ESSAYS ON CARRY STRATEGIES

by

Walid Khalfallah

A dissertation submitted in partial fulfilment
of the requirement for the degree of

Doctor of Philosophy
[EDHEC BUSINESS SCHOOL]

June 2022

Dissertation Committee:

Emmanuel Jurczenko, PhD
Pasquale Della Corte, PhD
Nikolaos Tessaromatis, PhD
Enrique Schroth, PhD

EDHEC BUSINESS SCHOOL

APPROVAL FORM

CANDIDATE'S NAME: Walid KHALFALLAH

TITLE OF DISSERTATION: **"Essays on Carry Strategies"**

APPROVAL:

Emmanuel Jurczenko		*Chair*
Pasquale Della Corte		*External Examiner*
Nikolaos Tessaromatis		*Member*
Enrique Schroth		*Member*

☐ with minor revisions

☐ with major revisions

DATE: 30 June 2022

Abstract

This thesis explores the carry factor in a cross-asset class setting. The first chapter analyses the carry factor along multiple markets and shows that the unconditional carry premia are present across currencies, equities, fixed income and commodities. It additionally shows that conditional cross-asset class premia are also present, with the carry factor predictable by the carry spread. The time-variation in carry premia is economically and statistically large with expected returns of cross-asset carry increasing in the carry spread. A standard deviation expansion in the carry spread foresees an increase in expected carry return broadly similar to the level of the unconditional carry premium. Further, pooled regressions assessing the joint time variation of carry premia shows evidence of cross-asset market integration. The study also assesses the economic benefits from timing the carry factor. It shows that the carry spread is useful to time carry in certain asset classes, whereby timing strategies can be an attractive complement to the unconditional carry strategy. Similarly, cross-asset rotation strategies based on relative carry spread are generally economically meaningful, yet they fail to beat unconditional benchmark portfolios on a risk adjusted basis. Overall, the study finds that while carry returns predictability is statistically strong across all asset classes, the economic benefits of timing the carry factor are less consistent.

The second chapter extends the notion of carry beyond conventional markets to the volatility asset class by examining spot and forward volatility risk premia in different asset classes. It identifies common risk factors in cross-sectional volatility carry returns across multiple markets. A cross-sectional strategy analogous to carry strategies in traditional asset classes which takes long and short positions in forward volatility agreements and volatility swaps of assets with respectively high and low volatility carry generate significant excess returns, indicating that volatility carry is a strong predictor of cross sectional volatility returns. Panel regressions of volatility returns on volatility carry show consistently positive relationship in each underlying asset class, validating volatility carry as strong predictor of volatility returns. This study complements previous research findings by showing that carry predicts returns not only in traditional asset classes but also across volatility. Based on the evidence of volatility carry returns predictability, timing strategies are implemented which show positive risk adjusted returns across various asset classes and instruments, exceeding those generated by carry strategies on underlying markets. While volatility carry returns are related to volatility premia (short volatility returns), carry still produces significant positive alpha in each market. In particular volatility carry subsumes volatility return predictability by the short volatility factor. Other risk factors proposed in the literature such as underlying asset carry, volatility changes, global liquidity shocks and transaction costs are not able to justify the variation in cross-sectional volatility returns. As such, the presence of substantial volatility carry risk premia seems to offer a compelling investment opportunity while challenging classic asset pricing models.

Table of contents

Acknowledgements

I would like to extend my deepest gratitude to my supervisor Nikos for his insightful comments and guidance. I am also grateful to my family, especially Danila, without her relentless support it would have not been possible to undertake this work.

List of Tables

List of Figures

Appendix

1. CROSS-ASSET CARRY, PREDICTIBILITY AND TIMING

by

Walid Khalfallah

Abstract

This paper shows the presence of both unconditional and conditional carry premia across various asset classes with the carry factor predictable by the carry spread. Time-variation in carry premia is economically and statistically large with expected returns of cross-asset carry increasing in the carry spread. Pooled regressions also provide evidence of cross-asset market integration. The study shows that the carry spread is useful to time carry in certain asset classes, whereby timing strategies can be an attractive complement to the unconditional carry strategy. Similarly, cross-asset rotation strategies based on relative carry spread are generally economically meaningful, yet they fail to beat unconditional benchmark portfolios on a risk adjusted basis. Overall, the study finds that while carry returns predictability is statistically strong across all asset classes, the economic benefits of timing the carry factor are less consistent.

Keywords: Carry Trade, Carry Spread, Predictability, Risk Premia, Factor Timing, Multi-asset class.

1.1 Introduction

Since the initial work of Fama and French (1992) the literature has seen an explosive growth in the number of factors many of which were recently questioned due to lack of robustness and weak statistical support (Hou, Xue, and Zhang (2017)). Only few factors, most notably carry, value and momentum have shown strong in and out of sample evidence motivating their inclusion in empirical asset pricing models. Indeed, these factors have been recently identified across multiple asset classes: “Value and Momentum Everywhere” (Asness, Moskowitz, and Pedersen (2013)) and “Carry” (Koijen et al. (2018)). These academic findings are being reflected in the financial services industry with momentum and carry strategies in particular being the most widely implemented (Hamdan et al. (2016))

Carry strategies were initially adopted in the currency markets in order to capitalise on the interest rate differential between two countries. While the uncovered interest rate parity stipulates that an adverse movement in the exchange rate should offset the interest rate differential, numerous empirical studies (Hansen and Hodrick (1980)) and Engel (1996) have shown that this is not always the case, leading to profitable carry trades, on average. Expanding the concept to a multi-asset setting Koijen et al. (2018) define carry as the return on an asset if market conditions remain the same. Indeed, carry measures the yield or the return that accrues on an asset in the absence of any price change either expected or unexpected. Thus, carry can be directly estimated without any model assumptions as the return on a futures position where the spot price does not change. Using the arbitrage free expression of a synthetic futures contract across various asset classes, Koijen et al. (2018) interpret carry as the interest rate differential for currencies, the expected dividend yield minus the risk free rate for equities, the convenience yield net of storage costs minus the risk free rate for commodities, the term spread and the roll down across the yield curve for fixed income securities and, similarly, the credit spread and roll down across the credit curve for credit securities.

This paper studies carry, in a long-short cross-asset setting that captures the cross-sectional variation in carry returns in FX, equities, fixed income, credit and commodities. Prior studies on the carry factor almost exclusively focus on the FX asset class with very limited research on cross-asset carry dynamics. Indeed very few papers cover multi-asset carry and display strong sample bias towards developed markets assets: Ahmerkamp and Grant (2013), Baz et al. (2015), Baltas (2017) and Koijen et al. (2018). This paper brings additional evidence on the cross-asset carry factor from significantly expanded cross-sectional sample (108 assets) by including emerging markets assets as well as expanding the credit asset class.

The first objective of the study is to define carry and analyse the performance of carry portfolios across different asset classes. The results indicate that carry strategies have significant positive excess returns in all asset classes including emerging and developed markets. Regarding higher moments, carry strategies returns exhibit negative skewness for FX, commodities and credit asset classes, while it is positive for equities and fixed income. Surprisingly in equities, the positive skewness is much larger for emerging markets compared to developed markets. These findings question downside risk explanation for carry strategies positive excess returns. On the other, most asset classes display excess kurtosis indicating fat-tailed returns. Consistently, excess kurtosis is much more pronounced in emerging than in developed markets.

The second objective is to assess the diversification benefits from combining various asset classes carry portfolios. The results indicate that building a multi-asset carry portfolio using equal volatility allocation achieves statistically strong average excess returns with an average Sharpe ratio of 0.91 and 1.20 for respective portfolios where the volatility was estimated in-sample or on a one-year rolling window. Higher moments of the diversified carry portfolio returns displays mildly negative skewness (-0.59 and -0.52 on average for the in-sample and rolling volatility estimation portfolios respectively) mainly driven by emerging markets. Interestingly, the kurtosis of the global diversified carry portfolio significantly declines from an average of 5.16 to 0.97 once the dynamic inverse volatility allocation is adopted using the rolling one-year historical volatility estimation.

Having established that a similar unconditional carry factor is present across various asset classes, the third objective of this study is to explore whether a conditional premium also exists across asset classes. Studies that look at a single factor across multiple asset classes are relatively recent and have mainly covered the value factor (Asness et al. (2017) and Baba Yara, Boons, and Tamoni (2021)). As such, this study expands the literature by examining the carry factor across multiple asset classes using the carry spread as a predictor (difference between the carry signal in the long versus the short portfolio). The relation between the carry premium and the carry spread can be motivated economically given that carry, alongside the price movement, is a key component of any asset expected returns Koijen et al. (2018).

The results indicate that expected carry returns are increasing with the carry spread across the different asset classes. The time-variation in carry premia is found to be statistically and economically significant. For a two-year horizon, the R^2 in a time-series predictive regression equals 61%, 30%, 29%, 7% for credit, FX, equities, commodities respectively, while it is weak for fixed income at 1%. Panel regressions across asset classes investigating the joint time variation in carry premia implied by time variation in the carry spread indicate an R^2 of 23% which shows evidence of cross-asset market integration. This analysis adds further to the literature on the carry factor. For all asset classes excluding fixed income, the results show that one standard deviation expansion in the carry spread foresees an increase in expected carry return broadly similar to the level of the unconditional carry premium. The same conclusion holds also for the pool of carry strategies, albeit in slightly lower magnitude.

In order to compare conditional and unconditional optimal carry portfolios, the fourth objective of the study is to assess the factor timing and rotation benefits to carry portfolios. Drawing on the literature (Ilmanen et al. (2019)) a number of out of sample strategies that take advantage of the real time information in the carry spread are implemented. The first approach consists in investing in the carry factor proportionally to its historical level by adjusting its weight according to the level and sign of its standardised carry spread or z-score. The next set of timing approaches employs a regression methodology based on the relation between the carry spread and the conditional carry return both in a single and pooled asset class setting. The study finds that constraining the beta coefficient sign in line with Campbell and Thompson (2008) improves the results. Timing strategies performance is mixed, while single asset timing returns are positive for FX, equities and credit they are negative for fixed income and commodities. Where positive and despite being economically strong, timing strategies risk adjusted returns are lower than those of the unconditional strategies except for credit and partially for FX. Pooled regression timing returns are however positive across various assets classes and portfolios with improved relative performance versus single asset class timing and unconditional strategies (although still not consistent across all asset classes). While mixed, the results still suggest that the carry spread is useful for timing carry returns in certain assets classes. Moreover, these timing strategies can be an attractive complement to the unconditional carry strategy. Finally, the study looks at rotation strategies across asset classes based on relative carry spread using alternative portfolio weighing schemes. Rotation strategies returns are generally economically and statistically meaningful, however they fail to beat the unconditional strategies on a risk adjusted basis.

This study contributes to the developing cross-asset pricing research which analyses factors along multiple markets jointly (Lettau, Maggiori, and Weber (2013) and Koijen et al. (2018)). It adds to previous research on cross-asset carry by exploring the conditional premium. Haddad, Kozak, and Santosh (2017) analyse conditional return variation for strategies in equities, currencies, and bonds using different predictors in each asset class, and, Baba Yara, Boons, and Tamoni (2021) analyse cross-asset value strategies returns using the value spread. This study, focuses on a single strategy (carry) and a single predictor (carry spread) in all asset classes. Kelly and Pruitt (2013) and Baba Yara, Boons, and Tamoni (2021) find the variation in cross-sectional value spread explain respectively equities and cross-asset returns. This study reaches similar conclusions for carry returns and the carry spread across different asset classes. Finally, by analysing the potential for out-of-sample timing and rotation, the study strengthens the evidence for carry returns predictability. Overall, the study finds that while carry returns predictability is statistically strong across all asset classes, the economic benefits of timing the carry factor are less consistent.

1.2 Definition of Carry

Carry strategies were initially adopted in the currency markets to capture the deviation from the interest rate parity (the "forward anomaly"). While the uncovered interest rate parity stipulates that an adverse movement in the exchange rate should offset the interest rate differential, numerous empirical studies (Hansen and Hodrick (1980) and Engel (1996)) have shown that this is not always the case, leading to profitable carry trades, on average. The covered interest rate parity instead fixes the forward rate for the conversion of the interest rate differential gain back into domestic currency:

$$F_t = S_t \frac{1 + r_t^f}{1 + r_t^{f*}} \quad (1)$$

where F_t and S_t respectively are the FX forward and spot rates, and r_t^f and r_t^{f*} respectively are the domestic and foreign interest rates.

Since the covered interest rate parity holds because of riskless arbitrage, it follows that the forward rate is a biased estimator of the future spot price. This discrepancy explains the risk premium behind the carry trade (Fama (1984) and Lustig, Roussanov, and Verdelhan (2011)). The FX carry risk premium has been attributed to negative skewness due to: currency crash risk (Brunnermeier, Nagel, and Pedersen (2008) and Farhi and Gabaix (2016)), funding liquidity risk (Brunnermeier and Pedersen (2009)), FX volatility risk (Menkhoff et al. (2012)), consumption growth risk (Lustig and Verdelhan (2007)) and equity markets risk (Lettau, Maggiori, and Weber (2013)), although these negative skewness explanations have been challenged by Bekaert and Panayotov (2020) and Daniel, Hodrick, and Lu (2017).

While carry is mostly intuitive in the currency markets, the concept can also be extended to other asset classes. Indeed, using equation (1) of the covered interest rate parity, the interest rate differential can be expressed as:

$$r_t^{f*} - r_t^f = (1 + r_t^f) \frac{S_t - F_t}{F_t} \quad (2)$$

Considering the term $(1 + r_t^f)$ a proportionality or a scaling factor, it follows that the carry trading signal simply represents the futures term structure curve (Baltas (2017)):

$$C_t = \frac{S_t - F_t}{F_t} \qquad (3)$$

Using the above relationship, the FX carry concept can be easily extended to a multi-asset setting by replacing F_t with the appropriate arbitrage free synthetic futures definition corresponding to the relevant asset class. In fact, the return on any asset can be decomposed as follows (Koijen et al. (2018)):

$$Return = Carry + E(price\ appreciation) + unexpected\ price\ shock \quad (4)$$

Given that for a futures the carry element can be mechanically measured, Koijen et al. (2018) define carry as "an asset's futures return, assuming that prices stay the same" both expected and unexpected. Following their work and assuming X_t the margin requirement for a futures contract F_t expiring in period $t+1$ and r_t^f the risk-free rate, the total return on allocated capital over the period t to $t+1$ is:

$$R_{t+1}^{total\ return} = \frac{X_t\left(1+r_t^f\right) + F_{t+1} - F_t - X_t}{X_t} = \frac{F_{t+1} - F_t}{X_t} + r_t^f \qquad (5)$$

therefore, the excess return is:

$$r_{t+1} = \frac{F_{t+1} - F_t}{X_t} \qquad (6)$$

consequently, the measure of carry is:

$$C_t = \frac{S_t - F_t}{X_t} \qquad (7)$$

given that under the scenario of no price change F_{t+1}, which expires into S_{t+1}, would be equal to S_t. Additionally, under the assumption of a fully collateralised position $X_t = F_t$ carry is precisely the futures term structure curve as already established above:

$$C_t = \frac{S_t - F_t}{F_t} \qquad (8)$$

Note that this expression of carry holds irrespective of the futures contract currency denomination as by definition carry entails no changes in spot asset prices as well as in foreign exchange rates. Combining this general definition of carry with the arbitrage free expression of futures contract specific to each asset class, one can determine the carry drivers and its interpretation across different assets as seen in Table 1.1.

Note that for equities, the carry risk premium relies on the expected future dividend yield implied by the slope of the equity index futures curves (Koijen et al. (2018)). This is in contrast to equity value premium strategy (Fama and French (1993)) which typically uses realised dividend yield.

For commodities carry represents the insurance that either the commodity producer (Keynes (1965)) or the commodity consumer pays as compensation for hedging unexpected future price changes. It is also interpreted as a compensation or a surplus convenience yield over storage costs. In particular, carry is considered as a key component of commodity returns (Gorton, Hayashi, and Rouwenhorst (2013) and Bhardwaj, Gorton, and Rouwenhorst (2015)).

For fixed income and credit, carry represents the spread between the yield to maturity and the risk-free rate as well as the roll-down across the yield or credit curves. The term spread is typically upward sloping in order to compensate for illiquidity, inflation, macro and credit risks. It is also a key component of bond returns (Fama and French (1993)).

According to the above classification, various carry products have been developed in the financial industry as mapped in Table 1.2. Equity carry for example includes two strategies: high dividend yield, which is a long short equity strategy based on the level of the dividend yield, and dividend futures, which is a strategy that captures the spread between implied and realised dividend. For fixed income and commodities carry covers three strategies: forward rate bias which is a level strategy, term structure slope which is a slope strategy and cross term structure which is a cross-sectional strategy.

1.3 Measurement of carry

Carry measurement consists in estimating the slope of the curve of futures or forward prices. Depending on data availability and peculiarities of different asset classes various approaches are available. Table 1.3 details the methods adopted in the literature (Koijen et al. (2018), Baltas (2017) and Baz et al. (2015)) as well as the chosen metrics in this study.

For currencies carry is estimated using the spot and one-month forward prices. The interest rate differential method would have yielded highly correlated results given the covered interest rate parity (Baltas (2017)). FX futures are not widely available hence were not considered.

For equity indices, the selected metric uses the index spot price and the one-month synthetic future contract estimated by linear interpolation of the first and second futures contracts (Koijen et al. (2018)) as follows:

$$Fut_t^{1M\ interpolated} = \frac{30-T_1}{T_2-T_1} Fut_t^{T_2} + \frac{T_2-30}{T_2-T_1} Fut_t^{T_1} \qquad (9)$$

Where $T_1$and T_2 are the respective days to expiry for the first and second futures contracts. The alternative approach which estimates the slope using the first and second contracts can lead to contrasting signals in case of a humped curve.

Regarding commodities, given illiquid spot markets these are usually traded using futures contracts. For consistency across asset classes, carry is estimated using the first two futures contracts to extrapolate the synthetic spot price and one-month futures prices in line with Koijen et al. (2018). Furthermore, to adjust for strong seasonality in commodities (Keloharju, Linnainmaa, and Nyberg (2021)) a one-year moving average filter is used in line with Baltas (2017) and Koijen et al. (2018).

For government bonds, given the lack of futures contracts for a large part of the universe, it is not possible to estimate carry using futures. Instead, carry is estimated from zero-coupon yields that are used to derive the bond spot and synthetic futures prices in line with Koijen et al. (2018):

$$\frac{Spot_t^{\tau-1M\ interpolated} - Fut_t^{1M\ \tau\ Synthetic}}{Fut_t^{1M\ \tau\ Synthetic}} \quad (10)$$

The spot in the above carry formula has a maturity of $\tau - 1M$ given that it will match the maturity of the underlying one-month futures $Fut_t^{1M\ \tau}$ upon expiry.

The spot bond price with $\tau - 1M$ time to maturity is:

$$Spot_t^{\tau-1M\ interpolated} = \frac{1}{(1+y_t^{\tau-1M\ interpolated})^{\tau-1M}} \quad (11)$$

where the $\tau - 1M$ yield is estimated using linear interpolation of the $\tau - 1$ and τ years zero-coupon yields:

$$y_t^{\tau-1M\ interpolated} = \frac{1}{12} y_t^{\tau-1M} + \frac{11}{12} y_t^{\tau} \quad (12)$$

The futures price with one-month maturity for a τ-year bond is simply its price accrued by r_t the risk-free interest rate (3-month sovereign rate is used as proxy):

$$Fut_t^{1M\ \tau\ Synthetic} = Spot_t^{\tau}(1 + r_t) = \frac{1+r_t}{(1+y_t^{\tau})^{\tau}} \quad (13)$$

For Credit, similarly to government bonds the slope of futures curve is estimated using the credit index average yield to maturity for a particular credit rating and maturity profile in order to estimate the spot and the synthetic future price as follows:

$$Fut_t^{1M\ \tau\ Synthetic} = Spot_t^{\tau}(1+r_t) = \frac{1+r_t}{(1+y_t^{\tau})^{\tau}} \qquad (14)$$

The spot price for the credit index with maturity τ is:

$$Spot_t^{\tau-1M\ interpolated} = \frac{1}{(1+y_t^{\tau-1M\ interpolated})^{\tau-1M}} \qquad (15)$$

$y_t^{\tau-1M\ interpolated}$ is interpolated using yield to maturity and weighted average maturity of the credit index across the relevant credit curve. Note that when computing carry for credit indices across different maturities, position sizing has to be adjusted to account for different riskiness using duration D_t^{τ} as follows:

$$\frac{Spot_t^{\tau-1M\ interpolated} - Fut_t^{1M\ \tau\ Synthetic}}{Fut_t^{1M\ \tau\ Synthetic} D_t^{\tau}} \qquad (16)$$

1.4 Data and summary statistics

This section presents the set of assets used in this study as well as some basic summary statistics.

1.4.1 The set of assets

This study considers a large set of 108 assets: 24 currency pairs (G10 plus 14 emerging markets), 28 equity markets (15 developed markets and 13 emerging markets), 25 commodities covering 9 in metals, 6 in energy, 7 in agriculture and 3 in live-stock, 26 government bond markets (14 developed markets and 12 emerging markets used to compute 10-year bond carry) and 5 credit indices (Bloomberg Barclays Credit Indices) covering US, Europe and Asia investment grades, US high yield and emerging markets over 5 maturities buckets (1-3 years, 3-5 years, 5-7 years, 7-10 years and 10+ years) where for each credit index the average maturity and average bond yield are provided. This data set expands significantly the cross-section sample compared to those used in previous research notably by including emerging markets assets as well as broadening the credit asset class.

Specifically for equity indices monthly data for spot, nearest and second to neariest index futures are collected from bloomberg to compute carry and monthly excess returns. Table A1.1 in the appendix reports the markets and their corresponding bloomberg tickers. For currencies the data consists of spot and one-month forward exchange rate prices for 24 countries. Table A1.2 in the appendix reports their Bloomberg tickers. For commodities data consists of the nearest and second nearest to expiration futures prices for 25 commodites downloaded from Bloomberg. These furutres contracts are used to linearly extrapolate the spot and 1-month maturity synthetic future which represent the inputs for carry computations as shown in Table 1.3. Commodities returns have three components, the spot return, the roll yield and the collateral yield. Given that commodities spot prices are difficult to obtain, front-month futures contracts are typicaly used as proxies, which, in order to maintain uninterrupted exposure requires continious reinvestment by rolling the position from expiring nearer dated contracts into longer dated contracts. According to whether the shape of the futures curve is upward or downward sloping, the roll yield will be respectively either negative or positive. Finally, the collateral yield refers to interest income received on futures collateral that is invested in fixed income instruments. Given these intricacies, various indices were set up in order to facilitate commodities return estimation. In this study excess returns are computed using Bloomberg Commodity indices (BCI). BCI are exposed to front futures contracts. These are rolled to the following futures from the fith to the ninth business day of the month, progressively increasing the weight of the new contract from 0% to 20%, then to 40%, 60%, 80% and finally to 100%. Table A1.3 in the appendix shows Bloomberg Commodity Indices and futures contracts tickers.

For fixed income given the lack of futures contracts for a large part of the universe, synthetic futures are estimated each month using zero coupn data as detailed in section 3 above. Table A1.4 in the appendix reports the bloomberg tickers of the zero coupon yields (9 and 10 years yields used to calculate the 10-year global carry and 3-month yields used as proxy for the risk free rate). Finally, for credit indices, synthetic futures are similarly estimated each month on the credit index and the price of the index with the same maturity minus one month (by linear interpolation of successive yields to maturity of the specific credit curve) using the yield to maturity, the average maturity and duration of the credit indices as detailed in section 3 above. Carry and return estimates are duration adjusted in order to reflect different risk profiles. Table A1.5 in the appendix reports Bloomberg tickers for the credit indices. Figure A1.1 in the appendix summarises the set of assets with their start dates.

1.4.2 Summary Statistics

Tables A1.6 to A1.10 in the appendix display for every class, the assets' annualised mean and standard deviation of carry and excess returns, in addition to the series start date. For the case of a totally collateralized position the excess return is derived as:

$$r_{t+1} = \frac{F_{t+1} - F_t}{F_t} \qquad (17)$$

In the case of a non-USD denominated futures, where e_t is exchange rate, the USD excess return is equal to (Koijen et al. (2018)):

$$r_{t+1} = \frac{e_{t+1}(F_{t+1} - F_t)}{e_t F_t} = \frac{F_{t+1} - F_t}{F_t} + \frac{e_{t+1} - e_t}{e_t} \frac{F_{t+1} - F_t}{F_t} \qquad (18)$$

which is very close to the original expression since the term $\frac{e_{t+1}-e_t}{e_t}\frac{F_{t+1}-F_t}{F_t}$ is a product of two returns. While this term is of secondary importance for developed markets, it can be important for emerging markets given more volatile exchange rates.

1.5 Defining and constructing a carry strategy portfolio

The carry strategy is a long-short portfolio within a given asset class based on the relative strength of the securities' carry. While various allocation methods are available to determine the cross-sectional portfolio weights a limited number of assets within each asset class can make the results sensitive to a particular weighting scheme. For robustness the study adopts three allocation methods (referred to later in the study as Rank, Median and Tercile) which expands the evidence on the carry factor compared to previous research on this topic.

The first method (Tercile) draws on Baz et al. (2015) and consists in taking equal-weight long short positions in the top and bottom terciles of securities respectively. The second method (Median) in line with Baba Yara, Boons, and Tamoni (2021) consists in building long and short equal weight portfolios around the median carry signal. The third method (Rank) in line with Asness, Moskowitz, and Pedersen (2013) is linear in the signal by taking a position in all securities in line with their carry ranking, which avoids the effect of outliers in the signal. The weight on each security i at time t is proportionally linear to the demeaned ranks as follows:

$$w_t^i = z_t(rank\left(C_t^i - \frac{N_t+1}{2}\right)) \quad (19)$$

where N_t is the securities number available at time t, C_t^i is the security i carry and z_t a normalisation scalar that ensures the absolute sum of positive and negative weights equals 100%.

Thus, the carry portfolio return is the weighted sum of the individual assets return:

$$r_{t+1} = \sum_i w_t^i \, r_{t+1}^i \qquad (20)$$

The second and the third weighting methods tends to produce more stable returns given improved diversification compared to the first which places more weights on fewer assets. Carry is measured monthly for all securities with the exception of commodities, where given their seasonality, it is estimated over a 12-month rolling period.

1.5.1 Single asset class carry strategy portfolios

For each asset class, a cross-sectional carry portfolio that takes long and short positions in securities based on their level of carry is built using the above weighting schemes (Rank, Median and Tercile). The portfolios are rebalanced every month and computed at the global, developed markets and emerging markets level starting at the date on which at least 5 securities are available. For comparison, the return on an equal-weight long-only portfolio is computed in each asset class (Koijen et al. (2018) and Baba Yara, Boons, and Tamoni (2021)). Table 1.4 reports various performance statistics for each asset class. It shows that global carry portfolios have significant positive returns in all asset classes with the results robust to different portfolio construction and weighting schemes. The returns of different weighting methods are highly correlated with an average correlation of 0.94 across asset classes.

Statistical significance of carry returns is highest for FX, equities (excluding the tercile allocation portfolio), commodities and fixed income at 1% confidence; global credit has also achieved significant excess returns at 5% level. Given significantly different volatilities looking at the strategies Sharpe ratio is more instructive. The average Sharpe ratio of the three portfolio weighting schemes for the carry strategies ranges from 0.39 for equities to 0.56 for fixed income carry with an average 0.47 across all strategies. Despite having minimal market exposure, most (long-short) carry strategies outperform the long equal-weight portfolios notably in FX, commodities and fixed income; thus increasing their investment appeal.

The above results are broadly in line with the findings of Koijen et al. (2018), however the Sharpe ratios for the different asset class strategies in this study are generally lower than those shown in Koijen et al. (2018) with a like for like average of 0.51 versus 0.64 for rank weighted portfolios. Differences in portfolio composition may explain the discrepancies in risk adjusted returns. This study expands significantly the cross-sectional sample by including emerging markets assets and global credit indices versus Koijen et al. (2018) sample which includes only developed markets and US credit indices.

Table 1.5 expands the global carry trade portfolios of the FX, equities and fixed income asset classes into emerging and developed markets carry portfolios, and for credit asset class into investment grade, high-yield and emerging markets carry portfolios. The trends observed in the global carry portfolio are broadly maintained. In particular carry returns for both emerging and developed markets are generally positive and significant for most asset classes. For 10-year fixed income carry, while mean excess returns are positive over the sample period, statistical significance is stronger for developed markets (1% level) compared to emerging markets (5% to 10% level).

Despite generally lower volatility, developed markets carry strategies performance is mixed compared to emerging markets, outperforming in the 10-year fixed income strategy and in the investment grade credit with respective average Sharpe ratios for the different portfolio weighting methods of 0.72 and 0.57 for developed market versus 0.44 and 0.46 for emerging markets. Conversely, emerging markets carry portfolios outperform in FX and equities with respective average Sharpe ratios (of the different weighting portfolios) of 0.57 and 0.53 versus 0.54 and 0.27 for developed markets respectively.

The strong results of carry portfolios shows that it represents a significant component of expected returns in different asset classes. While previous literature focuses mainly on FX and developed markets asset classes which indicate similar results to this study, carry strategies perform also well in other asset classes including emerging markets. The performance is particularly appealing for fixed income, FX and credit with respective Sharpe ratios of 0.56, 0.54 and 0.46.

Higher moments of carry returns indicate negative skewness for the FX, commodities and credit, in line with Koijen et al. (2018). The negative skewness is particularly pronounced for credit followed by FX while it is relatively moderate for commodities. In the FX asset class, emerging markets skewness is unsurprisingly higher than that of developed markets, however the pattern is particularly marked for the credit asset class where high yield and emerging market credit portfolios exhibit very large negative skewness compared to only moderate negative skewness for the investment grade portfolio.

Carry strategies in equities and fixed income exhibit positive skewness, consistent with the findings of Baltas (2017) and Koijen et al. (2018). Additionally in equities, the positive skewness is much larger for emerging markets compared to developed markets. These findings warrant further research as they question the downside risk explanation for carry strategies positive excess returns. Most carry strategies display excess kurtosis, denoting elevated probability of extreme returns. Consistently excess kurtosis is significantly more pronounced in emerging than in developed markets.

1.5.2 Diversified carry trade portfolio

Table 1.6 looks at selective correlation coefficients between rank weighted carry portfolios returns across the various asset classes. The results indicates generally low correlation between the different single asset class carry portfolios, either on a global, developed markets or emerging markets basis, therefore it would be interesting to assess the diversification characteristics of a multi-asset class carry portfolio. Given varying volatility for each asset class, a risk based portfolio allocation framework is adopted for the construction of the multi-asset class carry portfolio, in line with the approach of Moskowitz, Ooi, and Pedersen (2012), Asness, Moskowitz, and Pedersen (2013), Baltas (2017) and Koijen et al. (2018). Each asset class carry portfolio is scaled to 10% volatility before being combined into an equal-weight multi-asset carry portfolio. Volatility is estimated using two approaches, one in-sample Koijen et al. (2018) and one over one-year rolling window of data (Baltas (2017)). The latter approach results in a dynamic portfolio allocation with monthly rebalancing in line with the rolling changes in volatility estimates. For the former estimation approach, the multi-asset portfolio allocation is static since based on a single volatility estimates over the whole sample period. The multi-asset portfolios (global, developed markets and emerging markets) start at a date on which at least two single asset class portfolios are available. For comparison, a passive long-only multi-asset portfolio is constructed using the same weighting approach described above for the multi-asset carry portfolio i.e. equal weight combination of passive long positions scaled to 10% volatility.

