shocks are associated with gains from carry trade activity, while supply and monetary shocks have a relatively limited impact. Lustig & Verdelhan (2007) wanted to test whether excess carry trade returns are compensation for consumption growth risk. They found that high-interest rate currencies tend to depreciate, while low-interest rate currencies tend to appreciate when domestic (US) consumption is low. As such, US investors demand higher returns on the riskier, high-interest rate currencies. This means, excess returns on currency carry trades can be explained by the consumption-based asset pricing model to a large extent. With a slightly different approach, Zviadadze (2017) highlighted that the maturity structure of currency carry trade yields is downward sloping. The study discussed what sources of macroeconomic risks are compensated for in carry trade yields and found that inflation and interest rate shocks play the most prominent role as investor expect higher returns for being exposed to these risks for longer. Falconio (2016) focused on US monetary conditions, defined as expansive and non-expansive periods, based on the changes in the Fed's base rate and the 30-day eurodollar futures. The results indicate that before the 2008 financial crisis, US expansionary policy lowered global risk aversion and increased carry returns. However, during and after the crisis Fed policy had little impact on risk aversion or carry trade returns. Similarly, Burnside et al. (2006) also wanted to determine whether carry payoffs are related to monetary variables. The study carried out an analysis on the impact of the Federal Funds rate, inflation, and the growth rate of money supply on USD yields. Additionally, GBP returns were regressed to UK inflation and the UK 3-months treasury bill yield. The results were mixed. The payoff of the equally weighted carry strategy had significant positive relationship with US inflation, the Fed Funds rate, and the UK 3-month treasury bill yield. However, the authors note that the significant relationships can be partially explained by the decreasing trend of the variables over time. Kim & Song (2015) investigated the possibility that bank default risk of the destination country has an impact on profits carry trade profits. To measure bank insolvency risk, the authors averaged the distance to default of individual banks in the given countries. The findings revealed that default risk premium explained a significant part of changes in carry trade returns over time. Lower average distance to default (higher risk of bank defaults) meant higher returns. This is consistent with the idea, that higher interest rate often indicate underlying vulnerabilities. Kim & Song (2014) considered country fundamentals to explain excess carry returns, more specifically forward premium, distance to default, stock beta, capital controls, exchange rate regime, domestic credit, and per capita income. The study identified that the three-factor model (forward premium, default risk and exchange rate regime) explained a significant part of the cross section of FX excess returns. A study of AUD carry trade determinants carried out by Kim (2015) sectioned results by pre- and post- global financial crisis. The author considered many factors, among which were the number of transactions, order flow on the USD/AUD currency pair, Australian and US macroeconomic news intensity, and country specific macroeconomic indicators (such as inflation, current account balance, GDP, unemployment etc.). In the pre-crisis period, the probability of the AUD carry trades were increased by positive order flow and an unexpected RBA rate hike and discouraged by trading activity, Australian inflation or unemployment, and strong US GDP data. In the post-crisis period, most of the factors lost their explanatory effect. In general, Australian macroeconomic news had a greater impact than US news. To determine the effect of geopolitical risk on carry trade returns, Cepni et al. (2023) created a geopolitical risk index that is tracking keywords signalling geopolitical tensions rising in newspaper articles. The results indicated that geopolitical risk has a strong predictive power for carry returns in each of the BRICS countries.

4. Data

This chapter intends to provide a detailed overview of the dataset complied to conduct the empirical analysis of the thesis. It begins describing data sources of exchange rates, volatility, inflation, economic cycles, and liquidity indicators. This is supported by descriptive statistics, and explanations on the construction of macroeconomic variable dummies, such as high vs low volatility or recession vs expansion.

4.1. Exchange rates

This thesis will be working with data on the G10 currencies, which are the most developed and liquid currencies on the foreign exchange market, which are: AUD (Australian Dollar), CAD (Canadian Dollar), CHF (Swiss Franc), EUR (Euro), GBP (British Pound Sterling), JPY (Japanese Yen), NOK (Norwegian Krone), NZD (New Zealand Dollar), SEK (Swedish Krona), and the USD (United States Dollar). Throughout the study, all exchange rates are quoted against the USD. Since the USD is one of the G10 currencies, this results in nine currency pairs. To ensure consistency in the direction of return calculations, the USD is used as the base currency in all currency pairs (e.g., USDAUD, USDCAD, USDCHF, etc.).

1-month forward and spot exchange rates were gathered from Refinitiv (DataStream) with monthly frequency. For both spot and forward rates, the available data on bid and ask prices were downloaded, and the mid-price was calculated as their average. The dataset covers a 25-year period, from 1 January 2000 to 1 January 2025. This implies 301 monthly observations. The start date was selected with the introduction of the EUR in mind, while still allowing for an extensive historical coverage.

Working with monthly data and the use of the USD as base currency in the observed currency pairs is in line with significant pieces of literature, such as Menkhoff et al. (2012), Brunnermeier et al. (2009), and Lustig et al. (2011). As (Brunnermeier et al., 2009) also notes, although carry strategies are not always implemented relative to the USD, analysing excess currency returns this way still provides valuable insights into their expected profitability. For instance, traders may implement carry trades between JPY and AUD; the regression results still remain informative as they capture the relative movements of these currencies vis-à-vis the USD. The G10 currencies are an optimal choice for carry trade return analysis, as they offer good data availability, relatively high liquidity, and therefore relatively low transaction costs (Bertolini, 2011).

Table 12 and Table 13 consists of summary statistics for both spot and forward exchange rates. To better examine the interdependencies between currencies, a matrix table (Table 14) of monthly spot exchange rates was computed. These can all be found in Appendix A.

Variable construction

As already explained in the Chapter 2.4, the profit earned on carry trades depends on the interest rate differential and the changes in the spot rate. Interest rate differentials can be proxied by the forward rate discount, as shown by the CIP. To measure the monthly returns needed for the central analysis of this thesis, two key variables were computed: log spot rate changes and log forward discounts. The spot rate change is represented as the natural logarithmic difference of the spot exchange rate between two consecutive months:

$$Spot\ Change = \ln(S_t) - \ln(S_{t-1}), \tag{8}$$

where S_t stands for the spot exchange rate at time t and S_{t-1} is the spot exchange rate in the previous period t-1. This is the approximate percentage change in the spot exchange rate or in other words, the return gained from exchange rate movements. Following Asano et al. (2024), Menkhoff et al. (2012), and many more studies of the literature, these equations deploy natural logarithms to approximate percentage changes.

According to Mogensen & Nielsen (2020) forward discount can be calculated as the difference between natural logarithm of the 1-month forward rates and spot rate at time t:

$$Forward\ Discount = \ln(F_t) - \ln(S_t)\,. \tag{9}$$

A positive forward discount implies a higher interest rate in the foreign country, than in the United States which would give investors an incentive to go long in the foreign currency – using it as an investment currency. Conversely, a negative forward discount implies lower yields in the foreign country, which would make it a potential funding currency. These variables enable the construction of carry portfolios and the investigation of carry trade returns under different market conditions. Studies part of the literature on carry trade returns have applied the same method to compute excess returns.

Summary Statistics

To gain further insight into the data before starting the empirical analysis, the below table of descriptive statistics was constructed on the two elements of carry profits: spot rate changes and forward discounts. This provides a preliminary overview of the behaviour and distributional properties of variables later used in constructing portfolios.

Table 2: Summary Statistics of Log Spot Rates and Forward Discounts

Summary Statistics of Log Spot Rate Changes

Currency	Mean	Min	Max	Std Dev	Kurtosis	Skewness
USDAUD	0.0001	-0.0997	0.1735	0.0353	1.8574	0.4916
USDCAD	0.0000	-0.0904	0.1302	0.0249	2.9555	0.4885
USDCHF	-0.0020	-0.1287	0.1194	0.0283	1.9975	-0.1727
USDEUR	-0.0002	-0.0962	0.1023	0.0271	1.3950	0.1661
USDGBP	0.0009	-0.0903	0.1039	0.0248	1.3040	0.2970
USDJPY	0.0012	-0.0745	0.0880	0.0278	0.4831	0.0901
USDNOK	0.0010	-0.0788	0.1363	0.0337	0.6224	0.2403
USDNZD	-0.0004	-0.1245	0.1415	0.0371	1.2150	0.3460
USDSEK	0.0007	-0.0907	0.1178	0.0319	0.3415	0.0043

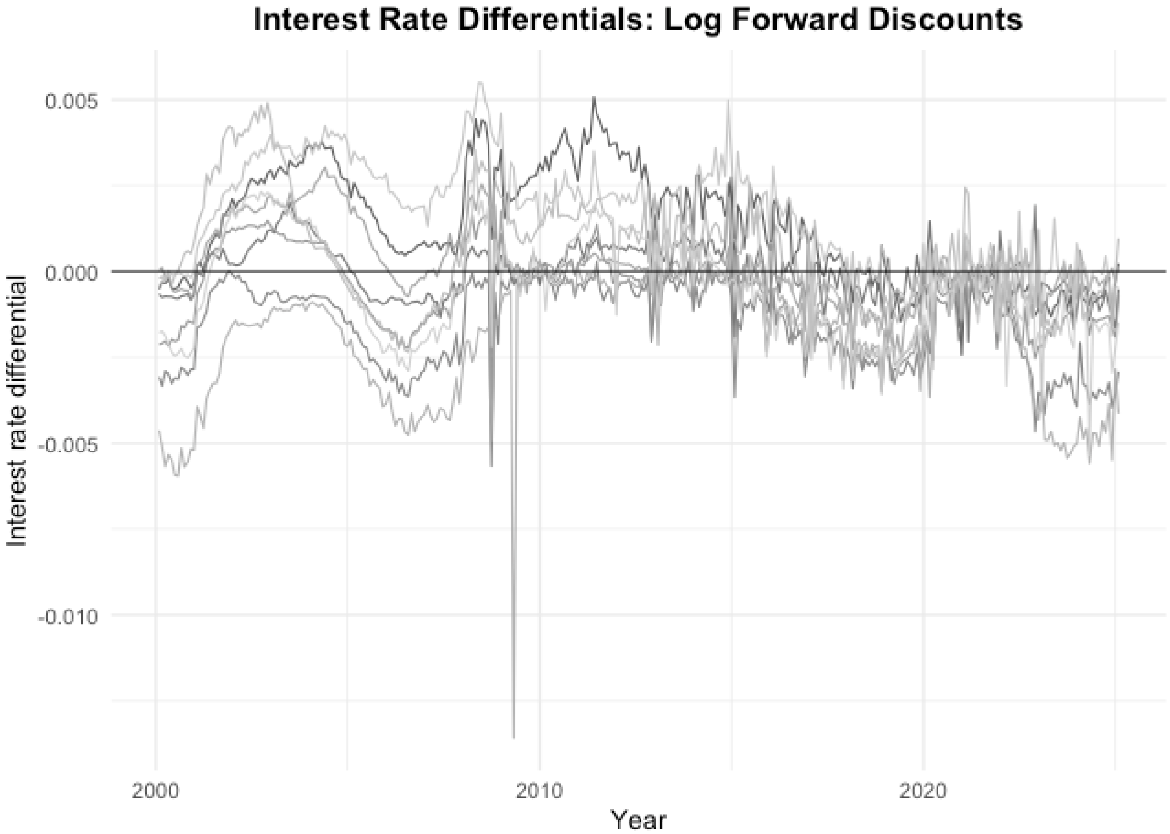
Summary Statistics of Log Forward Discounts

Currency	Mean	Min	Max	Std Dev	Kurtosis	Skewness
USDAUD	0.0013	-0.0026	0.0051	0.0016	-1.0792	0.0829
USDCAD	0.0000	-0.0024	0.0026	0.0008	-0.0220	0.1450
USDCHF	-0.0016	-0.0057	0.0003	0.0012	-0.9090	-0.4516
USDEUR	-0.0007	-0.0044	0.0016	0.0012	-0.6655	-0.0380
USDGBP	0.0002	-0.0026	0.0030	0.0011	0.0865	0.4253
USDJPY	-0.0019	-0.0136	0.0009	0.0018	3.9018	-1.3301
USDNOK	0.0005	-0.0023	0.0049	0.0016	-0.0898	0.5824
USDNZD	0.0016	-0.0041	0.0055	0.0016	-0.2609	-0.1998
USDSEK	-0.0005	-0.0054	0.0035	0.0015	-0.7399	0.0929

The mean returns of spot rate changes are close to zero for all currency pairs. The USDJPY exhibits the highest average log return, meaning that the USD appreciated the most against JPY. On the other hand, USDCHF produced the lowest average return, indicating the deprecation of USD against the CHF. The standard deviation ranges between 2.5% and 3.7%; higher volatility can be observed for currency pairs like USDNZD or USDNOK, while USDCAD and USDGBP showcase relatively lower volatility. The kurtosis values are above 3 in all cases, implying that the distribution of spot rate changes exhibit fat tails. Skewness values are generally low, the most significant asymmetry can be observed in USDCAD, which shows the strongest right skewness with 0.4885. USDCHF is the only left-skewed currency pair with -0.1727.

As for the forward discounts, the means vary across currency pairs. The lowest average forward discounts were exhibited by the USDJPY and the USDCHF, consistent with Japan's and Switzerland's historically low interest rates, relative to the United States. In contrast, the USNDNZD and USDAUD display the highest average forward discounts, in line with their reputation as relatively high-yielding currencies. The standard deviation of forward discounts ranges between 0.08% and 0.18%, indicating relatively stable interest rate differentials over the observed time period. Skewness values also vary across currency pairs. For example, the USDJPY shows strong left skewness with -1.3301, suggesting large negative forward discounts. On the other hand, the USDNOK and USDGBP showcases right skewness with 0.5824 and 0.4253.