The diversified global carry trade portfolio achieves statistically strong mean returns (at 1% confidence) with a Sharpe ratio (average of the different portfolio weighting methods) of 0.91 and 1.20 for the in-sample volatility and the one-year rolling volatility portfolios respectively. These numbers show a considerable improvement relative to the average Sharpe ratio of the single asset class carry portfolios of 0.47 indicating substantial diversification benefits across asset classes carry strategies. Despite different portfolio composition the results are broadly consistent with the findings of Koijen et al. (2018) that show a Sharpe ratio of 1.2 for the diversified portfolio.

The difference in risk adjusted returns between developed and emerging markets multi-asset carry portfolios varies according to the volatility estimation method. Under the in-sample volatility estimation, the Sharpe ratio of developed markets is slightly higher than that of emerging markets at 0.87 versus 0.80. Under the one-year rolling volatility estimation, the emerging markets average Sharpe ratio of 1.35 is significantly higher than in developed market at 1.09. Historically, emerging markets assets have been more prone to economic crises and episodes of extreme volatility compared to developed markets assets. A dynamic risk based allocation framework based on rolling volatility estimate can better calibrate the risk budget and adjust asset allocation in timely manner resulting in improved risk adjusted returns. Similarly, to the global diversified portfolio, the Sharpe ratios for developed and emerging markets multi-asset portfolios are higher than their respective passive long-only portfolios (0.53 and 0.85 for developed markets and 0.53 and 1.00 for emerging markets using in-sample volatility and one-year rolling volatility respectively).

Regarding higher moments, Table 1.7 indicates that the global diversified carry factor displays mild negative skewness (-0.59 and -0.52 on average for the in-sample and rolling volatility estimation portfolios) mainly driven by emerging markets. Interestingly the kurtosis of the global diversified carry portfolio significantly declines from an average of 5.16 to 0.97 once the dynamic inverse volatility allocation is adopted using the rolling one-year historical volatility estimation. As was the case for the single asset class portfolios, kurtosis is higher for emerging markets compared to developed markets.

Figure 1.1 shows the cumulative returns for the multi-asset carry portfolios (rank weighting method) using the static inverse volatility allocation based on in-sample volatility estimate and the dynamic inverse volatility allocation with monthly rebalancing based on one-year rolling window volatility estimate. The sample period for the graph is shortened to coincide with emerging markets data availability. Emerging markets multi-asset carry portfolio delivers higher returns throughout the sample period albeit at the expense of significantly wider tails. Note the drawdown for emerging and developed markets are simultaneous and expectedly more pronounced for emerging markets. As discussed earlier, the dynamic allocation framework based on rolling volatility estimate can better calibrate the risk budget and adjust asset allocation in timely manner resulting in higher returns.

1.6 Predicting Carry Returns with the Carry Spread

Having established the existence of a carry factor in several asset classes, this section considers the presence of a conditional premium by assessing the predictability of carry returns. Literature on predictability and timing has traditionally focused on single asset classes where one or multiple predictors (e.g. dividend yield, valuation spread etc…) are used to time one or multiple factors within a given asset class (e.g. Asness et al. (2000) and Arnott, Beck, and Kalesnik (2016)). More recently, research has shifted focus to cross-asset settings where single factors, in particular value, are timed with related predictors (Baba Yara, Boons, and Tamoni (2021) and Asness et al. (2017)). This study contributes to the literature by examining the carry factor across multiple asset classes using the carry spread. The predictive signal or the carry spread is defined according to the portfolio weighting method as follows:

- Rank-weighted average carry signal:

$$CS_t^{Rank} = \sum_i w_{i,t}^{Rank} C_{i,t} \qquad (21)$$

- Difference between average carry signal of the high and low carry securities portfolio around the median carry:

$$CS_t^{Median} = C_t^H - C_t^L \quad (22)$$

- Difference between average carry signal of top and bottom tercile carry securities portfolios:

$$CS_t^{Tercile} = C_t^{Top\ Tercile} - C_t^{Bottom\ Tercile} \qquad (23)$$

Predictive regressions of the carry strategy returns (compounded over a horizon h) are conducted on the lagged carry spread as follows:

$$R_{t+1:t+h}^{x} = a_h + b_h CS_t^x + \varepsilon_{t+1:t+h}^{x} \quad (24)$$

Where x refers to the rank, median and tercile weighted portfolios. The above regressions can be motivated economically given that carry alongside the price movement is a key component of any security expected returns. While Koijen et al. (2018) regression analysis focused on the relation of long-only single asset class returns versus the absolute level of carry, this study extends the analysis to the cross-sectional (long-short) carry returns and their relation to the carry spread, the latter being the carry of the carry trade strategy. Further, in order to analyse the combined strength of carry return predictability, pooled regressions are run across asset classes to evaluate the joint time variation in expected carry returns implied by the time variation in the carry spread. These joint tests also serve to increase the sample size and hence augment their power to detect long-horizon predictability (Boudoukh, Israel, and Richardson (2019)).

For the regressions of carry returns on the carry spread, different forecasting horizons h up to two years were considered given that horizons longer than one-month help mitigate the offsetting momentum effect (Asness and Frazzini (2013)). Previous predictability studies encountered two main inferential issues: high first-order correlation of the predictor (e.g. dividend yield) and the Stambaugh (1999) bias which stems from the contemporaneous correlation between current returns and the lagged explanatory variable (Valkanov (2003), Lewellen (2004), Boudoukh, Richardson, and Whitelaw (2008)). Consistent with Baba Yara, Boons, and Tamoni (2021) who adopt a valuation spread to time the value factor, this study is less impacted by these concerns. First, monthly autocorrelation of the carry spread across different asset classes (see Table 1.8) ranges from 0.80 to 0.97 (average 0.88) versus 0.95 to 0.98 (average 0.96) for the valuation spread in the study of Baba Yara, Boons, and Tamoni (2021). Both predictors' monthly autocorrelation is relatively lower than the autocorrelation of the dividend yield of 0.99 which results in inferential issues (Baba Yara, Boons, and Tamoni (2021)). Second, the Stambaugh (1999) bias is reduced given that both sides of the regression in equation (24) are based on differences (carry returns and carry spread) which break the mechanical relation encountered in common predictability regressions of long-only returns on price-related signals like the dividend yield. Indeed, Baba Yara, Boons, and Tamoni (2021) find that the Stambaugh (1999) bias negligible when estimating equity market cross-sectional value returns with the value spread compared to the dividend yield.

This study adopts different approaches to assess the magnitude of the conditional carry premium. The predictability of carry returns on the carry spread is initially evaluated in sample. Subsequently, various related timing strategies are assessed out of sample. This allows, their comparison by providing economic magnitudes of the conditioning information while also assessing the advantage of factor timing versus a passive carry portfolio. Statistical significance in predictability studies can be subject to biases that cloud inference Stambaugh (1999) and Boudoukh, Israel, and Richardson (2019), however the economic significance provided by actual timing returns can subsume these issues given that poor statistical model estimation should result in poor out of sample economic performance (Ilmanen et al. (2019)). In addition, Kandel and Stambaugh (1996), Kandel and Stambaugh (1996), Cenesizoglu and Timmermann (2011) and Timmermann (2018) argue and present evidence suggesting that weak forecasting models can produce economic gains. Cederburg, Johnson, and O'Doherty (2018) argue that the opposite is also true: good forecasting models do not necessarily entail economic benefits.

1.6.1 Time Variation in the Carry Spread

To facilitate comparison across asset classes, carry spreads are standardised to a time-series average of zero and a standard deviation of one. Figure 1.2 presents standardised carry spread time series for various asset classes (rank weighted portfolios) along with their cross-sectional average. A standardised carry spread of zero, indicates that a portfolio's carry is at its historical average, while a positive (negative) reading indicates a wider (narrower) measure than normal. Figure 1.2 shows periods with concomitant increase in the carry spread across several asset classes indicating a correlation in the carry spread. This can be seen in FX and equities after the burst of the dot-com bubble and in FX, equities, fixed income and credit after the 2008 financial crisis. The carry spreads also broadly move in tandem with the cross-sectional average suggesting some commonality across asset classes. Table 1.8 shows that carry spread correlation across asset classes is generally positive except for credit which is negatively correlated to commodities and equities. In particular carry spread in FX correlates relatively strongly with credit and fixed income and so does carry spread in commodities with fixed income and equities. Baba Yara, Boons, and Tamoni (2021) note that the valuation spread correlation is high across single equities, industries, global equity indices and commodities, however it is much lower and even negative across the remaining assets classes. In particular, they observe negative correlation in valuation spreads between global government bonds and other asset classes.

1.6.2 In Sample Return Predictability

This section investigates carry return predictability using separate time-series predictive regressions within each asset class in addition to pooled regressions, which allow to assess the joint strength of carry return predictability across asset classes.

1.6.2.1 Time Series Predictive Regressions

Table 1.9 displays the results from time-series predictive regressions of carry returns on the carry spread for all five global asset classes. The results are presented for different portfolio weighting schemes and using overlapping holding period returns of horizons $h = 1, 12$ and 24 months. For ease of comparison across asset classes, carry spreads, CS_t are standardised to have zero mean and a standard deviation of one; and, carry returns are scaled to have an annual standard deviation of 10%. Regression coefficients t-statistics are computed applying Newey and West (1987) and the rule suggested by Lazarus et al. (2018) for the lag truncation parameter (LLSW thereafter) in order to correct for the autocorrelation induced by overlapping returns. The LLSW correction leads to more conservative estimates than the standard Newey and West value of the lag truncation parameter.

The coefficient on the carry spread is generally positive for every asset class and horizon apart from fixed income for median and tercile portfolios where it is negative although not significant. The evidence is stronger at the bi-annual horizon and to a lesser degree at the one-year horizon where the coefficients estimates are generally significant and positive at 10% confidence for every asset classes but fixed income.

Coefficient estimates at one-month horizon are significant only for credit. Using rank portfolios as an example for interpretation, the coefficient estimate for the carry spread ranges from 1.3% (non-significant) for fixed income to 17.0% (p-value = 0.00) for credit at the bi-annual horizon; and, from 0.2% (non-significant) for fixed income to 10% (p-value = 0.00) for credit at the one-year horizon. The carry spread captures a considerable portion of the two-year carry returns variation with R^2at 61.4% for credit, 30.2% for FX, 29% for equities and 6.6% for commodities. For fixed income $R^2$is equal to 0.6% given non-significant slope estimate.

Overall, the results are supportive of the carry spread predicting the carry returns with the information in the carry spread taking longer to materialise. In fact, both the coefficient estimates as well as R^2 increase with the horizon. The economic magnitude of the coefficients on the carry spread can also be large in particular for the FX, equities and credit asset classes. For example, for the equity asset class (rank weighting scheme), the coefficient estimates translate in an increase of 11.6%, 5.6% and 0.4% in bi-annual, annual and monthly future returns respectively, for an increase of one standard deviation in the carry spread. The R^2 corresponding to the same regressions are 29.3%, 19.2% and 2.1% respectively implying that the carry spread explains almost one-third of the variation in the two-year returns of the carry strategy. Despite some variations among the various portfolio weighting schemes the conclusions described above generally hold for the rank, median and tercile portfolios across the various asset classes. The only notable observation is that the R^2 for the bi-annual predictive regression in the credit asset class is significantly higher for the rank and median portfolios at 61% and 60% respectively compared to 32% for the tercile portfolio.

In order to assess whether the above findings are robust to autocorrelation introduced by overlapping returns, the above times-series predictive regressions are rerun using non-overlapping 12 and 24 months holding periods returns as shown in Table 1.10. With the caveat of significantly reduced sample size, the results still corroborate those obtained with overlapping returns, that is, the carry spread statistically predicts carry returns with the information in the carry spread taking longer to materialise (R^2 increasing with the horizon). Again, the results are economically strongest for credit followed by equities and FX asset classes.

Given the standardisation of the carry spread in equation (24), the ratio of the beta to the intercept (b_h/a_h) evaluates the proportion of the unconditional carry premium to the implied standard deviation of expected carry returns (Baba Yara, Boons, and Tamoni (2021)). For the different horizons, the ratio averages 0.74, 0,75 and 0.70 for the rank, median and tercile portfolio respectively (0.90, 0.92 and 0.84 respectively excluding the fixed income asset class) further confirming the significance of the economic relationship between the carry premium and the carry spread. Looking at rank portfolios, the ratio of the beta on the carry spread to the intercept is large for credit with an average of 1.7 across the different horizons, followed by 1.1 for equities, 0.6 for FX and 0.3 for commodities.

Table 1.11 shows the time series predictive regressions for developed and emerging assets. The coefficients on the carry spread are mostly positive both for emerging and developed markets, apart from few cases that are statistically insignificant. Similarly to the global level, the evidence strengthens in the horizon. Interestingly, the relation between the carry spread and carry returns is generally stronger for emerging versus developed markets particularly in FX and equities, where R^2 reaches a respective 37% and 39% at the bi-annual horizon (rank portfolios). Potì, Levich, and Conlon (2020) provide evidence suggesting that emerging market currencies are more predictable than developed market currencies. By contrast, developed markets assets show high predictability only in the credit asset class and partially in the fixed income asset class (statistically significant only for rank portfolios). Strong predictability in the credit asset class both for emerging and developed markets explains the high level of predictability at the global level ($R^2$of 61% at the bi-annual horizon for rank portfolios) compared to FX and equites ($R^2$of 29% and 30% respectively) where predictability is mainly confined to emerging markets. This area can be subject to further future research.

1.6.2.2 Pooled Predictive Regressions

Pooled tests for carry strategies in different asset classes allow the analysis of the joint time variation in expected carry premia implied by time variation in the carry spread. Koijen et al. (2018) use regression analysis within single asset classes to separately assess the predictability of their returns by the level of carry. Using pooled predictive regressions, this study expands the literature on the carry factor by analysing the joint predictability of carry returns by the carry spread across currencies, equities, commodities, fixed income and credit. Pooled tests also expand the sample size, thus, increasing their power to detect longer horizon predictability (Boudoukh, Israel, and Richardson (2019)). In line with single asset class predictive regressions the following pooled regression is run:

$$R^x_{c,t+1:t+h} = a_h + b_h CS^x_{c,t} + \varepsilon^x_{c,t+1:t+h} \qquad (25)$$

where c denotes the asset class, x the portfolio weighting scheme (rank, median and tercile), h the holding period, a_h the intercept and b_h the beta coefficient that evaluates carry return predictability by the carry spread. As was for the case for single asset class predictive regressions, carry spreads $CS^x_{c,t}$ are standardised to have a mean equal to zero and a standard deviation equal to one; and, carry returns are scaled to have an annual standard deviation of 10%. Since pooling increases power, a longer four-year holding period is considered (h = 1, 12, 24 and 48 months). Further, the expanded sample size accommodates using both overlapping and non-overlapping holding period returns in order to control for autocorrelation. Regression coefficients t-statistics using overlapping returns are computed applying Newey and West (1987) and Lazarus et al. (2018) rule. Since the returns are cross-sectional (long-short) and the carry spreads are standardised (mean zero) for all asset classes, the coefficient estimate b_h would be the same had asset class fixed effects or time fixed effects been considered (Baba Yara, Boons, and Tamoni (2021)). Table 1.12 shows the results for pooled regressions. The results show that the joint evidence for carry return predictability is strong for the rank, median and tercile portfolios both in the case of overlapping and non-overlapping returns. Focusing on the rank portfolios for analysis for example, the beta coefficient on the carry spread is significant, economically large and increasing in the horizon. The ratio of the beta to the intercept (b_h/a_h) for the pool of carry strategies indicates that a standard deviation of expected carry returns represents 0.6 to 0.9 of the unconditional carry premium. For example, at the bi-annual horizon the coefficient estimate is 8.8% relative to an unconditional average carry premium of 11.6% (intercept) for the pooled overlapping returns regression. Consistent with beta estimates, R^2 expands with the horizon exceeding 20% at the bi-annual horizon for the overlapping returns regression.

In order to further analyse the predictability of carry returns over longer horizons, the coefficient on the carry spread from pooled predictive regression is estimated over successive non-overlapping annual returns as follows:

$$R_{c,t+h_1:t+h_2} = a_{h_1,h_2} + b_{h_1,h_2} CS_{c,t}^{x} + \varepsilon_{c,t+h_1:t+h_2} \qquad (26)$$

where for any carry spread observed in month t, $h_1$and h_2 reflect successive non-overlapping annual horizons (e.g. one year ahead: $h_1 = 1$ and $h_2 = 12$, two years ahead: $h_1 = 13$ and $h_2 = 24$, three years ahead: $h_1 = 25$ and $h_2 = 36$ etc…) and x is the portfolio weighting scheme (rank, median and tercile).

Figure 1.3 shows a steady decline in the coefficient on the carry spread which remains positive and significant until around five years after inception. This further supports prior findings that the carry spread is informative about carry returns at extended horizons.

Carry return joint predictability can be also assessed using a time series regression of the cross-asset class average carry return on the cross-asset class average carry spread as shown in the following regression:

$$\bar{R}_{t+1:t+h} = a_h + b_h \overline{CS}_t + \varepsilon_{t+1:t+h} \quad (27)$$

In addition to assessing the joint strength of carry return predictability, averaging carry returns and carry spreads in regression (27) allows also the evaluation of the common variation in the carry premium across different asset classes by smoothing out some of the noise in individual carry strategies.

The results in Table 1.13 indicate that the coefficient estimates on the carry premium are also economically large and statistically highly significant (Newey and West (1987)) for the annual and bi-annual returns, while significant at 10% level for monthly returns. The R^2 on the 12 and 24 month horizons are higher than those of pooled regressions, for example at 27% and 24% versus 23 and 17% for the rank portfolios respectively, since averaging reduces the noise in the individual carry strategies. Importantly, the results not only support the joint strength of carry return predictability but also the presence of common variation in the carry premium across different asset classes since averaging allows the evaluation of the common variation in the carry premium across the various asset classes.

1.6.3 Carry Timing

This section assesses the economic benefits from timing the carry factor. The first subsection considers timing of the carry factor in single asset class setting using standardised carry spreads and regressions of conditional carry return on the carry spread. The second considers timing in a joint asset setting using pooled and cross-asset average regressions. The third considers rotation strategies across asset classes based on relative carry spread using alternative portfolio weighing schemes.

1.6.3.1 Carry Timing in single asset classes

Drawing on the literature (Ilmanen et al. (2019)) several out of sample strategies that exploit the information embedded in the carry spread are implemented. The first approach consists in investing in the carry factor proportionally to its historical level by adjusting its weight according to the level and sign of its standardised carry spread or z-score. The latter is estimated monthly using only historical information, on an expanding window with a minimum five years period. Given that carry return predictability increases in the horizon, the z-score is based on the carry spread annual average (Baba Yara, Boons, and Tamoni (2021)) as follows:

$$CS_{t,His} = \frac{\sum_{s=0}^{11} CS_{t-s}/12 - \sum_{s=12}^{t-1} CS_{t-s}/(t-12)}{\sigma(CS_{1:t-12})} \qquad (28)$$

where $\sum_{s=0}^{11} CS_{t-s}/12$ is the 12-months carry spread moving average; $\sum_{s=12}^{t-1} CS_{t-s}/(t-12)$ and $\sigma(CS_{1:t-12})$ are the carry spread mean and standard deviation respectively estimated over an expanding monthly return window $[1, t-12]$. Therefore $CS_{t,His}$ captures the deviation of last year's average carry spread from its historical average. Two versions of z-score timing strategy are used: uncapped and capped at ±2 in order to reduce the impact of outliers.

The next set of timing approaches employ a regression methodology based on the relation between the carry spreads and conditional carry returns. An expanding historical window of data requiring at least 5 years of history is used to estimate a regression of returns in month t on the prior 12-month moving average carry spread at $t-1$ which is wholly out-of-sample:

$$R_t^x = a + b\left(\sum_{s=1}^{12} CS_{t-s}^x/12\right) + \varepsilon_t^x \quad (29)$$

where x refers to rank, median and tercile portfolios. The product of the estimated beta and the time t prior 12-month average carry spread provides the timing signal and the weight on the timing strategy. Initially no restrictions are placed on the estimated coefficients, allowing them to vary by asset class and by sign. This means that despite the expectation of a positive relationship between the carry spread and carry returns (otherwise it would suggest that the carry spread predicts a negative return exceeding the positive effect of carry), if the regression coefficient at any period indicates a negative relation, the negative coefficient will be used. A second specification, economically constrains a positive sign on the coefficients in line with Campbell and Thompson (2008).

Table 1.14 provides return statistics for three strategies in line with Baba Yara, Boons, and Tamoni (2021): an unconditional carry strategy, a timing strategy that allocates $CS_{t,His}$ or $\hat{b}_{t-1}\left(\sum_{s=0}^{11} CS_{t-s}^x/12\right)$ dollars to the carry strategy, and a combined strategy investing in the unconditional plus the timing strategy. The combined strategy can be thought of as an overlay of the conditional carry-timing strategy on top of the unconditional carry premium. Indeed, given that $CS_{t,His}$ is standardised, the timing strategy has on average no exposure to the unconditional carry premium, hence the rationale of combining the two. For comparability across asset classes, returns series are standardised to 10% ex-ante annualized standard deviation.

Timing strategies performance is mixed. While timing returns are positive for FX, equities and credit they are negative for fixed income and commodities. Statistically, the results are generally strongly significant (5% level) for FX and credit but less so (10% level) for equities. For bonds and commodities timing results whilst negative are generally non-significant. Where positive, and despite being economically strong, timing strategies risk adjusted returns are generally lower than those of the unconditional strategies except for credit and partially for FX. Taking for example rank portfolios, average Sharpe ratio for all timing strategies excluding commodities and fixed income is 0.50 versus an average Sharpe ratio of 0.52 for the unconditional strategies. Koijen et al. (2018) also find mixed performance for carry timing strategies in comparison to unconditional carry portfolios. It is interesting to note that combining timing and unconditional strategies can lead to an improvement in risk adjusted returns, for instance in FX, with a Sharpe ratios of 0.86 in the case of z-score timing for the rank portfolios versus 0.57 and 0.63 for the unconditional and timing portfolios respectively. Concerning the relative performance of timing methodologies, z-score method generally performs slightly better than regressions with average cross-asset Sharpe ratios of 0.22 and 0.19 respectively. Although there is no material difference in the timing results between capped and uncapped z-score with respective average Sharpe ratios of 0.21 and 0.23, economically restricted regressions (positive slope) consistently perform better than unconstrained regressions with respective average Sharpe ratios of 0.41 and -0.03. While there are some discrepancies in the results among rank, median and tercile weighted portfolios, the above observations broadly hold.

1.6.3.2 *Carry Timing in the Pool of carry Strategies*

In line with single asset class timing, out of sample timing strategies can also be applied in the pool of carry strategies, where the same coefficient is imposed for all asset classes. Pooling makes sense both statistically since it mitigates estimation error in the coefficient as well as economically given cross-asset commonality in the carry factor as shown in the predictive regression of average carry returns on average carry spreads (section 6.2.2.). Employing the same regression methodology based on the joint relation between the carry spreads and conditional carry returns, an expanding historical window of data requiring at least 5 years of history is used to estimate a pooled regression of returns in month t on the prior 12-month moving average carry spread at $t-1$:

$$R_{c,t}^{x} = a + b\left(\sum_{s=1}^{12} CS_{c,t-s}^{x}/12\right) + \varepsilon_{c,t}^{x} \qquad (30)$$

where c refers to the asset class and x refers to the rank, median and tercile portfolios. The joint carry returns timing is also assessed using an out of sample regression of the cross-asset class average carry returns in month t on the cross-asset class average of the prior 12-month moving average carry spread at $t-1$:

$$\bar{R}_{t}^{x} = a + b\left(\overline{\sum_{s=1}^{12} CS_{t-s}^{x}/12}\right) + \varepsilon_{t}^{x} \qquad (31)$$

where x refers to the rank, median and tercile portfolios.

The product of the estimated beta and the time t prior 12-month average carry spread provides the timing signal. Table 1.15 provides return statistics for three strategies: an unconditional carry strategy, a timing strategy that allocates $\hat{b}_{t-1}\left(\sum_{s=0}^{11} CS_{t-s}^{x}/12\right)$ dollars to the carry strategy, and a combined strategy investing in both the unconditional and the timing strategies. For comparability across asset classes, returns series are standardised to 10% ex-ante annualized standard deviation.

Pooled regression timing returns are positive across various assets classes and portfolios. The results are also statistically significant for all assets classes but equities. Timing returns however are economically weaker compared to those of the unconditional strategies although they exhibit lower volatility leading to comparable Sharpe ratios. Looking at rank portfolios for example average Sharpe ratio for the timing strategy is 0.61 versus 0.56 for the unconditional strategy and 0.57 for the combined strategy. For the cross-asset class average regression, while the timing returns are positive, statistically they are weaker than those derived using pooled regression with only FX, credit and commodities (tercile portfolio) asset classes showing significant returns. Where significant, timing Sharpe ratios are particularly close to those resulting from pooled regressions for rank weighted portfolios (timing Sharpe ratio for the FX and credit asset class is 0.77 and 0.79 respectively using the pooled regression and 0.75 and 0.81 respectively using the cross-asset class average regression). While not consistent across all asset classes, pooling generally improves risk adjusted results relative to single asset class timing (Table 1.14) and unconditional strategies.

1.6.3.3 Rotation in the Pool of Carry Strategies

This subsection assesses rotation strategies that in each month t overweight (underweight) asset classes where the carry spread is relatively high (low) across N_t carry strategies using two alternative weighting schemes (Baba Yara, Boons, and Tamoni (2021)): the first is linear in the signal and takes a position $w_{c,t}^{rot,1}$ in each asset class c:

$$w_{c,t}^{rot,1} = z_t(CS_{c,t,His} - \sum_{c=1}^{N_t} CS_{c,t,His}/N_t) \quad (32)$$

where z_t is a normalisation scalar that ensures the absolute sum of positive and negative weights equals 100%; the second takes equal weight positions $w_{c,t}^{rot,2}$ in the asset classes where $CS_{c,t,His}$ is above (below) the cross-asset class average carry spread. Table 1.16 displays return statistics for the above rotation strategies covering different portfolio styles (rank, median and tercile) and an unconditional benchmark (passive equal-weight strategy). All asset classes carry returns series are standardised to 10% ex-ante annualised standard deviation.

The two rotation strategies achieve positive returns for all portfolios, however returns are economically meaningful only for the rank and median portfolios. Returns for the tercile portfolios are low and non-significant. While for the rank and median portfolio rotation returns are strongly significant (bar the equal weight rotation strategy for the median portfolios), risk adjusted returns fail to beat the unconditional strategies. For example, for the rank portfolios rotation strategies' Sharpe ratios are about half that of the unconditional strategy at 1.07 versus 0.57 and 0.49 for the linear and equal weights rotation strategies, respectively. These results highlight that while comparing the carry spread across asset classes provides valuable information for carry rotation across asset classes, it is difficult to outperform the unconditional strategy as it was the case for carry factor timing in the above subsections.

1.7 Conclusion

This study contributes to the developing cross-asset class pricing research. By jointly analysing the carry factor along multiple markets it shows that the unconditional carry premia are present across various asset classes. While previous research mainly focuses on unconditional premia, this paper shows that cross-asset class conditional premia are also present, with the carry factor predictable by the carry spread. The results indicate that the time-variation in carry premia is economically and statistically large with expected returns of cross-asset carry increasing in the carry spread. A standard deviation expansion in the carry spread foresees an increase in expected carry return broadly similar to the level of the unconditional carry premium. Further, pooled regressions assessing the joint time variation of carry premia shows evidence of cross-asset market integration.

The study also assesses the economic benefits from timing the carry factor. It shows that the carry spread is useful to time carry in certain asset classes, whereby timing strategies can be an attractive complement to the unconditional carry strategy. Similarly, cross-asset rotation strategies based on relative carry spread are generally economically meaningful, yet they fail to beat unconditional benchmark portfolios on a risk adjusted basis. Overall, the study finds that while carry returns predictability is statistically strong across all asset classes, the economic benefits of timing the carry factor are less consistent.

Tables and figures

Table 1.1
Drivers and interpretation of carry for different asset classes.

Asset Class	Futures Price	Carry	Interpretation
FX	$F_t = S_t \frac{1+r_t^f}{1+r_t^{f*}}$ r_t^f and r_t^{f*}: domestic and foreign risk-free rates	$C_t = \frac{S_t - F_t}{F_t} = (r_t^{f*} - r_t^f)\frac{1}{1+r_t^f}$	Interest rate differential
Equities	$F_t = S_t(1 + r_t - q_t)$ q_t: expected –risk neutral– dividend yield	$C_t = \frac{S_t - F_t}{F_t} = (q_t - r_t^f)\frac{S_t}{F_t}$	Expected dividend yield over of the risk-free rate
Commodities	$F_t = S_t(1 + r_t^f - \delta_t)$ δ_t: expected convenience yield in excess of storage costs	$C_t = \frac{S_t - F_t}{F_t} = (\delta_t - r_t^f)\frac{1}{1 + r_t^f - \delta_t}$	Convenience yield net of the storage costs over of the risk-free rate
Fixed Income and Credit	$F_t^\tau = S_t^\tau\left(1 + r_t^f\right) = \frac{1+r_t^f}{(1+y_t^\tau)^\tau}$ S_t^τ: bond spot price with y_t^τyield and τ periods to maturity at time t	$C_t^\tau = \frac{S_t^{\tau-1} - F_t^\tau}{F_t^\tau}$ $= \frac{(1+y_t^\tau)^\tau}{(1+r_t^f)(1+y_t^{\tau-1})^{\tau-1}} - 1$ $\simeq \left(y_t^\tau - r_t^f\right) - D^{mod}(y_t^{\tau-1} - y_t^\tau)$ D^{mod} : modified duration For Credit, bond indices are classified by maturity and credit quality. Carry and returns for different maturities are adjusted (divided) by duration in order to put them on similar volatility scale: $C_t^\tau(X_t = F_t^\tau D_t^\tau) = \frac{C_t^\tau(X_t = F_t^\tau)}{D_t^\tau}$ D_t^τ: duration X_t: margin requirement	Term premium (Fama 1993) i.e., the slope or the yield to maturity in excess of the risk-free rate and roll-down of the bond across the yield curve Credit spread and roll-down of the credit curve

Source: Baltas (2017) and Koijen et al. (2018).

Table 1.2
Mapping of carry risk premia in the financial industry.

Strategy	Equities	Rates	Credit	Currencies	Commodities
Carry	High dividend yields Dividend futures	Forward rate bias Term structure slope Cross-term structure	Forward rate bias	Forward rate bias	Forward rate bias Term structure slope Cross-term structure

Source: Hamdan et al. (2016).

Table 1.3
Carry estimation in different asset classes.