Figure 1: Interest Rate Differentials (Log Forward Discounts)



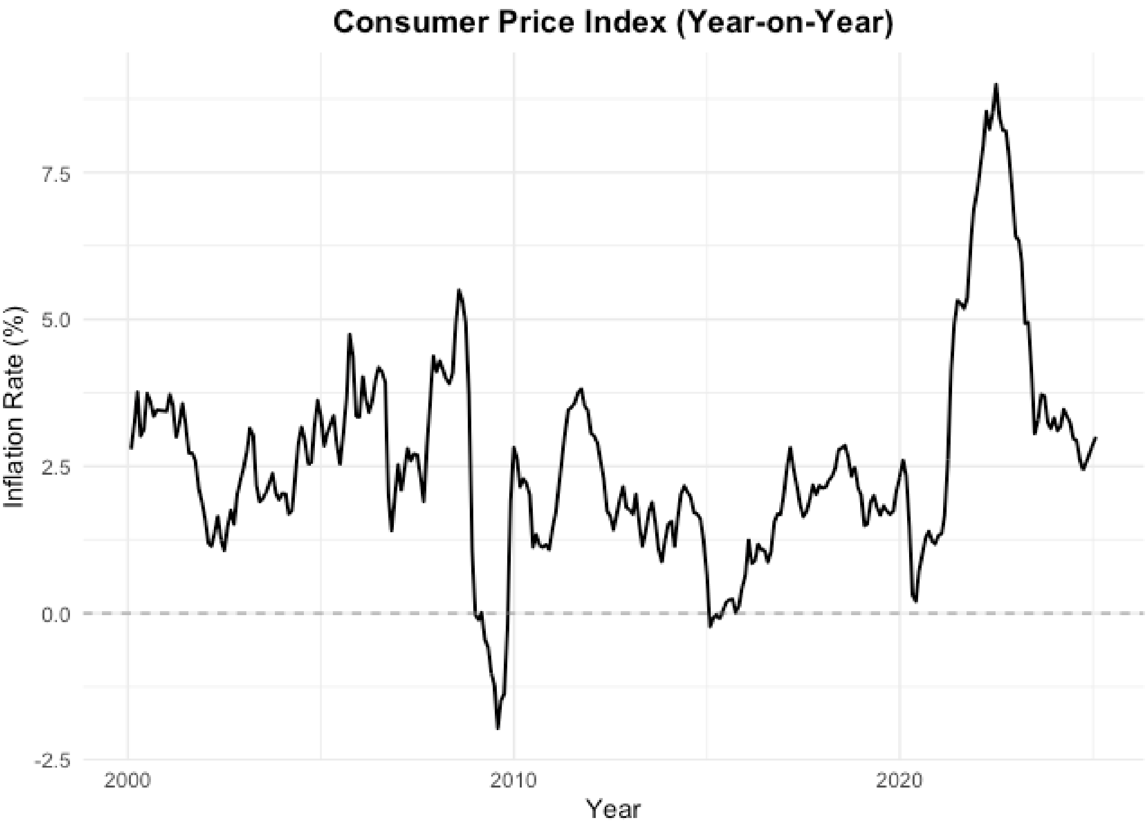
To further illustrate the extent of interest rate differentials across the observed time period, Figure 1 plots log forward discounts of all observed currency pairs. Before 2010, the majority of currencies exhibited consistent positive forward discounts. Around the 2008 global financial crisis, there is heightened volatility, including sharp, temporary spikes and sudden reversals. This reflects central bank interventions during the crisis. Post 2010, interest rate differentials converged towards 0. It is worth noting, that the USDJPY and the USDCHF display consistent negative forward discounts across the entire period.

4.2. Additional variables

The thesis sets out the objective of observing carry trade returns under high vs. low inflation environments, expansion vs. recession, in times of high vs. low investor sentiment, and liquid vs illiquid conditions. In addition to exchange rates, the following variables were incorporated in the dataset to capture the above mentioned global financial and economic conditions. To identify periods of elevated volatility, inflation, and liquidity stress, regime dummy variables are constructed using a 36-month rolling median threshold approach. This methodology is in line with the one used by Asano et al. (2024) in a recent study. The authors defined high regimes, as values in the current month greater than the 50th percentile, using a 36-month rolling window to calculate the average. This approach ensures regime classification is based on information available at time *t*, avoiding look-ahead bias.

Inflation: Monthly US Consumer Price Index (CPI) was sourced from the Federal Reserve Bank of St. Louis (FRED, 2025b). Year-on-Year inflation was computed using the monthly CPI data to capture the rate of inflation, rather than price levels. In order to facilitate analysis, a dummy variable was created by assigning 1 to datapoints which exceeded the 36-month rolling median of YoY CPI, and 0 otherwise. This classification allows the analysis to distinguish between high and low inflation regimes.

Figure 2: Year-on-Year Consumer Price Index (US)



Economic cycles: To identify periods recession and expansion, a ready-made recession dummy variable was used provided by the Federal Reserve Bank of St. Louis (FRED, 2025d). The variable is a binary indicator constructed by the National Bureau of Economic Research (NBER), where the value 1 indicates US economic recession for the given month, and 0 otherwise. The NBER's methodology defines recession as periods of strong decline in economic activity that lasts more than a few months. Real income, employment, industrial products, retails sales, and other indicators are tracked in order to identify recession periods. In the dataset spamming from 2000 to 2025, there are 31 months, where the dummy is indicating an economic recession in the United States.

Investor sentiment: To determine periods of high and low investor sentiment, two volatility measures were sourced. The most commonly used measure of volatility is the CBOE VIX which is widely used as a proxy for investment sentiment and market uncertainty. The VIX was designed by the Chicago Board Options Exchange for investors to help manage downside risk. It measures the implied market volatility over the next 30 days based on the prices of the S&P 500 options. It is often referred to as the 'fear gauge' because it can be interpreted as a proxy for risk appetite (CBOE, n.d.). This was downloaded directly from the website of the CBOE (CBOE, 2025). As the VIX is based on the S&P 500 it measures equity market volatility. To better capture the investor sentiment on FX markets, a second variable was also included. The JPMorgan G7 FX Volatility Index (VXY) captures implied volatility across major currency pairs to reflect sentiment in FX markets and extends the geographical coverage beyond the US. The VXY tracks 3-months option volatility of the G7 currencies (Lubbers, 2022). This was gathered from Refinitiv (DataStream). For both measures, dummy variables were created to distinguish periods of high and low investor sentiment using a rolling threshold approach. More specifically, a month was classified as high volatility regime if the previous month's index (VIX or VXY) exceeded its trailing 36-month rolling median. The value 1 is given to all the months classified as high volatility months, and 0 otherwise. The use of lagged signals ensures that the regime classification avoids look-ahead bias. By applying this dynamic method, the dummy variables construction provides a more robust foundation for later analysis of carry trade performance due to changes in market sentiment.

Figure 3: VIX and VXY Implied Volatility Levels

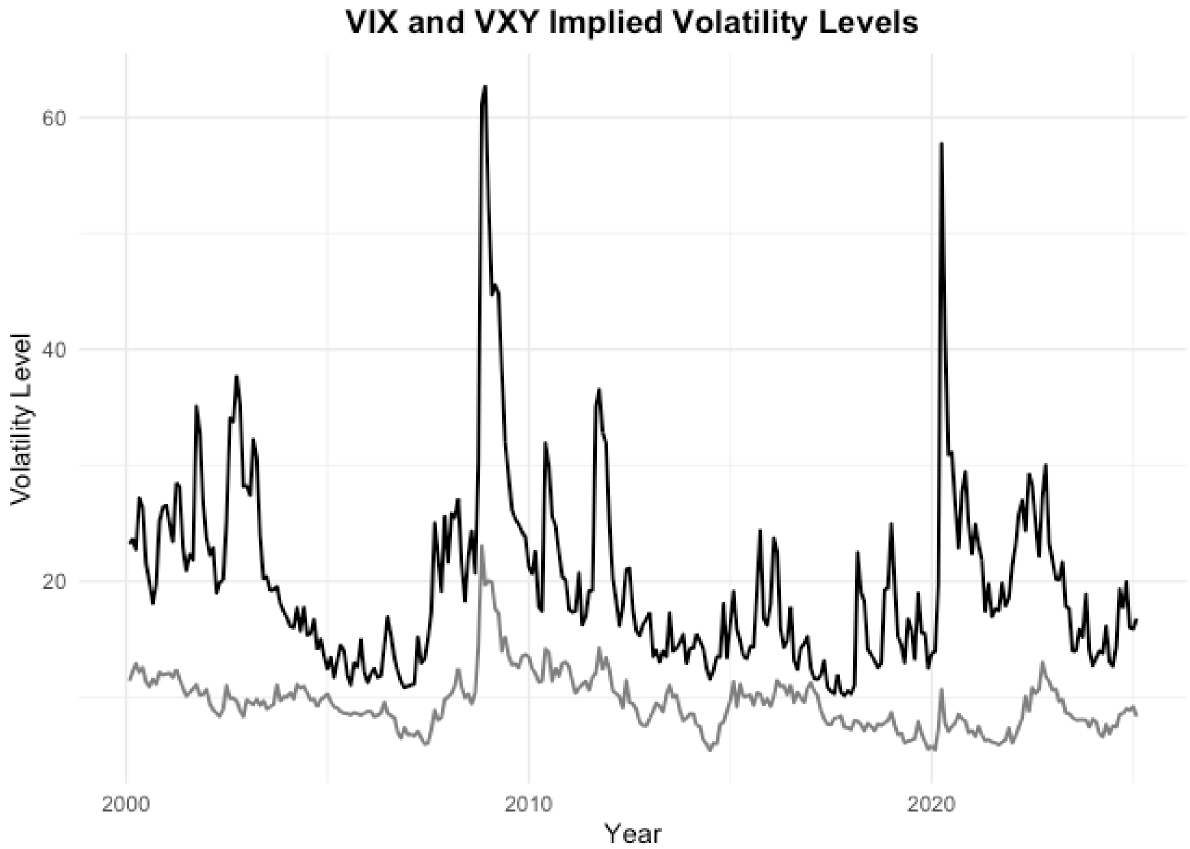


Figure 3 depicts the evolution of the VIX and VXY indices. The two peaks correspond with the 2008 global financial crisis and the Covid-19 crisis. As a consequence of market panic in November 2008, the VIX peaked at 62.67, while the VXY reached 23 in October of the same year. In March 2020, at the moment of the pandemic outbreak, the VIX climbed to 57.74 and the VXY to 10.66. It is worth noting the correlation between the two indices is 0.651, indicating a moderately strong positive relationship of the VIX and VYX generally moving together.

Liquidity / market depth: To include liquidity conditions, two measures were used. The TED spread reflects interbank credit and liquidity risk. It is calculated as the difference between interbank interest rates and short-term government debt interest rates, more specifically the 3-months LIBOR and the 3-months US Treasury Bill rate. However, due to the recent discontinuation of the LIBOR benchmark rates, the TED spread observations also stop at January 2022 (JP Morgan, 2022). For a full sample, a second measure was constructed based on the spread between the 90-day AA Commercial Paper interest rate and the 3-month Treasury Bill rate, which serves as a well-established proxy for funding market stress and liquidity conditions. For example, Nagel (2016) explains how the CP-T Bill spread reflects the liquidity premium investors demand for holding a less liquid asset, such as commercial papers over highly liquid assets, such as Treasury Bills. Both datasets were sourced from the Federal Reserve Bank of St. Louis (FRED, 2025a) (FRED, 2025c).

Figure 4: Liquidity Condition Indicators: TED and Commercial Paper - T-Bill Spreads

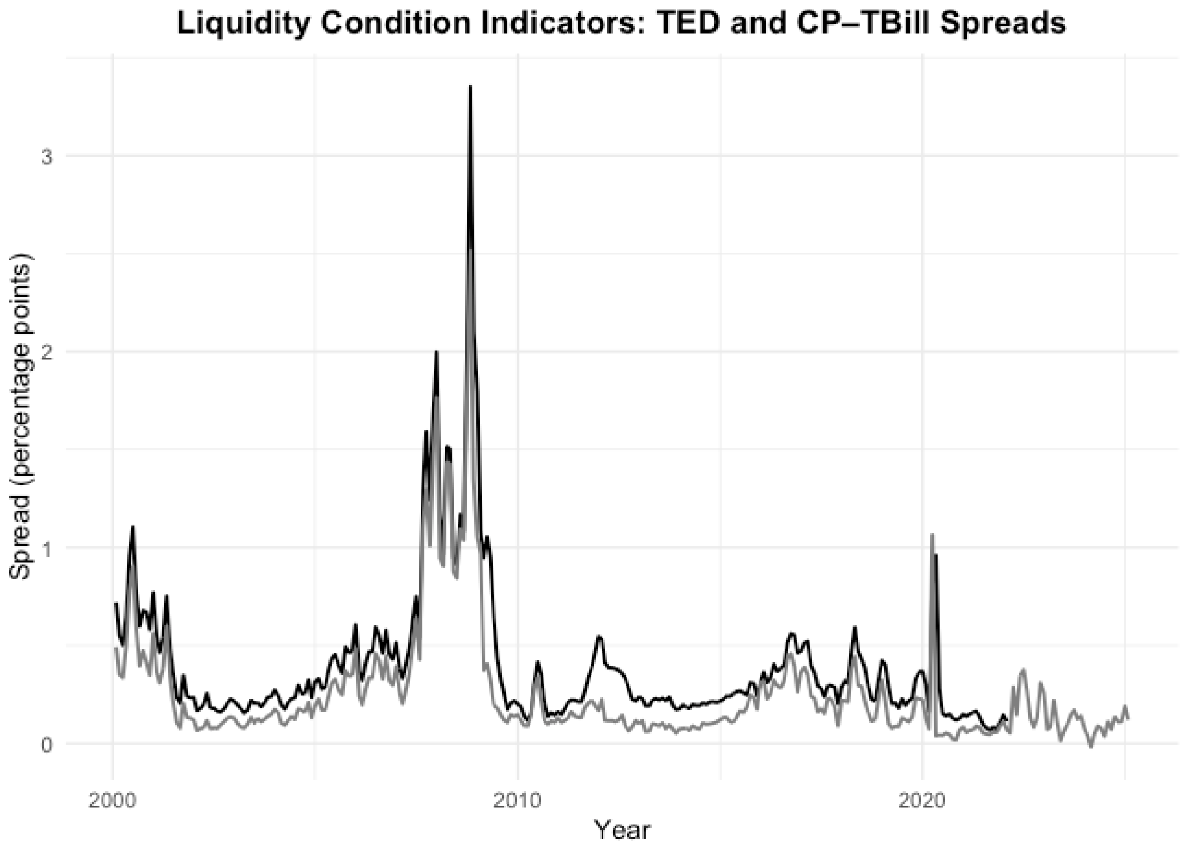


Figure 4 plots the TED spread and the CP-T Bill spread over the observed time period. There is strong co-movement between the two series (correlation is 0.957), which confirms their validity as complementary indicators. Both measures exhibit sharp spikes during the 2008 global financial crisis and again briefly in 2020 during the Covid-19 market shock. These episodes reflect disruptions in interbank and short-term funding markets. Periods of elevated spreads can be interpreted as heightened market illiquidity. Due to the very similar dynamics and high correlation and considering the fact that the TED spread was discontinued in recent years, the CP-T-Bill spread is going to be used as a proxy for liquidity conditions in all further analysis. The dummy variable to indicate months of elevated illiquidity were constructed as taking value 1 when the CP-T-bill spread was above its 36-month rolling median, and 0 otherwise.

This chapter has presented the sources, structure, and statistical characteristics of the dataset used to study carry trade returns. The combination of exchange rate data and financial and economic variables will allow the regime-dependent analysis of carry trade returns in the following chapters.

5. Methodology

This chapter is going to outline the methodologies and empirical framework used examine the carry trade performance under different market conditions. It will detail the construction of carry trade portfolios, the calculation of excess returns and the econometric models used to assess the sensitivity of carry trade profits to the aforementioned regimes. Several components of the analysis are introduced. This methodology aims to uncover how the external environment influences the profitability of currency carry trades.

5.1. Portfolio construction

To evaluate carry trade performance, the analysis is started by the construction of currency portfolios based on the interest rate differentials (proxied by forward discounts). This is done by ranking the nice USD-based currency pairs by forward discounts each month. The top three currency pairs with the highest forward discounts (largest interest rate differentials) are placed in "High" portfolio (denoted as P3), while the three currencies with the lowest forward discounts (smallest interest rate differentials) are assigned to a "Low" portfolio (denoted as P1). All of the portfolios are equally weighted and rebalanced each month, ensuring that the strategy follows changes in interest rate differentials. Then a carry trade portfolios is formed by going long on the high-interest rate portfolio, and short on the low-interest rate portfolio. As described more in detail in Chapter 2.4, monthly excess return of the carry trade portfolio is computed as the difference between log forward discount and the log spot rate changes, which after simplifications is:

$$R_{t+1} = \ln(F_t) - \ln(S_{t+1}). \tag{10}$$

This portfolio construction method is consistent with Christiansen et al. (2011) and Brunnermeier et al. (2009), taking long positions on the three currencies with the highest forward discounts and short on the three currencies with the lowest forward discount. This approach represents the standard carry trade strategy which focuses on the extremes of the interest rate spectrum. Lustig et al. (2011) and Menkhoff et al. (2012) apply a slightly different method, constructing quantile-based portfolios. However, due to the limited number of currency pairs in the sample, sorting to five portfolios would results in unstable sizes, therefore this analysis is going to go forward with the terciles approach. After Lustig et al. (2011), this portfolio is named HML (High Minus Low). Fo

In addition to the HML portfolio, following the methodology of Lustig et al. (2011) and Menkhoff et al. (2012) another portfolio is constructed which averages the returns across all currency positions. It reflects the excess return from borrowing USD and investing in foreign currencies. In other words, this portfolio produces positive returns when the USD weakens and negative returns when the USD strengthens. Since it reflects the investor's exposure to movements in the USD, it also acts as proxy for dollar risk. In line with the literature, it is going to be titled DOL.

<u>Transaction costs</u>

To better reflect real world conditions, the carry trade returns are adjusted for transaction costs, stemming from the bid-ask spreads. Following the methodology of Accominotti et al. (2019), this is done by calculating the trading costs incurred both on the spot and forward legs of the trade using the bid and ask quotes. Bid is the price at which one can sell currencies and ask is the price at which one can sell currencies. Under normal circumstances, the ask quote is higher than the bid, producing a small frictional gap between the two. The log spot and forward bid-ask spread of currency *i* at time *t* are denoted BAS and BAF respectively and they are calculated as:

$$BAS_{i,t} = \ln\left(Spot_{Ask_{i,t}}\right) - \ln\left(Spot_{Bid_{i,t}}\right) \tag{11}$$

$$BAF_{i,t} = \ln\left(Fwd_{Ask_{i,t}}\right) - \ln\left(Fwd_{Bid_{i,t}}\right). \tag{12}$$

Rebalancing of the portfolios happens at the end of each months. When from month *t-1* to *t*, the weight of currency changes from $w_{i,t-1}$ to $w_{i,t}$, the transaction costs incurred at time *t* are proportional to the absolute turnover $\left|w_{i,t} - w_{i,t-1}\right|$. For each currency, the cost incurred equals the fraction of the portfolio that must be traded and the log bid-ask spread of the currency's spot quote at time. Hence the total spot market transaction costs for the months over all currencies can be expressed as:

$$\tau_{s,t} = \sum_i \left|w_{i,t} - w_{i,t-1}\right| \times BAS_{i,t}. \tag{13}$$

As for forward transactions, the underlying logic similar. Since forward contracts for the upcoming month are executed at the start of the holding period, the exact wight $w_{i,t-1}$ has to be maintained into the new forward positions:

$$\tau_{f,t} = \sum_i \left|w_{i,t-1}\right| \times BAF_{i,t-1.} \tag{14}$$

After defining these two cost items, the net log-excess return of the any portfolio is written as:

$$R_{t+1}^{net} = R_{t+1}^{net} - \tau_{s,t} - \tau_{f,t}. \tag{15}$$

<u>Portfolio return calculation</u>

In order to evaluate the performance of carry trades, two profitability measures are observed over the sample period: mean excess return and Sharpe ratio. The mean excess returns shown are computed as the arithmetic average of the excess log returns produced by each monthly period:

$$\bar{R} = \frac{1}{T}\sum_{t=1}^{T} R_{t.} \tag{16}$$

where T is the total number of observations. For the sake of reporting, the mean excess return is annualized by multiplying by 12, since the observations monthly. This is done both for returns excluding and including transaction costs. The Sharpe ratio by definition is the measure of risk-adjusted return (Sharpe, 1994). It can be expressed mathematically as:

$$Sharpe = \frac{\bar{R}}{\sigma}. \tag{17}$$

where $\bar{R}$ is the average excess return on the portfolio and σ is the standard deviation of the portfolio's returns. The Sharpe ratio can be interpreted as the return received for taking on a unit of risk. A Sharpe ratio of 0 would indicate, that the average return is equal to the risk-free rate. A negative Sharpe implies that the strategy is underperforming, while a positive ratio implies that the strategy is overperforming the risk-free investment. The larger the Sharper ratio is, the better the risk-adjusted return of the portfolio is. To obtain the annualized Sharpe ratios, the monthly mean return figure are multiplied by 12 and the standard deviation is multiplied by $\sqrt{12}$ following the methodology of Lustig et al. (2011).

Table 3: Portfolio Annualized Log Return Summary Tables

Summary Statistics of Portfolio Returns (Without Transaction Costs)

Portfolio	Mean	Median	Std Dev	Skewness	Kurtosis	Sharpe	AC1
P1	-1.50	-2.00	7.92	0.20	-0.18	-0.19	0.01
P2	-1.35	-1.96	8.67	-0.30	1.52	-0.16	0.05
P3	1.92	0.88	10.51	-0.43	1.91	0.18	0.04
HML	3.42	4.64	7.33	-0.81	4.05	0.47	0.07
DOL	-0.31	-0.17	8.31	-0.13	0.77	-0.04	0.03

Summary Statistics of Portfolio Returns (With Transaction Costs)

Portfolio	Mean	Median	Std Dev	Skewness	Kurtosis	Sharpe	AC1
P1	-1.67	-2.00	7.91	0.19	-0.17	-0.21	0.01
P2	-1.47	-1.90	8.68	-0.30	1.52	-0.17	0.05
P3	1.64	0.62	10.50	-0.43	1.93	0.16	0.04
HML	3.31	4.58	7.33	-0.81	4.06	0.45	0.07
DOL	-0.50	-0.20	8.31	-0.14	0.78	-0.06	0.03

Table 3 presents summary statistics for the annualized log returns of the three currency portfolios sorted by forward discounts and rebalanced each month, plus the HML and DOL portfolios both before and after adjusting for transaction costs using the bid-ask spread.

Consistent with the results of Menkhoff et al. (2012), the returns are the lowest produced by portfolio 1, which acts as the funding leg. The lower yielding portfolios 1 and 2 both lose on average: -1.50% and -1.35% respectively). At the same time, portfolio 3 displayed the highest average annualized log returns out of the three base portfolios: 1.92% before applying transaction costs, and 1.64% after. The average of the three portfolios (DOL) sits at -0.31% before and -0.50% after costs, while the long-short HML portfolio delivers 3.42% before costs and 3.31% after. This confirms that transaction costs erode but do not eliminate carry trade profits.

The Sharpe ratio of portfolios 1 and 2 are negative, signalling that on a risk-adjusted basis they underperform a risk-free investment. In other words, the volatility of their returns outweighs the small average gains and losses in those portfolios. Portfolio 3 produces a Sharpe ratio of 0.16 after adjusting for transaction costs, which implies that its average excess return compensates for its volatility. The HML portfolio shows an even stronger Sharpe ratio, as it is combines the performance of P1 and P3, demonstrating that combining the two legs enhances risk-adjusted performance.

The skewness and kurtosis statistics also reveal important characteristics of the carry trade portfolios. The skewness is displaying decreasing tendency, moving from portfolio 1 to portfolio 3 and HML, similarly to what Menkhoff et al. (2012) reported. P1 is mildly right-skewed (0.19), P2 and

P3 are increasingly left-skewed (-0.30; -0.43). This goes hand in hand with elevated kurtosis, indicating that while these portfolios generate higher average returns, they are also vulnerable to large losses. The HML portfolio presents the most amplified pattern with a significant left skew of -0.81 and fat tails indicated by the kurtosis value of 7.04. Adjusting for transaction costs has a negligible impact on skewness and kurtosis across portfolios. Several studies documented fat tails (high kurtosis) in carry trade return distributions. Burnside et al. (2008) highlight that carry trade payoffs are leptokurtic. Similarly, Spronk et al. (2013) document the existence of heavy tails of exchange rate returns. Jurek (2014) also finds that carry trade payoffs exhibit fat-tailed returns, consistent with extreme crash risk.

All portfolios have a small positive first-order autocorrelation measure (AC1). This implies small serial correlation.

Figure 5: Cumulative Carry Trade Log Returns (HML Portfolio)

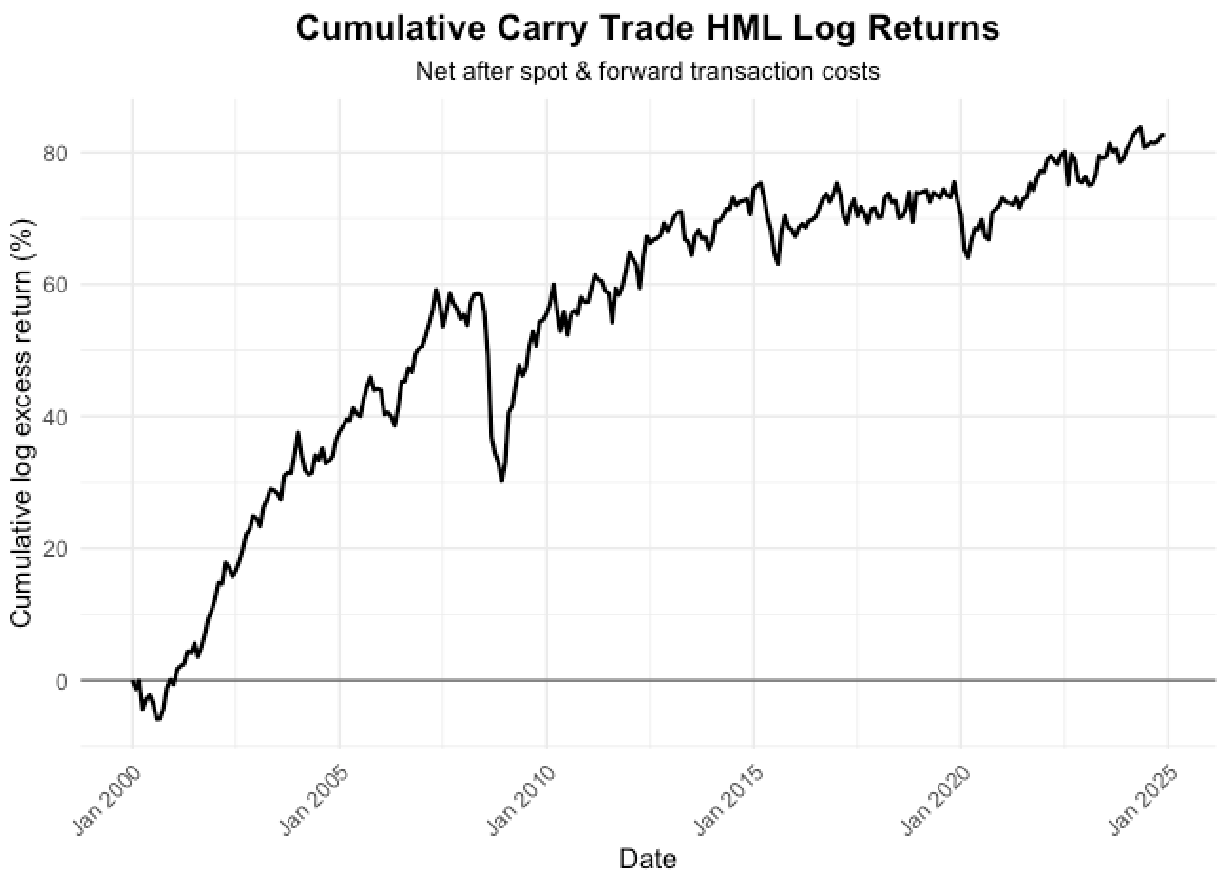


Figure 5 plots the cumulative log-excess return of the HML carry strategy over the full sample. Starting at 0 in 2000, the carry log-return steadily compounds through two and a half decades, producing roughly 80% cumulative gain by the beginning of 2025. The chart displays sharp downturns during the dot-com bubble in the early 2000's, the 2008-2009 financial crisis, and at the beginning of the Covid-19 pandemic in early 2020. The persistent upward trend verifies that carry trade profits are economically significant but vulnerable to stress-driven reversals.

5.2. Dummy regressions

This section formally quantifies how carry-trade returns vary under different market conditions. Previously a set of six binary indicators were defined highlighting high vs low inflation, episodes of economic recession and expansion, spikes in equity and FX market sentiment, and episodes of high vs low market liquidity. This was done with the objective of testing weather the average excess return of the High Minus Low (HML) portfolio exhibits shifts when each of these regimes are "on". The following regression model provides a transparent assessment of carry trade performance under these high vs. low market conditions.

$$HML_t = \alpha + \beta_1 HighInfl_t + \beta_2 IsRecession_t + \beta_3 HighSent\_VXY_t + \beta_4 Illiquid_t + \varepsilon_t. \quad (18)$$

where HML_t is the month t excess return of the High Minus Low portfolio, $HighInfl_t$ is a dummy equal to 1 if inflation (proxied by year-on-year CPI) was above its rolling 36-month median, $IsRecession_t$ is a dummy equal to 1 if the US economy is in recession, $HighSent\_VXY_t$ is a dummy equal to 1 if the VXY index exceeds its 36-month rolling median, and $Illiquid_t$ is a dummy equal to 1 if the CP-T-Bill spread is above its 36-month rolling median. ε_t is a zero mean error term. Newly-West standard errors are used with a lag length of six months. This estimator accounts for heteroskedasticity and autocorrelation up to six months.

The VIX sentiment dummy was excluded from the regression due to its high correlation with the VXY-based dummy, which raised concerns of multicollinearity. Since VYX captures implied volatility in FX markets, it was deemed to be the more relevant indicator for analysing carry trade performance. To ensure that the rest of the explanatory variables do not suffer from multicollinearity, Variance Inflation Factors (VIF) were computed. The VIF values ranged between 1 and 1.11, below the conventional thresholds, therefore indicating negligible correlations between indicators.

Another potential concern was nonlinearity between carry trade returns and the macro-financial variables. To assess this, diagnostic tests were performed. A Ramsey RESET test was implemented, which suggested the absence of omitted nonlinear relationships in the model. Additionally, a polynomial-augmented model was estimated, which indicated no improvement in explanatory power of the augmented model (with squared terms) comparing to the original. These findings confirmed that nonlinearity is not a significant issue and that the linear parametric models (regressions) will provide valid results.