Asset Class	Chosen Metric	Alternatives
FX	$\frac{\mathrm{Spot}_t - \mathrm{Fwd}_t^{1M}}{\mathrm{Fwd}_t^{1M}}$	$r_t^* - r_t$ $\frac{1}{T_2 - T_1}\frac{\mathrm{Fut}_t^{T_1} - \mathrm{Fut}_t^{T_2}}{\mathrm{Fut}_t^{T_2}}$ T_1 and T_2 times to expiry for nearest and second nearest futures contracts.
Equity Indices	$\frac{\mathrm{Spot}_t - \mathrm{Fut}_t^{1M\ \mathrm{interpolated}}}{\mathrm{Fut}_t^{1M\ \mathrm{interpolated}}}$	$\frac{1}{T_2 - T_1}\frac{\mathrm{Fut}_t^{T_1} - \mathrm{Fut}_t^{T_2}}{\mathrm{Fut}_t^{T_2}}$
Commodities	$\frac{\mathrm{Spot}_t^{\mathrm{interpolated}} - \mathrm{Fut}_t^{1M\ \mathrm{interpolated}}}{\mathrm{Fut}_t^{1M\ \mathrm{interpolated}}}$ Seasonally adjusted (12 months moving average).	$\frac{1}{T_2 - T_1}\frac{\mathrm{Fut}_t^{T_1} - \mathrm{Fut}_t^{T_2}}{\mathrm{Fut}_t^{T_2}}$ Seasonally adjusted (12 months). $\frac{\mathrm{Fut}_t^{T_1} - \mathrm{Fut}_t^{T_1+1y}}{\mathrm{Fut}_t^{T_1+1y}}$ 1-year expiry future overcomes the need for seasonality adjustment.
Government Bonds	$\frac{\mathrm{Spot}_t^{\tau-1M\ \mathrm{interpolated}} - \mathrm{Fut}_t^{1M\ \tau\ \mathrm{Synthetic}}}{\mathrm{Fut}_t^{1M\ \tau\ \mathrm{Synthetic}}}$ For global fixed income carry τ is equal to 10 years.	$\frac{1}{T_2 - T_1}\frac{\mathrm{Fut}_t^{T_1} - \mathrm{Fut}_t^{T_2}}{\mathrm{Fut}_t^{T_2}}$
Credit	$\frac{\mathrm{Spot}_t^{\tau-1M\ \mathrm{interpolated}} - \mathrm{Fut}_t^{1M\ \tau\ \mathrm{Synthetic}}}{\mathrm{Fut}_t^{1M\ \tau\ \mathrm{Synthetic}} D_t^{\tau}}$ τ equal to the average portfolio maturity of the credit index for a given maturity bucket. Carry signal for different maturities is duration adjusted.	

Source: Koijen et al. (2018), Baltas (2017) and Baz et al. (2015).

Table 1.4

Carry strategies returns per asset class.

The table displays return statistics for carry strategies and a long equal-weights exposure in each asset class (annualised mean, p-value, annualised standard deviation, skewness, kurtosis and annualised Sharpe ratio). The data is provided for various long short portfolio weighting schemes: rank, median and tercile including their returns correlation.

Asset Class	Strategy	Portfolio construction	Start date	Mean	P value	Standard deviation	Skewness	Kurtosis	Sharpe ratio	Correlation		
										L/S Rank	L/S Median	L/S Tercile
FX	Global	L/S Rank	28/02/1990	5.79%	0.10%	10.29%	-0.80	2.03	0.56	1.00		
		L/S Median	28/02/1990	4.38%	0.11%	7.73%	-0.71	1.89	0.57	0.96	1.00	
		L/S Tercile	28/02/1990	4.96%	0.39%	10.27%	-1.05	3.29	0.48	0.99	0.95	1.00
		L equal weight	28/02/1990	-0.16%	90.79%	3.89%	0.62	1.58	-0.04			
Equities	Global	L/S Rank	31/05/1990	5.36%	0.54%	11.56%	1.27	6.37	0.46	1.00		
		L/S Median	31/05/1990	4.42%	0.15%	9.03%	0.87	4.66	0.49	0.91	1.00	
		L/S Tercile	31/05/1990	2.76%	13.09%	12.83%	0.95	4.22	0.22	0.94	0.81	1.00
		L equal weight	31/05/1990	6.66%	0.69%	15.65%	-0.64	1.62	0.43			
Commodities		L/S Rank	29/01/1988	7.73%	0.34%	17.57%	-0.68	2.71	0.44	1.00		
		L/S Median	29/01/1988	5.76%	0.00%	14.15%	-0.57	1.85	0.41	0.93	1.00	
		L/S Tercile	29/01/1988	7.57%	0.54%	18.69%	-0.87	3.93	0.40	0.97	0.89	1.00
		L equal weight	29/01/1988	1.03%	40.60%	12.91%	-0.69	3.60	0.08			
Credit	Global	L/S Rank	31/05/1993	0.59%	1.33%	1.27%	-2.54	18.95	0.47	1.00		
		L/S Median	31/05/1993	0.41%	1.66%	0.90%	-2.67	19.38	0.46	0.99	1.00	
		L/S Tercile	31/05/1993	0.59%	1.91%	1.32%	-2.80	21.50	0.44	0.99	0.98	1.00
		L equal weight	31/05/1993	0.59%	0.04%	0.86%	-1.85	12.70	0.68			
Fixed Income	Global 10Y	L/S Rank	31/01/1995	5.77%	0.15%	9.64%	0.65	5.46	0.60	1.00		
		L/S Median	31/01/1995	4.02%	0.15%	6.60%	0.72	4.92	0.61	0.95	1.00	
		L/S Tercile	31/01/1995	4.57%	0.95%	9.60%	0.64	5.56	0.48	0.97	0.93	1.00
		L equal weight	31/01/1995	0.00%	87.51%	6.37%	0.29	1.83	0.00			

Table 1.5

Carry strategies returns per asset class split between developed and emerging markets and for credit between investment grade, high yield and emerging markets.

The table displays return statistics for carry strategies in each asset class split between developed and emerging markets and for credit between investment grade, high yield and emerging markets (annualised mean, p-value, annualised standard deviation, skewness, kurtosis and annualised Sharpe ratio). The data is provided for various long short portfolio weighting schemes: rank, median and tercile including their returns correlation as well as a long equal-weight exposure in each asset class.

Asset Class	Strategy	Portfolio construction	Start date	Mean	P value	Standard deviation	Skewness	Kurtosis	Sharpe ratio	Correlation		
										L/S Rank	L/S Median	L/S Tercile
FX	Global	L/S Rank	28/02/1990	5.79%	0.10%	10.29%	-0.80	2.03	0.56	1.00		
		L/S Median	28/02/1990	4.38%	0.11%	7.73%	-0.71	1.89	0.57	0.96	1.00	
		L/S Tercile	28/02/1990	4.96%	0.39%	10.27%	-1.05	3.29	0.48	0.99	0.95	1.00
		L equal weight	28/02/1990	-0.16%	90.79%	3.89%	0.62	1.58	-0.04			
	DM	L/S Rank	28/02/1990	6.41%	0.12%	11.72%	-0.51	1.60	0.55	1.00		
		L/S Median	28/02/1990	5.47%	0.09%	9.60%	-0.47	1.45	0.57	0.95	1.00	
		L/S Tercile	28/02/1990	6.15%	0.26%	12.30%	-0.44	1.96	0.50	0.98	0.94	1.00
		L equal weight	28/02/1990	1.00%	8.19%	3.32%	-0.08	1.08	0.30			
	EM	L/S Rank	30/06/1998	5.72%	0.17%	8.95%	-0.96	3.38	0.64	1.00		
		L/S Median	30/06/1998	2.92%	4.84%	7.57%	-1.37	4.75	0.39	0.94	1.00	
		L/S Tercile	30/06/1998	7.13%	0.08%	10.35%	-0.01	5.57	0.69	0.85	0.71	1.00
		L equal weight	30/06/1998	-1.62%	33.04%	6.83%	0.91	2.85	-0.24			
Equities	Global	L/S Rank	31/05/1990	5.36%	0.54%	11.56%	1.27	6.37	0.46	1.00		
		L/S Median	31/05/1990	4.42%	0.15%	9.03%	0.87	4.66	0.49	0.91	1.00	
		L/S Tercile	31/05/1990	2.76%	13.09%	12.83%	0.95	4.22	0.22	0.94	0.81	1.00
		L equal weight	31/05/1990	6.66%	0.69%	15.65%	-0.64	1.62	0.43			
	DM	L/S Rank	31/05/1990	2.64%	6.11%	8.76%	0.70	5.75	0.30	1.00		
		L/S Median	31/05/1990	2.61%	0.15%	7.93%	0.51	5.52	0.33	0.92	1.00	
		L/S Tercile	31/05/1990	1.75%	22.80%	10.29%	0.71	5.49	0.17	0.94	0.79	1.00
		L equal weight	31/05/1990	4.58%	3.96%	15.04%	-0.74	1.13	0.30			
	EM	L/S Rank	28/06/1996	10.87%	0.21%	19.16%	2.11	11.37	0.57	1.00		
		L/S Median	28/06/1996	8.88%	0.00%	16.47%	1.79	8.59	0.54	0.93	1.00	
		L/S Tercile	28/06/1996	10.08%	0.63%	20.93%	2.09	11.06	0.48	0.96	0.88	1.00
		L equal weight	28/06/1996	8.55%	1.02%	19.25%	-0.20	1.78	0.44			
Commodities		L/S Rank	29/01/1988	7.73%	0.34%	17.57%	-0.68	2.71	0.44	1.00		
		L/S Median	29/01/1988	5.76%	0.00%	14.15%	-0.57	1.85	0.41	0.93	1.00	
		L/S Tercile	29/01/1988	7.57%	0.54%	18.69%	-0.87	3.93	0.40	0.97	0.89	1.00
		L equal weight	29/01/1988	1.03%	40.60%	12.91%	-0.69	3.60	0.08			
Credit	Global	L/S Rank	31/05/1993	0.59%	1.33%	1.27%	-2.54	18.95	0.47	1.00		
		L/S Median	31/05/1993	0.41%	1.66%	0.90%	-2.67	19.38	0.46	0.99	1.00	
		L/S Tercile	31/05/1993	0.59%	1.91%	1.32%	-2.80	21.50	0.44	0.99	0.98	1.00
		L equal weight	31/05/1993	0.59%	0.04%	0.86%	-1.85	12.70	0.68			
	IG	L/S Rank	31/05/1993	0.33%	0.24%	0.57%	-0.39	6.46	0.58	1.00		
		L/S Median	31/05/1993	0.28%	0.22%	0.48%	-0.36	5.23	0.59	0.98	1.00	
		L/S Tercile	31/05/1993	0.34%	0.40%	0.62%	-0.39	5.09	0.55	0.98	0.96	1.00
		L equal weight	31/05/1993	0.42%	0.01%	0.57%	-0.42	1.74	0.74			
	HY_EM	L/S Rank	28/02/2003	0.84%	0.32%	1.19%	-3.34	22.65	0.70			
		L/S Median	28/02/2003	0.67%	0.37%	0.97%	-2.17	19.57	0.69	0.91	1.00	
		L/S Tercile	28/02/2003	1.03%	0.12%	1.33%	-2.72	16.42	0.78	0.97	0.85	1.00
		L equal weight	28/02/2003	1.42%	0.29%	2.00%	-3.10	22.56	0.71			
	EM	L/S Rank	28/02/2003	0.72%	4.31%	1.52%	-5.48	45.87	0.48	1.00		
		L/S Median	28/02/2003	0.62%	6.92%	1.45%	-5.23	46.01	0.43	0.98	1.00	
		L/S Tercile	28/02/2003	0.75%	7.02%	1.77%	-5.96	53.22	0.42	0.96	0.93	1.00
		L equal weight	28/02/2003	1.14%	2.15%	2.10%	-4.40	31.88	0.54			
Fixed Income	Global 10Y	L/S Rank	31/01/1995	5.77%	0.15%	9.64%	0.65	5.46	0.60	1.00		
		L/S Median	31/01/1995	4.02%	0.15%	6.60%	0.72	4.92	0.61	0.95	1.00	
		L/S Tercile	31/01/1995	4.57%	0.95%	9.60%	0.64	5.56	0.48	0.97	0.93	1.00
		L equal weight	31/01/1995	0.00%	87.51%	6.37%	0.29	1.83	0.00			
	DM 10Y	L/S Rank	31/01/1995	3.57%	0.01%	4.49%	-0.50	3.20	0.79	1.00		
		L/S Median	31/01/1995	2.41%	0.05%	3.54%	-0.26	2.35	0.68	0.92	1.00	
		L/S Tercile	31/01/1995	3.21%	0.04%	4.62%	-0.34	2.88	0.70	0.96	0.91	1.00
		L equal weight	31/01/1995	0.66%	46.77%	5.71%	0.04	0.15	0.11			
	EM 10Y	L/S Rank	31/07/1998	6.68%	2.41%	16.29%	-0.11	6.43	0.41	1.00		
		L/S Median	31/07/1998	4.13%	7.94%	13.29%	-0.50	8.59	0.31	0.92	1.00	
		L/S Tercile	31/07/1998	9.34%	0.25%	15.73%	0.51	6.38	0.59	0.87	0.73	1.00
		L equal weight	31/07/1998	-0.01%	83.06%	9.34%	0.26	3.19	0.00			

Table 1.6

Selective correlation coefficients between rank weighted carry portfolios returns across global, developed markets and emerging markets asset classes.

Correlation		FX			Equities			Commodities	Credit			Fixed income 10Y		
		Global	DM	EM	Global	DM	EM		Global	IG	EM	Global	DM	EM
FX	Global	1.00												
	DM		1.00											
	EM			1.00										
Equities	Global	0.05			1.00									
	DM		0.04			1.00								
	EM			0.20			1.00							
Commodities		0.10			0.09			1.00						
Credit	Global	0.48			0.09			0.24	1.00					
	IG		0.02			0.10				1.00				
	EM			0.19			0.15				1.00			
Fixed Income 10Y	Global	0.04			-0.12			-0.01	0.05			1.00		
	DM		0.23			-0.06				0.15			1.00	
	EM			-0.16			0.04				0.02			1.00

Table 1.7

Returns to equal volatility weighted multi-asset carry portfolios for global, developed and emerging markets with volatility estimated in sample or using one year rolling window.

The table displays return statistics (annualised mean, p-value, annualised standard deviation, skewness, kurtosis and annualised Sharpe ratio) for two equal volatility weighted multi-asset class strategies, using in-sample and one year rolling volatility estimation. The data is provided for various long short portfolio weighting schemes: rank, median and tercile including their returns correlation as well as for a passive equal weight exposure in each asset class. Returns correlation are also shown for long short, rank weighted, global, developed and emerging markets multi-asset portfolios.

Asset Class	**Strategy**	**Portfolio Construction**	**Mean**	**P value**	**Standard deviation**	**Skewness**	**Kurtosis**	**Sharpe ratio**	**Correlation**					
									L/S Rank	*L/S Median*	*L/S Tercile*	*Global*	*DM*	*EM*
Multi In-sample vol	Global	L/S Rank	5.40%	0.00%	5.50%	-0.43	4.43	0.98	1.00			1.00		
		L/S Median	5.31%	0.00%	5.62%	-0.64	4.62	0.94	0.96	1.00				
		L/S Tercile	4.33%	0.00%	5.47%	-0.59	5.40	0.79	0.98	0.94	1.00			
		L equal weight	2.22%	1.04%	4.99%	-1.12	5.58	0.45						
	DM	L/S Rank	4.80%	0.00%	6.00%	0.62	5.13	0.80	1.00			0.57	1.00	
		L/S Median	4.80%	0.00%	5.86%	0.29	4.58	0.82	0.95	1.00				
		L/S Tercile	3.83%	0.03%	5.86%	0.69	4.63	0.65	0.96	0.89	1.00			
		L equal weight	3.32%	0.19%	6.08%	-0.39	1.60	0.55						
	EM	L/S Rank	4.97%	0.00%	5.31%	-0.39	3.60	0.94	1.00			0.76	0.28	1.00
		L/S Median	3.71%	0.06%	5.12%	-0.61	4.36	0.72	0.92	1.00				
		L/S Tercile	5.23%	0.00%	5.77%	1.31	15.79	0.91	0.84	0.68	1.00			
		L equal weight	3.06%	0.31%	5.00%	-3.06	22.28	0.61						
Multi 1Y-rolling vol	Global	L/S Rank	6.78%	0.00%	5.38%	-0.48	0.98	1.26	1.00			1.00		
		L/S Median	6.57%	0.00%	5.53%	-0.60	0.88	1.19	0.95	1.00				
		L/S Tercile	6.03%	0.00%	5.25%	-0.47	1.03	1.15	0.98	0.92	1.00			
		L equal weight	3.46%	0.03%	5.31%	-0.21	0.48	0.65						
	DM	L/S Rank	6.59%	0.00%	5.85%	-0.19	0.40	1.12	1.00			0.49	1.00	
		L/S Median	6.25%	0.00%	5.81%	-0.23	0.61	1.08	0.94	1.00				
		L/S Tercile	6.16%	0.00%	5.81%	-0.28	0.31	1.06	0.97	0.90	1.00			
		L equal weight	5.47%	0.00%	6.44%	-0.18	0.19	0.85						
	EM	L/S Rank	7.92%	0.00%	5.51%	-0.66	1.16	1.44	1.00			0.72	0.13	1.00
		L/S Median	6.70%	0.00%	5.35%	-0.70	1.14	1.25	0.94	1.00				
		L/S Tercile	7.38%	0.00%	5.47%	-0.61	1.20	1.35	0.97	0.90	1.00			
		L equal weight	4.68%	4.46%	4.68%	-0.49	0.55	1.00						

Table 1.8

Correlation of carry spreads across asset classes.

The table presents the correlation matrix of the standardised carry spreads (rank portfolios) across the different asset classes with first-order autocorrelations on the diagonal.

	FX	Commodities	Credit	Fixed Income	Equities
FX	0.82				
Commodities	0.12	0.96			
Credit	0.22	-0.09	0.97		
Fixed Income	0.63	0.21	0.08	0.88	
Equities	0.09	0.21	-0.40	0.03	0.80

Table 1.9

Time series predictive regression of carry returns on carry spread (overlapping holding period returns).

The table displays results from time-series predictive regressions of carry returns on carry spread for all five global asset classes. The results are presented for different portfolio weighting schemes (rank, median and tercile) and overlapping holding period returns of horizons $h = 1, 12$ and 24 months. For ease of comparison across asset classes, carry spreads, CS_t are standardised to have zero mean and a standard deviation of one; and, carry returns are scaled to have an annual standard deviation of 10%. Regression coefficients t-statistics are computed applying Newey and West (1987) and Lazarus et al. (2018) for the lag truncation parameter.

				RANK							MEDIAN								TERCILE						
Asset class		**h**	**START DATE**	**a**	t_a^{nw}	p_a	**b**	t_b^{nw}	p_b	R^2	**a**	t_a^{nw}	p_a	**b**	t_b^{nw}	p_b	R^2	**SE**	**a**	t_a^{nw}	p_a	**b**	t_b^{nw}	p_b	R^2
		1	31/08/1992	0.00	2.68	0.01	0.00	0.71	0.47	0.00	0.00	2.75	0.01	0.00	0.70	0.48	0.00	0.03	0.00	2.69	0.01	0.00	0.71	0.48	0.00
FX	**GLOBAL**	12	31/08/1992	0.06	3.80	0.00	0.05	3.55	0.00	0.17	0.06	4.00	0.00	0.04	3.30	0.00	0.16	0.10	0.05	3.49	0.00	0.04	3.77	0.00	0.15
		24	31/08/1992	0.13	4.40	0.00	0.09	3.37	0.00	0.30	0.12	4.44	0.00	0.08	3.49	0.00	0.26	0.14	0.11	3.99	0.00	0.08	3.43	0.00	0.27
		1	31/08/1992	0.00	2.67	0.01	0.00	1.22	0.22	0.02	0.00	2.44	0.02	0.00	1.39	0.16	0.03	0.03	0.00	1.90	0.06	0.00	0.88	0.38	0.01
Equities	**GLOBAL**	12	31/08/1992	0.05	2.89	0.00	0.06	1.92	0.05	0.19	0.05	2.74	0.01	0.05	1.73	0.08	0.18	0.11	0.03	1.94	0.05	0.05	1.75	0.08	0.15
		24	31/08/1992	0.11	3.21	0.00	0.12	3.61	0.00	0.29	0.10	3.24	0.00	0.10	3.50	0.00	0.26	0.17	0.06	2.08	0.04	0.08	2.79	0.00	0.20
		1	31/01/1997	0.01	2.92	0.00	0.00	0.48	0.60	0.00	0.01	2.83	0.00	0.00	0.69	0.49	0.00	0.03	0.00	2.78	0.01	0.00	1.67	0.10	0.01
Bonds	**GLOBAL**	12	31/01/1997	0.07	3.28	0.00	0.00	0.19	0.85	0.00	0.08	3.22	0.00	0.00	-0.07	0.90	0.00	0.13	0.06	3.14	0.00	0.01	0.55	0.59	0.01
		24	31/01/1997	0.16	3.74	0.00	0.01	0.63	0.52	0.01	0.17	3.67	0.00	-0.01	-0.50	0.60	0.01	0.20	0.13	3.82	0.00	-0.02	-0.64	0.52	0.01
		1	31/01/1990	0.00	3.26	0.00	0.00	0.98	0.32	0.00	0.00	2.56	0.01	0.00	1.46	0.14	0.00	0.03	0.00	3.06	0.00	0.00	-0.10	0.91	0.00
Commodities		12	31/01/1990	0.05	3.56	0.00	0.01	0.85	0.40	0.01	0.04	2.80	0.01	0.01	1.04	0.30	0.02	0.10	0.05	3.43	0.00	0.00	0.15	0.88	0.00
		24	31/01/1990	0.11	4.20	0.00	0.04	1.95	0.05	0.07	0.10	3.50	0.00	0.03	1.53	0.13	0.05	0.15	0.11	3.89	0.00	0.73	0.47	0.46	0.01
		1	29/09/1995	0.00	2.47	0.01	0.01	3.19	0.00	0.06	0.00	2.60	0.01	0.01	3.12	0.00	0.05	0.03	0.01	2.96	0.00	0.01	2.51	0.01	0.05
Credit	**GLOBAL**	12	29/09/1995	0.05	3.30	0.00	0.10	3.60	0.00	0.46	0.06	3.56	0.00	0.09	3.73	0.00	0.42	0.11	0.06	3.56	0.02	0.10	2.79	0.01	0.36
		24	29/09/1995	0.11	4.10	0.00	0.17	4.80	0.00	0.61	0.11	4.38	0.00	0.16	5.03	0.00	0.60	0.13	0.10	2.99	0.00	0.13	2.21	0.00	0.32

Table 1.10

Time series predictive regression of carry returns on carry spread (non-overlapping holding period returns).

The table shows the results from time-series predictive regressions of carry returns on the carry spread for all five global asset classes. The results are presented for different portfolio weighting schemes (rank, median and tercile) and non-overlapping holding period returns of horizons $\mathrm{h} = 12$ and 24 months. For ease of comparison across asset classes, carry spreads, $\mathrm{CS_t}$ are standardised to have zero mean and a standard deviation of one; and, carry returns are scaled to have an annual standard deviation of 10%.

				RANK								MEDIAN								TERCILE						
Asset class		h	START DATE	a	t_a	p_a	b	t_b	p_b	R^2	SE	a	t_a	p_a	b	t_b	p_b	R^2	SE	a	t_a	p_a	b	t_b	p_b	R^2
FX	GLOBAL	12	31/08/1992	0.06	3.49	0.00	0.03	3.36	0.00	0.10	0.10	0.06	3.39	0.00	0.05	3.23	0.00	0.28	0.10	0.06	3.25	0.00	0.06	3.33	0.00	0.29
		24	31/08/1992	0.11	3.18	0.01	0.11	3.52	0.00	0.49	0.14	0.10	3.12	0.01	0.09	3.04	0.01	0.42	0.14	0.09	2.85	0.01	0.11	3.28	0.01	0.45
Equities	GLOBAL	12	31/08/1992	0.05	2.41	0.02	0.07	4.17	0.00	0.39	0.12	0.05	2.06	0.05	0.07	3.68	0.00	0.33	0.11	0.03	1.40	0.17	0.07	3.89	0.00	0.36
		24	31/08/1992	0.12	2.01	0.07	0.19	2.39	0.03	0.31	0.18	0.12	1.98	0.07	0.17	2.28	0.04	0.29	0.17	0.05	0.83	0.42	0.12	1.32	0.21	0.12
Bonds	GLOBAL	12	31/01/1997	0.07	3.80	0.00	0.01	0.46	0.65	0.01	0.12	0.08	3.41	0.00	0.00	0.04	0.97	0.00	0.13	0.06	3.54	0.00	0.02	0.77	0.45	0.03
		24	31/01/1997	0.14	3.30	0.01	0.01	0.27	0.80	0.01	0.19	0.15	3.08	0.01	-0.01	-0.27	0.80	0.01	0.20	0.11	3.21	0.01	0.03	0.90	0.39	0.08
Commodities		12	31/01/1990	0.05	2.08	0.05	0.13	5.89	0.00	0.58	0.10	0.05	2.09	0.05	0.11	5.18	0.00	0.52	0.10	0.05	1.71	0.10	0.09	3.33	0.00	0.31
		24	31/01/1990	0.11	3.93	0.00	0.24	12.22	0.00	0.93	0.14	0.11	3.72	0.00	0.23	10.23	0.00	0.90	0.15	0.12	2.01	0.07	0.25	4.77	0.00	0.67
Credit	GLOBAL	12	29/09/1995	0.05	2.75	0.01	0.01	0.69	0.50	0.02	0.11	0.04	2.21	0.04	0.02	0.89	0.38	0.03	0.11	0.05	2.77	0.01	0.01	0.52	0.60	0.01
		24	29/09/1995	0.11	2.80	0.01	0.01	0.20	0.84	0.00	0.14	0.10	2.29	0.04	0.00	0.09	0.93	0.00	0.13	0.11	2.83	0.01	-0.01	-0.31	0.76	0.01

Table 1.11

Time series predictive regression of carry returns on carry spread for developed and emerging markets across asset classes.

The table shows the results from time-series predictive regressions of carry returns on the carry spread for all five global asset classes for developed and emerging markets. The results are presented for different portfolio weighting schemes (rank, median and tercile) and overlapping holding period returns of horizons $h = 1, 12$ and 24 months. For ease of comparison across asset classes, carry spreads, CS_t are standardised to have zero mean and a standard deviation of one; and, carry returns are scaled to have an annual standard deviation of 10%. Regression coefficients t-statistics are computed applying Newey and West (1987) and Lazarus et al. (2018) for the lag truncation parameter.

				RANK							MEDIAN								TERCILE						
Asset class		h	START DATE	a	t_a^{nw}	p_a	b	t_b^{nw}	p_b	R^2	a	t_a^{nw}	p_a	b	t_b^{nw}	p_b	R^2	SE	a	t_a^{nw}	p_a	b	t_b^{nw}	p_b	R^2
FX		1	31/08/1992	0.00	1.71	0.08	0.00	-1.24	0.21	0.01	0.00	1.70	0.09	0.00	-1.20	0.23	0.01	0.03	0.00	1.71	0.08	0.00	-1.24	0.21	0.01
	DM	12	31/08/1992	0.06	2.73	0.00	0.00	-0.05	0.95	0.00	0.06	2.62	0.00	0.00	0.05	0.96	0.00	0.12	0.06	2.59	0.01	0.01	0.27	0.79	0.00
		24	31/08/1992	0.12	2.88	0.00	0.01	0.35	0.70	0.00	0.12	2.73	0.00	0.01	0.49	0.63	0.00	0.19	0.12	2.66	0.08	0.01	0.46	0.65	0.00
		1	30/06/2000	0.01	3.02	0.00	0.00	1.37	0.17	0.01	0.01	2.12	0.03	0.00	1.23	0.22	0.01	0.03	0.01	3.00	0.00	0.00	1.36	0.18	0.01
	EM	12	30/06/2000	0.07	4.04	0.00	0.07	4.60	0.00	0.25	0.05	2.76	0.01	0.06	4.18	0.00	0.23	0.09	0.06	3.74	0.00	0.08	4.53	0.00	0.22
		24	30/06/2000	0.15	4.35	0.00	0.11	3.46	0.00	0.37	0.09	2.73	0.01	0.09	2.91	0.00	0.33	0.14	0.14	3.75	0.00	0.05	1.18	0.24	0.10
Equities		1	31/08/1992	0.00	2.95	0.00	0.00	1.64	0.10	0.01	0.00	1.91	0.06	0.00	1.91	0.06	0.01	0.03	0.00	2.50	0.01	0.00	0.75	0.45	0.00
	DM	12	31/08/1992	0.03	3.08	0.00	0.01	1.30	0.20	0.01	0.03	2.00	0.05	0.01	1.14	0.25	0.01	0.09	0.02	3.25	0.01	0.00	-0.20	0.83	0.00
		24	31/08/1992	0.06	3.40	0.00	0.02	2.48	0.01	0.05	0.05	2.23	0.02	0.03	2.06	0.04	0.06	0.12	0.04	3.43	0.00	0.00	-0.07	0.94	0.00
		1	31/07/1998	0.00	2.64	0.01	0.01	2.80	0.00	0.02	0.00	2.19	0.03	0.00	2.41	0.02	0.01	0.02	0.00	1.83	0.07	0.00	1.38	0.17	0.01
	EM	12	31/07/1998	0.06	3.17	0.00	0.07	7.58	0.00	0.31	0.06	2.84	0.00	0.08	4.60	0.00	0.27	0.10	0.04	2.53	0.01	0.06	5.53	0.00	0.27
		24	31/07/1998	0.12	3.08	0.00	0.15	3.93	0.00	0.39	0.12	2.83	0.00	0.15	3.99	0.00	0.39	0.20	0.11	2.02	0.04	0.06	2.79	0.01	0.06
Bonds		1	31/01/1997	0.00	6.90	0.00	0.00	0.96	0.30	0.00	0.00	6.29	0.00	0.00	1.30	0.19	0.01	0.01	0.00	6.78	0.00	0.00	0.91	0.37	0.00
	DM	12	31/01/1997	0.05	8.80	0.00	0.01	2.30	0.02	`	0.04	7.64	0.00	0.01	1.78	0.08	0.13	0.03	0.04	8.05	0.00	0.01	1.34	0.18	0.06
		24	31/01/1997	0.09	9.95	0.00	0.03	2.80	0.00	0.24	0.07	9.00	0.00	0.02	1.74	0.08	0.17	0.04	0.08	8.37	0.00	0.01	0.62	0.53	0.02
		1	31/07/2000	0.00	2.54	0.01	0.00	1.45	0.15	0.01	0.00	2.32	0.02	0.00	1.34	0.18	0.01	0.02	0.00	2.38	0.02	0.00	1.75	0.08	0.01
	EM	12	31/07/2000	0.06	3.10	0.00	0.01	0.45	0.66	0.00	0.05	2.79	0.00	0.00	0.33	0.70	0.00	0.09	0.05	2.83	0.00	0.00	-0.38	0.71	0.00
		24	31/07/2000	0.12	3.40	0.00	0.01	0.37	0.70	0.00	0.09	2.90	0.00	-0.01	-0.48	0.63	0.00	0.13	0.11	3.41	0.00	-0.01	-0.38	0.70	0.00
Credit		1	29/09/1995	0.01	5.43	0.00	0.01	7.65	0.00	0.11	0.01	6.09	0.00	0.01	7.30	0.00	0.10	0.03	0.01	3.74	0.00	0.01	2.47	0.01	0.04
	DM	12	29/09/1995	0.07	5.34	0.00	0.10	5.14	0.00	0.53	0.07	5.69	0.00	0.10	5.22	0.00	0.56	0.09	0.07	3.11	0.00	0.06	1.53	0.13	0.13
		24	29/09/1995	0.14	3.90	0.00	0.12	4.18	0.00	0.31	0.14	3.92	0.00	0.12	4.25	0.00	0.30	0.18	0.13	3.13	0.00	0.00	0.10	0.14	0.92
		1	31/03/2005	0.00	2.90	0.00	0.01	2.99	0.00	0.05	0.00	2.57	0.01	0.01	2.96	0.00	0.05	0.03	0.01	3.77	0.00	0.01	3.26	0.00	0.00
	EM	12	31/03/2005	0.06	3.40	0.00	0.08	3.95	0.00	0.47	0.05	3.08	0.00	0.08	3.66	0.00	0.50	0.08	0.06	3.43	0.00	0.06	2.16	0.03	0.29
		24	31/03/2005	0.10	2.70	0.01	0.10	3.50	0.00	0.37	0.09	2.75	0.01	0.11	4.40	0.00	0.48	0.12	0.10	2.55	0.02	0.08	2.33	0.02	0.24

Table 1.12

Pooled regressions of carry returns on carry spreads.