To better understand the dynamics between macro-financial conditions and carry trade performance, the analysis is repeated with lagged explanatory variables. More specifically, the regressions is estimated using independent variables observed at time t-1. Contemporaneous variables allow for examination of co-movements between the regime indicators and carry trade returns. In contrast, regressions using lagged variables enable assessment of predictive relationship, reflecting information that was available to investors at the time of decision-making. This temporal separation helps mitigate concerns of reverse causality. Moreover, by isolating predictive signals from contemporaneous correlations, the analysis provides a more robust and rigorous evaluation of carry trade profitability. Asano et al. (2024) deploys a similar strategy and investigates both contemporaneous and lagged regimes. Based on this logic, the dummy regression is repeated with lagged variables at t-1:

$$HML_t = \alpha + \beta_1 HighInfl_{t-1} + \beta_2 IsRecession_{t-1} + \beta_3 HighSent\_VXY_{t-1} + \beta_4 Illiquid_{t-1} + \varepsilon_t. (19)$$

5.3. Subsample period analysis

To explore how the effect of the different market conditions on carry trade returns changed over time, the dummy regressions are estimated across four distinct subsample periods. Dividing up the full sample size into sub periods was done by Mogensen & Nielsen (2020), when developing dynamic carry trades using VIX and VYX in their study. The chosen periods mark key turning points in the global economic environment:

1. Pre-Global Financial Crisis (January 2000 – June 2007)
2. Global Financial Crisis (July 2007 – June 2009)
3. Post-Global Financial Crisis (July 2009 – December 2019)
4. Covid & Volatility (January 2020 – January 2025)

These periods were chosen with consideration to consensus on certain key turning points in economic events over the full sample period spanning from January 2000 to January 2025. The Pre-Global Financial Crisis period was a time of stable growth, low volatility, and moderate macroeconomic conditions. Mid-2007 is often mentioned as the start of the crisis period when financial markets started exhibiting abnormal signs of severe stress. Baba & Packer (2009) mention, that money markets were already severely impaired in the summer of 2007 which was observable in the loss of liquidity in money markets, the widened spreads between treasury bill and OIS rates, and increased volatility in the FX markets. In a Financial Stability Report published in June 2008, the European Central Bank mentions July 2007 as the moment of sudden loss of liquidity (ECB, 2008). June 2009 was chosen as the end of the second period, as that was the month determined by the National Bureau of Economic Research (NBER) that marked the end of the recession that was triggered by the financial crisis (NBER, 2010). Following the end of recession, global economies entered a recovery phase, marked by low interest rates and muted inflation. Finally, the Covid and volatility period begun in 2020 with the start of the global pandemic that brought another major financial shock to markets and economies. A sharp economic contraction was followed by a pandemic-induced recession that lasted until April 2020. The period remains highly volatile due to geopolitical tensions and inflation.

For each subsample period the two dummy regressions (contemporaneous and lagged) are estimated in order to assess differences in regime-specific sensitivities of FX carry trade returns.

5.4. Continuous variable regressions

With a slightly different approach, continuous variable regression models are estimated to further assess the relationship between macro-financial conditions and carry trade returns. These regressions are using actual economic and market values, not the binary regime dummies earlier constructed. Two sets of univariate regressions are calculated. The dependent variable in each is the net HML carry trade profit. The independent variables include the volatility indicators, CBOE Volatility Index and JPMorgan FX Volatility Index, the US inflations rate (year-on-year CPI) and the commercial paper-Treasury Bill spread, a proxy for liquidity stress. The first set continuous variable regressions investigate what effect the level of each indicator at time *t* have on carry return in month *t:*

$$HML_t = \alpha + \beta_1 VIX_t + \varepsilon_t \tag{20}$$

$$HML_t = \alpha + \beta_2 VXY_t + \varepsilon_t$$

$$HML_t = \alpha + \beta_3 CPI_t + \varepsilon_t$$

$$HML_t = \alpha + \beta_4 CP - TB_t + \varepsilon_t.$$

This is then repeated similarly to the dummy regressions by taking each independent variable at t-1:

$$HML_t = \alpha + \beta_1 VIX_{t-1} + \varepsilon_t \tag{21}$$

$$HML_t = \alpha + \beta_2 VXY_{t-1} + \varepsilon_t$$

$$HML_t = \alpha + \beta_3 CPI_{t-1} + \varepsilon_t$$

$$HML_t = \alpha + \beta_4 CP - TB_{t-1} + \varepsilon_t.$$

Each model is estimated separately to avoid issues of multicollinearity and to see the undisturbed effect of each independent variable. The coefficient β captured the marginal effect of a one-unit increase in the level of the respective variable.

The second set of continuous variable regressions use the differences in the same indicators calculated as the change between *t-2* and *t-1*, to examine whether recent shifts in macroeconomic or financial conditions impact carry trades returns. This approach aims to capture market reactions to sudden changes or spikes. Again, each model is estimated separately to isolate the predictive content of each variable. The model uses lagged monthly changes in the VIX, VYX, CPI, and CP-TB spread as explanatory variables. The dependent variable is unchanged, the one month ahead return on the HML carry trade portfolio, net of transaction costs:

$$HML_t = \alpha + \beta_1 \Delta VIX_{t-1} + \varepsilon_t \tag{22}$$

$$HML_t = \alpha + \beta_2 \Delta VXY_{t-1} + \varepsilon_t$$

$$HML_t = \alpha + \beta_3 \Delta CPI_{t-1} + \varepsilon_t$$

$$HML_t = \alpha + \beta_4 \Delta CP - TB_{t-1} + \varepsilon_t.$$

5.5. Subsample mean and t-test

To complement the regressions, a subsample comparison of carry returns under each market regimes is performed. This exercise serves both as a robustness check and as an intuitive illustration of how average performance varies in low vs high periods. A similar analysis was carried out by Asano et al. (2024), reporting summary statistics of carry trade portfolio returns under high and low market regimes. For each of the five binary indicators, the monthly HML_t return is divided into two subsamples and simple summary statistics is estimated:

- n_0 observations in the low regime months, where the observed variable equals 0, with sample mean $\bar{R}_0$ and variance s_0^2
- n_1 observations in the high regime months, where the observed variable equals 1, with sample mean $\bar{R}_1$ and variance s_1^2

Each subsample contains all observations for which the corresponding dummy is not missing. Based on this logic, there will be two groups per regime indicators. To assess whether the difference in mean returns is statistically significant, a standard two-sample t-test is calculated:

$$t = \frac{\bar{R}_1 - \bar{R}_0}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_0^2}{n_0}}} \sim t(v), \tag{23}$$

where v is the Welch-Satterthwaite formula:

$$v = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_0^2}{n_0}\right)}{\frac{s_1^4}{n_1^2\,(n_1 - 1)} + \frac{s_0^4}{n_0^2\,(n_0 - 1)}} \tag{24}$$

A p-value below the conventional threshold of 0.05 indicates that the average carry return in high-regime months differ materially from its average on low-regime months. The exercise is repeated using lagged regime variables.

6. Results

In the following chapter, the outcomes of the previous described econometric models are going to be interpreted with the objective of uncovering patterns and comparing them to results of existing literature. The chapter is composed of four sections, following the same structure as the previous chapter. First, the interpretation of the dummy regression results are going to be presented, alongside with the subsample dummy regressions. Then the continuous variable regression results are discussed, followed by the subsample mean and t-test. The findings of each component of the analysis are summarized. All the models were implemented in R, for which the whole script is provided in Appendix B.

6.1. Dummy regression results

The dummy regressions were set up using the observe how the carry trade returns behave under high vs low market conditions. For this reason, "dummy" binary variables were constructed to mark high vs low inflationary environment, recession vs expansion periods, times of high vs low investor sentiment, and periods of liquid vs illiquid conditions.

Table 4: Dummy Regressions

Dummy Regression with Contemporaneous Regimes

Term	Estimate	Std. Error	t-stat	p-value	
HighInfl	-0.0015	0.0018	-0.82	0.415	
IsRecession	-0.0053	0.0052	-1.03	0.302	
HighSent_VXY	-0.0038	0.0019	-2.01	0.045	**
Illiquid_CP_TB	0.0012	0.0018	0.67	0.501	

Dummy Regression with Lagged Regimes

Term	Estimate	Std. Error	t-stat	p-value	
$HighInfl_{t-1}$	-0.0014	0.0018	-0.81	0.418	
$IsRecession_{t-1}$	-0.0050	0.0052	-0.97	0.331	
$HighSent\_VXY_{t-1}$	-0.0030	0.0018	-1.67	0.096	*
$Illiquid\_CP\_TB_{t-1}$	0.0009	0.0018	0.53	0.599	

The first regression investigates how the carry trade performance behaved with regime indicators observed within the same months. The regression outputs are summarized in Table 4. All of the coefficients are negative however only one of them is statistically significant, suggesting that contemporaneous macro-financial variables do not have a significant effect on carry trade returns. The HighSent_VXY dummy capturing periods of elevated FX volatility is a producing a negative (-0.0038) coefficient and is statistically significant. This implies that months with elevated FX market volatility produce 0.38% lower carry returns The HighInfl dummy carries a coefficient of -0.0015, implying that during the months with high inflation, the return of the HML portfolio is slightly lower than in the low inflation months. However, these result is not significant (p=0.415). Similarly, IsRecession shows a negative coefficient, implying lower carry returns during recessionary months, but showcase no statistical significance (p=0.331). Lastly, Illiquid_CP_TB, indicating periods of low liquidity shows a small positive coefficient, but the results is not meaningful due to p=0.599. Overall, the lack of statistical significance of the contemporaneous variables might be dure to market lags and investors reliance on past information when it comes to decision making.

The second regression introduced lagged regime indicators, to examine whether these variables would have any predicative power for future carry trade returns. Similarly to the previous model, the only significant lagged variables is $HighSent\_VXY_{t-1}$. The coefficients are small in magnitude, and they exhibit similar results compared to the contemporaneous model.

6.2. Robustness check: cutoff rate

Table 5: Dummy Regressions (80th Percentile Cutoff)

Dummy Regression with Contemporaneous Regimes (80th percentile cutoff rate)

Term	Estimate	Std.	t-stat	p-value
HighInfl_p80	-0.0019	0.0019	-1.04	0.299
IsRecession	-0.0057	0.0052	-1.10	0.270
HighSent_VXY_p80	-0.0021	0.0028	-0.75	0.454
Illiquid_CP_TB_p80	0.0005	0.0023	0.24	0.811

Dummy Regression with Lagged Regimes (80th percentile cutoff rate)

Term	Estimate	Std.	t-stat	p-value
$HighInfl\_p80_{t-1}$	-0.0019	0.0019	-1.01	0.314
$IsRecession_{t-1}$	-0.0052	0.0051	-1.02	0.308
$HighSent\_VXY\_p80_{t-1}$	-0.0021	0.0028	-0.75	0.451
$Illiquid\_CP\_TB\_p80_{t-1}$	0.0006	0.0023	0.25	0.804

To assess the robustness of the previous findings, the same regressions are repeated with an alternative classification criterion for high and low regimes. As presented in Chapter 4.2, the cutoff rate for the classification of the binary dummy variables was the median using a 36-month rolling window (except the recession indicator dummy, which was a ready-made 0-1 indicator). In this sections, the cutoff rate is changed from $\eta = 50$ to $\eta = 80$, meaning the 80th percentile of each variable's 36-month rolling distribution was adopted. This approach allows for the identification of more extreme periods as high inflation, volatility, and illiquidity regimes, which may better capture extreme market conditions. Table 5 presents the results of the repeated full-sample contemporaneous and lagged dummy regressions. Across both specifications, the coefficients for all four regimes remain statistically insignificant. Furthermore, the direction of the estimates is broadly consistent with those observed using the average cutoff rate. Notably, the only coefficient switching from negative to positive is the ones associated with the illiquidity conditions. These findings imply that even when restricting the regimes classification to more extreme periods, there is no robust evidence for systematic relationship with monthly carry trade returns considering only the G10 currencies.

6.3. Subsample dummy regression results

The following section presents the results of the same analysis repeated for four subsamples. The subsamples were determined by taking major economic events and turning points to split up the full sample period in order to explore whether the regime variables had a different effect on carry trade returns in different subsample periods.

Pre-Global Financial Crisis

Table 6: PreGFC Dummy Regressions

PreGFC Dummy Regression with Contemporaneous Regimes

Term	Estimate	Std. Error	t-stat	p-value	
HighInfl	0.0088	0.0024	3.69	0.000	***
IsRecession	0.0057	0.0036	1.58	0.115	
HighSent_VXY	0.0010	0.0025	0.38	0.701	
Illiquid_CP_TB	0.0049	0.0025	1.97	0.049	**

PreGFC Dummy Regression with Lagged Regimes

Term	Estimate	Std. Error	t-stat	p-value	
$HighInfl_{t-1}$	0.0086	0.0023	3.73	0.000	***
$IsRecession_{t-1}$	0.0055	0.0036	1.51	0.131	
$HighSent\_VXY_{t-1}$	0.0009	0.0023	0.39	0.695	
$Illiquid\_CP\_TB_{t-1}$	0.0037	0.0024	1.56	0.119	

The first period, called the Pre-Global Financial crisis spams from the beginning of the sample period, January 2000 to June 2007, which according to multiple sources was when some warning signs of the financial crisis were already present. These years are characterised by rather stable macroeconomic and financial conditions, with relatively low volatility. As shown in Table 6, two of the contemporaneous dummy variables exhibit statistically significant effects on carry trade returns during this period. The coefficients are interestingly all positive. HighInfl and Illiquid_CP_TB are both significant at the 1% and 5% levels respectively, suggesting that higher inflation and tighter liquidity conditions are associated with higher contemporaneous carry trade returns. IsRecession and HighSent_VXY show a small positive coefficient however remain unsignificant. This suggests that US recessions and elevated FX volatility were not associated with material differences in carry trade returns during this period.

In the lagged model, which uses prior-month regime dummies, only one variable exhibits statistically significant effects. Similarly to the contemporaneous results, coefficients all have positive signals. $HighInfl_{t-1}$ is significant at the 1% level, suggesting that elevated US inflation in the previous month is associated with higher returns during this period. The estimates of the rest of the dummy variables are statistically insignificant at conventional levels.

Global Financial Crisis

Table 7: GFC Dummy Regressions

GFC Dummy Regression with Contemporaneous Regimes

Term	Estimate	Std. Error	t-stat	p-value	
HighInfl	-0.0130	0.0106	-1.23	0.221	
IsRecession	-0.0263	0.0164	-1.60	0.111	
HighSent_VXY	-0.0298	0.0106	-2.80	0.006	***
Illiquid_CP_TB	-0.0117	0.0149	-0.78	0.435	

GFC Dummy Regression with Lagged Regimes

Term	Estimate	Std. Error	t-stat	p-value	
$HighInfl_{t-1}$	-0.0168	0.0107	-1.57	0.117	
$IsRecession_{t-1}$	-0.0245	0.0164	-1.49	0.138	
$HighSent\_VXY_{t-1}$	-0.0258	0.0107	-2.42	0.016	**
$Illiquid\_CP\_TB_{t-1}$	-0.0117	0.0139	-0.84	0.401	

The Global Financial Crisis (July 2007 – June 2009) was a period of of high volatility, liquidity shortages, and rapid shifts of investor sentiment. The same analysis (contemporaneous and lagged dummy regressions) was implemented to observe whether carry trade returns exhibited a different behaviour during this turbulent period. Table 7 summarizes the results of the dummy regressions during the GFC period. The HighSent_VXY dummy is statistically significant (p=0.006), with an estimated coefficient of -0.0298. This suggests, that during months of high FX volatility the HML carry portfolio earned on average 2.98% lower monthly returns as opposed to low-volatility months. To coefficients of IsRecession, Illiquid_CP_TB, and HighInfl are also all negative, however statistically insignificant. This implies that US recessions and periods of elevated FX inflation and illiquidity were not significantly associated with lower carry trade returns, although the direction of the estimates align with the expectations.

The results of the lagged model offer further insights by evaluating whether prior-month variables have predictive power over carry trade returns in the subsequent month during the Global Financial Crisis. Among the lagged variables, only $HighSent\_VXY_{t-1}$ is significant (p=0.016), with a coefficient of -0.0258. This suggests that a high FX volatility (low investor sentiment) in the preceding month is associated with a 2.58% decline in the monthly returns of the HML portfolio in the current month. The other lagged indicators are also exhibiting negative estimates, however, remain statistically insignificant.

Post-Global Financial Crisis

Table 8: PostGFC: Dummy Regressions

PostGFC Dummy Regression with Contemporaneous Regimes

Term	Estimate	Std. Error	t-stat	p-value	
HighInfl	-0.0053	0.0025	-2.07	0.039	**
HighSent_VXY	0.0005	0.0027	0.18	0.859	
Illiquid_CP_TB	0.0012	0.0026	0.48	0.633	

PostGFC Dummy Regression with Lagged Regimes

Term	Estimate	Std. Error	t-stat	p-value	
$HighInfl_{t-1}$	-0.0044	0.0025	-1.77	0.077	*
$IsRecession_{t-1}$	0.0082	0.0022	3.78	0.000	***
$HighSent\_VXY_{t-1}$	0.0010	0.0026	0.39	0.700	
$Illiquid\_CP\_TB_{t-1}$	0.0012	0.0024	0.48	0.634	

The Post-Global Financial Crisis (July 2009 – December 2019) was a period characterized by relative stability and recovery of economies and markets. This environment provides an interesting backdrop to repeat the dummy regression analyses with the same binary variables. The IsRecession dummy was omitted from the Post-GFC contemporaneous regression due to the lack of variation in the sample, as all months were classified as recessionary in the subsample resulting in prefect collinearity with the intercept and automatic exclusion from the regression model. It is however included in the lagged version, because the first observation of the Post-GFC subsample (June 2009) was non-recessionary, which means a small degree of variation was retained. As shown in Table 8, only one of the contemporaneous variables is statistically significant. HighInfl is marginally significant (p=0.039) with a negative coefficient of -0.0053, suggesting that in the Post-GFC period elevated US inflation in the same month is associated with 0.53% lower carry trade returns. Overall, these results indicated a limited role for these macro-financial conditions in explaining carry trade returns over the 10 years after the GFC.

The lagged variation of the post-GFC model reveals some more significant results. $HighInfl_{t-1}$ variable has a negative coefficient of -0.0044 and is significant (p=0.077). This suggests that high inflation in the preceding month is associated with a 0.44% decline of carry trade returns in the current month. To other statistically significant result (p=0.003) is produced by the $IsRecession_{t-1}$ variable with a positive coefficient, indicating recessionary conditions in the previous month are associated with a 0.83% increase in returns. The other lagged variables remain insignificant.

Covid & Volatility

Table 9: Covid & Volatility: Dummy Regressions

Covid &Volatility Dummy Regression with Contemporaneous Regimes

Term	Estimate	Std. Error	t-stat	p-value
HighInfl	-0.0015	0.0036	-0.42	0.672
IsRecession	-0.0130	0.0141	-0.92	0.356
HighSent_VXY	-0.0040	0.0034	-1.17	0.241
Illiquid_CP_TB	0.0001	0.0030	0.03	0.973

Covid &Volatility Dummy Regression with Lagged Regimes

Term	Estimate	Std. Error	t-stat	p-value
HighInfl_{t-1}	-0.0018	0.0036	-0.51	0.613
IsRecession_{t-1}	-0.0110	0.0139	-0.79	0.428
$\text{HighSent\_VXY}_{t-1}$	-0.0029	0.0033	-0.87	0.387
$\text{Illiquid\_CP\_TB}_{t-1}$	0.0000	0.0030	0.01	0.994

The Covid & Volatility period (January 2020 – January 2025) was characterized by market volatility, economic downturn and recovery, and shifts in global monetary policy. According to the results of the dummy regressions under the Covid and Volatility period shown in Table 9, none of the contemporaneous dummy variables are statistically significant at conventional levels during the Covid and Volatility period. All variables produced inconsistent estimates, with mixed signs and no evidence of systematic effects on carry trade returns during this period.

According to the lagged regression focusing on the Covid & Volatility period, none of the regime indicators are statistically significant at conventional levels. The pattern is similar to the contemporaneous model in the same period, with only $\text{Illiquid\_CP\_TB}_{t-1}$ producing a positive coefficient.

6.4. Continuous variable regression results

This section briefly departs from the earlier dummy-based analysis and instead explores the relationship between carry trade returns and continuous macro-financial indicators. Unlike the regime-based regressions in the previous regression models, which used binary dummy variables to represent periods of high and low conditions, the regressions here include the actual levels of global FX volatility (VYX), inflation (CPI YoY), and liquidity conditions (CP-TB spread). This allows for further assessment of how changes in these variables relate to the performance of the HML carry trade portfolio. The exercise is repeated twice: for the first time using contemporaneous variables, and the second time using lagged (*t-1*) variables.

Table 10: Continuous Variable Regressions

Continuous Variable Regression with Contemporaneous Variables

Term	Estimate	Std. Error	t-stat	p-value	
VXY	0.0008	0.0005	1.57	0.118	
CPI_YoY	-0.0008	0.0006	-1.34	0.179	
CP_TB	-0.0141	0.0058	-2.43	0.015	**

Continuous Variable Regression with Lagged Variables

Term	Estimate	Std. Error	t-stat	p-value	
VXY_{t-1}	0.0008	0.0005	1.67	0.096	*
CPI_YoY_{t-1}	-0.0008	0.0006	-1.38	0.168	
CP_TB_{t-1}	-0.0138	0.0057	-2.44	0.015	**

Table 10 summarizes the results of the continuous variable regressions. The contemporaneous model shows that the CP-T-bill spread is statistically significant at the 5% level (p=0.015). The negative coefficient (-0.0141) implies that tighter funding liquidity conditions (indicated by a higher spread) are associated with lower carry trade returns. This confirms the sensitivity of carry trades to worsening liquidity conditions. The coefficients of VYX and CPI_YoY are both statistically insignificant, with p-values of 0.118 and 0.179 respectively.

Using lagged variables, the results for CP_TB_{t-1} remain consistent, the variable is again statistically significant with a negative coefficient of -0.0138, reinforcing the conclusions of the previous model. Somewhat surprisingly, the lagged VXY_{t-1} is marginally significant (p=0.096) and produced a positive estimate, suggesting that increased FX volatility in the prior month may lead to higher carry returns in the subsequent month. The lagged inflation indicator remains insignificant.

6.5. Subsample mean and t-test results

As for the last piece of the comprehensive analysis presented in this chapter on the relationship of carry trade profits and various variables describing different market conditions, this section presents the results of the subsample summary statistics and t-tests of each high and low regimes. After the brief departure from the binary variables in the previous chapter, this section returns to the binary variables, classifying periods as high and low according to rolling medians of macro-financial indicators, further described in Chapter 4.2.

Unlike the regressions before, the focus here is on identifying mean return differences between subsamples using a non-parametric approach. For each regime, the mean return, standard deviation, and sample size is reported for both low and high states, followed by the difference in means, t-statistics, and p-values.

Table 11: Subsample Means & Two-Sample t-Tests

Subsample summary statistics and two-sample t-test with contemporaneous variables

Regime	N (Low)	N (High)	Mean (Low)	Mean (High)	Std dev (Low)	Std dev (High)	Δ Mean	t-stat	p-value
HighInfl	145	151	0.0035	0.0024	0.0236	0.0185	-0.0011	0.44	0.661
IsRecession	269	31	0.0033	-0.0020	0.0188	0.0356	-0.0054	0.82	0.416
HighSent_VIX	160	136	0.0049	0.0006	0.0186	0.0236	-0.0043	1.72	0.087
HighSent_VXY	144	152	0.0030	0.0029	0.0197	0.0224	-0.0001	0.04	0.972
Illiquid_CP_TB	145	151	0.0035	0.0024	0.0236	0.0185	-0.0011	0.44	0.661

Subsample summary statistics and two-sample t-test with lagged variables

Regime	N (Low)	N (High)	Mean (Low)	Mean (High)	Std dev (Low)	Std dev (High)	Δ Mean	t-stat	p-value
$HighInfl_{t-1}$	145	150	0.0047	0.0012	0.0203	0.0218	-0.0035	1.44	0.151
$IsRecession_{t-1}$	268	31	0.0029	0.0013	0.0191	0.0346	-0.0016	0.25	0.803
$HighSent\_VIX_{t-1}$	160	135	0.0015	0.0046	0.0198	0.0226	0.0032	-1.27	0.205
$HighSent\_VXY_{t-1}$	144	151	0.0049	0.0010	0.0208	0.0213	-0.0039	1.60	0.110
$Illiquid\_CP\_TB_{t-1}$	145	150	0.0047	0.0012	0.0203	0.0218	-0.0035	1.44	0.151

Table 11 reports the results of the analysis for both contemporaneous and lagged regimes. In the contemporaneous specification, none of the regime dummies yield statistically significant differences in mean carry trade returns at conventional significance levels. However, from the consistent negative mean differences we can see that in all cases, the mean return during months classified into high regimes (high volatility, recessions, illiquidity, high inflation) is always lower than in the low months. The largest difference is observed for the IsRecession (Δ Mean of -0.0054) and the HighSent_VIX (Δ Mean of -0.0043), although both insignificant.

As for the lagged regime indicator model, the findings are similar to the contemporaneous results. No statistically significant differences are detected between high and low states across any of the five regimes; however, the mean differences still point in the same direction, with one exception showcased by $HighSent\_VXY_{t-1}$. The largest gap in means is shown by the $HighSent\_VXY_{t-1}$ dummy (Δ Mean of -0.0039).

Overall, the t-test results across both contemporaneous and lagged specifications suggest that the average monthly carry trade returns are not systematically different across high and low macro-financial conditions. While some patterns hint at meaningful effects, these do not meet statistical thresholds.

7. Conclusions

This final chapter summarizes and interprets the main findings of the empirical analysis conducted in the previous section. The objectives to evaluate how and to what extent carry trade performance across the G10 currencies varies under different economic and market conditions. By synthetizing the insights gained from various models, this chapter aims to provide a comprehensive overview of the results and their implications, potentially identifying limiting factors and areas for further research surrounding the topic.

7.1. Limitations

Several limitations must be acknowledged. Firstly, the empirical models assume linearity in the relationship of carry trade returns and the other variables. While diagnostic tests did not suggest specification errors, nonlinearities may still exist. More flexible models often implemented in the literature (e.g. Markov-switching models, quantile regressions) might better capture the dynamics. Secondly, the regime classification approach based on rolling medians might be overly simplistic and may not reflect truthfully investor sentiment and market responses realistically. Thirdly, the study focuses on a relatively narrow segment, using data from G10 currencies for only the past 25 years. Expanding the dataset could yield additional results. Lastly, the research intentionally excludes forward-looking measures and potential interactions between risk factors are not modelled. More complex analyses could capture further ways carry trade returns are impacted. In any case, there are countless opportunities to advance the study of this topic in the future.

7.2. Summary of results

The empirical findings from the various quantitative models suggest that carry trade excess returns exhibit limited sensitivity to the analysed economic and financial indicators. More specifically, most of the dummy-based regressions fail to deliver statistically significant estimates. These results contrast with several studies of the existing literature pool that have highlighted regime-dependent variation in carry trade performance. This thesis does not uncover such patterns consistently observed across time periods or regimes.

The few statistically significant findings are broadly in line with expectations and prior work with a few surprises. Nonetheless, these results are modest in magnitude and not robust across specifications and subsamples. The VYX volatility indicator produced a negative and significant estimate in the full sample dummy regression model, by both contemporaneous and lagged versions. The same was true for the GFC period dummy regressions on both time specifications. However, the lagged continuous variable regression produced a small, marginally significant positive coefficient, suggesting an opposite result. The inflation indicator produced contrasting results. In the pre-GFC subsample, the contemporaneous regression indicated a highly significant, positive estimate, while in the post-GFC period, the sign switched for both lagged and contemporaneous models. Similarly, the illiquidity measure also showed contrasting results. In the pre-GFC subsample regression it produced a positive, significant estimate, while in the continuous variable regression, both specifications suggest a negative relationship to carry trade returns.

Despite the lack of robust findings with strong statistically significance, this work has contributed to the broader understanding of the behaviour of currency carry trade returns and its relation to various economic and market indicators. The results provide partial empirical support for the themes often mentioned in the existing literature concerning the sensitivity of carry trades to volatile and illiquid periods. The absence of consistent patterns hint at the complex nature of currency markets and reassure the need for more refined indicators, the use of alternative, more dynamic econometric models, and more extensive datasets to capture the significant results. This does not diminish the importance of studying these links, rather highlights the need for continued research of this topic.