The table show results for panel regressions of carry returns on carry spreads over overlapping and non-overlapping holding periods 1, 12, 24 and 48 months, for the three types of weighting portfolios: rank, median and tercile. Carry returns are scaled to 10% standard deviation and carry spreads are standardised to have zero mean and one standard deviation. Regression coefficients t-statistics using overlapping returns are computed applying Newey and West (1987) and Lazarus et al. (2018) for the lag truncation parameter.

Overlapping	RANK							MEDIAN							TERCILE						
h	a	b	t_a^{nw}	p_a	t_b^{nw}	p_b	R^2	a	b	t_a^{nw}	p_a	t_b^{nw}	p_b	R^2	a	b	t_a^{nw}	p_a	t_b^{nw}	p_b	R^2
12	0.06	0.05	6.67	0.00	3.44	0.00	0.17	0.06	0.05	6.61	0.00	3.85	0.00	0.17	0.05	0.04	5.80	0.00	2.36	0.02	0.10
24	0.12	0.09	7.32	0.00	4.07	0.00	0.23	0.11	0.08	7.14	0.00	4.08	0.00	0.21	0.10	0.07	6.29	0.00	2.88	0.00	0.14
48	0.25	0.15	8.49	0.00	4.80	0.00	0.25	0.25	0.14	8.25	0.00	4.26	0.00	0.21	0.21	0.10	7.25	0.00	2.98	0.00	0.13
Non overlapping	**RANK**							**MEDIAN**							**TERCILE**						
h	a	b	t_a	p_a	t_b	p_b	R^2	a	b	t_a	p_a	t_b	p_b	R^2	a	b	t_a	p_a	t_b	p_b	R^2
1	0.00	0.00	5.65	0.00	3.12	0.00	0.02	0.00	0.00	5.50	0.00	3.28	0.00	0.02	0.00	0.00	5.04	0.00	2.06	0.04	0.01
12	0.06	0.06	5.68	0.00	6.51	0.00	0.26	0.06	0.06	5.32	0.00	5.84	0.00	0.22	0.05	0.06	5.16	0.00	5.68	0.00	0.21
24	0.12	0.13	4.81	0.00	5.69	0.00	0.36	0.11	0.10	4.44	0.00	4.50	0.00	0.26	0.18	0.15	2.79	0.01	2.84	0.01	0.22
48	0.22	0.21	3.75	0.00	4.67	0.00	0.44	0.20	0.18	3.46	0.00	4.03	0.00	0.37	0.18	0.15	2.79	0.01	2.84	0.01	0.22

Table 1.13

Times series regressions of cross-asset class average carry return on the cross-asset class carry spread.

The table show results for times series regressions of cross-asset class average carry return on the cross-asset class carry spread for the three types of weighting portfolios: rank, median and tercile, and over three holding periods 1, 12 and 24 months. Carry returns are scaled to 10% volatility and carry spread standardised to have a mean equal to zero and a standard deviation equal to one. Regression coefficients t-statistics are computed applying Newey and West (1987) and Lazarus et al. (2018) for the lag truncation parameter.

	RANK							MEDIAN							TERCILE						
h	a	b	t_a^{nw}	p_a	t_b^{nw}	p_b	R^2	a	b	t_a^{nw}	p_a	t_b^{nw}	p_b	R^2	a	b	t_a^{nw}	p_a	t_b^{nw}	p_b	R^2
1	0.00	0.00	4.40	0.00	1.90	0.06	0.02	0.00	0.01	4.40	0.00	2.27	0.02	0.03	0.00	0.00	4.58	0.00	1.70	0.09	0.02
12	0.06	0.06	5.58	0.00	2.09	0.04	0.24	0.06	0.06	5.60	0.00	2.54	0.00	0.30	0.05	0.05	5.26	0.00	2.06	0.04	0.20
24	0.12	0.09	6.74	0.00	2.38	0.02	0.27	0.11	0.09	6.79	0.00	2.88	0.00	0.31	0.10	0.07	5.83	0.00	2.19	0.03	0.19

Table 1.14

Summary performance statistics of timing strategies for alternative asset classes.

The table presents for alternative asset classes the performance statistics (mean annualised return, p-value, annualised standard deviation, Sharpe ratio) for three strategies: 1) an unconditional carry strategy, 2) a timing strategy using z-score methodology ($CS_{t,His} = \frac{\sum_{s=0}^{11} CS_{t-s}/12 - \sum_{s=12}^{t-1} CS_{t-s}/(t-12)}{\sigma(CS_{1:t-12})}$ capped at ± 2 and uncapped) and a regression methodology ($R_t^x = a + b\,(\sum_{s=1}^{12} CS_{t-s}^x/12) + \varepsilon_t^x$; constrained and unconstrained) that respectively allocates $CS_{t,His}$ or $\hat{b}_{t-1}(\sum_{s=0}^{11} CS_{t-s}^x/12)$ dollars to the carry strategy and 3) a combined strategy that invests in the unconditional plus the timing strategy. The data is presented for three portfolios weighting methods: rank, median and tercile. For comparability across asset classes, returns series are standardised to 10% ex-ante annualized standard deviation.

		Rank				Median				Tercile			
ASSET CLASS	PORTFOLIO	Mean return	p-value	Standard deviation	Sharpe ratio	Mean return	p-value	Standard deviation	Sharpe ratio	Mean return	p-value	Standard deviation	Sharpe ratio
	$CS_{t,His}$ timing	5.35%	0.00	8.53%	0.63	5.17%	0.00	7.82%	0.66	4.45%	0.02	9.96%	0.45
	Unconditional	5.74%	0.00	9.99%	0.57	5.68%	0.00	9.93%	0.57	5.01%	0.01	9.92%	0.51
	Combined	11.37%	0.00	13.29%	0.86	11.19%	0.00	12.36%	0.91	9.69%	0.00	14.01%	0.69
	$CS_{t,His}$ capped timing	4.47%	0.00	7.64%	0.59	4.27%	0.00	7.72%	0.55	3.51%	0.03	8.74%	0.40
	Unconditional	5.74%	0.00	9.99%	0.57	5.68%	0.00	9.93%	0.57	5.01%	0.01	9.92%	0.51
FX	Combined	10.47%	0.00	12.56%	0.83	10.23%	0.00	12.32%	0.83	8.74%	0.00	12.85%	0.68
	Regression timing	2.29%	0.19	10.58%	0.22	1.46%	0.35	10.44%	0.14	1.85%	0.21	8.62%	0.21
	Unconditional	5.74%	0.00	9.99%	0.57	5.68%	0.00	9.93%	0.57	5.01%	0.01	9.92%	0.51
	Combined	7.57%	0.01	17.76%	0.43	6.58%	0.03	18.04%	0.36	6.42%	0.02	16.35%	0.39
	Const. regression timing	4.06%	0.01	8.20%	0.50	3.63%	0.03	8.62%	0.42	3.34%	0.01	6.82%	0.49
	Unconditional	5.74%	0.00	9.99%	0.57	5.68%	0.00	9.93%	0.57	5.01%	0.01	9.92%	0.51
	Combined	9.20%	0.00	17.73%	0.52	8.65%	0.01	18.09%	0.48	7.81%	0.01	16.39%	0.48
	$CS_{t,His}$ timing	3.38%	0.06	9.66%	0.35	2.73%	0.09	8.90%	0.31	3.39%	0.03	8.27%	0.41
	Unconditional	4.88%	0.01	9.61%	0.51	4.17%	0.02	9.14%	0.46	3.32%	0.04	8.92%	0.37
	Combined	8.09%	0.01	16.27%	0.50	6.74%	0.01	14.95%	0.45	6.50%	0.02	14.82%	0.44
	$CS_{t,His}$ capped timing	2.99%	0.07	9.15%	0.33	2.77%	0.08	8.72%	0.32	3.19%	0.04	8.03%	0.40
	Unconditional	4.88%	0.01	9.61%	0.51	4.17%	0.02	9.14%	0.46	3.32%	0.04	8.92%	0.37
Equities	Combined	7.70%	0.01	15.87%	0.49	6.80%	0.01	14.80%	0.46	6.30%	0.02	14.63%	0.43
	Regression timing	3.55%	0.08	11.36%	0.31	2.12%	0.19	9.35%	0.23	1.77%	0.19	7.73%	0.23
	Unconditional	4.88%	0.01	9.61%	0.51	4.17%	0.02	9.14%	0.46	3.32%	0.04	8.92%	0.37
	Combined	7.70%	0.02	20.06%	0.38	5.72%	0.05	17.16%	0.33	4.59%	0.08	15.83%	0.29
	Const. regression timing	3.78%	0.06	11.29%	0.33	2.82%	0.10	9.64%	0.29	2.16%	0.12	7.58%	0.29
	Unconditional	4.88%	0.01	9.61%	0.51	4.17%	0.02	9.14%	0.46	3.32%	0.04	8.92%	0.37
	Combined	7.93%	0.02	20.12%	0.39	6.40%	0.03	17.69%	0.36	4.98%	0.06	15.91%	0.31
	$CS_{t,His}$ timing	-1.50%	0.27	5.44%	-0.28	-3.54%	0.01	5.79%	-0.61	-4.36%	0.01	7.06%	-0.62
	Unconditional	7.81%	0.00	7.53%	1.04	7.80%	0.00	7.94%	0.98	6.17%	0.00	7.21%	0.86
	Combined	6.28%	0.00	8.51%	0.74	4.28%	0.00	6.75%	0.63	1.86%	0.17	6.60%	0.28
	$CS_{t,His}$ capped timing	-1.50%	0.27	5.44%	-0.28	-3.54%	0.01	5.79%	-0.61	-4.09%	0.01	6.41%	-0.64
	Unconditional	7.81%	0.00	7.53%	1.04	7.80%	0.00	7.94%	0.98	6.17%	0.00	7.21%	0.86
Fixed Income	Combined	6.28%	0.00	8.51%	0.74	4.28%	0.00	6.75%	0.63	2.13%	0.10	6.20%	0.34
	Regression timing	-6.11%	0.00	6.38%	-0.96	-16.06%	0.00	17.58%	-0.91	12.37%	0.01	23.99%	0.52
	Unconditional	7.81%	0.00	7.53%	1.04	7.80%	0.00	7.94%	0.98	6.21%	0.00	7.24%	0.86
	Combined	1.68%	0.09	4.60%	0.36	-8.22%	0.00	12.04%	-0.68	18.20%	0.00	28.60%	0.64
	Const. regression timing	0.01%	0.41	0.03%	0.19	0.00%	0.00	0.00%	0.00	10.94%	0.01	22.86%	0.48
	Unconditional	7.81%	0.00	7.53%	1.04	7.80%	0.00	7.94%	0.98	6.17%	0.00	7.21%	0.86
	Combined	7.82%	0.00	7.53%	1.04	7.80%	0.00	7.94%	0.98	16.75%	0.00	27.52%	0.61

(continued on next page)

Table 1.14: continued

ASSET CLASS	PORTFOLIO	Rank				Median				Tercile			
		Mean return	p-value	Standard deviation	Sharpe ratio	Mean return	p-value	Standard deviation	Sharpe ratio	Mean return	p-value	Standard deviation	Sharpe ratio
	$CS_{t,His}$ timing	-1.03%	0.82	9.27%	-0.11	-0.86%	1.00	10.54%	-0.08	-2.20%	0.46	11.53%	-0.19
	Unconditional	3.95%	0.01	9.97%	0.40	3.40%	0.03	10.19%	0.33	3.68%	0.02	9.70%	0.38
	Combined	3.26%	0.04	10.50%	0.31	2.94%	0.06	11.38%	0.26	1.74%	0.28	12.35%	0.14
	$CS_{t,His}$ capped timing	-1.03%	0.82	9.27%	-0.11	-0.85%	0.98	10.21%	-0.08	-1.90%	0.39	9.88%	-0.19
	Unconditional	3.95%	0.01	9.97%	0.40	3.40%	0.03	10.19%	0.33	3.68%	0.02	9.70%	0.38
Commodities	Combined	3.26%	0.04	10.50%	0.31	2.96%	0.05	10.94%	0.27	2.14%	0.18	10.24%	0.21
	Regression timing	-4.63%	0.00	9.29%	-0.50	-2.93%	0.03	7.12%	-0.41	-0.17%	0.12	3.94%	-0.04
	Unconditional	3.95%	0.01	9.97%	0.40	3.40%	0.03	10.19%	0.33	3.68%	0.02	9.70%	0.38
	Combined	-0.21%	0.64	7.76%	-0.03	0.54%	0.54	11.01%	0.05	3.66%	0.06	8.74%	0.42
	Const. regression timing	0.33%	0.62	1.53%	0.22	0.32%	0.68	3.81%	0.08	0.05%	0.92	2.21%	0.02
	Unconditional	3.95%	0.01	9.97%	0.40	3.40%	0.03	10.19%	0.33	3.68%	0.02	9.70%	0.38
	Combined	4.22%	0.02	10.72%	0.39	3.52%	0.06	12.58%	0.28	3.68%	0.04	10.36%	0.35
	$CS_{t,His}$ timing	12.05%	0.00	20.69%	0.58	9.16%	0.02	22.20%	0.41	7.05%	0.00	10.82%	0.65
	Unconditional	5.64%	0.01	11.22%	0.50	5.46%	0.01	11.19%	0.49	5.19%	0.02	11.19%	0.46
	Combined	16.10%	0.00	29.67%	0.54	12.72%	0.01	31.02%	0.41	12.16%	0.00	17.83%	0.68
	$CS_{t,His}$ capped timing	8.12%	0.01	15.27%	0.53	6.99%	0.02	15.21%	0.46	6.49%	0.00	10.25%	0.63
	Unconditional	5.64%	0.01	11.22%	0.50	5.46%	0.01	11.19%	0.49	5.19%	0.02	11.19%	0.46
Credit	Combined	12.44%	0.00	24.76%	0.50	11.11%	0.01	24.66%	0.45	11.59%	0.00	17.34%	0.67
	Regression timing	13.42%	0.00	17.19%	0.78	10.88%	0.00	15.35%	0.71	10.66%	0.00	11.00%	0.97
	Unconditional	5.62%	0.01	11.20%	0.50	5.45%	0.01	11.17%	0.49	5.18%	0.02	11.17%	0.46
	Combined	17.64%	0.00	26.84%	0.66	14.99%	0.00	25.26%	0.59	15.57%	0.00	19.67%	0.79
	Const. regression timing	13.73%	0.00	16.98%	0.81	11.01%	0.00	15.29%	0.72	10.67%	0.00	10.96%	0.97
	Unconditional	5.64%	0.01	11.22%	0.50	5.46%	0.01	11.19%	0.49	5.19%	0.02	11.19%	0.46
	Combined	17.87%	0.00	26.90%	0.66	15.09%	0.00	25.25%	0.60	15.49%	0.00	19.83%	0.78

Table 1.15

Summary performance statistics for joint timing strategies in the pool of asset classes.

The table presents asset class performance statistics (mean annualised return, p-value, annualised standard deviation, Sharpe ratio) for three strategies: 1) an unconditional carry strategy, 2) a timing strategy using: a pooled regression ($R^{x}_{c,t} = a + b\,(\sum_{s=1}^{12} CS^{x}_{c,t-s}/12) + \varepsilon^{x}_{c,t}$) and a cross-asset class average regression ($\overline{R}^{x}_{t} = a + b(\overline{\sum_{s=1}^{12} CS^{x}_{t-s}/12}) + \varepsilon^{x}_{t}$) that allocates $\hat{b}_{t-1}(\sum_{s=0}^{11} CS^{x}_{t-s}/12)$ dollars in the carry strategy , and 3) a combined strategy investing in both the unconditional and the timing strategy. The data is presented for three weighting portfolios: rank, median and tercile. For comparability across asset classes, returns series are standardised to 10% ex-ante annualized standard deviation.

		Rank				Median				Tercile			
ASSET CLASS	PORTFOLIO	Mean return	p-value	Standard deviation	Sharpe ratio	Mean return	p-value	Standard deviation	Sharpe ratio	Mean return	p-value	Standard deviation	Sharpe ratio
	Pooled regression												
FX	Linear timing	1.91%	0.00	2.46%	0.77	1.00%	0.00	1.39%	0.72	1.67%	0.00	2.46%	0.68
	Unconditional	5.11%	0.02	10.25%	0.50	4.41%	0.03	10.21%	0.43	4.32%	0.04	10.25%	0.42
	Combined	6.85%	0.01	12.46%	0.55	5.36%	0.02	11.46%	0.47	5.80%	0.02	12.53%	0.46
Equities	Linear timing	0.58%	0.22	2.20%	0.27	0.38%	0.19	1.32%	0.29	0.51%	0.35	2.53%	0.20
	Unconditional	2.16%	0.11	6.67%	0.32	1.74%	0.18	6.45%	0.27	1.29%	0.31	6.56%	0.20
	Combined	2.65%	0.13	8.71%	0.30	2.04%	0.18	7.64%	0.27	1.64%	0.32	9.01%	0.18
Fixed Income	Linear timing	0.66%	0.00	0.86%	0.77	0.42%	0.00	0.50%	0.83	0.92%	0.00	1.19%	0.77
	Unconditional	7.19%	0.00	7.70%	0.93	7.23%	0.00	8.04%	0.90	5.71%	0.00	7.30%	0.78
	Combined	8.05%	0.00	8.45%	0.95	7.89%	0.00	8.48%	0.93	6.74%	0.00	8.44%	0.80
Commodities	Linear timing	2.01%	0.04	4.41%	0.46	1.03%	0.09	2.77%	0.37	0.54%	0.00	0.69%	0.78
	Unconditional	4.08%	0.03	9.21%	0.44	3.38%	0.08	9.85%	0.34	6.26%	0.01	11.40%	0.55
	Combined	5.50%	0.04	13.31%	0.41	3.88%	0.10	12.34%	0.31	7.03%	0.01	12.04%	0.58
Credit	Linear timing	0.26%	0.00	0.33%	0.79	0.15%	0.00	0.19%	0.82	0.54%	0.00	0.69%	0.78
	Unconditional	6.71%	0.01	11.44%	0.59	6.42%	0.01	11.37%	0.56	6.26%	0.01	11.40%	0.55
	Combined	7.25%	0.00	11.75%	0.62	6.81%	0.01	11.56%	0.59	7.03%	0.01	12.04%	0.58
	Cross-asset class average regression												
FX	Linear timing	6.77%	0.00	8.97%	0.75	4.13%	0.02	8.01%	0.52	4.31%	0.01	7.05%	0.61
	Unconditional	5.11%	0.02	10.25%	0.50	4.41%	0.03	10.21%	0.43	4.32%	0.04	10.25%	0.42
	Combined	11.60%	0.00	17.06%	0.68	7.90%	0.02	18.07%	0.44	8.03%	0.02	17.14%	0.47
Equities	Linear timing	0.26%	0.74	8.27%	0.03	2.11%	0.15	7.15%	0.29	2.09%	0.16	7.31%	0.29
	Unconditional	2.16%	0.11	6.67%	0.32	1.74%	0.18	6.45%	0.27	1.29%	0.31	6.56%	0.20
	Combined	2.10%	0.32	13.47%	0.16	3.42%	0.16	13.45%	0.25	2.93%	0.22	13.77%	0.21
Fixed Income	Linear timing	1.35%	0.10	3.82%	0.35	2.00%	0.00	2.52%	0.79	2.51%	0.00	3.41%	0.74
	Unconditional	7.19%	0.00	7.70%	0.93	7.23%	0.00	8.04%	0.90	5.71%	0.00	7.30%	0.78
	Combined	8.64%	0.00	10.49%	0.82	9.41%	0.00	10.47%	0.90	8.24%	0.00	10.66%	0.77
Commodities	Linear timing	2.31%	0.32	15.45%	0.15	4.28%	0.15	17.74%	0.24	1.88%	0.00	1.97%	0.96
	Unconditional	4.08%	0.03	9.21%	0.44	3.38%	0.08	9.85%	0.34	6.26%	0.01	11.40%	0.55
	Combined	5.20%	0.13	22.56%	0.23	5.58%	0.13	27.42%	0.20	8.30%	0.00	13.23%	0.63
Credit	Linear timing	0.60%	0.00	0.74%	0.81	1.11%	0.00	1.21%	0.92	1.88%	0.00	1.97%	0.96
	Unconditional	6.71%	0.01	11.44%	0.59	6.42%	0.01	11.37%	0.56	6.26%	0.01	11.40%	0.55
	Combined	7.59%	0.00	12.02%	0.63	7.70%	0.00	12.52%	0.62	8.30%	0.00	13.23%	0.63

Table 1.16

Cross-asset class carry rotation strategies.

The table provides returns statistics (mean annualised return, p-value, annualised standard deviation, Sharpe ratio) for three strategies: two timing strategies that overweight (underweight) asset classes where the carry spread is relatively high (low) across N_t carry strategies using two alternative weighting schemes: the first is linear in the carry spread signal and the second takes equal weight positions above and below the mean carry spread; the third is an unconditional passive equal-weight strategy. The data is presented for three carry weighting portfolios: rank, median and tercile. All asset classes carry returns series are standardised to 10% ex-ante annualized standard deviation

	RANK				MEDIAN				TERCILE			
Strategy	Mean return	p-value	Standard deviation	Sharpe ratio	Mean return	p-value	Standard deviation	Sharpe ratio	Mean return	p-value	Standard deviation	Sharpe ratio
Unconditional	6.15%	0.00	5.77%	1.07	5.79%	0.00	5.79%	1.00	5.12%	0.00	5.60%	0.91
Rotation linear weight	6.96%	0.00	12.15%	0.57	4.50%	0.03	11.00%	0.41	0.15%	0.73	11.29%	0.01
Rotation equal weight	5.31%	0.01	10.84%	0.49	2.70%	0.15	11.16%	0.24	1.82%	0.24	9.44%	0.19

Figure 1.1

Cumulative returns of multi-asset carry portfolios.

The figure displays cumulative returns of multi-asset rank weighted carry portfolios for global (Div GL Port), developed (Div DM Port) and emerging markets (Div EM Port), using static equal volatility allocation (estimated in sample) and dynamic equal volatility allocation (estimated using one year rolling window).

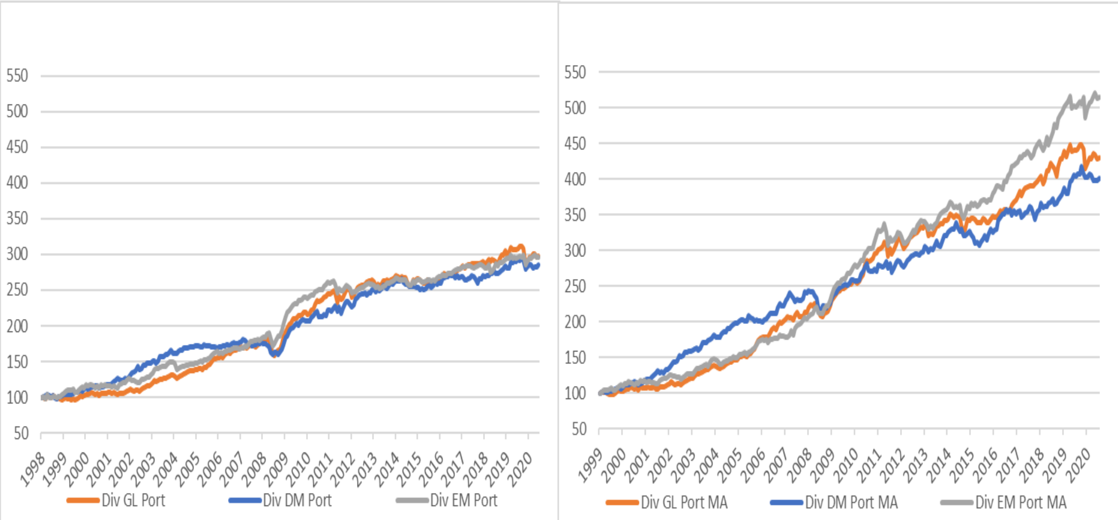


Figure 1.2

The carry spread in various asset classes.

The figure displays for various asset classes (rank portfolios) times series of standardised and cross-asset average carry spreads (in blue and red respectively).

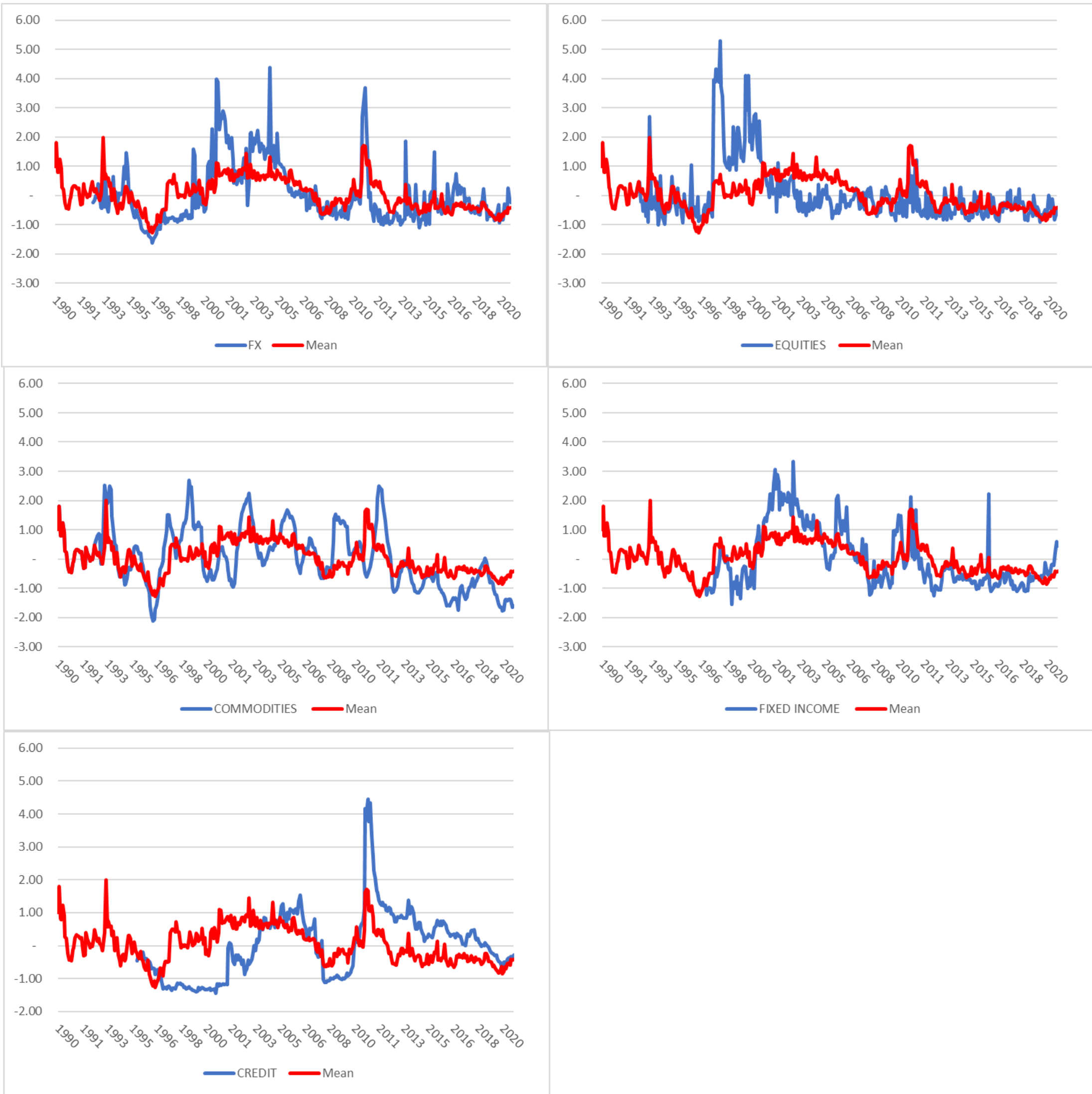
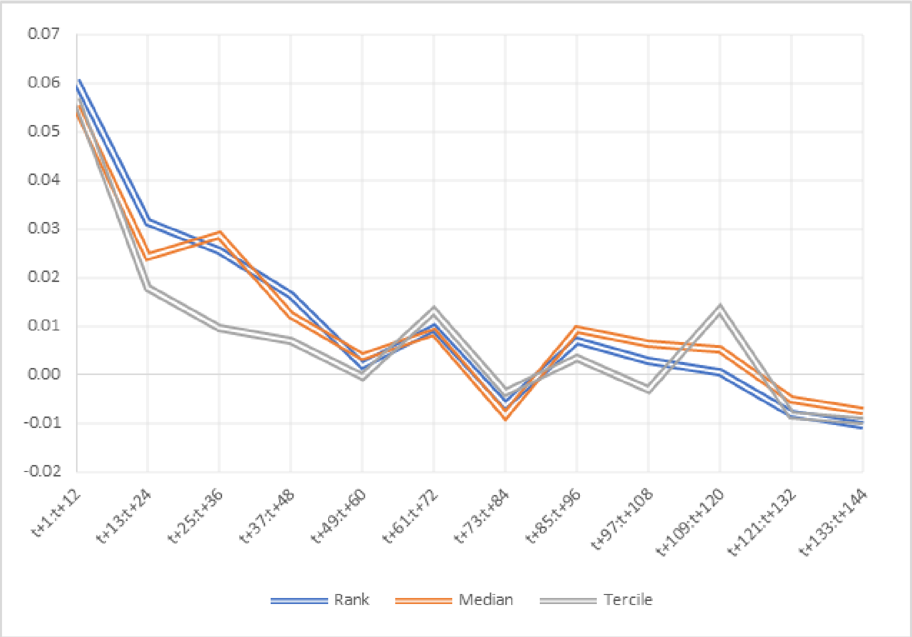


Figure 1.3

Annual future carry returns on the carry spread at time t.