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Appendix A

Table 12: Descriptive Statistics of Spot Exchange Rates

Descriptive Statistics of Spot Exchange Rates

Statistic	USDAUD	USDCAD	USDCHF	USDEUR	USDGBP	USDJPY	USDNOK	USDNZD	USDSEK
Spot_Mid_Mean	1.3573	1.2495	1.1011	0.8562	0.6686	111.110	7.6370	1.5492	8.2952
Spot_Mid_Min	0.9095	0.9439	0.7856	0.6340	0.4804	76.2300	5.0847	1.1375	5.9451
Spot_Mid_Max	2.0599	1.6015	1.7975	1.1821	0.8959	160.855	11.3816	2.5205	11.1763
Spot_Mid_SD	0.2509	0.1685	0.2419	0.1184	0.0949	17.1135	1.6194	0.3076	1.4010
Spot_Mid_Kurtosis	0.1218	-0.7974	0.8796	0.1496	-0.9145	0.5604	-0.9034	1.7802	-0.9975
Spot_Mid_Skewness	0.5171	0.0551	1.3538	0.6480	-0.0209	0.3513	0.3488	1.4919	0.2691

Table 13: Descriptive Statistics of Forward Exchange Rates

Descriptive Statistics of Forward Exchange Rates

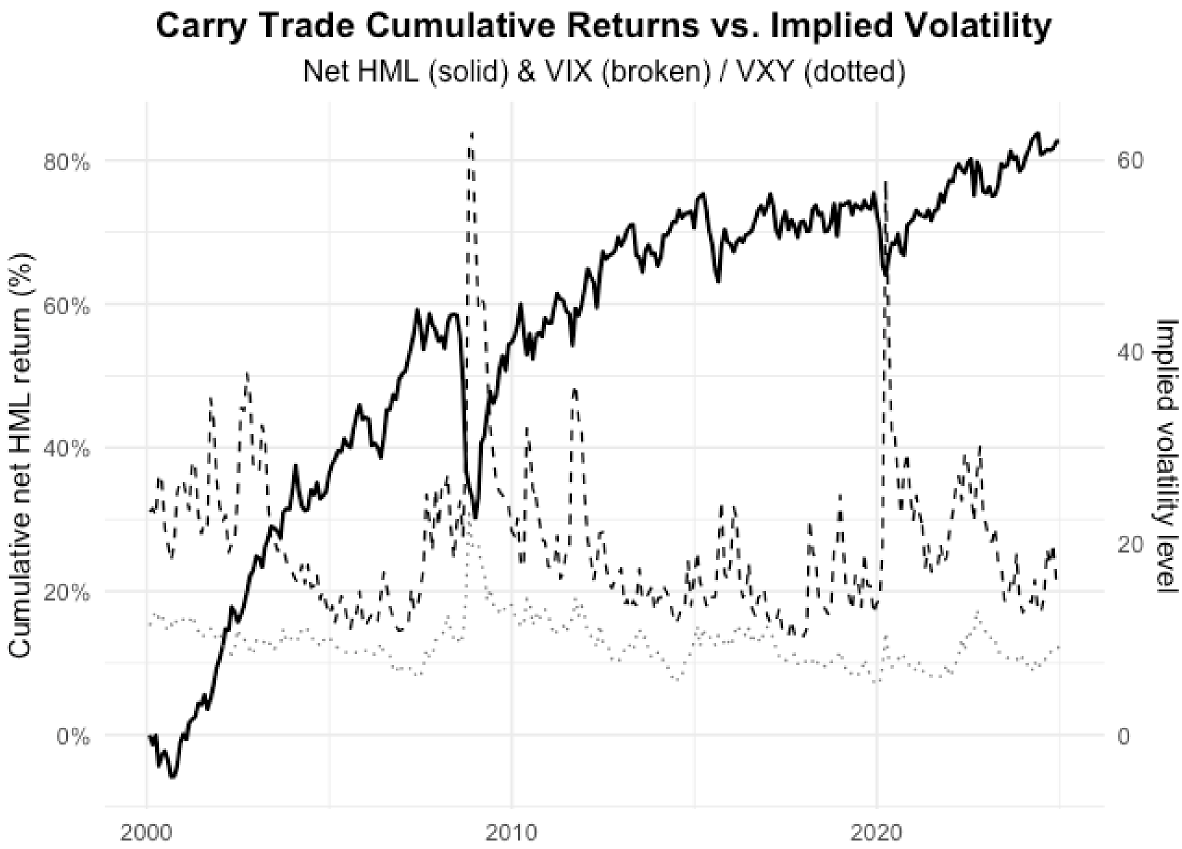
Statistic	USDAUD	USDCAD	USDCHF	USDEUR	USDGBP	USDJPY	USDNOK	USDNZD	USDSEK
Forward_Mid_Mean	1.3589	1.2495	1.0993	0.8556	0.6687	110.878	7.6406	1.5517	8.2903
Forward_Mid_Min	0.9135	0.9432	0.7851	0.6350	0.4808	76.2065	5.1018	1.1399	5.9556
Forward_Mid_Max	2.0600	1.6018	1.7954	1.1827	0.8953	160.098	11.3803	2.5202	11.1546
Forward_Mid_SD	0.2504	0.1685	0.2416	0.1182	0.0945	16.9644	1.6172	0.3078	1.3963
Forward_Mid_Kurtosis	0.1419	-0.7937	0.8801	0.1753	-0.9111	0.5481	-0.9106	1.7854	-0.9968
Forward_Mid_Skewness	0.5301	0.0609	1.3541	0.6628	-0.0239	0.3419	0.3460	1.4963	0.2731

Table 14: Correlation Matrix of Spot Exchange Rates

Correlation Matrix of Spot Exchange Rates

	USDAUD	USDCAD	USDCHF	USDEUR	USDGBP	USDJPY	USDNOK	USDNZD	USDSEK
USDAUD	100%								
USDCAD	94%	100%							
USDCHF	68%	55%	100%						
USDEUR	89%	90%	57%	100%					
USDGBP	37%	49%	-29%	54%	100%				
USDJPY	62%	62%	13%	56%	40%	100%			
USDNOK	68%	75%	1%	75%	83%	74%	100%		
USDNZD	93%	82%	81%	84%	22%	43%	49%	100%	
USDSEK	81%	83%	20%	84%	79%	74%	95%	66%	

Figure 6: Dual-Axis Plot: Cummulative Carry Trade Log Returns (HML Portfolio) vs. Implied Volatility