The figure presents estimates of the beta coefficient on the carry spread from pooled predictive regressions estimated over successive non-overlapping annual carry returns as follows: $R_{c,t+h_1:t+h_2} = a_{h_1,h_2} + b_{h_1,h_2} CS^x_{c,t} + \varepsilon^x_{c,t+h_1:t+h_2}$ where for any carry spread observed in month t, $h_1 = 1$ and $h_2 = 12$; $h_1 = 13$ and $h_2 = 24$; $h_1 = 25$ and $h_2 = 36$ etc… and x is the portfolio weighting scheme (rank, median and tercile). Carry returns are scaled to 10% standard deviation and carry spreads are standardised to have zero mean and one standard deviation.



Appendix

Table A1.1: Global equities indices and futures tickers.

The table shows global equities indices and futures Bloomberg tickers (x=1 and x=2 respectively for 1st and 2nd generic futures).

Asset		
Equities	**Spot ticker**	**Futures ticker**
Developed markets		
AUSTRALIA	AS51 Index	XPx Index
BRITAIN	UKX Index	Z x Index
CANADA	SPTSX60 Index	PTx Index
EUROZONE	SX5E Index	VGx Index
FRANCE	CAC Index	CFx Index
GERMANY	DAX Index	GXx Index
ITALY	FTSEMIB Index	STx Index
JAPAN	NKY Index	NKx Index
NETHERLAND	AEX Index	EOx Index
SPAIN	IBEX Index	IBx Index
SWEDEN	OMX Index	QCx Index
SWITZERLAND	SMI Index	SMx Index
UNITED STATES	SPX Index	ESx Index
Emerging markets		
BRAZIL	IBOV Index	BZV0 Index
CHINA	XIN9I Index	XUx Index
HONG KONG	HSI Index	HIx Index
INDIA	NIFTY Index	NZx Index
INDONESIA	MXID INDEX	IDOx Index
MALAYSIA	FBMKLCI index	IKx Index
MEXICO	MEXBOL Index	ISx Index
POLAND	WIG20 Index	KRSx Index
RUSSIA	RTSI$ Index	VEx Index
SINGAPORE	STI Index	SDx Index
SOUTH AFRICA	TOP40 Index	AIx Index
SOUTH KOREA	KOSPI Index	KMx Index
TAIWAN	TAMSCI INDEX	TWx Index
THAILAND	SET50 Index	BCx Index
TURKEY	XU030 Index	A5V0 Index

Table A1.2: Spot and one-month forward exchange rates tickers.

The table shows spot and one-month forward exchange rates Bloomberg tickers.

Currencies		
Markets	**Spot Ticker**	**1M Forward Ticker**
Developed Markets		
AUSTRALIA	AUDUSD	AUD1M BGN Curncy
BRITAIN	GBPUSD	GBP1M BGN Curncy
CANADA	CADUSD	CAD1M BGN Curncy
DENMARK	USDDKK	DKK1M BGN Curncy
EUROZONE	EURUSD	EUR1M BGN Curncy
JAPAN	USDJPY	JPY1M BGN Curncy
NEW ZEALAND	NZDUSD	NZD1M BGN Curncy
NORWAY	USDNOK	NOK1M BGN Curncy
SWEDEN	USDSEK	SEK1M BGN Curncy
SWITZERLAND	USDCHF	CHF1M BGN Curncy
Emerging Markets		
BRAZIL	USDBRL	BCN+1M BGN Curncy
CHINA	USDCNY	CCN+1M BGN Curncy
INDONESIA	USDIDR	IHN+1M BGN Curncy
INDIA	USDINR	IRN+1M BGN Curncy
HONG KONG	USDHKD	HKD1M BGN Curncy
MEXICO	USDMXN	MXN1M BGN Curncy
POLAND	USDPLN	PLN1M BGN Curncy
RUSSIA	USDRUB	RUB1M BGN Curncy
SINGAPORE	USDSGD	SGD1M BGN Curncy
SOUTH AFRICA	USDZAR	ZAR1M BGN Curncy
SOUTH KOREA	USDKRW	KWN+1M BGN Curncy
TAIWAN	USDTWD	NTN+1M BGN Curncy
THAILAND	USDTHB	THB1M BGN Curncy
TURKEY	USDTRY	TRY1M BGN Curncy

Table A1.3: Commodities Bloomberg indices and futures tickers.

The table shows commodities Bloomberg indices and futures tickers (x=1 and x=2 respectively for 1st and 2nd generic futures).

Asset		
Commodities	**GSCI**	**Futures ticker**
Crude Oil	SPGCBRP Index	COx Comdty
Gas Oil	SPGCHUP Index	QSx Comdty
Gasoline	SPGCGOP Index	XBx Comdty
Heating oil	SPGCHOP Index	HOx Comdty
Light Sweet Crude Oil	SPGCCLP Index	CLx Comdty
Natural Gas	SPGCNGP Index	NGx Comdty
Gold	SPGCGCP Index	GCx Comdty
Palladium	SPGCPAP Index	PAx Comdty
Platinum	SPGCPLP Index	PLx Comdty
Silver	SPGCSIP Index	SIx Comdty
Aluminum	SPGCIAP Index	LAx Comdty
Copper	SPGCICP Index	HGx Comdty
Lead	SPGCILP Index	LLx Comdty
Nickel	SPGCIKP Index	LNx Comdty
Zinc	SPGCIZP Index	LXx Comdty
Cocoa	SPGCCCP Index	CCx Comdty
Coffee	SPGCKCP Index	KCx Comdty
Corn	SPGCCNP Index	Cx Comdty
Cotton	SPGCCTP Index	CTx Comdty
Soybean	SPGCSOP Index	Sx Comdty
Sugar	SPGCSBP Index	SBx Comdty
Wheat	SPGCWHP Index	Wx Comdty
Feeder Cattle	SPGCFCP Index	FCx Comdty
Lean Hogs	SPGCLHP Index	LHx Comdty
Live Cattle	SPGCLCP Index	LCx Comdty

Table A1.4: Fixed income zero coupon yields tickers.

The table shows Bloomberg tickers for zero coupon yields of bonds of global and emerging markets countries with maturities of 9 and 10 years.

Fixed Income		
	Ticker	
Markets	Zero coupon 9Y	Zero coupon 10Y
Developed markets		
AUSTRALIA	F12709Y Index	F12710Y Index
BRITAIN	F11009Y Index	F11010Y Index
CANADA	F10109Y Index	F10110Y Index
FRANCE	F90509Y Index	F90510Y Index
GERMANY	F90509Y Index	F90510Y Index
ITALY	F90509Y Index	F90510Y Index
JAPAN	I01809Y Index	I01810Y Index
NEW ZEALAND	F25009Y Index	F25010Y Index
NORWAY	F26609Y Index	F26610Y Index
SWEDEN	F25909Y Index	F25910Y Index
SWITZERLAND	F25609Y Index	F25610Y Index
UNITED STATES	F08209Y Index	F08210Y Index
Emerging markets		
BRAZIL	I39309Y Index	I39310Y Index
CHILE	I35109Y Index	I35110Y Index
CHINA	F02009Y Index	F02010Y Index
COLOMBIA	F47709Y Index	F47710Y Index
HONG KONG	F12509Y Index	F12510Y Index
HUNGARY	F11409Y Index	F11410Y Index
INDONESIA	F13209Y Index	F13210Y Index
MEXICO	F47609Y Index	F47610Y Index
PHILIPPINE	I10509Y Index	I10510Y Index
POLAND	F11909Y Index	F11910Y Index
RUSSIA	F49609Y Index	F49610Y Index
SINGAPORE	F12409Y Index	F12410Y Index
SOUTH AFRICA	F26209Y Index	F26210Y Index
TURKEY	F96509Y Index	F96510Y Index

Table A1.5: Bloomberg credit indices tickers.

The table shows Bloomberg tickers for credit indices across different geographies, ratings and maturities.

Asset	
US Credit - IG	**Ticker**
1-3Y	LU13TRUU Index
3-5Y	LU35TRUU Index
5-7Y	LU57TRUU Index
7-10Y	LU71TRUU Index
10+Y	LU10TRUU Index
Pan-European Credit - IG	
1-3Y	I02553EU Index
3-5Y	I02554EU Index
5-7Y	I02555EU Index
7-10Y	I02556EU Index
10+Y	I02557EU Index
APAC Credit - IG	
1-3Y	I02849JP Index
3-5Y	I02850JP Index
5-7Y	I02851JP Index
7-10Y	I02852JP Index
10+Y	I02853JP Index
US Credit - HY	
3-5Y	I33393 Index
5-7Y	I33391 Index
7-10Y	I33392 Index
EM credit	
1-3Y	I12885US Index
3-5Y	I12886US Index
5-7Y	I12887US Index
7-10Y	I12888US Index
10+Y	I12889US Index

Table A1.6: Equities descriptive statistics.

Equities country list with series start date and annualised mean and standard deviation of carry and excess returns.

Asset	Start date	Carry		Excess Return	
		Mean	St. dev.	Mean	St. dev.
Equities					
Developed markets					
AUSTRALIA	15/03/2001	2.67%	1.71%	3.75%	13.51%
BRITAIN	20/06/1988	0.33%	1.91%	3.51%	14.38%
CANADA	15/06/2000	0.18%	1.93%	3.47%	13.99%
EUROZONE	18/12/1998	1.75%	2.94%	-0.52%	18.86%
FRANCE	28/02/1989	1.51%	1.91%	3.28%	18.29%
GERMANY	14/03/1991	-2.68%	1.99%	7.12%	20.19%
ITALY	17/09/2004	1.95%	2.86%	-1.96%	20.31%
JAPAN	07/03/1989	0.22%	1.75%	-0.78%	21.00%
NETHERLAND	17/03/1989	0.93%	1.43%	4.63%	18.20%
SPAIN	21/08/1992	2.32%	1.83%	4.13%	20.65%
SWEDEN	22/04/2005	2.37%	1.94%	5.72%	16.08%
SWITZERLAND	30/06/2000	2.31%	1.95%	0.99%	13.78%
UNITED STATES	16/09/1982	-0.82%	1.16%	9.02%	15.18%
Emerging markets					
BRAZIL	14/02/1996	-8.75%	4.22%	15.80%	28.48%
CHINA	30/01/2007	3.68%	3.94%	6.08%	31.53%
HONG KONG	29/06/1992	1.79%	2.04%	5.43%	25.50%
INDIA	28/09/2000	-0.95%	1.61%	12.26%	23.46%
INDONESIA	30/08/2012	-1.82%	2.73%	3.17%	16.23%
MALAYSIA	29/02/1996	1.16%	1.30%	2.36%	21.64%
MEXICO	28/09/1999	-4.80%	2.13%	10.23%	18.92%
POLAND	21/03/2014	0.48%	2.30%	-5.50%	17.17%
RUSSIA	14/12/2005	6.07%	4.85%	4.98%	32.58%
SINGAPORE	30/08/2000	-4.80%	4.81%	0.89%	17.45%
SOUTH AFRICA	15/12/1994	-17.73%	10.97%	9.46%	19.25%
SOUTH KOREA	12/09/1996	-0.31%	4.96%	6.08%	31.77%
TAIWAN	28/03/1997	4.74%	3.49%	2.35%	24.23%
THAILAND	29/06/2006	5.89%	2.04%	-3.61%	16.32%
TURKEY	30/12/2005	7.83%	3.28%	10.55%	28.04%

Table A1.7: Currencies descriptive statistics.

Currencies country list with series start date and annualised mean and standard deviation of carry and excess returns.

Currencies	Start date	Carry		Excess Return	
		Mean	St. dev.	Mean	St. dev.
Markets					
Developed Markets					
AUSTRALIA	31/01/1990	2.01%	0.58%	1.70%	11.29%
BRITAIN	31/01/1990	1.12%	0.60%	0.27%	9.16%
CANADA	31/01/1990	-0.47%	0.65%	-0.84%	7.79%
DENMARK	31/01/1990	-0.16%	0.88%	-0.23%	9.91%
EUROZONE	31/12/1998	-0.70%	0.41%	-0.69%	9.76%
JAPAN	31/01/1990	2.26%	0.64%	1.20%	10.40%
NEW ZEALAND	31/01/1990	2.48%	0.49%	2.80%	11.37%
NORWAY	31/01/1990	-1.27%	0.90%	-0.04%	11.07%
SINGAPORE	31/01/1990	0.66%	0.54%	-0.35%	5.57%
SWEDEN	31/01/1990	-0.67%	0.92%	0.52%	11.45%
SWITZERLAND	31/01/1990	1.47%	0.60%	-0.15%	10.56%
Emerging Markets					
BRAZIL	30/09/1998	-8.61%	4.36%	-1.87%	22.60%
CHINA	31/12/1998	-0.09%	1.57%	-1.04%	2.99%
INDONESIA	30/03/2001	-7.78%	3.05%	-6.14%	11.05%
INDIA	31/12/1998	-5.41%	1.50%	-2.96%	7.05%
HONG KONG	31/01/1990	0.04%	0.33%	0.01%	0.58%
MEXICO	28/11/1997	-6.30%	1.56%	-2.35%	11.72%
POLAND	31/07/1998	-3.46%	1.20%	-2.86%	13.54%
RUSSIA	31/08/2001	-6.22%	2.22%	-1.23%	14.03%
SINGAPORE	31/01/1990	0.66%	0.54%	-0.35%	5.57%
SOUTH AFRICA	31/01/1990	-6.97%	0.79%	-1.22%	14.76%
SOUTH KOREA	31/12/1998	-1.45%	1.56%	-1.71%	10.32%
TAIWAN	30/11/1998	1.75%	1.32%	1.13%	4.66%
THAILAND	29/09/1995	-2.53%	1.45%	-1.69%	10.57%
TURKEY	31/12/1996	-17.91%	4.75%	-4.15%	18.20%

Table A1.8: Commodities descriptive statistics.

Commodities list with series start date and annualised mean and standard deviation of carry and excess returns.

Asset	Start date	Carry		Excess Return	
		Mean	St. dev.	Mean	St. dev.
Commodities					
Crude Oil	31/01/1991	0.04%	6.16%	2.27%	30.18%
Gas Oil	31/01/1991	0.00%	5.66%	-0.13%	29.74%
Gasoline	30/01/1987	0.92%	15.05%	-8.89%	36.05%
Heating oil	30/01/1987	1.88%	11.36%	0.48%	30.83%
Light Sweet Crude Oil	31/01/1984	-1.01%	7.52%	-1.36%	35.40%
Natural Gas	31/01/1991	-23.59%	20.27%	-18.50%	44.72%
Gold	31/01/1980	-4.04%	0.91%	-0.98%	16.17%
Palladium	31/12/1997	-0.71%	1.99%	10.68%	35.19%
Platinum	31/01/1991	-0.03%	1.08%	2.74%	20.76%
Silver	31/01/1980	-5.26%	1.79%	-3.09%	28.88%
Aluminum	31/01/1991	-4.69%	1.68%	-3.56%	18.90%
Copper	31/01/1989	1.66%	2.44%	3.73%	24.66%
Lead	31/01/1991	-1.70%	2.65%	3.72%	28.03%
Nickel	31/01/1991	0.45%	2.07%	4.51%	34.89%
Zinc	31/01/1991	-3.17%	1.92%	-0.42%	25.76%
Cocoa	31/01/1980	-5.39%	3.17%	-6.73%	28.89%
Coffee	31/01/1980	-2.74%	34.39%	-6.69%	36.35%
Corn	31/01/1980	-8.96%	5.12%	-8.47%	25.01%
Cotton	31/01/1980	-3.52%	6.37%	-2.59%	24.39%
Soybean	31/01/1980	-0.61%	5.88%	-0.64%	22.79%
Sugar	31/01/1980	-13.27%	17.65%	-7.32%	36.01%
Wheat	31/01/1980	-8.16%	5.19%	-8.61%	25.57%
Feeder Cattle	31/01/1991	-0.48%	4.42%	0.31%	14.83%
Lean Hogs	30/01/1987	-19.62%	18.99%	-9.50%	25.39%
Live Cattle	31/01/1980	2.72%	6.20%	0.89%	14.45%

Table A1.9: Fixed income descriptive statistics.

10-year bond country list with series start date and annualised mean and standard deviation of carry and excess returns.

Asset	Start date	Carry		Excess Return	
		Mean	St. dev.	Mean	St. dev.
Fixed Income 10Y					
Developed markets					
AUSTRALIA	30/12/1994	1.24%	0.30%	-0.87%	8.91%
BRITAIN	30/12/1994	1.45%	0.66%	0.12%	7.54%
CANADA	30/12/1994	2.18%	0.42%	0.57%	7.12%
FRANCE	30/04/1998	2.68%	0.40%	0.95%	6.61%
GERMANY	31/10/1991	1.93%	0.43%	0.53%	6.54%
ITALY	30/09/1998	3.29%	0.49%	0.08%	8.90%
JAPAN	28/04/1989	1.83%	0.53%	0.63%	6.63%
NEW ZEALAND	30/12/1994	1.00%	0.53%	-1.80%	8.51%
NORWAY	31/07/1998	1.15%	0.41%	-0.99%	6.85%
SWEDEN	30/12/1994	2.11%	0.33%	1.77%	7.69%
SWITZERLAND	30/12/1994	2.23%	0.30%	1.50%	5.42%
UNITED STATES	30/12/1994	2.12%	0.57%	0.35%	8.84%
Emerging markets					
BRAZIL	30/03/2007	1.80%	0.61%	-4.70%	25.71%
CHILE	30/09/2005	1.20%	0.84%	-2.08%	10.28%
CHINA	30/09/2003	1.82%	0.40%	-2.56%	6.54%
COLOMBIA	29/04/2005	2.97%	0.56%	-0.37%	15.50%
HONG KONG	31/07/1997	2.58%	0.50%	1.15%	11.00%
HUNGARY	30/06/1998	-0.25%	1.12%	0.03%	18.97%
INDONESIA	28/02/2003	3.08%	0.88%	-2.74%	23.21%
MEXICO	30/09/2002	2.32%	0.53%	-2.99%	12.11%
PHILIPPINES	28/06/1996	3.42%	1.51%	-0.76%	32.63%
POLAND	29/05/1998	-0.51%	1.37%	1.42%	14.20%
RUSSIA	31/01/2007	1.12%	0.78%	-4.80%	23.10%
SINGAPORE	30/06/1998	2.47%	0.45%	0.34%	8.23%
SOUTH AFRICA	30/12/1994	1.89%	0.81%	-5.45%	16.08%
TURKEY	29/04/2005	-0.35%	1.00%	-6.92%	32.16%

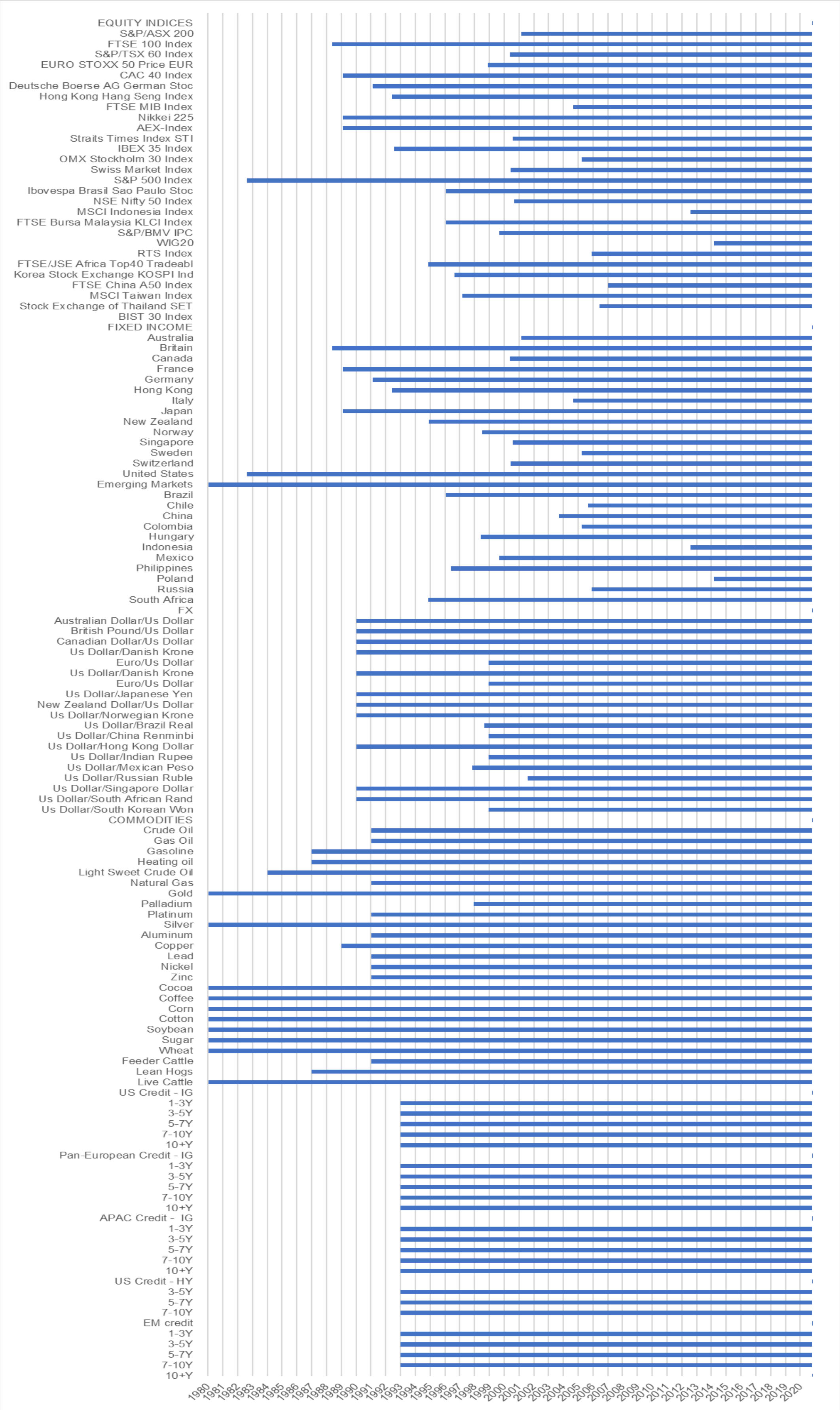
Table A1.10: Credit descriptive statistics.

Credit curves by maturity list with series start date and annualised mean and standard deviation of carry and excess returns.

Asset	Start date	Carry		Excess Return	
		Mean	St. dev.	Mean	St. dev.
US Credit - IG					
1-3Y	29/01/1993	0.72%	0.15%	0.56%	0.72%
3-5Y	29/01/1993	0.84%	0.15%	0.58%	0.71%
5-7Y	29/01/1993	0.74%	0.11%	0.51%	0.68%
7-10Y	29/01/1993	0.45%	0.08%	0.49%	0.74%
10+Y	29/01/1993	0.27%	0.05%	0.37%	0.72%
Pan-European Credit - IG					
1-3Y	EUR % CH M	0.86%	0.14%	0.83%	1.04%
3-5Y	EUR % CH M	0.68%	0.09%	0.74%	0.91%
5-7Y	EUR % CH M	0.62%	0.09%	0.67%	0.92%
7-10Y	EUR % CH M	0.56%	0.07%	0.58%	0.93%
10+Y	EUR % CH M	0.36%	0.03%	0.36%	0.83%
APAC Credit - IG					
1-3Y	JPY % CH M	0.33%	0.04%	0.34%	0.99%
3-5Y	JPY % CH M	0.20%	0.03%	0.29%	0.43%
5-7Y	JPY % CH M	0.22%	0.03%	0.31%	0.37%
7-10Y	JPY % CH M	0.21%	0.03%	0.31%	0.35%
10+Y	JPY % CH M	0.15%	0.02%	0.25%	0.33%
US Credit - HY					
3-5Y	30/07/1999	2.25%	0.23%	1.83%	2.77%
5-7Y	30/07/1999	1.47%	0.21%	1.41%	2.27%
7-10Y	30/07/1999	0.76%	0.10%	0.86%	1.87%
EM credit					
1-3Y	29/08/2003	2.39%	0.38%	1.68%	2.99%
3-5Y	29/08/2003	1.65%	0.25%	1.26%	2.75%
5-7Y	29/08/2003	1.10%	0.19%	1.16%	2.00%
7-10Y	29/08/2003	0.75%	0.13%	0.86%	1.73%
10+Y	29/08/2003	0.78%	0.09%	0.79%	1.35%

Figure A1.1: Asset universe and data series start date.

The figure presents the asset universe per asset class and the data series start date.



References

Ahmerkamp, Jan Danilo, and James Alexander Grant, 2013, The Returns to Carry and Momentum Strategies: Business Cycles, Hedge Fund Capital and Limits to Arbitrage, *SSRN Electronic Journal*.

Arnott, Robert D., Noah Beck, and Vitali Kalesnik, 2016, Timing “smart beta" Strategies? Of course! Buy Low, Sell High!, Research Affiliates Publications

Asness, Clifford, and Andrea Frazzini, 2013, The Devil in HML’s Details, *The Journal of Portfolio Management* 39, 49–68.

Asness, Clifford S., Jacques A. Friedman, Robert J. Krail, and John M. Liew, 2000, Style Timing, *The Journal of Portfolio Management* 26, 50–60.

Asness, Clifford S., John M. Liew, Lasse Heje Pedersen, and Ashwin K Thapar, 2017, Deep Value, *SSRN Electronic Journal*.

Asness, Clifford S., Tobias J. Moskowitz, and Lasse Heje Pedersen, 2013, Value and Momentum Everywhere, *The Journal of Finance* 68, 929–985.

Baba Yara, Fahiz, Martijn Boons, and Andrea Tamoni, 2021, Value Return Predictability across Asset Classes and Commonalities in Risk Premia, *Review of Finance* 25, 449–484.

Baltas, Nick, 2017, Optimizing Cross-Asset Carry, Factor Investing (Elsevier).

Baz, Jamil, Nicolas M Granger, Campbell R. Harvey, Nicolas le Roux, and Sandy Rattray, 2015, Dissecting Investment Strategies in the Cross Section and Time Series, *SSRN Electronic Journal*.

Bekaert, Geert, and George Panayotov, 2020, Good Carry, Bad Carry, *Journal of Financial and Quantitative Analysis* 55, 1063–1094.

Bhardwaj, Geetesh, Gary B. Gorton, and K. Geert Rouwenhorst, 2015, Facts and Fantasies About Commodity Futures Ten Years Later, *SSRN Electronic Journal*.

Boudoukh, Jacob, Ronen Israel, and Matthew Richardson, 2019, Long-Horizon Predictability: A Cautionary Tale, *Financial Analysts Journal* 75, 17–30.

Boudoukh, Jacob, Matthew Richardson, and Robert F. Whitelaw, 2008, The Myth of Long-Horizon Predictability, *Review of Financial Studies* 21, 1577–1605.

Brunnermeier, Markus K., Stefan Nagel, and Lasse H. Pedersen, 2008, Carry Trades and Currency Crashes, *NBER Macroeconomics Annual* 23, 313–348.

Brunnermeier, Markus K., and Lasse Heje Pedersen, 2009, Market Liquidity and Funding Liquidity, *Review of Financial Studies* 22, 2201–2238.

Campbell, John Y., and Samuel B. Thompson, 2008, Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average?, *Review of Financial Studies* 21, 1509–1531.

Cederburg, Scott, Travis L. Johnson, and Michael S. O'Doherty, 2018, On the Economic Value of Stock Market Return Predictors, *SSRN Electronic Journal*.

Cenesizoglu, Tolga, and Allan G. Timmermann, 2011, Do Return Prediction Models Add Economic Value?, *SSRN Electronic Journal*.

Daniel, Kent, Robert J. Hodrick, and Zhongjin Lu, 2017, The Carry Trade: Risks and Drawdowns, *Critical Finance Review* 6, 211–262.

Engel, Charles, 1996, The forward discount anomaly and the risk premium: A survey of recent evidence, *Journal of Empirical Finance* 3, 123–192.

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

Fama, Eugene F., and Kenneth R. French, 1992, The Cross-Section of Expected Stock Returns, *The Journal of Finance* 47, 427–465.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Farhi, Emmanuel, and Xavier Gabaix, 2016, Rare Disasters and Exchange Rates, *The Quarterly Journal of Economics* 131, 1–52.

Gorton, Gary B., Fumio Hayashi, and K. Geert Rouwenhorst, 2013, The Fundamentals of Commodity Futures Returns, *Review of Finance* 17, 35–105.

Haddad, Valentin, Serhiy Kozak, and Shrihari Santosh, 2017, Predicting Relative Returns. No 23886, *NBER Working Papers*, National Bureau of Economic Research, Inc.

Hamdan, Rayann, Fabien Pavlowsky, Thierry Roncalli, and Ban Zheng, 2016, A Primer on Alternative Risk Premia, *SSRN Electronic Journal*.

Hansen, Lars Peter, and Robert J. Hodrick, 1980, Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis, *Journal of Political Economy* 88, 829–853.

Hou, Kewei, Chen Xue, and Lu Zhang, 2017, Replicating Anomalies, *SSRN Electronic Journal*.

Ilmanen, Antti S., Ronen Israel, Tobias J. Moskowitz, Ashwin K Thapar, and Franklin Wang, 2019, Factor Premia and Factor Timing: A Century of Evidence, *SSRN Electronic Journal*.

Kandel, Shmuel, and Robert F. Stambaugh, 1996, On the Predictability of Stock Returns: An Asset-Allocation Perspective, *The Journal of Finance* 51, 385–424.

Kelly, Bryan, and Seth Pruitt, 2013, Market Expectations in the Cross-Section of Present Values, *The Journal of Finance* 68, 1721–1756.

Keloharju, Matti, Juhani T. Linnainmaa, and Peter Nyberg, 2021, Are return seasonalities due to risk or mispricing?, *Journal of Financial Economics* 139, 138–161.

Keynes, John Maynard, 1965, A Treatise on Money. 15th ed. (Macmillan & Co., London).

Koijen, Ralph S.J., Tobias J. Moskowitz, Lasse Heje Pedersen, and Evert B. Vrugt, 2018, Carry, *Journal of Financial Economics* 127, 197–225.

Lazarus, Eben, Daniel J. Lewis, James H. Stock, and Mark W. Watson, 2018, HAR Inference: Recommendations for Practice, *Journal of Business & Economic Statistics* 36, 541–559.

Lettau, Martin, Matteo Maggiori, and Michael Weber, 2013, Conditional Risk Premia in Currency Markets and Other Asset Classes, *SSRN Electronic Journal*.

Lewellen, Jonathan, 2004, Predicting returns with financial ratios, *Journal of Financial Economics* 74, 209–235.

Lustig, Hanno, Nikolai Roussanov, and Adrien Verdelhan, 2011, Common Risk Factors in Currency Markets, *Review of Financial Studies* 24, 3731–3777.

Lustig, Hanno, and Adrien Verdelhan, 2007, The Cross Section of Foreign Currency Risk Premia and Consumption Growth Risk, *American Economic Review* 97, 89–117.

Menkhoff, Lukas, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf, 2012, Carry Trades and Global Foreign Exchange Volatility, *The Journal of Finance* 67, 681–718.

Moskowitz, Tobias J., Yao Hua Ooi, and Lasse Heje Pedersen, 2012, Time series momentum, *Journal of Financial Economics* 104, 228–250.

Newey, Whitney K., and Kenneth D. West, 1987, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703.

Potì, Valerio, Richard Levich, and Thomas Conlon, 2020, Predictability and pricing efficiency in forward and spot, developed and emerging currency markets, *Journal of International Money and Finance* 107, 102223.

Stambaugh, Robert F., 1999, Predictive regressions, *Journal of Financial Economics* 54, 375–421.

Timmermann, Allan, 2018, Forecasting Methods in Finance, *Annual Review of Financial Economics* 10, 449–479.

Valkanov, Rossen, 2003, Long-horizon regressions: theoretical results and applications, *Journal of Financial Economics* 68, 201–232.

2. VOLATILITY CARRY

by

Walid Khalfallah

Abstract

This paper identifies common risk factors in cross-sectional volatility carry returns across various asset classes. A strategy which takes long and short positions in forward volatility agreements and volatility swaps of assets with respectively high and low volatility carry generate significant excess returns. Panel regressions of volatility returns on volatility carry show consistently positive relationship in each underlying asset class, confirming volatility carry as strong predictor of volatility returns. Timing strategies based on this evidence show positive risk adjusted returns exceeding those generated by carry strategies on underlying markets. While volatility carry returns are related to volatility premia, carry still produces significant positive alpha in each market. Other risk factors proposed in the literature such as underlying asset carry, volatility changes, global liquidity shocks and transaction costs are not able to justify the variation in cross-sectional volatility returns.

Keywords: Forward Volatility Agreement, Volatility Swaps, Multi-asset Class, Risk Premia, Factor Timing, Liquidity Risk, Volatility Risk.

2.1 Introduction

The literature on volatility risk premia has been traditionally split by asset class, thus ignoring their cross asset class dynamics. Indeed, numerous studies document the presence of significant volatility risk premia in equities, fixed income, and foreign exchange markets (e.g. Carr and Wu (2009), Kozhan, Neuberger, and Schneider (2013), Della Corte, Kozhan, and Neuberger (2021)) however the cross asset properties of these premia remain unexplored. Similarly research on carry has covered almost exclusively currencies, with very few studies on cross asset class carry interaction (Baltas (2017), Koijen et al. (2018), Baz et al. (2015)). Although Koijen et al. (2018) expanded considerably the asset class mix, volatility products were limited to only puts and calls on US equity indices. Trading volatility using options is inefficient since it exposes the investor to other risks (directional risk of the underlying and time to expiry) besides volatility.

This paper contributes to the literature by extending the notion of carry beyond conventional markets to include volatility, while also analyzing volatility risk premia in cross asset setting using volatility swaps (VS) and forward volatility agreements (FVA). These are ‘pure play’ volatility instruments that do not require the risk hedging associated with options trading. High average returns obtained on these instruments confirms that volatility risk premia are present across all underlying asset classes, both in spot and forward markets. However, risk adjusted returns are consistently higher for VS compared to FVA indicating that spot volatility premia are wider than forward volatility premia. . This is explained by the fact that the bias of implied versus realised volatility is larger than the bias of forward implied versus spot implied volatility. The findings also show that while risk adjusted returns for VS are broadly comparable at various asset classes those of FVA are more heterogeneous.

Koijen et al. (2018) define carry as the return on a forward or futures when the underlying spot price stays constant. Applying this general definition, volatility carry refers to the roll down along the implied volatility curve term structure, whereby volatility futures (or forwards) are essentially forward contracts on future implied volatility. However, there is no cost of carry relationship between the underlying volatility and its futures, as is standard between spot and futures prices of other exchange-traded assets.

This paper studies cross-asset volatility carry by analyzing the cross-sectional variation in volatility returns for various underlying asset classes. A volatility carry strategy that holds long positions in high-carry instruments and short positions in low-carry instruments performs well in each underlying market with a Sharpe ratio of 1.9 and 2.2 for FVA and VS portfolios respectively, confirming that volatility carry is a strong predictor of cross sectional volatility returns. Moreover, a diversified volatility carry strategy across various asset classes achieves a Sharpe ratio of 3.9 and 4.9 for FVA and VS portfolios respectively using dynamic asset allocation. These returns are much higher than those achieved on carry trade strategies in traditional asset classes where Koijen et al. (2018) obtain Sharpe ratios averaging 0.8 across several markets and 1.2 for the global diversified portfolio.

Volatility carry returns generally exhibit symmetrical to mildly negative skewness, indicating that market downside risks are unlikely to explain these returns. FVA based strategies generally show excess kurtosis compared to VS based strategies. Among the various asset classes, commodities (VS and FVA strategies) and emerging market assets (equities and FX) display particularly large excess kurtosis indicating fat-tailed positive and negative excess returns. Compared to single asset class strategies the diversified volatility carry portfolio shows significantly reduced skewness (less than -0.50) and much thinner tails.

The paper also examines the time-series predictability of volatility carry strategies. Panel regressions of volatility returns on volatility carry show consistently positive and significant beta in each underlying asset class, validating volatility carry as strong predictor of volatility returns. Generally, the beta coefficient is lower than one, with relatively little variation across various asset classes both for FVA and VS instruments, indicating that the market recovers part of the volatility carry. Overall, the results fail to support the expectation hypothesis and indicate a time varying volatility risk premia. Volatility term structure is thus a biased predictor of future volatility, either implied or realised; and a strategy consisting in selling (buying) forward or spot implied volatility when they are at a respective premium (discount) to spot or realised is profitable on average. This strategy is exactly analogous to carry strategies in traditional asset classes.

While volatility carry returns are related to volatility premia (short volatility returns), carry still produces significant positive alpha in each market. This study complements Koijen et al. (2018) paper by showing that carry predicts returns not only among traditional asset classes but also across volatility. In particular volatility carry subsumes volatility return predictability by the short volatility factor.

Based on the evidence suggesting that the return on volatility carry is predictable two volatility carry timing strategies are constructed. The first buys (sells) a security showing a positive carry (negative), while the second buys (sells) a security showing an above (below) historical average carry. In line with the panel regressions results, carry timing strategies generate positive Sharpe ratios averaging from 1.3 to 1.5 for the FVA and VS portfolios. A global carry timing strategy combining volatility portfolios across asset classes results in attractive Sharpe ratios ranging from 1.8 to 2.6 for the FVA portfolios and from 1.7 to 4.0 for the VS portfolios, depending on whether the asset allocation is static or dynamic.

Having demonstrated that volatility carry returns are predictable across time and various underlying asset classes, the study assesses potential economic sources behind these returns. First it examines if underlying asset carry factor can explain volatility carry returns (Della Corte, Kozhan, and Neuberger (2021), Koijen et al. (2018)). None of the underlying assets carry produces significant betas with positive alpha with respect to the carry factor across all asset classes. Second, the study considers for each underlying asset class, downside risk measures developed by Henriksson and Merton (1981), Lettau, Maggiori, and Weber (2013). The results are mixed across FVA and VS strategies with downside betas significant mainly for the tail risk measure. These findings support the idea that downside risk explains part of volatility carry returns, remaining alphas are positive and significant suggesting that downside risk is not the whole story. Third, the study considers carry returns vulnerability to liquidity and volatility risks (Acharya and Pedersen (2005), Campbell et al. (2018)). The exposure to volatility risk has mainly a negative sign across assets classes and volatility instruments, whereas for liquidity risk the sign of the relationship is less consistent. Apart from equities, where liquidity and volatility risks seems to largely explain volatility carry returns, alphas remain significant across the remaining asset classes and the multiasset portfolios indicating that these risks are insufficient to account for volatility carry returns. Further, looking at the volatility carry strategies drawdowns versus a global recession indicator, historically none of the biggest drawdowns coincide with increased probability of global recessions.

Volatility carry strategies entail substantial amount of turnover ranging from 52.5% to 64.7% per month across various asset classes and volatility instruments. Using delta neutral straddles as proxy for FVA and VS instruments (Della Corte, Kozhan, and Neuberger (2021)), associated estimated transaction costs were found to considerably impact risk adjusted returns. Still, most strategies achieve positive Sharpe ratios even under a full bid-ask spread cost scenario (excluding FX FVA and emerging markets equities FVA portfolios). Taken together, high transaction costs do not explain volatility carry returns with carry strategies typically achieving positive performance net of trading costs.

This paper contributes to recent literature on risk premia, which studies the carry factor in a cross-sectional and multiasset class setting (Koijen et al. (2018), Baltas (2017)) by expanding the analysis to the volatility asset class. Studying volatility across various markets concurrently determines both general and distinct aspects of volatility return predictability. The study also adds to the literature on volatility risk premia and their term structure, where traditionally the research has been segregated by asset class most notably equities (Johnson (2017)) and currencies (Della Corte, Kozhan, and Neuberger (2021)), as well as on the time-varying characteristic of volatility risk which changes with the volatility level and market environment (Todorov (2010), Aït-Sahalia, Karaman, and Mancini (2020)).

The remainder of the study is set as follows. Section 2 defines volatility carry, its term structure as well as the instruments considered. Section 3 lays the context for the study and outlines the data set used. Section 4 explores single asset class and global volatility premia. Section 5 examines conditioning volatility risk premia on volatility carry across multiple asset classes and instruments. Section 6 analyses the cross-section of volatility risk premia within single and multiasset classes, assesses their relation to the short volatility strategy and evaluates timing strategies. Section 7 tests potential explanations for volatility carry returns including liquidity, volatility, downside, and transaction costs. Section 8 concludes indicating the significance of the findings for the carry factor, asset pricing and the volatility risk premia.

2.2 Definition of carry on volatility

Koijen et al. (2018) define an asset's carry as the pay off on a long futures or a forward position when the underlying spot price remains the same during the holding period. Therefore, an asset's carry can be observed in the behaviour of its underlying futures or forward market whereby it represents the slope of the futures or forward curve. Under stable market conditions no shifts occur in the term structure and therefore excess return is equal to the futures (or forward) roll yield (Baltas (2017)). The latter is expected to be positive (negative) for a downward (upward) sloping term structure. Volatility term structure is generally in contango, hence volatility carry is on average negative, but it becomes positive following financial and economic turmoil during which the term structure typically inverts as volatility bursts upwards (Koijen et al. (2018)). Volatility futures (or forwards) are essentially forward contracts on future implied volatility, therefore volatility carry can be considered as the roll down along the implied volatility curve term structure. However, there is no cost of carry relationship between the underlying volatility and its futures, as is standard between spot and futures prices of other exchange-traded assets (volatility futures prices do not contain elements related to insurance, storage, and transportation costs as it is the case for commodities for example). Instead, by construction, a position in a volatility futures or forward is an expression which links today's expected volatility to tomorrow's expected volatility. To understand this dynamic and taking the VIX as an example, the volatility index represents the conditional risk-neutral expectation of the square root of the realised variance for the SPX index over the next calendar month (Cheng (2019)):

$$VIX_t = \sqrt{E_t^Q[VAR_{t,t+1}^{SPX}]} \qquad (1)$$

which can be written as:

$$VIX_t \cong E_t^Q[\sigma_{t,t+1}^{SPX}] \qquad (2)$$

where VIX_t, $VAR_{t,t+1}^{SPX}$ and $\sigma_{t,t+1}^{SPX}$ respectively represent the implied volatility estimate, the realised variance and the realized volatility of the SPX from time t to $t+1$ months later. VIX futures instead link expected volatility over time:

$$F_t^T = E_t^Q[VIX_T] \qquad (3)$$

where F_t^T represents the forward price on date t with expiration date T that is the conditional risk neutral expectation at time t of the VIX at date T. Joining these two definitions allow to link expected volatility over time to realised volatility which forms the backdrop of various traded volatility products. Indeed combining equations (2) and (3) allows the expression of the futures price as the iterative expectation at time t of the realized volatility of the SPX index over the period T to T+1, where T represents the first future date:

$$F_t^T = E_t^Q[E_T^Q[\sigma_{T,T+1}^{SPX}]] \qquad (4)$$

This dynamic or interaction between VIX, VIX futures and SPX realised volatility is illustrated in Figure 1. The dashed arrows represent the periods over which expectations apply and show that the first futures on VIX maturing at date T (F_t^T) is the iterative expectation at time t of the SPX index realized volatility over the period T to $T+1$ ($\sigma_{T,T+1}^{SPX}$).

2.2.1 *Volatility carry and volatility risk term premia*

Volatility products are relatively new, for example futures on the VIX index (where their payoff equals VIX) were only launched in 2004 by the Chicago Board Options Exchange. While new volatility futures on various indices are being introduced across the globe, these still suffer from low liquidity and a short trading history. Therefore this study will analyse volatility carry using over the counter (OTC) instruments such as forward volatility agreements (FVAs) and volatility swaps (VSs). Indeed, in addition to futures, the volatility term structure can be also traded via FVA and VS instruments. These OTC derivatives are forward contracts enabling market participants to bet on the future level of implied (FVA) or realised volatility (VS) for a specific asset. The pay-off of a FVA contract initiated at time t and expiring at time $t + \tau_1$ is (Della Corte, Kozhan, and Neuberger (2021)):

$$(SVOL_{t+\tau_1}^{\tau_2} - FVOL_{t,\tau_1}^{\tau_2}) \times M \qquad (5)$$

whereby $SVOL_{t+\tau_1}^{\tau_2}$denotes the floating leg of the contract which equals implied volatility over some specified horizon τ_2 observed at maturity $t + \tau_1$; $FVOL_{t,\tau_1}^{\tau_2}$denotes the fixed leg of the contract or strike price which equals forward implied volatility at time t over $(t + \tau_1, t + \tau)$ period, where $\tau = \tau_1 + \tau_2$; and M is the contact's notional amount also called Vega notional which is the dollar value associated with a unit change (1%) in volatility. The sequence is illustrated in Figure 2.

VS is a forward contract similar to a FVA where the fixed leg or strike price is replaced by the implied volatility, $SVOL_t^{\tau_1}$, observed at time t over a specific horizon τ_1, while the floating leg is replaced by the realised volatility, $VOL_{t+\tau_1}^{\tau_1}$, computed at maturity $t + \tau_1$ using daily returns over the same $\tau_1$horizon. The payoff of a VS initiated at time t and expiring at time $t + \tau_1$ is:

$$(VOL_{t+\tau_1}^{\tau_1} - SVOL_t^{\tau_1}) \times M \quad (6)$$

A one-month VS could be construed as the limit case of a 0/1 month FVA strategy (τ_1/τ month FVA where $\tau_1 = 0$, $\tau_2 = 1$ and $\tau = \tau_1 + \tau_2 = 1$).

Della Corte, Kozhan, and Neuberger (2021) define the excess return on a τ_1/τ FVA between months t and $t + 1$ as:

$$r_{t+1}^{FVA} = \frac{FVOL_{t+1,\tau_1-1}^{\tau_2} - FVOL_{t,\tau_1}^{\tau_2}}{FVOL_{t,\tau_1-1}^{\tau_2}} \quad (7)$$

Similarly the excess return on a $\tau_1$volatility swap between months t and $t + 1$ is:

$$r_{t+1}^{VS} = \frac{VOL_{t+1}^{\tau_1} - SVOL_t^{\tau_1}}{VOL_t^{\tau_1}} \quad (8)$$

Using Koijen et al. (2018) definition of carry, volatility carry equals:

$$C_t^{FVA} = \frac{FVOL_{t,\tau_1-1}^{\tau_2} - FVOL_{t,\tau_1}^{\tau_2}}{FVOL_{t,\tau_1-1}^{\tau_2}} \quad (9)$$

and correspondingly the carry for a volatility swap is:

$$C_t^{VS} = \frac{VOL_t^{\tau_1} - SVOL_t^{\tau_1}}{VOL_t^{\tau_1}} \quad (10)$$

The above carry measures are effectively slope estimates of the volatility term structure. Baltas (2017), Koijen et al. (2018) measure carry either via the first and second generic futures or the spot and first generic futures depending on the idiosyncrasies of the market under consideration. For FVA and VS, carry is measured by the spot and forward implied volatility and, the spot implied and ex-post realised volatility for FVA and VS respectively.

Table 2.1 by Hamdan et al. (2016) shows under two separate groupings the classification for carry and volatility risk premia in the financial services industry. Accordingly, volatility risk premia cover two strategies namely carry and term structure (the latter prevalent mainly in the equities asset class). These are short-volatility strategies that respectively capture the spot (difference between implied and realised volatility) and forward (difference between forward and implied volatility) volatility premia. In this study, consistent with Della Corte, Kozhan, and Neuberger (2021), the volatility carry strategy refers to a cross-sectional (long-short) strategy of spot and forward volatility risk premia, using carry measure as the sorting variable (see section 2.4).

2.3 Data construction

The empirical focus of this paper is the implementation of volatility carry strategies covering an extensive volatility universe and spanning several markets. This section presents the data set, volatility carry measures and some descriptive statistics.

Forward and spot volatility risk premia reflect the returns on FVA and VS respectively, therefore performance estimates of carry strategies require measures of (future) realised volatility and contemporaneous measures of spot and forward implied volatility. As implied variance is time additive, forward variance is effectively the difference in time weighted spot variances (Carr and Wu (2009)):

$$SVAR_t^{\tau} = \frac{\tau_1}{\tau} SVAR_t^{\tau_1} + \frac{\tau_2}{\tau} FVAR_{t,\tau_1}^{\tau_2} \quad (11)$$

where $SVAR_t^{\tau}$ is the current annualised spot implied variance over the period t and $t+\tau$, and $FVAR_{t,\tau_1}^{\tau_2}$ is the current annualised forward implied variance over the period $t+\tau_1$ and $t+\tau$. Implied volatility is simply the square root of implied variance. While this method can introduce a convexity bias as the square root of expected variance is usually higher than expected volatility, empirical studies indicate only a minor effect (Della Corte, Kozhan, and Neuberger (2021)).

For VS, implied volatility has one-month horizon ($\tau_1 = 1$) in line with major volatility indices such as the VIX index. For FVA, this study also considers the one-month forward implied volatility with one-month to maturity ($\tau_1 = \tau_2 = 1$). Based on equation (11), computing $FVOL_{t,1}^{1}$ would therefore require measures of $SVOL_t^1$ and $SVOL_t^2$ the spot one-month and two-months implied volatilities respectively. Note that for the considered time horizons where $\tau_1 = \tau_2 = 1$, $FVOL_{t,\tau_1-1}^{\tau_2}$ is $FVOL_{t,0}^{1}$ which also is $SVOL_t^1$ given that the current one-month forward volatility with zero time to maturity is effectively the current one-month spot implied volatility. As an example, the first futures contract on the VIX index would correspond to a FVA with one-month forward implied volatility and one-month to maturity ($\tau_1 = \tau_2 = 1$). Koijen et al. (2018) use one-month futures to estimate carry across various asset classes. Dew-Becker et al. (2017), Della Corte and Kozhan, and Neuberger (2021) respectively show that forward volatility premia in equities and FX markets are non-significant for durations exceeding one month. Realised volatility is estimated by the standard deviation of daily returns over the subsequent month. The above measured variables can then be combined to estimate the excess return to a VS or a FVA as per equations (7) and (8) described above.

Realised volatility is based on daily returns calculated from daily closing prices from Bloomberg. For equities the study uses data for market indices or exchange traded funds (ETFs), for fixed income and commodities the front month futures contracts and for FX spot prices. The realised volatility series for each asset is calculated as the annualised standard deviation of daily log returns over 30-day periods.

Implied volatility measures based on the model free approach of Demeterfi et al. (1999) have the advantage of being independent from option pricing model assumptions like the log normality of asset returns. Demeterfi et al. (1999) show that a properly weighted average of all out-of-the-money options can be used as a model independent measure of implied volatility. This approach provides the basis for volatility listed products, like the VIX (CBOE (2014)). Unfortunately the Demeterfi et al. (1999) requirement of employing all out-of-the money options in the calculation not feasible for many assets that do not have liquid options at some strikes. As a result, this study uses at the money option series from Bloomberg as a conservative alternative for implied volatility estimation ignoring the presence of an option skew. In most option markets, implied volatility increases as the strike price decreases, while in the currencies asset class, implied volatility increases for strikes both higher and lower than the spot price (Knauf (2003)). Della Corte, Kozhan, and Neuberger (2021) find that analysis of FX volatility risk premia is unaffected by various implied volatility estimation approaches such as the model-free method (Britten-Jones and Neuberger (2000)) the modified model-free method (Martin (2017)) or at the money implied volatility method. 30 day at the money implied volatility data are downloaded from Bloomberg database which derives implied volatility by equating the option price to the Black-Scholes formula. 30 and 60 days at the money implied volatility data series are used to estimate the 30 days forward implied volatility for a period of 30 days as per equation (10) presented above. Specifically, monthly data is collected by sampling end of month implied volatilities from November 2005 to April 2021. For equity, fixed-income and commodity asset classes, the implied volatility series is computed as the average of the call and put implied for the at-the-money option of the first listed expiry at least 20 business days from the date under consideration. For currencies, implied volatility is sampled by Bloomberg from major banks' FX trading desks.

The cross-section includes 56 series covering relatively active and liquid options markets. The underlying securities cover four asset classes: FX, fixed income, equities and commodities and vary with respect to the type of risks they are exposed to. For example agricultural commodities have less exposure to the economic cycle unlike equity-related indices or energy commodities. Equities and currencies include a mix of developed and emerging markets while the fixed income asset class include only developed markets given dearth of instruments in emerging markets for this segment. Every asset class sample starts with a minimum of 3 securities.

Table A2.1 in the appendix documents the selected assets with their Bloomberg tickers along with their associated average of 1-month implied volatility, 2-month implied volatility, 1-month forward volatility with 1-month maturity, and 1-month realised volatility over the sample period that runs from November 2005 to April 2021.

2.4 Single asset class and global volatility premia

Using data on spot, forward and realised volatilities, monthly excess returns on FVA and VS contracts are computed using equations (7) and (8). Table A2.2 and Figure A.1 in the appendix, detail for each underlying asset the unconditional spot and forward volatility premia, their associated level of carry as per equations (9) and (10) and Sharpe ratio. Table 2.2 presents performance statistics for equal-weight portfolios invested in spot and forward volatility premia across FX, equities, commodities and fixed income as well as a global portfolio combining all asset classes. The latter is based on equal-risk allocation whereby the portfolios in each asset class are scaled to 10% volatility (estimated in sample) before being added into a diversified equal-weight portfolio.

Excess returns are large and generally negative for both FVA and VS portfolios given typically upward sloping term structures (hence the motivation for short volatility strategies). Except for fixed income and commodities where forward premia are positive, spot and forward volatility premia are negative for all other portfolios. Positive risk premia which result from inverted term structure can be explained by sustained period of elevated volatility in the front end of the term structure for example during periods of supply shortages in the commodities space. Further research is needed to clarify the divergence between spot (upward sloping) and forward (inverted) term structures for the fixed income and commodities markets.

Previous research on volatility premia typically focuses on a single asset class and/or volatility premium e.g. Della Corte, Kozhan and Neuberger (2020) analyse the forward volatility premium in currencies, Dew-Becker et al. (2016) analyse the spot volatility premium in equities (US and European markets) and Fallon, Park and Yu (2015) cover the spot volatility premium in multiple asset classes. For the spot volatility premium, absolute Sharpe ratios[1] in this study are slightly higher than the findings of Fallon, Park, and Yu (2015) for currencies (G10 only) and fixed income at 0.66 and 0.56 versus 0.49 and 0.51 respectively, while it is lower for equities, commodities and the global portfolio at 0.36, 0.27 and 0.61 versus 0.64, 1.50 and 1.02 respectively. However, for equities the Sharpe ratio for spot volatility premium is in line with the findings of Dew-Becker et al. (2016) at 0.38 (1-month maturity). For the forward volatility premium, this study absolute Sharpe ratio for currencies at 0.24 is lower than Della Corte, Kozhan, and Neuberger (2021) at 0.77 (short horizon), although not directly comparable since they use 1-month/3-month FRAs versus 1-month/2-month FRAs in this study. In term of statistical significance, excess returns are significant for fixed income (both spot and forward premia), currencies (spot premium), and commodities (forward premium). Fallon, Park, and Yu (2015) find the spot volatility premium strongly significant for all asset classes but currencies (significant at 10%). Della Corte, Kozhan, and Neuberger (2021) and Dew-Becker et al. (2017) find the FX

[1] Sharpe ratios in Table 2 reflect returns on long volatility positions versus returns on short volatility positions for the other papers.

forward and equities spot volatility premium significant only at the short horizon (1-month/3-month FRA and 1 month respectively).

Generally, spot premia are wider than forward premia resulting in predominantly higher risk adjusted returns for VS compared to FVA portfolios. This might reflect the larger bias of implied versus realised volatility compared to the bias of forward versus spot implied volatility. Interestingly there seems to be no apparent association between the volatility of volatility risk premia and that of its underlying asset class (for example volatility of fixed income spot premium at 78.67% exceeds that of higher-risk commodities at 50.9%). Expectedly, spot and forward volatility premia display both substantial positive skewness and high kurtosis indicating fat-tailed excess returns.

2.5 Conditional volatility premia on volatility carry

Recent studies by Johnson (2017) and Della Corte, Kozhan, and Neuberger (2021) reject the expectations hypothesis showing that the slope of the volatility curve is indicative of a time-varying volatility premia in the equity and currency markets. This study extends the analysis to volatility in a multiasset class setting using a significantly expanded sample. In particular, the analysis covers the time-variation in volatility risk premia at short horizon (1-month) for a cross-section of 56 assets across four markets between November 2005 to April 2021.

Unlike previous studies that focus on one aspect of the volatility curve, this study covers the entire spectrum by deriving both a spot and a forward volatility return relationship with their corresponding carry as per equations (9) and (10) above. The motivation for conditioning volatility risk premia on volatility carry stems from general carry trade mechanics that are encountered across different asset classes. Koijen et al. (2018) show that "carry is an important component of expected returns". Assuming V_t and C_t are volatility and carry at time t, then the one-period profit on a long position in a forward volatility contract is $V_{t+1} - V_t + C_t$. The volatility premium is therefore $E[V_{t+1} - V_t] + C_t$ where $E[V_{t+1} - V_t]$ constitutes the expected change in spot volatility. The expectation hypothesis stipulates that "high carry should not predict a high return as it is compensated by an offsetting low expected price appreciation" (Koijen et al. (2018)). Therefore, in the absence of a volatility risk premium the expected change in spot volatility should negate the carry return i.e. $E[V_{t+1} - V_t] = -C_t$. Alternatively, a time varying volatility risk premium should entail a positive correlation with carry provided that the regression beta of the volatility returns to carry is less than or equal to -1 (Della Corte, Kozhan, and Neuberger (2021)).

Building on Koijen et al. (2018) cross asset carry evidence, a panel regression of volatility monthly excess returns on lagged volatility carry is run for each asset class as follows:

$$r_{t+1}^{x,i} = a^{x,i} + b_t^x + cC_t^x + \varepsilon_{t+1}^{x,i} \qquad (12)$$

whereby $x = VS, FVA$; $a^{x,i}$ is an instrument specific intercept, b_t^x is a time fixed effect, C_t^x is the volatility carry on asset i at time t, and c the coefficient of concern which determines whether volatility carry predicts volatility excess returns. The lack of volatility premia would result in zero expected return given that the prevailing forward and spot implied volatility would be an unbiased predictor of the future implied and realised volatility respectively. Five hypotheses are considered (Koijen et al. (2018)): first, $c = 0$ indicating that the volatility carry does not predict volatility returns in line with the expectation hypothesis where total volatility return (carry plus the change in volatility level) is unpredictable; second, $c = 1$ indicating that the expected volatility return moves in line with carry. The change in volatility level (total volatility return net of carry) is unpredictable by carry; third, $0 < c < 1$ indicating that part of the positive carry is offset by an expected negative change in the volatility level; fourth, $c > 1$ indicating that a positive carry is also augmented by an expected positive change in the volatility level; and finally $c < 0$ indicating that a positive carry is more than offset by an expected negative change in volatility level.

Table 2.3 shows the findings per asset class for FVA and VS instruments including and excluding fixed effects. Time and instrument fixed effects respectively control for the volatility return component associated with common exposure to volatility premia at a specific time as well as for the passive exposure to volatilities premia having different average unconditional returns. Hence, excluding fixed effects, the regression coefficient measures overall (passive and dynamic) volatility return predictability from volatility carry, while including fixed effects it measures only the predictability associated with changes in volatility carry (Koijen et al. (2018)).

Table 2.3 indicates high predictability of volatility returns with consistently positive and highly significant beta coefficient (different from zero) on volatility carry across various volatility instruments and asset classes. For VSs the coefficient estimate is always lower than one with relatively little variation across asset classes (although not significantly different from one for fixed income). This indicates that when an asset has a low implied versus realised volatility, implying an elevated carry, the realised volatility tends to decline, hence reducing the overall volatility return. However, the market takes back only a limited proportion of the return and an investor would still enjoy on average well over two-third of the carry across the different asset classes. For FVAs, the coefficient estimate for c is also less than one for commodities, fixed income and equities (including fixed effects) resulting in a similar return dynamic as for VSs. For currencies, the predictability coefficient estimate is equal to one, which means that for high volatility carry currencies, implied volatility neither increases nor declines, and the FX FVA investor earns on average the volatility carry in full. Note that, Della Corte, Kozhan, and Neuberger (2021) using a panel regression with currency fixed effects find this coefficient equal to 0.65 in the front end of the FX volatility curve[2].

Table 2.3 displays various regression specifications with instrument and time fixed effects and their impact on the estimated predictive coefficient in the presence or absence of passive and dynamic exposures. For VSs, the volatility carry coefficient estimate across different asset classes drops only marginally with the inclusion of fixed effects indicating that the predictability of volatility returns is mainly dominated by the dynamic component of volatility carry. Conversely, for FVAs the coefficient on volatility carry drops meaningfully (in descending order equities, fixed income, FX and commodities) once fixed effects are added (particularly time fixed effects) indicating that besides the dynamic component, there is also a significant passive component controlling the volatility returns predictability. Overall, the above findings reject the hypotheses that the implied forward and spot volatilities are respectively unbiased predictors of the future spot implied and realised volatilities, indicating the presence of time-varying risk premia across various asset class volatilities. Hence, a strategy consisting of buying (selling) forward and spot implied volatility when they are at respective discount (premium) to spot and realised is on average profitable. This is in line with typical carry trade strategies in traditional asset classes where an investor takes long and short position in respectively high and low carry securities (Koijen et al. (2018)).

[2] In fact Della Corte, Kozhan and Neuberger (2020) report a coefficient of -0.65 consistent with the way they define carry. In their paper, carry is the negative of the definition used in this study.

2.6 The cross-section of volatility returns

In light of the above analysis which shows that volatility carry predicts future excess volatility returns, this section extends the analysis to the cross-section by assessing whether volatility carry is also informative about future VS and FVA cross-sectional returns.