Appendix B

```
###########################
# 1. SETTING UP ENVIRONMENT
###########################

# 1A) Clear workspace and console
rm(list=ls()); cat("\014")

# 1B) Load libraries
library(readxl)
library(dplyr)
library(tidyr)
library(lubridate)
library(ggplot2)
library(zoo)
library(moments)
library(lmtest)
library(sandwich)
library(knitr)
library(tibble)
library(officer)
library(flextable)
library(e1071)
library(PerformanceAnalytics)
library(xts)
library(broom)
library(purrr)
library(scales)

# 1C) Set working directory
setwd("/Users/tothveronika/Documents/MSc/4 THESIS/data")

# 1D) Load raw data
df_raw <- read_excel("dataset_new.xlsx") %>%
  mutate(
    Date = as.Date(Date),
    Currency_Pair = as.factor(Currency_Pair),
    `Commercial Paper-T-Bill Spread` = as.numeric(`Commercial Paper-T-Bill
Spread`)
  )

###########################
# 2. DESCRIPTIVE STATISTICS
###########################

# 2A) Compute simple summary stats for Spot_Mid and Forward_Mid
df_stats <- df_raw %>%
  group_by(Currency_Pair) %>%
  summarise(
    Spot_Mid_Mean       = mean(Spot_Mid, na.rm=TRUE),
    Spot_Mid_Min        = min(Spot_Mid, na.rm=TRUE),
    Spot_Mid_Max        = max(Spot_Mid, na.rm=TRUE),
    Spot_Mid_SD         = sd(Spot_Mid, na.rm=TRUE),
```

```
    Spot_Mid_Kurtosis    = kurtosis(Spot_Mid, na.rm=TRUE),
    Spot_Mid_Skewness    = skewness(Spot_Mid, na.rm=TRUE),
    Forward_Mid_Mean     = mean(Forward_Mid, na.rm=TRUE),
    Forward_Mid_Min      = min(Forward_Mid, na.rm=TRUE),
    Forward_Mid_Max      = max(Forward_Mid, na.rm=TRUE),
    Forward_Mid_SD       = sd(Forward_Mid, na.rm=TRUE),
    Forward_Mid_Kurtosis= kurtosis(Forward_Mid, na.rm=TRUE),
    Forward_Mid_Skewness= skewness(Forward_Mid, na.rm=TRUE),
    .groups = "drop"
  ) %>%
  mutate(across(where(is.numeric), ~ round(.x, 4)))

# 2B) Build Spot table via pivot
spot_tbl <- df_stats %>%
  select(Currency_Pair, starts_with("Spot_Mid")) %>%
  pivot_longer(
    cols      = -Currency_Pair,
    names_to  = "Statistic",
    values_to = "Value"
  ) %>%
  pivot_wider(
    names_from  = Currency_Pair,
    values_from = Value
  )

ft_spot <- flextable(spot_tbl) %>%
  set_caption("Table B.1: Descriptive Statistics of Spot Exchange Rates")
%>%
  autofit() %>%
  theme_vanilla()

# 2C) Build Forward table via pivot
fwd_tbl <- df_stats %>%
  select(Currency_Pair, starts_with("Forward_Mid")) %>%
  pivot_longer(
    cols      = -Currency_Pair,
    names_to  = "Statistic",
    values_to = "Value"
  ) %>%
  pivot_wider(
    names_from  = Currency_Pair,
    values_from = Value
  )

ft_fwd <- flextable(fwd_tbl) %>%
  set_caption("Table B.2: Descriptive Statistics of Forward Exchange Rates
") %>%
  autofit() %>%
  theme_vanilla()

# 2D) Export both tables to Word
read_docx() %>%
  body_add_par("Table B.1: Descriptive Statistics of Spot Exchange Rates",
style="heading 1") %>%
```

```r
  body_add_flextable(ft_spot) %>%
  body_add_par("Table B.2: Descriptive Statistics of Forward Exchange Rate
s", style="heading 1") %>%
  body_add_flextable(ft_fwd) %>%
  print(target = "descriptive_tables.docx")


#######################################
# 3. EXPLORATORY PLOTS & SUMMARY STATS
#######################################

df_plot <- df_raw %>%
  arrange(Currency_Pair, Date) %>%
  group_by(Currency_Pair) %>%
  mutate(Forward_Discount = log(Forward_Mid) - log(Spot_Mid)) %>%
  ungroup()

# 3A) Line plot of log forward discounts
ggplot(df_plot, aes(x = Date, y = Forward_Discount, group = Currency_Pair)
) +
  geom_line(aes(color = Currency_Pair), size = 0.4, alpha = 0.9) +
  geom_hline(yintercept = 0, color = "black", size = 0.4) +
  scale_color_grey(start = 0.3, end = 0.8) +  # various greys for currenci
es
  labs(title = "Interest Rate Differentials: Log Forward Discounts",
       x = "Year", y = "Interest rate differential") +
  theme_minimal() +  # use default theme to match other plots
  theme(
    legend.position = "none",
    plot.title = element_text(hjust = 0.5, face = "bold")
  )

vix_df <- df_raw %>%
  select(Date, VIX, VXY) %>%
  pivot_longer(c(VIX, VXY), names_to = "Index", values_to = "Level")

# 3B) Line plot for VIX & VXY
ggplot(vix_df, aes(Date, Level)) +
  geom_line(data = subset(vix_df, Index == "VIX"), color = "black", size =
0.7) +
  geom_line(data = subset(vix_df, Index == "VXY"), color = "grey50", size
= 0.7) +
  labs(title = "VIX and VXY Implied Volatility Levels",
       x = "Year", y = "Volatility Level") +
  theme_minimal() +
  theme(
    legend.position = "none",
    plot.title = element_text(hjust = 0.5, face = "bold")
  )

# Correlation between VIX & VXY
cor_vix_vxy <- cor(df_raw$VIX, df_raw$VXY, use = "complete.obs")
message("Correlation VIX vs VXY: ", round(cor_vix_vxy, 3))
```

```
## Correlation VIX vs VXY: 0.651

liq_df <- df_raw %>%
  select(Date, `TED spread`, `Commercial Paper-T-Bill Spread`) %>%
  pivot_longer(
    cols = c(`TED spread`, `Commercial Paper-T-Bill Spread`),
    names_to = "Liquidity_Measure",
    values_to = "Spread"
  )

# 3C) Line plot for liquidity measures
ggplot(liq_df, aes(Date, Spread)) +
  geom_line(data = subset(liq_df, Liquidity_Measure == "TED spread"), colo
r = "black", size = 0.7) +
  geom_line(data = subset(liq_df, Liquidity_Measure == "Commercial Paper-T
-Bill Spread"), color = "grey50", size = 0.7) +
  labs(title = "Liquidity Condition Indicators: TED and CP-TBill Spreads",
       x = "Year", y = "Spread (percentage points)") +
  theme_minimal() +
  theme(
    legend.position = "none",
    plot.title = element_text(hjust = 0.5, face = "bold")
  )

# Correlation between TED spread and CP-TB spread
cor_liq <- cor(df_raw$`TED spread`, df_raw$`Commercial Paper-T-Bill Spread
`, use = "complete.obs")
message("Correlation TED vs CP-TB Spread: ", round(cor_liq, 3))

## Correlation TED vs CP-TB Spread: 0.957

# 3D) Line plot of year-on-year inflation
inflation_df <- df_raw %>%
  select(Date, `CPI YoY`) %>%
  filter(!is.na(`CPI YoY`))

ggplot(inflation_df, aes(x = Date, y = `CPI YoY`)) +
  geom_line(color = "black", size = 0.7) +
  geom_hline(yintercept = 0, linetype = "dashed", size = 0.3, color = "gre
y50") +
  labs(title = "Consumer Price Index (Year-on-Year)",
       x = "Year", y = "Inflation Rate (%)") +
  theme_minimal() +
  theme(
    plot.title = element_text(hjust = 0.5, face = "bold")
  )

# 3E) Count number of recession and non-recession months
recession_summary <- df_raw %>%
  mutate(Date = as.yearmon(Date)) %>%
  group_by(Date) %>%
  summarise(IsRecession = last(Recession), .groups = "drop") %>%
  group_by(IsRecession) %>%
  summarise(
    n_months = n(),
```

```r
    first_month = min(Date),
    last_month  = max(Date),
    .groups = "drop"
  )

print("Recession vs Non-Recession Periods:")

## [1] "Recession vs Non-Recession Periods:"

print(recession_summary)

## # A tibble: 2 × 4
##   IsRecession n_months first_month last_month
##         <dbl>    <int> <yearmon>   <yearmon>
## 1           0      270 Jan 2000    Jan 2025
## 2           1       31 Mar 2001    Apr 2020

# 3F) Correlation matrix of Spot_Mid
spot_wide <- df_raw %>%
  select(Date, Currency_Pair, Spot_Mid) %>%
  pivot_wider(names_from=Currency_Pair, values_from=Spot_Mid)
cor_mat <- round(cor(spot_wide[-1], use="pairwise.complete.obs")*100,0)
cor_df <- as.data.frame(cor_mat) %>%
  rownames_to_column("Currency")
# blank upper triangle
for(i in 1:nrow(cor_mat)) for(j in (i+1):ncol(cor_mat)) cor_df[i,j+1]<-""
ft_cor <- flextable(cor_df) %>%
  set_header_labels(Currency="") %>%
  colformat_char(j=-1, suffix="%") %>%
  set_caption("Table: Correlation Matrix of Spot Exchange Rates") %>%
  autofit()
doc2 <- read_docx() %>%
  body_add_par("Correlation Matrix of Spot Exchange Rates", style="heading
1") %>%
  body_add_flextable(ft_cor)
print(doc2, target="correlation_matrix.docx")

# 3G) Log forward discount and spot changes summary statistics

# compute the two series: log-spot changes & log forward discounts
df2 <- df_raw %>%
  arrange(Currency_Pair, Date) %>%
  group_by(Currency_Pair) %>%
  mutate(
    log_spot_change       = log(Spot_Mid) - lag(log(Spot_Mid)),
    log_forward_discount  = log(Forward_Mid) - log(Spot_Mid)
  ) %>%
  ungroup()

# helper to summarize one series
summ_stats <- function(data, var){
  data %>%
    filter(!is.na(.data[[var]])) %>%
    group_by(Currency_Pair) %>%
    summarise(
```

```
      Mean     = mean(.data[[var]], na.rm=TRUE),
      Min      = min(.data[[var]], na.rm=TRUE),
      Max      = max(.data[[var]], na.rm=TRUE),
      `Std Dev`= sd(.data[[var]], na.rm=TRUE),
      Kurtosis = kurtosis(.data[[var]], na.rm=TRUE),
      Skewness = skewness(.data[[var]], na.rm=TRUE),
      .groups  = "drop"
    ) %>%
    mutate(across(where(is.numeric), ~round(.x,4)))
}

# build two summary tables
spot_tbl <- summ_stats(df2, "log_spot_change")
fwd_tbl  <- summ_stats(df2, "log_forward_discount")

# render as flextables
ft_spot <- flextable( spot_tbl ) %>%
  set_header_labels(
    Currency_Pair = "Currency",
    Mean          = "Mean",
    Min           = "Min",
    Max           = "Max",
    `Std Dev`     = "Std Dev",
    Kurtosis      = "Kurtosis",
    Skewness      = "Skewness"
  ) %>%
  add_header_row(
    values = c("","Summary Statistics of Log Spot Rate Changes"),
    colwidths = c(1,6)
  ) %>%
  theme_vanilla() %>%
  autofit()

ft_fwd <- flextable( fwd_tbl ) %>%
  set_header_labels(
    Currency_Pair = "Currency",
    Mean          = "Mean",
    Min           = "Min",
    Max           = "Max",
    `Std Dev`     = "Std Dev",
    Kurtosis      = "Kurtosis",
    Skewness      = "Skewness"
  ) %>%
  add_header_row(
    values = c("","Summary Statistics of Log Forward Discounts"),
    colwidths = c(1,6)
  ) %>%
  theme_vanilla() %>%
  autofit()

# 3H) Export both into one Word doc
doc <- read_docx() %>%
  body_add_par("Table XX: Summary Statistics of Log Spot Rates and Forward
Discounts", style="heading 1") %>%
```

```r
  body_add_flextable(ft_spot) %>%
  body_add_par("") %>%  # blank line
  body_add_flextable(ft_fwd)

print(doc, target = "log_summary_stats.docx")


###########################
# 4. PORTFOLIO CONSTRUCTION
###########################

df <- df_raw %>%

# 4A) Month-end index & next-month quotes
  mutate(Date = as.yearmon(Date)) %>%
  arrange(Currency_Pair, Date) %>%
  group_by(Currency_Pair) %>%
  mutate(
    Spot_Bid_next     = lead(Spot_Bid),
    Spot_Mid_next     = lead(Spot_Mid),
    Spot_Ask_next     = lead(Spot_Ask),
    Forward_Bid_next = lead(Forward_Bid),
    Forward_Mid_next = lead(Forward_Mid),
    Forward_Ask_next = lead(Forward_Ask)
  ) %>%
  ungroup() %>%
  filter(!is.na(Spot_Mid_next)) %>%

# 4B) Forward-discount terciles on month-end
  group_by(Date) %>%
  mutate(
    fwd_disc = log(Forward_Mid) - log(Spot_Mid),
    bucket   = factor(
      ntile(fwd_disc, 3),
      levels = 1:3,
      labels = c("P1", "P2", "P3")
    )
  ) %>%
  ungroup() %>%

# 4C) Gross carry payoff per currency (long forward, short spot)
  mutate(
    ret_gross_log = log(Forward_Mid) - log(Spot_Mid_next)
  ) %>%

# 4D) Contemporaneous (time-t) bid-ask spreads
  mutate(
    BAS     = log(Spot_Ask)     - log(Spot_Bid),    # spot bid-ask
    BAF_tm1 = lag(log(Forward_Ask) - log(Forward_Bid))  # forward bid-ask
at t-1
  ) %>%

# 4E) HML portfolio weights at time t
  group_by(Date) %>%
```

```r
  mutate(
    N1 = sum(bucket == "P1"),
    N3 = sum(bucket == "P3"),
    w_t = case_when(
      bucket == "P3" ~  1 / N3,
      bucket == "P1" ~ -1 / N1,
      TRUE           ~  0
    )
  ) %>%
  ungroup() %>%

# 4F) Carry forward last month’s weight
  arrange(Currency_Pair, Date) %>%
  group_by(Currency_Pair) %>%
  mutate(
    w_tm1 = lag(w_t)
  ) %>%
  ungroup() %>%

# 4G) Per-currency transaction-cost contributions
  mutate(
    tc_spot_i = abs(w_t   - w_tm1) * BAS,     # spot-cost
    tc_fwd_i  = abs(w_tm1)   * BAF_tm1        # forward-cost
  ) %>%

# 4H) Net log return *by currency* = gross – its own costs
  mutate(
    ret_net_tc = ret_gross_log - tc_spot_i - tc_fwd_i
  ) %>%
  ungroup()


###########################
# 5. SUMMARY TABLES & GRAPHS
###########################

# 5A) Roll-up helper: compute bucket returns, DOL & HML
rollup_log <- function(dat, col) {
  dat %>%
    group_by(Date, bucket) %>%
    summarise(ret = mean(.data[[col]], na.rm=TRUE), .groups="drop") %>%
    complete(Date, bucket=c("P1","P2","P3"), fill=list(ret=0)) %>%
    pivot_wider(names_from=bucket, values_from=ret) %>%
    arrange(Date) %>%
    mutate(
      DOL = (P1 + P2 + P3) / 3,
      HML = P3 - P1
    )
}

# 5B) Build the series
rets_gross  <- rollup_log(df, "ret_gross_log")
rets_net_tc <- rollup_log(df, "ret_net_tc")
```

```r
# 5C) Annualized summary-stats helper
summarize_log_annual <- function(wide_df) {
  wide_df %>%
    pivot_longer(P1:HML, names_to="Portfolio", values_to="Ret") %>%
    group_by(Portfolio) %>%
    summarise(
      m         = mean(Ret, na.rm=TRUE),
      s         = sd(Ret,   na.rm=TRUE),
      Skewness = skewness(Ret, na.rm=TRUE),
      Kurtosis = kurtosis(Ret, na.rm=TRUE),
      AC1       = acf(Ret, lag.max=1, plot=FALSE)$acf[2],
      Mean      = m * 12 * 100,
      Median    = median(Ret, na.rm=TRUE) * 12 * 100,
      `Std Dev`= s * sqrt(12) * 100,
      Sharpe    = (m * 12) / (s * sqrt(12)),
      .groups   = "drop"
    ) %>%
    select(Portfolio, Mean, Median, `Std Dev`, Skewness, Kurtosis, Sharpe,
AC1)
}

stats_gross  <- summarize_log_annual(rets_gross)
stats_net_tc <- summarize_log_annual(rets_net_tc)

# 5D) Build and export flextables
ft_gross <- flextable(stats_gross) %>%
  set_header_labels(
    Portfolio = "Portfolio",
    Mean      = "Mean Ann (%)",
    Median    = "Median Ann (%)",
    `Std Dev` = "Vol Ann (%)",
    Skewness  = "Skewness",
    Kurtosis  = "Kurtosis",
    Sharpe    = "Sharpe Ann",
    AC1       = "AC(1)"
  ) %>%
  colformat_double(j = -1, digits = 2) %>%
  theme_vanilla()

ft_net_tc <- flextable(stats_net_tc) %>%
  set_header_labels(
    Portfolio = "Portfolio",
    Mean      = "Mean Ann (%)",
    Median    = "Median Ann (%)",
    `Std Dev` = "Vol Ann (%)",
    Skewness  = "Skewness",
    Kurtosis  = "Kurtosis",
    Sharpe    = "Sharpe Ann",
    AC1       = "AC(1)"
  ) %>%
  colformat_double(j = -1, digits = 2) %>%
  theme_vanilla()

read_docx() %>%
```

```r
  body_add_par("Table 1: Annualized Log Returns WITHOUT Transaction Costs"
, style="heading 2") %>%
  body_add_flextable(ft_gross) %>%
  body_add_par("Table 2: Annualized Log Returns WITH Transaction Costs", s
tyle="heading 2") %>%
  body_add_flextable(ft_net_tc) %>%
  print(target="portfolio_log_return_summary.docx")

# 5E) Cumulative HML plot
cum_hml_net <- rets_net_tc %>%
  arrange(Date) %>%
  mutate(cum_HML = cumsum(HML) * 100)

ggplot(cum_hml_net, aes(Date, cum_HML)) +
  geom_line(size=0.8) +
  geom_hline(yintercept=0, size=0.3) +
  labs(
    x="Date",
    y="Cumulative log excess return (%)",
    title="Cumulative Carry Trade HML Log Returns",
    subtitle="Net after spot & forward transaction costs"
  ) +
  theme_minimal() +
  theme(
    plot.title    = element_text(face="bold", size=14, hjust=0.5),
    plot.subtitle = element_text(size=10, hjust=0.5),
    axis.text.x   = element_text(angle=45, hjust=1)
  )

# 5F) Dual-Axis Plot: Cumulative HML vs VIX & VXY
# Build cumulative HML series
cum_hml_df <- rets_net_tc %>%
  arrange(Date) %>%
  mutate(
    # turn yearmon → real Date at month-end
    Date       = as.Date(as.yearmon(Date), frac = 1),
    cum_HML    = cumsum(HML) * 100
  ) %>%
  select(Date, cum_HML)

# Build monthly VIX/VXY series from raw data
vol_df <- df_raw %>%
  mutate(
    Date = as.Date(as.yearmon(Date), frac = 1)
  ) %>%
  group_by(Date) %>%
  summarise(
    VIX = last(VIX),
    VXY = last(VXY),
    .groups = "drop"
  )

#Merge cumulative HML with VIX/VXY
plot_df <- left_join(cum_hml_df, vol_df, by = "Date")
```

```r
#Compute a scale factor so that VIX/VXY share the same y-range as cum_HML
sf <- max(plot_df$cum_HML, na.rm = TRUE) / max(plot_df$VIX,    na.rm = TRU
E)

#Plot
ggplot(plot_df, aes(x = Date)) +

  # cumulative carry-spread (left axis)
  geom_line(aes(y = cum_HML),                color = "black",   size = 0.8
) +

  # implied vols (right axis, scaled up)
  geom_line(aes(y = VIX  * sf),              linetype = "dashed", color =
"black") +
  geom_line(aes(y = VXY  * sf),              linetype = "dotted", color =
"grey50") +

  # set up dual y-axes
  scale_y_continuous(
    name      = "Cumulative net HML return (%)",
    labels    = percent_format(scale = 1),
    sec.axis  = sec_axis(~ . / sf, name = "Implied volatility level")
  ) +

  # titles & theme
  labs(
    title    = "Carry Trade Cumulative Returns vs. Implied Volatility",
    subtitle = "Net HML (solid) & VIX (broken) / VXY (dotted)"
  ) +
  theme_minimal(base_size = 12) +
  theme(
    plot.title      = element_text(face = "bold", hjust = 0.5),
    plot.subtitle   = element_text(hjust = 0.5),
    axis.title.x    = element_blank(),
    legend.position= "none"
  )

#########################
# 6. BUILD REGIME DUMMIES
#########################

df_flags <- df_raw %>%
  arrange(Date) %>%
  mutate(
    # Rolling median for VIX
    VIX_roll_median = rollmedian(VIX, 36, align = "right", fill = NA),
    HighSent_VIX    = as.integer(lag(VIX) > lag(VIX_roll_median)),

    # Rolling median for VXY
    VXY_roll_median = rollmedian(VXY, 36, align = "right", fill = NA),
    HighSent_VXY    = as.integer(lag(VXY) > lag(VXY_roll_median)),

    # Rolling median for CPI YoY (Inflation)
```

```
    CPI_roll_median = rollmedian(`CPI YoY`, 36, align = "right", fill = NA
),
    HighInfl        = as.integer(lag(`CPI YoY`) > lag(CPI_roll_median)),

    # Rolling median for Commercial Paper-T-Bill Spread (Liquidity)
    CP_TB_roll_median = rollmedian(`Commercial Paper-T-Bill Spread`, 36, a
lign = "right", fill = NA),
    Illiquid_CP_TB    = as.integer(lag(`Commercial Paper-T-Bill Spread`) >
lag(CP_TB_roll_median)),

    # Recession dummy remains as-is
    IsRecession = as.integer(Recession == 1)
  ) %>%
  select(Date, HighInfl, IsRecession, HighSent_VIX, HighSent_VXY, Illiquid
_CP_TB)

df_flags2 <- df_flags %>%
  mutate(Date = as.yearmon(Date))


################
# 7. REGRESSIONS
################

# 7A) Dummy regressions

# Create dataset with both contemporaneous and lagged regime dummies
df_reg_dual_vxy <- df_flags2 %>%
  mutate(
    L1_HighInfl          = lag(HighInfl, 1),
    L1_IsRecession       = lag(IsRecession, 1),
    L1_HighSent_VXY      = lag(HighSent_VXY, 1),
    L1_Illiquid_CP_TB    = lag(Illiquid_CP_TB, 1)
  ) %>%
  left_join(rets_net_tc %>% select(Date, HML), by = "Date") %>%
  filter(!is.na(HML))

# Helper for formatting regression tables
format_reg_table <- function(model, vcov_matrix) {
  broom::tidy(coeftest(model, vcov. = vcov_matrix)) %>%
    filter(term != "(Intercept)") %>%
    mutate(
      Estimate     = round(estimate, 4),
      `Std. Error` = round(std.error, 4),
      `t-stat`     = round(statistic, 2),
      `p-value`    = round(p.value, 3),
      stars        = ifelse(p.value < .01, "***",
                     ifelse(p.value < .05, "**",
                     ifelse(p.value < .1, "*", "")))
    ) %>%
    select(term, Estimate, `Std. Error`, `t-stat`, `p-value`, stars) %>%
    flextable() %>%
    set_header_labels(term = "Term", Estimate = "Estimate", `Std. Error` =
"Std. Error",
```

```
                      `t-stat` = "t-stat", `p-value` = "p-value", stars =
"") %>%
    theme_booktabs() %>%
    autofit()
}

# Contemporaneous dummies only
mod_vxy_contemp <- lm(HML ~ HighInfl + IsRecession + HighSent_VXY + Illiqu
id_CP_TB,
                      data = df_reg_dual_vxy)
nw_contemp <- NeweyWest(mod_vxy_contemp, lag = 6, prewhite = FALSE)
ft_contemp <- format_reg_table(mod_vxy_contemp, nw_contemp)

# Lagged dummies only
mod_vxy_lagged <- lm(HML ~ L1_HighInfl + L1_IsRecession + L1_HighSent_VXY
+ L1_Illiquid_CP_TB,
                     data = df_reg_dual_vxy)
nw_lagged <- NeweyWest(mod_vxy_lagged, lag = 6, prewhite = FALSE)
ft_lagged <- format_reg_table(mod_vxy_lagged, nw_lagged)

# Export both into a single Word document
read_docx() %>%
  body_add_par("Table 7A.1: Dummy Regression with Contemporaneous Regimes
(VXY)", style = "heading 2") %>%
  body_add_flextable(ft_contemp) %>%
  body_add_par("Table 7A.2: Dummy Regression with Lagged Regimes (VXY)", s
tyle = "heading 2") %>%
  body_add_flextable(ft_lagged) %>%
  print(target = "regression_dummy.docx")


# Helper function:single predictive regression with robust SE and CI
run_pred_reg <- function(varname, label, df) {
  fml <- as.formula(paste("HML ~", varname))
  mod <- lm(fml, data = df)
  nw  <- NeweyWest(mod, lag = 6, prewhite = FALSE)
  ci  <- confint(mod)[-1, , drop = FALSE]

  broom::tidy(coeftest(mod, vcov. = nw)) %>%
    filter(term != "(Intercept)") %>%
    mutate(
      term = label,
      Estimate = round(estimate, 4),
      `Std. Error` = round(std.error, 4),
      z = round(statistic, 3),
      `p-value` = round(p.value, 3),
      CI_low = round(ci[1, 1], 4),
      CI_high = round(ci[1, 2], 4)
    ) %>%
    select(term, Estimate, `Std. Error`, z, `p-value`, CI_low, CI_high)
}

# 7B) Continous variable regressions
```

```r
# Prepare base dataset with levels and lags
df_pred_lvls_dual <- df_raw %>%
  arrange(Date) %>%
  mutate(Date = as.yearmon(Date)) %>%
  mutate(
    L1_VXY       = lag(VXY),
    L1_CPI_YoY   = lag(`CPI YoY`),
    L1_CP_TB     = lag(`Commercial Paper-T-Bill Spread`)
  ) %>%
  transmute(Date,
            VXY, L1_VXY,
            CPI_YoY = `CPI YoY`, L1_CPI_YoY,
            CP_TB = `Commercial Paper-T-Bill Spread`, L1_CP_TB) %>%
  left_join(rets_net_tc %>% select(Date, HML), by = "Date") %>%
  drop_na()

# Helper for table formatting
format_reg_table <- function(model, vcov_matrix) {
  broom::tidy(coeftest(model, vcov. = vcov_matrix)) %>%
    filter(term != "(Intercept)") %>%
    mutate(
      Estimate     = round(estimate, 4),
      `Std. Error` = round(std.error, 4),
      `t-stat`     = round(statistic, 2),
      `p-value`    = round(p.value, 3),
      stars        = ifelse(p.value < .01, "***",
                       ifelse(p.value < .05, "**",
                              ifelse(p.value < .1, "*", "")))
    ) %>%
    select(term, Estimate, `Std. Error`, `t-stat`, `p-value`, stars) %>%
    flextable() %>%
    set_header_labels(term = "Term", Estimate = "Estimate", `Std. Error` =
"Std. Error",
                      `t-stat` = "t-stat", `p-value` = "p-value", stars =
"") %>%
    theme_booktabs() %>%
    autofit()
}

# Contemporaneous levels only
mod_lvls_contemp <- lm(HML ~ VXY + CPI_YoY + CP_TB, data = df_pred_lvls_du
al)
nw_lvls_contemp <- NeweyWest(mod_lvls_contemp, lag = 6, prewhite = FALSE)
ft_lvls_contemp <- format_reg_table(mod_lvls_contemp, nw_lvls_contemp)

# Lagged levels only
mod_lvls_lagged <- lm(HML ~ L1_VXY + L1_CPI_YoY + L1_CP_TB, data = df_pred
_lvls_dual)
nw_lvls_lagged <- NeweyWest(mod_lvls_lagged, lag = 6, prewhite = FALSE)
ft_lvls_lagged <- format_reg_table(mod_lvls_lagged, nw_lvls_lagged)

# 7C) Export results to Word
read_docx() %>%
  body_add_par("Table 7B.1: Predictive Regressions – Levels (Contemporaneo
```

```
us)", style = "heading 2") %>%
  body_add_flextable(ft_lvls_contemp) %>%
  body_add_par("Table 7B.2: Predictive Regressions – Levels (Lagged)", sty
le = "heading 2") %>%
  body_add_flextable(ft_lvls_lagged) %>%
  print(target = "predictive_regressions.docx")


##############################
# 8. SUBSAMPLE MEANS & T-TESTS
##############################

# Already one HML return per month
df_monthly <- rets_net_tc %>%
  select(Date, HML)  # single portfolio series

# Join with regime dummies
df_ttest <- df_monthly %>%
  left_join(df_flags2, by = "Date")

# 8A) Contemporaneous regimes

# Define contemporaneous regimes
contemp_regimes <- c("HighInfl", "IsRecession", "HighSent_VXY", "Illiquid_
CP_TB")

# Compute subsample means & t-tests
sub_stats_contemp <- map_df(contemp_regimes, function(dummy) {
  df_sub <- df_ttest %>%
    filter(!is.na(.data[[dummy]])) %>%
    mutate(flag = .data[[dummy]])

  # Counts
  n_low  <- sum(df_sub$flag == 0, na.rm = TRUE)
  n_high <- sum(df_sub$flag == 1, na.rm = TRUE)

  # Means and SDs
  sums <- df_sub %>%
    group_by(flag) %>%
    summarise(
      mean = mean(HML, na.rm = TRUE),
      sd   = sd(HML, na.rm = TRUE),
      .groups = "drop"
    ) %>%
    pivot_wider(names_from = flag, values_from = c(mean, sd), names_sep =
"_")

  # T-test
  tt <- t.test(HML ~ flag, data = df_sub)

  tibble(
    Regime      = dummy,
    N_low       = n_low,
    N_high      = n_high,
```

```
    Mean_low   = round(sums$mean_0, 4),
    Mean_high  = round(sums$mean_1, 4),
    SD_low     = round(sums$sd_0, 4),
    SD_high    = round(sums$sd_1, 4),
    Diff       = round(sums$mean_1 - sums$mean_0, 4),
    t_stat     = round(as.numeric(tt$statistic), 2),
    p_value    = round(tt$p.value, 3)
  )
})

# Format table
ft_sub_contemp <- flextable(sub_stats_contemp) %>%
  set_header_labels(
    Regime = "Regime", N_low = "N (Low)", N_high = "N (High)",
    Mean_low = "Mean (Low)", Mean_high = "Mean (High)",
    SD_low = "SD (Low)", SD_high = "SD (High)",
    Diff = "\u0394 Mean", t_stat = "t-stat", p_value = "p-value"
  ) %>%
  theme_booktabs() %>%
  autofit()


# 8B) Lagged regimes

# Add lagged regimes
df_ttest_lagged <- df_ttest %>%
  mutate(
    L1_HighInfl       = lag(HighInfl, 1),
    L1_IsRecession    = lag(IsRecession, 1),
    L1_HighSent_VXY   = lag(HighSent_VXY, 1),
    L1_Illiquid_CP_TB = lag(Illiquid_CP_TB, 1)
  )

# Define lagged regimes
lagged_regimes <- c("L1_HighInfl", "L1_IsRecession", "L1_HighSent_VXY", "L
1_Illiquid_CP_TB")

# Compute subsample means & t-tests
sub_stats_lagged <- map_df(lagged_regimes, function(dummy) {
  df_sub <- df_ttest_lagged %>%
    filter(!is.na(.data[[dummy]])) %>%
    mutate(flag = .data[[dummy]])

  # Counts
  n_low  <- sum(df_sub$flag == 0, na.rm = TRUE)
  n_high <- sum(df_sub$flag == 1, na.rm = TRUE)

  # Means and SDs
  sums <- df_sub %>%
    group_by(flag) %>%
    summarise(
      mean = mean(HML, na.rm = TRUE),
      sd   = sd(HML, na.rm = TRUE),
      .groups = "drop"
```

```r
    ) %>%
    pivot_wider(names_from = flag, values_from = c(mean, sd), names_sep =
"_")

  # T-test
  tt <- t.test(HML ~ flag, data = df_sub)

  tibble(
    Regime      = dummy,
    N_low       = n_low,
    N_high      = n_high,
    Mean_low    = round(sums$mean_0, 4),
    Mean_high   = round(sums$mean_1, 4),
    SD_low      = round(sums$sd_0, 4),
    SD_high     = round(sums$sd_1, 4),
    Diff        = round(sums$mean_1 - sums$mean_0, 4),
    t_stat      = round(as.numeric(tt$statistic), 2),
    p_value     = round(tt$p.value, 3)
  )
})

# Format table
ft_sub_lagged <- flextable(sub_stats_lagged) %>%
  set_header_labels(
    Regime = "Regime (Lagged)", N_low = "N (Low)", N_high = "N (High)",
    Mean_low = "Mean (Low)", Mean_high = "Mean (High)",
    SD_low = "SD (Low)", SD_high = "SD (High)",
    Diff = "\u0394 Mean", t_stat = "t-stat", p_value = "p-value"
  ) %>%
  theme_booktabs() %>%
  autofit()


# 8C) Export to Word
read_docx() %>%
  body_add_par("Table 10.1: Subsample Means & Two-Sample t-Tests (Contempo
raneous)", style = "heading 2") %>%
  body_add_flextable(ft_sub_contemp) %>%
  body_add_par("Table 10.2: Subsample Means & Two-Sample t-Tests (Lagged)"
, style = "heading 2") %>%
  body_add_flextable(ft_sub_lagged) %>%
  print(target = "subsample_stats_tables.docx")


###########################################
# 9. ROBUSTNESS CHECK: 80th PERCENTILE CUT
###########################################

# 9A) Build regime dummies using 80th percentile instead of mean
df_flags_80th <- df_raw %>%
  arrange(Date) %>%
  mutate(
    # 80th percentile cutoff for VXY (volatility)
    VXY_roll_p80 = rollapply(VXY, 36, function(x) quantile(x, 0.8, na.rm=T
```

```
RUE), align = "right", fill = NA),
    HighSent_VXY_p80 = as.integer(lag(VXY) > lag(VXY_roll_p80)),

    # 80th percentile cutoff for CPI YoY (inflation)
    CPI_roll_p80 = rollapply(`CPI YoY`, 36, function(x) quantile(x, 0.8, n
a.rm=TRUE), align = "right", fill = NA),
    HighInfl_p80 = as.integer(lag(`CPI YoY`) > lag(CPI_roll_p80)),

    # 80th percentile cutoff for CP-TB spread (liquidity stress)
    CP_TB_roll_p80 = rollapply(`Commercial Paper-T-Bill Spread`, 36, funct
ion(x) quantile(x, 0.8, na.rm=TRUE), align = "right", fill = NA),
    Illiquid_CP_TB_p80 = as.integer(lag(`Commercial Paper-T-Bill Spread`)
> lag(CP_TB_roll_p80)),

    # Recession dummy stays the same
    IsRecession = as.integer(Recession == 1)
  ) %>%
  select(Date, HighInfl_p80, IsRecession, HighSent_VXY_p80, Illiquid_CP_TB
_p80) %>%
  mutate(Date = as.yearmon(Date))


# 9B) Prepare regression dataset by merging with portfolio returns
df_reg_dual_vxy_80th <- df_flags_80th %>%
  mutate(
    L1_HighInfl_p80       = lag(HighInfl_p80, 1),
    L1_IsRecession        = lag(IsRecession, 1),
    L1_HighSent_VXY_p80   = lag(HighSent_VXY_p80, 1),
    L1_Illiquid_CP_TB_p80 = lag(Illiquid_CP_TB_p80, 1)
  ) %>%
  left_join(rets_net_tc %>% select(Date, HML), by = "Date") %>%
  filter(!is.na(HML))


# 9C) Contemporaneous regression (80th percentile)
mod_contemp_80th <- lm(HML ~ HighInfl_p80 + IsRecession + HighSent_VXY_p80
+ Illiquid_CP_TB_p80,
                       data = df_reg_dual_vxy_80th)
nw_contemp_80th <- NeweyWest(mod_contemp_80th, lag = 6, prewhite = FALSE)
ft_contemp_80th <- format_reg_table(mod_contemp_80th, nw_contemp_80th)


# 9D) Lagged regression (80th percentile)
mod_lagged_80th <- lm(HML ~ L1_HighInfl_p80 + L1_IsRecession + L1_HighSent
_VXY_p80 + L1_Illiquid_CP_TB_p80,
                      data = df_reg_dual_vxy_80th)
nw_lagged_80th <- NeweyWest(mod_lagged_80th, lag = 6, prewhite = FALSE)
ft_lagged_80th <- format_reg_table(mod_lagged_80th, nw_lagged_80th)


# 9E) Export to Word
read_docx() %>%
  body_add_par("Table R1: Dummy Regressions (Contemporaneous, 80th Percent
ile Cutoff)", style = "heading 2") %>%
```

```
  body_add_flextable(ft_contemp_80th) %>%
  body_add_par("Table R2: Dummy Regressions (Lagged, 80th Percentile Cutof
f)", style = "heading 2") %>%
  body_add_flextable(ft_lagged_80th) %>%
  print(target = "robustness_dummy_regressions_80th.docx")
```