2.6.1 Volatility carry portfolios

Carry effectively corresponds to the slope of the implied volatility curve, indeed a long (short) position in a FVA or a VS with positive (negative) carry is equivalent to buying a FVA or a VS when the volatility curve is in backwardation (contango). To examine how volatility carry returns vary across securities within its asset class, portfolios of FVAs and VSs are built using volatility carry as a sort attribute. As such a volatility carry trade is a long-short portfolio based on the proportional strength of the assets volatility carry in a particular market. The portfolio allocation approach is based on the rank methodology used by Asness, Moskowitz, and Pedersen (2013) and , Koijen et al. (2018). Empirically the rank methodology tends to increase returns stability given improved diversification whereby it considers all securities proportionally to their carry ranking. The rank allocation method also avoids the effect of extreme observations compared to other allocations approaches that base significant weight on the extremities by going long the top x % and short bottom x% of the securities while ignoring securities in between. The time t security i weight is linearly determined according to its demeaned rank as follows:

$$w_t^{i,x} = z_t(rank\left(C_t^{i,x} - \frac{N_t+1}{2}\right)) \qquad (13)$$

where $x = FVA, VS$; N_t is the available securities number in period t, C_t^i is the volatility carry of security i and z_t a normalisation scalar which secures that the absolute value of the sum of the long and short positions weights equals one. Assets with large volatility carry will have a larger weight relative to the rest of the universe and vice versa. Using the weights defined by equation (13), the return of the volatility carry trade portfolio is the weighted sum of individual assets volatility returns:

$$r_{t+1}^{x} = \sum_i w_t^{i,x} \, r_{t+1}^{i,x} \qquad (14)$$

2.6.2 Volatility carry strategy portfolios in single asset classes

Two cross sectional volatility carry trade portfolios based on FVAs and VSs are created in each asset class by going long and short selling high and low volatility carry securities respectively. Each instrument weight is determined by its volatility carry rank of as per equation (13). These portfolios are rebalanced monthly and formed when a minimum of 3 assets are available. Alongside the volatility carry portfolio, denoted L/S Rank, a zero-cost short volatility strategy is also presented, denoted Short Vol. The short volatility strategy returns have the opposite sign to those shown in Table 2.2 as it short sells (as opposed to being long) implied volatility instruments within a given asset class (Lustig, Roussanov, and Verdelhan (2011) and Della Corte, Kozhan, and Neuberger (2021)).

Table 2.4 reports per asset class various performance statistics for the reruns on volatility carry trade portfolios based on FVAs and VSs. Average excess returns on short volatility portfolios are mainly positive reflecting typically upward sloping volatility curves for the different asset classes (refer to discussion on Table 2.2). The results however are not always statistically significant particularly for the FVA based strategies. In contrast, average excess returns for volatility carry portfolios are consistently positive and highly significant both for the VS and FVA based portfolios. Average excess returns vary from 118.32% (global equities) to 209.52% (fixed income) for the VS based portfolios and from 41.45% (FX global) to 146.39% (commodities) for the FVA based portfolios. Where applicable the table presents portfolio performance for developed and emerging markets assets. While for FVA portfolios, emerging and developed markets performance is comparable for both FX and equities markets; for VS portfolios, emerging markets FX and equities returns are notably higher, although at the cost of increased volatility. To take into account the different volatility levels across strategies it is more pertinent to compare their risk adjusted excess returns. The Sharpe ratio of the FVA portfolios varies from 1.29 (FX) to 2.80 (commodities) and for the VS portfolios from 1.78 (fixed income) to 2.81 (FX). VS strategies' average Sharpe ratio (2.20) exceeds that of FVA portfolios (1.87) owing to wider spot versus forward volatility premia as shown in Figure A.1 in annex.

While prior research focused mainly on FX forward volatility premium (Della Corte, Kozhan, and Neuberger (2021)) which shows findings comparable to this paper, volatility carry strategies work also well in other markets by capitalising on both the spot and forward volatility premia. While the performance is broad based, it is particularly attractive for commodities VS and FX FVA strategies with a 2.80 and 2.81 Sharpe ratio respectively.

Looking at higher-order moments of the volatility carry trade returns, except for high positive skewness for commodities (FVA strategy), return series generally exhibit symmetrical to mildly negative skewness (commodities (VS strategy), fixed income (VS strategy) and FX (FVA strategy)). For all asset classes, volatility carry strategy excess return series display significantly lower kurtosis than those of the long equal-weight strategies, with the FVA based strategies generally exhibiting excess kurtosis compared to VS based strategies. Among various asset classes, commodities (VS and

FVA strategies) and emerging market (equities and FX) display particularly large excess kurtosis indicating fat-tailed positive and negative excess returns.

Overall the results confirm a considerable variation in the cross-section of FVA and VS excess returns. These are both economically and statistically significant as well as predictable in the volatility carry.

2.6.3 Diversified volatility carry strategy portfolio

Table 2.5 presents correlation coefficients across FVA and VS carry portfolio returns in various markets. Of the 16 pair-wise correlations, 15 are positive which is indicative of a volatility carry risk premium across asset classes. Moreover a relatively low level of correlation motivates exploring the diversification benefits of combining the single asset class volatility carry strategies into a global diversified portfolio. Using a risk based allocation as per Asness, Moskowitz, and Pedersen (2013), Koijen et al. (2018) and Moskowitz, Ooi, and Pedersen (2012) carry portfolios in each asset class are scaled to 10% volatility before being added into a diversified equal-weight portfolio. Volatility is measured both in-sample (Koijen et al. (2018)) leading to a static portfolio allocation, since based on a single estimate over the entire sample period, and out of sample using twelve-month rolling returns (Baltas (2017)) resulting in a dynamic allocation with monthly rebalancing in line with rolling volatility estimates. As a benchmark, a diversified short volatility portfolio across the single asset classes (see Table 2.4) is also built according the same portfolio allocation methodology.

Table 2.6 shows that the diversified global volatility carry trade portfolios deliver statistically strong average excess returns. The Sharpe ratio of the FVA portfolios ranges from 3.41 to 3.93 and for the VS portfolios from 4.27 to 4.87 for the static and dynamic allocation respectively. These results denote significant diversification benefits with substantial improvement in risk adjusted performance versus individual strategies (average Sharpe ratio of 1.9 and 2.2 for FVA and VS portfolios respectively). Table 2.6 also indicates notable improvement in the global portfolios' higher moments with significantly reduced skewness (less than -0.50) and much thinner tails compared to the single asset class portfolios.

2.6.4 How does volatility carry strategy relates to short volatility strategy?

The evidence in Table 2.4 suggests that volatility carry is a predictor of cross-sectional volatility returns across various markets, it would be also relevant to assess its relation to the short volatility strategy which is considered by Koijen et al. (2018) as the main predictor for option carry trades. Indeed, it is possible that volatility carry strategy returns are partly exposed to short volatility returns (or volatility premium). Using spanning tests, Table 2.7 examines in each asset class the relation between volatility carry (FVA and VS) and short volatility strategies (Short volatility returns are shown in Table 2.4).

Panel A presents per asset class regression results of volatility carry returns on short volatility returns. While the relationship is generally positive, betas are not always significant across all asset classes. For VSs the beta ranges from 0.15 for FX (non-significant) to 0.64 for commodities. For FVAs the relationship is significant only for FX and fixed income with respective betas of 0.16 and 0.31. The estimated alphas are consistently positive and statistically significantly different from zero, ranging from 0.03 to 0.12 and from 0.09 to 0.16 per month for FVA and VS strategies respectively.

Panel B presents per asset class, the reverse regression results of short volatility returns on volatility carry returns. Although carry returns capture short volatility returns with generally significant betas across the different asset classes except for commodities in FVA and currencies in VS, alphas are often negative and non-significant indicating that volatility carry spans short volatility returns Koijen et al. (2018).

Overall, the results indicate that volatility carry provides a profitable alternative to short volatility. The strategy delivers predictive power for volatility returns beyond the returns from shorting volatility. Indeed, carry explains and spans the predictive power of short volatility across different assets classes. These results extends the findings of Koijen et al. (2018) who find carry a unifying framework for cross-assets returns predictability.

2.6.5 Volatility carry timing

The results in Table 2.3 suggest that volatility carry observed at time t is a good predictor of subsequent month volatility returns. This section assesses possible benefits from a timing strategy based on volatility carry. Following Koijen et al. (2018) an out of sample timing strategy is considered where the weight in security i is given by the following rule:

$$w_t^{i,x} = z_t(2\mathbb{I}\left(C_t^{i,x} - \overline{C^x} > 0\right) - 1) \qquad (15)$$

where $x = FVA, VS$; C_t^i is volatility carry for security i at time t, $\mathbb{I}\left(C_t^{i,x} - \overline{C^x} > 0\right)$ is an indicator function that takes a value of one if $C_t^{i,x} > \bar{C}$ and zero otherwise and z_t a normalisation scalar which secures a gross position equal to 2. Unlike in equation (13) where z_t secures that the absolute value of the sum of the long and short positions weights equals one i.e. market neutral, this timing strategy has generally a long or short bias. $\overline{C^x}$ is the average volatility carry in a specific asset class. An additional case where $\overline{C^x} = 0$ is also considered i.e. going long positive volatility carry assets and short negative volatility carry assets.

Table 2.8 shows that the above timing strategy produces appealing returns and outperforms the short volatility strategy with significantly positive alphas in all markets. The only exception is FX FVA portfolio for which total returns and alphas are not significantly different from zero. Comparing the volatility carry $C_t^{i,x}$ to the zero benchmark consistently produces higher returns than when setting it equal to the asset class average volatility carry. However, this outperformance does not necessarily hold on a risk adjusted basis. Indeed, for FVA instrument the cross asset average Sharpe ratio for the mean benchmark is 1.27 versus 1.25 for the zero benchmark, while for the VS instrument the Sharpe ratio is 1.50 and 1.27 respectively. Regarding the multiasset class portfolios, the dynamic asset allocation which continuously adjusts the risk exposure by timely modifying the portfolio allocation to the single volatility carry strategies, leads to higher Sharpe ratios of 2.55 and 4.01 for the FVA and VS portfolios respectively (mean benchmark for $C_t^{i,x}$). Regarding higher moments, the timing strategy displays significantly higher Kurtosis than the unconditional one particularly for the zero benchmark, since it mostly takes an aggregate net long or short position. The dynamic allocation results in improved risk calibration with Kurtosis of the multi-asset portfolio declining from 22.12 for the static allocation to 1.99 (zero benchmark for $C_t^{i,x}$).

2.7 Examining potential drivers for volatility carry

After determining volatility carry returns predictability across various asset classes and time, this section assesses potentials drivers accounting for the volatility carry premia. It investigates whether volatility carry returns can be related to the underlying asset carry factor and explores possible explanations based on crash, volatility, liquidity, and macroeconomic risks. It also considers the worst periods for volatility carry returns to ascertain whether these drawdowns overlap with known economic shocks. The following sub-sections present regression results for returns on single and multi-asset class volatility carry trade portfolios versus various factors F ($r_{volatility\,carry,t} = \alpha + \beta'.F + \epsilon_t$). Beta measures whether volatility carry strategies are exposed to a particular factor, while alpha indicates if volatility carry reruns are fully explained by that factor. R^2 measures the proportion of the variation in volatility carry returns explained by the factor.

2.7.1 Carry factor exposure

Results from Table 2.5 show a positive correlation across volatility carry returns in different markets suggesting the presence of a volatility carry risk factor. Analysing potential economic drivers that may explain the common variation in volatility carry returns, can shed light on whether the factor's returns reflect a reward for a systematic risk or are just a mispricing driven by behavioural biases. In particular this study assesses whether the underlying asset carry factor can explain the volatility carry in a given asset class. For example, Baltas (2017) equates the FX carry portfolio with a short volatility strategy given that both display return cyclicality and negative skewness. For each asset class, excess returns of volatility carry portfolios (FVA and VS) are regressed on the carry factor (Koijen et al. (2018)) as well as a passive short volatility portfolio.

Table 2.9 reports that the alphas for the volatility carry strategies (FVA and VS) are positive and significant for all asset classes. In line with the results from section 6.4. the loadings on the passive short volatility strategy are generally positive and statistically significant in particular for VS, however the betas on the carry factor are non-significant for all markets. The results suggest that the volatility carry trade delivers abnormal returns exceeding a simple passive short volatility exposure however there is no relation between volatility carry and its underlying asset carry. Similar results also hold for the multi-asset class portfolio.

2.7.2 *Crash and downside risks exposure*

In light of volatility carry strategies high Sharpe ratios shown in Table 2.4, this section assesses the strategies' vulnerability to downside exposure and crash risks by regressing the returns to volatility carry trade portfolios on:

- Downside risk measure which considers only negative return months as per Henriksson and Merton (1981):

$$r_{market,t,down} = -r_{market,t}.\mathbb{I}\{r_{market,t} < 0\} \qquad (16)$$

- Tail risk or crash measure which considers only extreme (more than one standard deviation) negative return months as per Lettau, Maggiori, and Weber (2013):

$$r_{market,t,tail} = -r_{market,t}.\mathbb{I}\{r_{market,t} < -\sigma_{market}\} \qquad (17)$$

The standard deviation σ_{market} is estimated using the full sample.

For equations (16) and (17), the minus sign serves identifying a negative (positive) coefficient on the above measures as a loading (hedge) on downside risk. Each asset class is associated with a respective downside measures, whereby the Trade-Weighted USD Index, JPMorgan Aggregate Bond Index, Bloomberg Commodity Index and MSCI World Index are used as proxies for FX, government bonds, commodities and equity markets respectively (Baltas (2017)). Table 2.10 presents per asset class the regression results for FVA and VS volatility carry strategies returns on the respective market and associated downside and crash risk measures. Market risk betas are predominantly significant for the crash risk measure, and show mixed results according to the volatility carry strategy. For FVA beta is significant for fixed income (crash and downside risk measures) and currencies (crash measure). For VS beta is significant for equities (crash and downside risk measures), commodities, fixed income and the multiasset class portfolio (crash measure). Where significant, the downside beta estimates are negative indicating a downside risk loading except for fixed income, where the downside beta is positive indicating a hedge against downside. While these findings may suggest that some component of volatility carry returns can be attributed to downside risks, positive and significant alphas for all strategies, indicate that the Henriksson and Merton (1981), Lettau, Maggiori, and Weber (2013) risk measures are insufficient to completely explain the returns to volatility carry strategies across various asset classes.

2.7.3 Global volatility and liquidity risks exposure

This section assesses whether volatility carry returns are exposed to volatility and liquidity risks. Volatility risk is measured by changes in JPM Global FX Volatility Index for currencies, MOVE Index for fixed income and VIX Index for equities, commodities and the multiasset class portfolio (no volatility specific index is available for commodities). Liquidity risk is represented by the US repo T-bill spread (Baba Yara, Boons, and Tamoni (2021), Nagel (2014)) whereby a liquidity shock is defined as the residuals from AR(2) model in line with Korajczyk and Sadka (2008), Moskowitz, Ooi, and Pedersen (2012). Table 2.11 presents regression results of volatility carry portfolio returns on volatility changes and global liquidity shocks. In order to insure comparability across asset classes volatility carry portfolio returns are standardised to 10% volatility. The results indicate a negative exposure to volatility risk across all markets and volatility instruments except for FX VS portfolio, however the loadings are significant for only equities and multiasset class portfolios. For liquidity risk, the sign of the relationship is inconsistent across markets and volatility instruments.

In general, alphas decline meaningfully across the board (apart from the FX FVA portfolio), in particular liquidity and volatility risks seem to largely explains equities volatility carry where the alphas for FVA portfolios become non-significant and for VS portfolios significant only at the 10% level. Despite these declines, the alphas remain significantly positive in all other asset classes and the multiasset portfolio suggesting that liquidity and volatility risks are insufficient explanations for the cross section of volatility carry returns.

2.7.4 Combining carry, downside, global liquidity and volatility risks

This section considers combining the previous risk factors (carry risk premium, downside, global liquidity and volatility risks) in order to assess their combined effect on volatility carry premia. Table 2.12 presents regression outputs of FVA and VS volatility carry portfolios' returns on an equal-weight short volatility portfolio, the carry factor, downside risk measure (Henriksson and Merton (1981)), volatility changes and global liquidity risks as per sections 7.1 to 7.3 above. For comparability volatility carry returns are standardised to have 10% volatility over the sample.

Table 2.12 shows that the loadings on the passive short volatility strategy are mostly positive and significant, however the betas on carry, downside risk, volatility changes and liquidity shocks are generally non-significant. For FVA portfolios alphas are positive and significant for commodities, fixed income and the multi-asset portfolio and weakly significant (10% level) for FX. For VS portfolios alphas are positive and significant for fixed income and the multi-asset portfolio and weakly significant (10% level) for FX and commodities. Alphas are non-significant for equities for both FVA and VS portfolios. While the evidence is less conclusive, apart from equities, the results indicate that the volatility carry trade still offers abnormal returns exceeding those of a passive short volatility exposure and that the considered risks on the whole are insufficient to jointly justify the cross section of volatility carry strategy returns.

2.7.5 Carry drawdowns and economic shocks

This section examines the lowest returns for volatility carry portfolios and assesses if they are associated with specific macroeconomic events. Focusing on the global volatility carry portfolios (FVA and VS using dynamic portfolio allocation as described in section 5.3 above) the drawdowns are computed as per Koijen et al. (2018):

$$D_t = \sum_{s=1}^{t} r_s - max_{u \in \{1,\ldots,t\}} \sum_{s=1}^{u} r_s \qquad (18)$$

where r_s indicates the global volatility carry portfolio excess return.

Figure 3 indicates that there is a degree of overlap (although not consistently) between the drawdowns of the global volatility carry portfolio for the FVA and VS instruments. Given the high level of their Sharpe ratios (3.9 and 4.9 for FVA and VS global volatility carry portfolios respectively), the magnitude of the drawdowns over the sample period are relatively muted with the worst readings at -3.1% in 2012 for the FVA strategy and -5.2% in 2015 for the VS strategy. The largest drawdown for the VS strategy is also the longest lasting covering the period from May 2012 to June 2012. Interestingly, neither of the biggest drawdowns coincided with increased probability of global recessions. Indeed, the probability of recession averaged 0.31 and 0.29 for FVA and VS strategies respectively during negative drawdowns episodes versus 0.29 for both strategies during volatility carry expansions. The global recession indicator is broadly equal during volatility carry drawdowns and expansions. Overall, volatility carry drawdowns do not appear to correspond with poor global economic and financial conditions.

2.7.6 Turnover and trading costs

This section assess the impact of transaction costs on the profitability of volatility carry strategies. Bid-ask spread costs for over the counter volatility derivative products are especially difficult to obtain. Following Della Corte, Kozhan, and Neuberger (2021), trading costs for FVA and VS instruments are estimated using Bloomberg quoted spreads for delta neutral straddles with the same underlying asset and maturity. The resultant average bid-ask spread in volatility points[3] per straddle leg varies between 20bps for fixed income to 95pbs for equities. Spreads and transaction costs are significantly wider for emerging versus developed markets. For FX and equities the bid-ask spreads are 81bps and 95bps for developed markets versus 115bps and 155bps for emerging markets respectively. For commodities no data on bid-ask spreads are available. While a half spread is considered as an appropriate cost associated with opening or closing a position (Menkhoff et al. (2012)), transaction costs associated with a full bid-ask spread are also considered as shown in Table 2.13. Turnover over a specific period is calculated according to Koijen et al. (2018):

$$Turnover_t = \frac{1}{4}\sum_i |w_{t-1}^i\left(1 + r_t^i\right) - w_t^i| \qquad (19)$$

where the division by four serves adjusting by a factor of two for double-counting of sales and purchases and another factor of two for the long-short gross exposure of 200%. Average turnover is computed monthly. Table 2.13 shows that the turnover is consistently high ranging from 52.5% to 64.7% per month across various asset classes and volatility instruments.

While the effect of trading costs on the Sharpe ratio of volatility carry portfolios is relatively large, most strategies still achieve a positive risk adjusted performance even with full bid-ask spreads apart from FX (FVA and developed markets VS) and emerging markets equities (FVA) strategies. At half-spread, most strategies still achieve a Sharp ratio above one. For commodities given lack of data the impact of

[3] Transaction costs are determined by dividing the bid-ask spread (expressed in volatility points) by the volatility level.

transaction costs could not be determined, however considering the strength of the strategies Sharpe ratios, they are likely to withstand transaction costs. For example applying the most punitive transaction costs level (emerging markets equities) still results in Sharpe ratios of 2 and 1.7 at half-spread and 1.3 and 1.1 at full-spread for the FVA and VS strategies respectively. Overall the results suggest volatility carry strategies are generally implementable especially for VS portfolios and that except for FVS FX their returns cannot be fully explained or subsumed by trading costs. It should be noted that the volatility carry strategies may overstate the cost of trading because they were constructed so that returns are maximized, without a consideration for transaction costs. Using transaction cost mitigation techniques might reduce the impact of transaction costs on volatility strategies' returns. This is a topic for further research but beyond the scope of this paper.

2.8 Conclusion

This paper examines spot and forward volatility risk premia in cross asset setting and extends the notion of carry beyond conventional markets to the volatility asset class. It identifies common risk factors in cross-sectional volatility carry returns across various markets. A cross-sectional strategy analogous to carry strategies in traditional asset classes which takes long positions in FVA and VS of assets with the high volatility carry and short positions in FVA and VS of assets with low volatility carry generate significant excess returns, indicating that volatility carry is a strong predictor of cross sectional volatility returns. Panel regressions of volatility returns on volatility carry show consistently positive relationship in each underlying asset class, validating volatility carry as strong predictor of volatility returns.

This study complements Koijen et al. (2018) paper by showing that carry predicts returns not only among traditional asset classes but also across volatility. Based on the evidence of volatility carry returns predictability, timing strategies are implemented which show positive risk adjusted returns across various asset classes and instruments, exceeding those generated by carry strategies on underlying markets.

While volatility carry returns are related to volatility premia (short volatility returns), carry still produces significant positive alpha in each market. In particular volatility carry subsumes volatility return predictability by the short volatility factor. Other risk factors proposed in the literature such as underlying asset carry, volatility changes, global liquidity shocks and transaction costs are not able to justify the variation in FVA and VS cross-sectional returns. The presence of substantial volatility carry risk premia seems to offer a compelling investment opportunity while challenging classic asset pricing models.

Tables and figures

Table 2.1

Classification of carry risk premia in the financial services industry.

Strategy	Equites	Fixed Income	Credit	FX	Commodities
Carry	High dividend yields Dividend futures	Forward rate bias Term structure slope Cross-term structure	Forward rate bias	Forward rate bias	Forward rate bias Term structure slope Cross-term structure
Volatility	Carry Term structure	Carry		Carry	Carry

Source: Hamdan, Pavlowski and Roncalli (2016).

Tables 2.2

Descriptive statistics and returns to spot and forward volatility premia for single and multi-asset class portfolios.

The table reports for FX, equities, commodities, fixed income and a global multi-asset class portfolio the performance statistics (annualised excess returns and standard deviation, p-value for testing the hypothesis mean is zero, skewness, kurtosis and Sharpe ratio) for FVA and VS portfolios. Single asset class portfolios are based on an equal-weight allocation. The global multi-asset class portfolio is based on an equal volatility allocation whereby the portfolios in each asset class are scaled to 10% volatility before being added into a diversified equal-weight portfolio (volatility estimated over the entire sample period). Forward and spot volatility premia are estimated as follows: $r_{t+1}^{FVA} = \frac{FVOL_{t+1,\tau_1-1}^{\tau_2} - FVOL_{t,\tau_1}^{\tau_2}}{FVOL_{t,\tau_1-1}^{\tau_2}}$ and $r_{t+1}^{VS} = \frac{VOL_{t+1}^{\tau_1} - SVOL_{t}^{\tau_1}}{VOL_{t}^{\tau_1}}$ where $\tau_1 = \tau_2 = 1$. Note that $FVOL_{t,0}^{1}$=$SVOL_{t}^{1}$. Underlying securities instruments list and returns are shown in table A.2 as an appendix. Sample period runs from February 2006 to April 2021.

Asset Class		Portfolio construction	Start date	Securities at start	Mean	P value	Standard deviation	Skewness	Kurtosis	Sharpe ratio
				FVA						
FX	**Global**	EW	28/02/2006	19	-13.92%	34.31%	57.17%	2.78	12.58	-0.24
	DM	EW	28/02/2006	10	-18.00%	19.67%	54.25%	2.11	7.51	-0.33
	EM	EW	28/02/2006	9	-8.81%	58.00%	62.08%	3.16	16.25	-0.14
Equities	**Global**	EW	28/02/2006	6	-10.53%	56.16%	70.72%	2.27	7.76	-0.15
	DM	EW	28/02/2006	6	-14.41%	47.04%	77.79%	2.25	8.50	-0.19
	EM	EW	28/09/2007	3	-3.64%	84.49%	68.75%	2.41	8.15	-0.05
Commodities		EW	28/02/2006	9	28.41%	0.60%	39.86%	3.07	17.43	0.71
Fixed Income		EW	28/02/2006	3	29.51%	3.75%	54.99%	1.64	4.63	0.54
Multi-asset class	**Global**	EV	28/02/2006	4	1.85%	29.96%	8.04%	2.54	10.71	0.23
				VS						
FX	**Global**	EW	28/02/2006	19	-55.14%	0.35%	72.84%	3.20	17.62	-0.76
	DM	EW	28/02/2006	10	-48.81%	1.09%	74.09%	3.80	26.28	-0.66
	EM	EW	28/02/2006	9	-62.17%	0.27%	79.76%	2.64	11.06	-0.78
Equities	**Global**	EW	28/02/2006	6	-35.68%	16.43%	99.76%	2.32	8.89	-0.36
	DM	EW	28/02/2006	9	-36.65%	16.18%	101.89%	1.55	3.27	-0.36
	EM	EW	28/09/2007	3	-31.91%	30.28%	114.11%	3.45	18.09	-0.28
Commodities		EW	28/02/2006	9	-13.52%	30.10%	50.90%	2.61	18.78	-0.27
Fixed Income		EW	28/02/2006	3	-43.99%	3.03%	78.67%	3.33	22.05	-0.56
Multi-asset class	**Global**	EV	28/02/2006	4	-5.05%	2.40%	8.32%	4.16	31.39	-0.61

Table 2.3

Predictive regressions of volatility returns on volatility carry.

The table reports for various asset classes panel regression results including and excluding fixed effects: $r_{t+1}^{x,i} = a^{x,i} + b_t^x + cC_t^x + \varepsilon_{t+1}^{x,i}$, where $x =$ VS, FVA; $a^{x,i}$ is an asset specific intercept, b_t^x is a time fixed effect, C_t^x is the volatility carry on asset i at time t, and c the coefficient of concern which determines whether volatility carry predicts volatility excess returns. Time and instrument fixed effects respectively control for the volatility return component associated with common exposure to volatility premia at a specific time as well as for the passive exposure to volatilities premia having different average unconditional returns. Hence, excluding fixed effects, the regression coefficient measures overall (passive and dynamic) volatility return predictability from volatility carry, while including fixed effects it measures only the predictability associated with changes in volatility carry (Koijen et al. (2018)).Coefficient estimates for c and p-values for c=0 and c=1 are also reported. Standard errors are time clustered.

Asset class	Instrument fixed effect	Time fixed effect	FVA			VS		
			c	p-value		*c*	p-value	
				c=0	c=1		c=0	c=1
	X	X	1.00	0.00	0.98	0.76	0.00	0.00
FX	X		1.33	0.00	0.00	0.75	0.00	0.00
		X	0.99	0.00	0.95	0.77	0.00	0.00
			1.32	0.00	0.00	0.75	0.00	0.00
	X	X	0.66	0.00	0.00	0.67	0.00	0.00
Equities	X		1.28	0.00	0.02	0.74	0.00	0.00
		X	0.66	0.00	0.00	0.67	0.00	0.00
			1.27	0.00	0.02	0.73	0.00	0.00
	X	X	0.63	0.00	0.00	0.68	0.00	0.00
Commodities	X		0.77	0.00	0.02	0.72	0.00	0.00
		X	0.67	0.00	0.00	0.69	0.00	0.00
			0.79	0.00	0.02	0.73	0.00	0.00
	X	X	0.76	0.02	0.47	0.75	0.00	0.26
Fixed Income	X		1.18	0.00	0.57	0.72	0.00	0.12
		X	0.81	0.01	0.55	0.82	0.00	0.41
			1.19	0.00	0.52	0.76	0.00	0.17

Table 2.4

Returns per asset class to volatility carry portfolios based on FVAs and VSs.

The table reports for each asset class the mean annualised excess return, p-value for testing the hypothesis mean is zero, annualised standard deviation of returns, the skewness and kurtosis of monthly returns and the annualised Sharpe ratio for FVA and VS based strategies. The data is provided for a long short portfolio denoted L/S Rank whereby securities' weight is determined by their volatility carry rank and a short volatility strategy denoted Short Vol that equally short sells implied volatility instruments in a given asset class.

Asset Class		Portfolio construction	Start date	Securities at start	Mean	P value	Standard deviation	Skewness	Kurtosis	Sharpe ratio
				FVA						
FX	Global	L/S Rank	28/02/2006	19	41.45%	0.00%	32.19%	-0.59	2.82	1.29
		Short Vol			13.92%	34.31%	57.17%	-2.78	12.58	0.24
	DM	L/S Rank	28/02/2006	10	30.62%	0.02%	31.25%	-0.72	1.37	0.98
		Short Vol			18.00%	19.67%	54.25%	-2.11	7.51	0.33
	EM	L/S Rank	28/02/2006	9	36.65%	0.33%	48.03%	-0.90	4.77	0.76
		Short Vol			8.81%	58.00%	62.08%	-3.16	16.25	0.14
Equities	Global	L/S Rank	28/02/2006	6	73.88%	0.00%	40.92%	-0.03	3.65	1.81
		Short Vol			10.53%	56.16%	70.72%	-2.27	7.76	0.15
	DM	L/S Rank	28/02/2006	6	71.29%	0.00%	40.90%	0.49	3.33	1.74
		Short Vol			14.41%	47.04%	77.79%	-2.25	8.50	0.19
	EM	L/S Rank	28/09/2007	3	75.87%	0.00%	55.27%	1.68	10.65	1.37
		Short Vol			3.64%	84.49%	68.75%	-2.41	8.15	0.05
Commodities		L/S Rank	28/02/2006	9	146.39%	0.00%	52.35%	1.69	10.57	2.80
		Short Vol			-28.41%	0.60%	39.86%	-3.07	17.43	-0.71
Fixed Income		L/S Rank	28/02/2006	3	130.20%	0.00%	82.04%	0.30	3.26	1.59
		Short Vol			-29.51%	3.75%	54.99%	-1.64	4.63	-0.54
				VS						
FX	Global	L/S Rank	28/02/2006	19	156.49%	0.00%	55.61%	0.47	2.27	2.81
		Short Vol			55.14%	0.35%	72.84%	-3.20	17.62	0.76
	DM	L/S Rank	28/02/2006	10	117.81%	0.00%	50.68%	-0.67	3.04	2.32
		Short Vol			48.81%	1.09%	74.09%	-3.80	26.28	0.66
	EM	L/S Rank	28/02/2006	9	174.32%	0.00%	86.71%	0.06	1.76	2.01
		Short Vol			62.17%	0.27%	79.76%	-2.64	11.06	0.78
Equities	Global	L/S Rank	28/02/2006	6	118.32%	0.00%	61.26%	-0.31	2.66	1.93
		Short Vol			35.68%	16.43%	99.76%	-2.32	8.89	0.36
	DM	L/S Rank	28/02/2006	9	87.55%	0.00%	68.65%	-1.23	4.59	1.28
		Short Vol			36.65%	16.18%	101.89%	-1.55	3.27	0.36
	EM	L/S Rank	28/09/2007	3	124.70%	0.00%	71.23%	-1.07	13.36	1.75
		Short Vol			31.91%	30.28%	114.11%	-3.45	18.09	0.28
Commodities		L/S Rank	28/02/2006	9	155.13%	0.00%	67.97%	-0.98	4.93	2.28
		Short Vol			13.52%	30.10%	50.90%	-2.61	18.78	0.27
Fixed Income		L/S Rank	28/02/2006	3	209.52%	0.00%	117.68%	-0.59	2.69	1.78
		Short Vol			43.99%	3.03%	78.67%	-3.33	22.05	0.56

Table 2.5
Correlation coefficients between volatility carry portfolios returns (FVA and VS) across various markets (FX, equities, commodities and fixed income).