EXECUTIVE SUMMARY

This thesis investigated the performance of currency carry trades under different economic and market conditions across the G10 currencies. The carry trade is a frequently used trading method in the FX market, exploiting the interest rate differentials between currencies. The carry trade has historically generated attractive excess returns but is known to be vulnerable to heightened volatility or adverse market shifts.

Using monthly exchange rate data from the past 25 years, the study constructs carry trade portfolios and examines excess returns through regime-based dummy variable regressions and continuous variable models. Regimes are using a 36-month rolling median approach to classify key indicators into "high" and "low" months, including inflation, liquidity, volatility, and recession indicators. Subsample analyses and robustness checks are carried out.

The empirical results revealed limited evidence about the dynamics of carry trade profitability and the studied regimes. Most dummy-based regressions produced statistically insignificant estimates, in contrast to several prior studies reporting robust findings. Significant findings partially align with theoretical expectations: high volatility corresponds with lower carry returns, while inflation and liquidity effects vary across subsamples and specifications.

This thesis contributes to the literature by providing a comprehensive study of carry trade profitability with a perspective on the stability of carry trade performance across market conditions. The lack of consistent and robust findings highlight the complex nature of currency markets and call for future research to adopt more dynamic econometric models, refined measures, and richer datasets.

KEYWORDS: foreign exchange, carry trade, return, profitability, currency, inflation, volatility, liquidity, market, interest rate differential, regime, portfolio

WORD COUNT: 20,625 total (15,249 net)

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