Correlation (FVA)	FX	Equities	Commodities	Fixed income
FX	1.00			
Equities	0.21	1.00		
Commodities	0.06	0.23	1.00	
Fixed Income	0.10	0.10	0.10	1.00

Correlation (VS)	FX	Equities	Commodities	Fixed income
FX	1.00			
Equities	0.11	1.00		
Commodities	0.15	0.18	1.00	
Fixed Income	0.08	0.14	-0.09	1.00

Table 2.6

Return statistics for diversified FVA and VS volatility carry and short volatility portfolios using risk based portfolio allocation.

The table displays performance statistics for FVA and VS multiasset class volatility carry and short volatility portfolios based on equal volatility allocation (volatility estimated over the entire sample period or out of sample using twelve-month rolling returns): annualised mean excess return, standard deviation and Sharpe ratio, p-value for testing the hypothesis mean is zero and monthly returns skewness and kurtosis. L/S Rank strategies are long short volatility carry portfolios in given asset class whereby securities' weight is determined by their volatility carry rank. Short Vol strategies are short volatility portfolios that equally short sells implied volatility instruments in a given asset class.

Asset Class	Strategy	Portfolio Construction	Start date	Portfolios at start	Mean	P value	Standard deviation	Skewness	Kurtosis	Sharpe ratio
Multi In-sample vol	Global FVA	L/S Rank	28/02/2006	4	20.18%	0.00%	5.91%	0.04	1.56	3.41
		Short Vol	28/02/2006	4	-1.85%	29.96%	8.04%	-2.54	10.71	-0.23
	Global VS	L/S Rank	28/02/2006	4	24.19%	0.00%	5.67%	-0.42	0.76	4.27
		Short Vol	28/02/2006	4	5.05%	2.40%	8.32%	-4.16	31.39	0.61
Multi 1Y-rolling vol	Global FVA	L/S Rank	31/01/2007	4	22.45%	0.00%	5.72%	-0.32	0.34	3.93
		Short Vol	31/01/2007	4	0.65%	89.39%	8.46%	0.32	0.68	0.08
	Global VS	L/S Rank	31/01/2007	4	28.20%	0.00%	5.79%	-0.26	-0.20	4.87
		Short Vol	31/01/2007	4	7.66%	0.10%	8.54%	0.26	1.55	0.90

Table 2.7

Spanning tests by asset class of volatility carry (FVA and VS) versus short volatility.

Panel A presents regression results per asset class of volatility carry returns on short volatility returns (alpha, beta, p-values and R^2). Panel B presents reverse regression results of short volatility returns on volatility carry returns. Standard errors are HAC consistent.

Panel A: Regressing carry returns on short vol. returns								
	FVA				VS			
	FX	Fixed income	Equities	Commodities	FX	Fixed income	Equities	Commodities
alpha	0.03	0.12	0.06	0.12	0.12	0.16	0.09	0.12
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Beta	0.16	0.31	0.11	-0.19	0.15	0.43	0.34	0.64
p-value	0.00	0.01	0.15	0.55	0.12	0.02	0.00	0.00
R2	7.6%	4.2%	3.5%	2.1%	3.8%	8.4%	30.4%	22.9%
Panel B: Regressing short vol. returns on carry returns								
	FVA				VS			
	FX	Fixed income	Equities	Commodities	FX	Fixed income	Equities	Commodities
alpha	-0.01	-0.04	-0.01	-0.01	0.01	0.00	-0.06	-0.04
p-value	0.77	0.01	0.48	0.61	0.63	0.89	0.07	0.13
Beta	0.49	0.14	0.32	-0.11	0.26	0.19	0.90	0.36
p-value	0.02	0.02	0.05	0.56	0.08	0.00	0.00	0.00
R2	7.6%	4.2%	3.5%	2.1%	3.7%	8.4%	30.4%	22.9%

Table 2.8

Returns to volatility carry timing strategies for FVA and VS instruments by asset class.

The table presents per asset class, the annualized mean excess return and standard deviation, p-value for testing the hypothesis mean is zero, the skewness and kurtosis of monthly returns, the annualized Sharpe ratio and alpha versus a short volatility strategy benchmark. Data are presented for two timing strategies where in the first volatility carry is compared with the asset class average volatility carry and in the second volatility carry is compared with zero. Data are also presented for FVA and VS multi asset class volatility carry portfolios (long short portfolios where the securities' weight is determined by their volatility carry rank) based on equal volatility allocation (volatility estimated over the entire sample period resulting in a static portfolio allocation or out of sample using twelve-month rolling returns resulting in a dynamic portfolio allocation).

Asset Class	Benchmark	Mean	p-value	Standard deviation	Skewness	Kurtosis	Sharpe ratio	Alpha	p-value
				FVA					
FX	Mean	14.72%	0.13	38.25%	3.52	31.99	0.38	0.01	0.10
	0	81.75%	0.13	87.52%	2.52	25.44	0.93	0.07	0.00
Equities	Mean	54.57%	0.00	41.06%	-0.17	3.46	1.33	0.04	0.00
	0	65.04%	0.00	116.77%	1.20	10.55	0.56	0.05	0.03
Commodities	Mean	94.31%	0.00	47.13%	1.96	14.15	2.00	0.08	0.00
	0	129.39%	0.00	59.06%	3.86	29.64	2.19	0.09	0.00
Fixed Income	Mean	103.20%	0.00	76.03%	-1.04	5.88	1.36	0.10	0.00
	0	110.68%	0.00	83.65%	0.05	6.34	1.32	0.09	0.00
Multi asset class	Mean (static allocation)	13.26%	0.00	5.87%	1.43	9.44	2.26	0.01	0.00
	Mean (dynamic allocation)	14.46%	0.00	5.67%	0.06	0.40	2.55	0.01	0.00
	0 (static allocation)	12.98%	0.00	7.20%	3.12	22.12	1.80	0.01	0.00
	0 (dynamic allocation)	16.74%	0.00	6.74%	0.23	1.99	2.48	0.01	0.00
				VS					
FX	Mean	112.48%	0.00	76.32%	5.92	52.27	1.47	0.12	0.00
	0	125.02%	0.00	99.20%	-3.74	27.60	1.26	0.06	0.00
Equities	Mean	80.69%	0.00	60.85%	0.14	3.54	1.33	0.07	0.00
	0	110.85%	0.00	161.94%	-2.89	18.10	0.68	0.06	0.02
Commodities	Mean	117.65%	0.00	57.10%	-0.97	4.67	2.06	0.09	0.00
	0	146.98%	0.00	64.08%	-1.65	9.92	2.29	0.11	0.00
Fixed Income	Mean	131.80%	0.00	116.63%	-0.12	8.42	1.13	0.09	0.00
	0	124.22%	0.00	148.96%	-3.95	28.80	0.83	0.05	0.02
Multi asset class	Mean (static allocation)	15.93%	0.00	4.59%	-0.36	0.88	3.47	0.01	0.00
	Mean (dynamic allocation)	20.74%	0.00	5.20%	-0.04	0.36	3.99	0.02	0.00
	0 (static allocation)	13.09%	0.00	7.64%	-5.83	55.98	1.71	0.01	0.00
	0 (dynamic allocation)	18.90%	0.00	6.71%	-0.93	4.90	2.82	0.01	0.00

Table 2.9

Volatility carry trade exposure to the carry factor.

The table presents regression ($r_{\text{volatility carry},t} = \alpha + \beta'.F + \epsilon_t$) results (alphas, betas, p-values and R^2) of returns on FVA and VS volatility carry strategies on returns of an equal weight short volatility portfolio and the carry factor (Koijen et al. (2018)) for single and multi-asset class portfolios (dynamic asset allocation). Standard errors are HAC consistent.

	FVA				
	FX	Equities	Commodities	Fixed Income	Multi Asset Class
Alpha	0.034	0.061	0.118	0.116	0.017
p-value	0.000	0.000	0.000	0.000	0.000
Passive short vol	0.128	0.107	-0.196	0.235	0.118
p-value	0.007	0.162	0.485	0.062	0.013
Carry	0.132	-0.207	0.028	1.228	0.128
p-value	0.677	0.702	0.931	0.307	0.232
R Square	0.060	0.033	0.602	0.448	0.069
	VS				
	FX	Equities	Commodities	Fixed Income	Multi Asset Class
Alpha	0.124	0.084	0.124	0.158	0.019
p-value	0.000	0.000	0.000	0.000	0.000
Passive short vol	0.184	0.330	0.602	0.448	0.302
p-value	0.040	0.000	0.000	0.010	0.000
Carry	-0.290	0.421	0.369	-0.636	0.094
p-value	0.502	0.435	0.222	0.739	0.167
R Square	0.034	0.305	0.241	0.087	0.236

Table 2.10

Volatility carry trade downside risks exposure.

The table reports per asset class the regression results (alphas, betas, p-values and R^2) of FVA and VS volatility carry portfolio's returns on their respective markets (Trade-Weighted USD Index, JPMorgan Aggregate Bond Index, Bloomberg Commodity Index and MSCI World Index as proxies for FX, government bonds, commodities and equity markets respectively) and two risk measures: 1) Downside risk measure which considers only negative return months as per Henrikson and Merton (1981) ($r_{market,t,down} = -r_{market,t} \cdot \mathbb{I}\{r_{market,t} < 0\}$), and 2) Tail risk or crash measure which considers only extreme (more than one standard deviation) negative return months ($r_{market,t,tail} = -r_{market,t} \cdot \mathbb{I}\{r_{market,t} < -\sigma_{market}\}$) as per Lettau et al. (2014). The standard deviation σ_{market} is estimated using the full sample. Carry returns volatilities are standardised to 10%. For the multi asset portfolio (dynamic allocation) the market is the MSCI World Index. Standard errors are HAC consistent.

	FVA									
	FX		Equities		Commodities		Fixed Income		Multi Asset	
	Down	*Tail*	*Down*	*Tail*	*Down*	*Tail*	*Down*	*Tail*	*Down*	*Tail*
Alpha	0.028	0.026	0.072	0.064	0.110	0.119	0.081	0.113	0.019	0.018
p-value	0.012	0.004	0.000	0.000	0.000	0.000	0.002	0.000	0.000	0.000
Market return	-2.581	-4.450	0.011	0.322	0.557	0.296	10.146	24.915	0.022	0.077
p-value	0.080	0.008	0.975	0.115	0.351	0.607	0.057	0.000	0.618	0.075
Market downside	-1.682	-3.536	-0.466	0.008	0.793	0.375	11.038	24.729	-0.078	0.005
p-value	0.299	0.037	0.529	0.984	0.428	0.610	0.041	0.000	0.286	0.929
R Square	0.094	0.122	0.021	0.018	0.006	0.002	0.025	0.034	0.056	0.051
	VS									
	FX		Equities		Commodities		Fixed Income		Multi Asset	
	Down	*Tail*	*Down*	*Tail*	*Down*	*Tail*	*Down*	*Tail*	*Down*	*Tail*
Alpha	0.128	0.124	0.135	0.118	0.175	0.166	0.172	0.190	0.024	0.023
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Market return	0.056	1.798	-0.298	-0.407	-0.566	-1.075	10.677	50.591	0.010	-0.020
p-value	0.987	0.697	0.518	0.234	0.468	0.161	0.337	0.000	0.837	0.641
Market downside	0.310	2.182	-1.846	-1.687	-1.866	-2.293	8.924	48.327	-0.115	-0.136
p-value	0.936	0.638	0.049	0.005	0.087	0.014	0.454	0.000	0.148	0.019
R Square	0.001	0.006	0.092	0.096	0.057	0.075	0.033	0.084	0.075	0.086

Table 2.11

Volatility carry trade exposure to volatility changes and global liquidity shocks.

The table presents per asset class and a multi asset portfolio (dynamic allocation) regression results (alphas, betas, p-values and R^2) of FVA and VS volatility carry portfolio returns on volatility changes and liquidity shocks. Liquidity shocks are measured as AR(2) model residuals of the US repo T-bill spread. Volatility risk is measured by changes in JPM Global FX Volatility Index for currencies, MOVE Index for fixed income and VIX Index for equities, commodities and the multiasset class portfolio (no volatility specific index is available for commodities). In order to insure comparability across asset classes volatility carry portfolio returns are standardised to 10% volatility. Standard errors are HAC consistent.

			FVA		
	FX	Equities	Commodities	Fixed Income	Multi Asset
Alpha	0.031	-0.004	0.020	0.019	0.021
p-value	0.000	0.713	0.004	0.006	0.000
Volatility changes	-0.026	-0.025	-0.006	-0.003	-0.012
p-value	0.074	0.025	0.480	0.795	0.015
Liquidity shocks	6.812	-6.554	-1.000	1.587	1.190
p-value	0.004	0.072	0.668	0.531	0.389
R Square	0.037	0.072	0.004	0.002	0.042
			VS		
	FX	Equities	Commodities	Fixed Income	Multi Asset Class
Alpha	0.022	0.013	0.020	0.024	0.020
p-value	0.007	0.055	0.016	0.012	0.000
Volatility changes	0.003	-0.035	-0.008	-0.002	-0.011
p-value	0.862	0.000	0.376	0.810	0.008
Liquidity shocks	-0.605	-1.071	0.411	3.252	-0.298
p-value	0.816	0.667	0.874	0.330	0.852
R Square	0.000	0.097	0.005	0.007	0.030

Table 2.12

Volatility carry trade exposure to the carry factor, downside, global liquidity and volatility risks.

The table presents regression outputs (alphas, betas, p-values and R^2) of FVA and VS volatility carry strategies returns on an equal weight short volatility portfolio returns, the carry factor (Koijen et al. (2018)), downside risk measure which considers only negative return months as per Henrikson and Merton (1981) ($r_{market,t,down} = -r_{market,t} \cdot \mathbb{I}\{r_{market,t} < 0\}$), global volatility changes and liquidity risks. Liquidity shocks are measured as the residuals from AR(2) model of the US repo T-bill spread. Volatility risk is measured by changes in JPM Global FX Volatility Index for currencies, MOVE Index for fixed income and VIX Index for equities, commodities and the multiasset class portfolio (no volatility specific index is available for commodities). In order to insure comparability across asset classes volatility carry portfolio returns are standardised to 10% volatility. Standard errors are HAC consistent.

	FVA				
	FX	Equities	Commodities	Fixed Income	Multi Asset
Alpha	0.018	-0.004	0.019	0.017	0.021
p-value	0.052	0.640	0.020	0.023	0.000
Passive short vol	0.046	0.007	-0.049	0.030	0.087
p-value	0.016	0.758	0.386	0.079	0.177
Carry	-0.040	-0.030	-0.002	0.147	0.123
p-value	0.694	0.736	0.974	0.303	0.291
Market downside	0.301	0.026	-0.015	0.030	-0.022
p-value	0.002	0.731	0.800	0.812	0.573
Volatility changes	-0.025	-0.023	-0.014	0.001	-0.001
p-value	0.080	0.145	0.139	0.928	0.841
Liquidity shocks	4.221	-6.519	-1.397	1.125	1.428
p-value	0.109	0.023	0.590	0.659	0.366
R Square	0.139	0.073	0.036	0.042	0.078

	VS				
	FX	Equities	Commodities	Fixed Income	Multi Asset Class
Alpha	0.017	0.008	0.015	0.023	0.015
p-value	0.065	0.320	0.060	0.018	0.011
Passive short vol	0.034	0.060	0.084	0.035	0.305
p-value	0.039	0.000	0.000	0.017	0.000
Carry	-0.062	0.069	0.057	-0.043	0.111
p-value	0.435	0.419	0.204	0.799	0.163
Market downside	0.088	0.095	-0.072	-0.156	-0.029
p-value	0.505	0.133	0.055	0.191	0.631
Volatility changes	0.003	-0.008	0.009	-0.005	0.006
p-value	0.865	0.387	0.195	0.544	0.373
Liquidity shocks	-1.333	-1.623	-1.615	2.637	-1.408
p-value	0.617	0.506	0.515	0.414	0.392
R Square	0.050	0.316	0.255	0.102	0.240

Table 2.13

Volatility carry strategies estimated turnover, transactions costs and Sharpe ratios net of trading costs.

The table presents per asset class for volatility carry strategies (FVA and VS instruments), turnover, average bid-ask spread and transaction costs per one leg of the straddle, as well as Sharpe ratios net of trading costs where available. To measure trading costs for FVA and VS instruments, Bloomberg quoted spreads for delta neutral straddles with the same underlying asset and maturity are used as proxy. Trading costs impact on Sharpe ratios is stated in half-spreads (0 implies no trading costs while 2 implies a full bid-ask spread). Transaction costs are determined by dividing the bid-ask spread (expressed in volatility points) by the volatility level. Total trading costs equal transaction costs multiplied by turnover.

Asset Class	Average spread in vol bps (one leg)	Average transaction cost (one leg)	Monthly turnover	Sharpe ratio net of trading costs (1/2 spread sensitivity)		
				0	1	2
	FVA					
FX	81	6.22%	52.46%	1.29	0.07	-1.15
DM	61	5.49%	57.97%	0.98	-0.24	-1.46
EM	115	7.25%	53.74%	0.76	-0.21	-1.18
Equities	95	4.51%	57.46%	1.81	1.05	0.29
DM	66	3.72%	53.99%	1.74	1.15	0.57
EM	155	6.09%	53.99%	1.37	0.66	-0.05
Commodities	n.a	n.a	54.49%	2.80	n.a	n.a
Fixed Income	20	4.06%	64.67%	1.59	1.20	0.82
	VS					
FX	81	6.22%	55.51%	2.74	1.94	1.14
DM	61	5.49%	54.93%	2.32	1.56	-0.44
EM	115	7.25%	56.67%	1.90	1.28	0.66
Equities	95	4.51%	59.62%	1.93	1.41	0.88
DM	66	3.72%	59.88%	1.28	0.80	0.33
EM	155	6.09%	57.88%	1.75	1.31	0.87
Commodities	n.a	n.a	60.07%	2.27	n.a	n.a
Fixed Income	20	4.06%	55.75%	1.78	1.55	1.32

Figure 2.1

VIX, VIX futures and expectations of SPX realised volatility.

This figure illustrates the interaction across VIX, VIX futures and expectations of SPX realized volatility. Dashed arrows represent the periods over which expectations apply. VIX_t, F_t^T and $\sigma_{t,t+1}^{SPX}$ respectively represent VIX index at time t, first futures on VIX maturing at T, and SPX realised volatility for the period t, t+1. VIX_t represents the conditional risk-neutral expectation of the square root of the realised variance for the SPX index over the next calendar month ($\sigma_{t,t+1}^{SPX}$). F_t^T represents the forward price on date t with expiration date T that is the conditional risk neutral expectation at time t of the VIX at date T, which also is the iterative expectation at time t of the realized volatility of the SPX index over the period T to T+1 ($\sigma_{T,T+1}^{SPX}$).

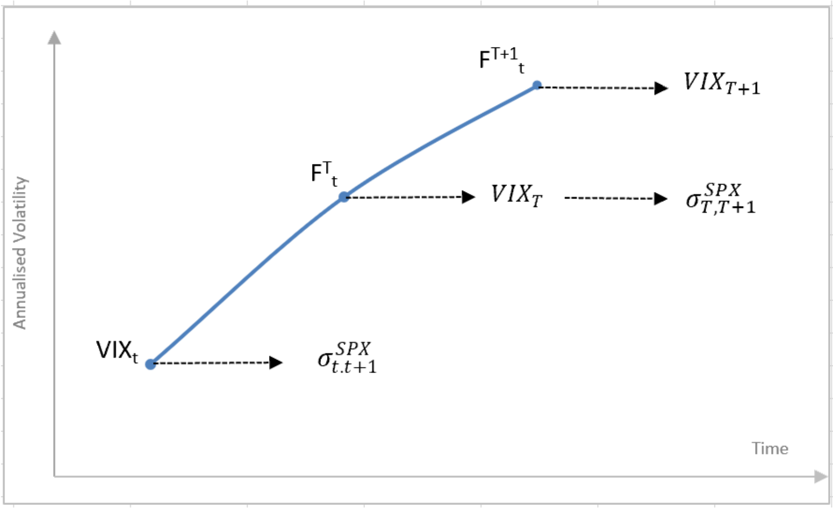


Figure 2.2

Forward volatility agreement (FRA).

This figure outlines a FRA namely a forward contract exchanging at time $t + \tau_1$ the spot implied volatility over τ_2 horizon ($SVOL^{\tau_2}_{t+\tau_1}$) for the current forward implied volatility over an identical τ_2 future horizon ($FVOL^{\tau_2}_{t,\tau_1}$). The time $t + \tau_1$ payout for a contract written at time t equals ($SVOL^{\tau_2}_{t+\tau_1} - FVOL^{\tau_2}_{t,\tau_1}$) times the Vega notional. If $\tau_1 = \tau_2 = 1$, for example, $FVOL^{\tau_2}_{t,\tau_1}$ denotes the current time t, one-month forward implied volatility that starts within a month at time $t + 1$, and $SVOL^{\tau_2}_{t+\tau_1}$ is the one-month spot volatility observed within a month at time $t + 1$ (Della Corte, Kozhan and Neuberger (2020)).

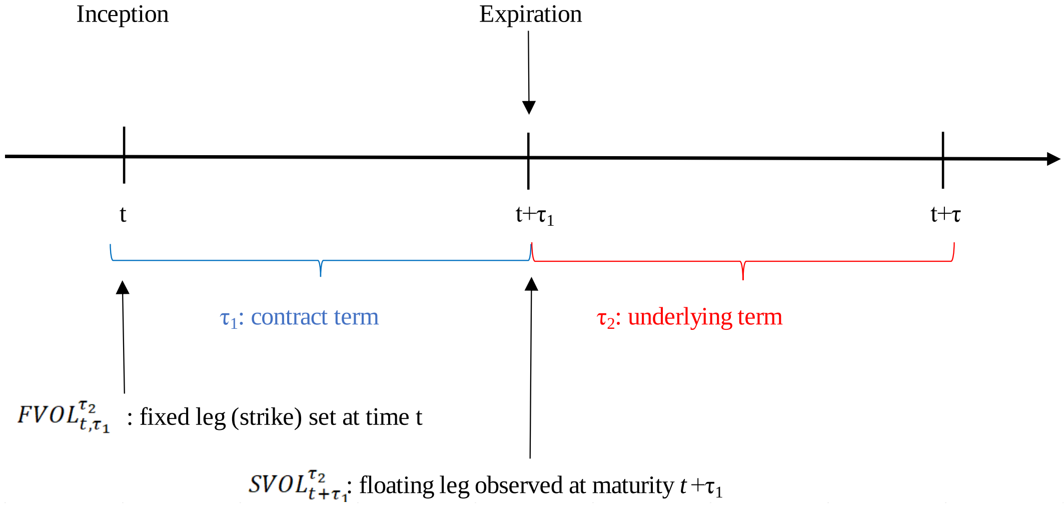
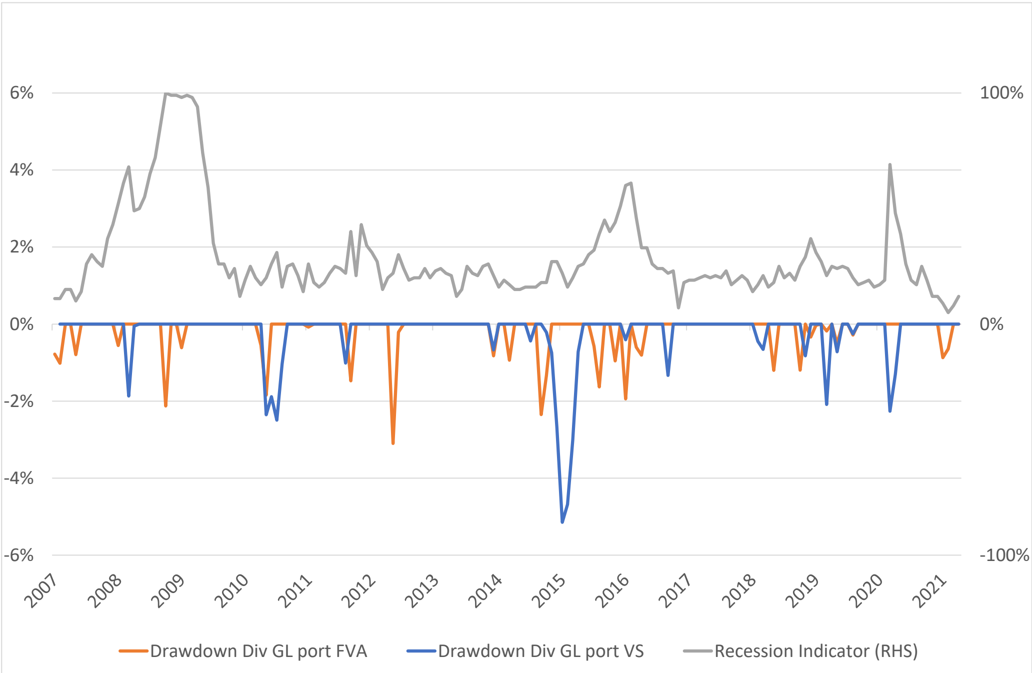


Figure 2.3

Global volatility carry portfolios drawdowns.

The figure displays drawdown fluctuations of the global volatility carry portfolio for the FVA and VS instruments. Drawdown is defined as $D_t = \sum_{s=1}^{t} r_s - \max_{u \in \{1,\ldots,t\}} \sum_{s=1}^{u} r_s$, where r_s indicates the global volatility carry portfolio excess return. The global volatility carry portfolio is a multiasset class volatility carry portfolio based on an equal volatility dynamic allocation where volatility is estimated out of sample using twelve-month rolling returns. The recession indicator is the US Federal Reserve credit probability recession model.



Appendix

Table A2.1: List of the selected securities per asset class with their Bloomberg tickers and associated volatility parameters.

The table presents the list of the selected securities per asset class with their Bloomberg tickers and associated volatility parameters. Monthly observations of 1-month and 2-month at the money implied volatilities are downloaded from Bloomberg database. Forward volatility is computed using the following formula: $\mathrm{SVAR}_t^2 = \frac{1}{2}\mathrm{SVAR}_t^1 + \frac{1}{2}\mathrm{FVAR}_{t,1}^1$, where $\mathrm{SVAR}_t^\tau$is the annualised spot implied variance during the period t and $t+2$, and $\mathrm{FVAR}_{t,1}^1$ is the time t annualised forward implied variance during the period $t+1$ and $t+2$. Implied volatility is calculated by taking the square root of the implied variance. The realised volatility series for each asset class is computed as the annualised standard deviation of daily log returns over 30-day periods. The arithmetic average is computed over the sample period which extends from February 2006 to April 2021.

	Bloomberg ticker	Average implied ATM volatility 1M	Average implied ATM volatility 2M	Average forward implied volatility	Average realised volatility 1M
Equities					
ISHARES MSCI EMERGING MARKET	EEM US Equity	26.0	26.2	26.2	25.4
ISHARES MSCI MEXICO ETF	EWW US Equity	26.1	26.1	26.1	26.0
ISHARES MSCI BRAZIL ETF	EWZ US Equity	35.5	35.3	35.1	35.3
ISHARES CHINA LARGE-CAP ETF	FXI US Equity	28.2	28.1	28.0	29.4
VANECK RUSSIA ETF	RSX US Equity	33.5	33.8	33.9	34.7
ISHARES MSCI SOUTH KOREA ETF	EWY US Equity	27.0	27.2	27.4	27.0
ISHARES MSCI INDIA ETF	INDA US Equity	23.9	23.7	24.2	22.4
ISHARES MSCI SOUTH AFRICA ET	EZA US Equity	32.9	32.9	32.8	33.1
AEX-Index	AEX Index	19.0	19.0	19.0	18.1
CAC 40 INDEX	CAC Index	20.1	20.1	20.1	20.0
DAX INDEX	DAX Index	20.1	20.2	20.3	19.8
HANG SENG INDEX	HSI Index	21.6	21.7	21.6	21.0
NIKKEI 225	NKY Index	21.3	21.4	21.3	21.5
FTSE 100 INDEX	UKX Index	17.3	17.4	17.5	16.7
SWISS MARKET INDEX	SMI Index	16.0	16.1	16.1	15.8
S&P 500 INDEX	SPX Index	16.7	17.3	17.8	16.6
NASDAQ 100 STOCK INDX	NDX Index	18.9	19.5	20.0	19.6
Euro Stoxx 50 Pr	SX5E Index	20.5	20.5	20.5	20.0
Commodities					
ICE Brent Crude Oil Future	CO1 Comdty	33.8	33.1	32.4	32.1
NYMEX Light Sweet Crude Oil Fu	CL1 Comdty	35.0	34.1	32.8	37.5
ICE Gas Oil Future	QS1 Comdty	31.6	31.0	30.2	28.1
NYMEX Henry Hub Natural Gas Fu	NG1 Comdty	46.0	44.0	41.7	49.3
NYMEX Reformulated Gasoline Bl	XB1 Comdty	35.8	34.6	32.0	37.4
COMEX Gold 100 Troy Ounces Fut	GC1 Comdty	17.1	17.6	18.0	17.2
NYMEX Platinum Future	PL1 Comdty	23.0	22.7	22.3	23.2
NYMEX Palladium Future	PA1 Comdty	30.1	29.6	28.9	31.1
LME Nickel Future	LN1 Comdty	38.8	38.0	34.2	35.6
COMEX Copper Future	HG1 Comdty	26.3	27.2	27.8	25.8
CBOT Corn Future	C 1 Comdty	27.7	27.7	27.6	27.7
CBOT Soybean Future	S 1 Comdty	22.7	22.8	22.9	22.1
CBOT Wheat Future	W 1 Comdty	13.1	13.1	9.3	13.0
NYBOT CSC C Coffee Future	KC1 Comdty	32.5	32.4	32.2	30.7
NYBOT CSC Cocoa Future	CC1 Comdty	29.3	28.6	27.9	28.0
Currencies					
EUR-USD X-RATE	EURUSD Curncy	9.1	9.2	9.3	8.5
USD-JPY X-RATE	USDJPY Curncy	9.7	9.8	9.7	9.1
GBP-USD X-RATE	GBPUSD Curncy	9.1	9.3	9.4	8.8
AUD-USD X-RATE	AUDUSD Curncy	11.1	11.2	11.2	11.2
USD-CHF X-RATE	USDCHF Curncy	9.2	9.3	9.4	9.2
USD-CAD X-RATE	USDCAD Curncy	8.8	8.8	8.8	8.5
USD-MXN X-RATE	USDMXN Curncy	12.3	12.3	12.2	11.5
USD-BRL X-RATE	USDBRL Curncy	15.4	15.3	15.1	15.7
USD-NOK X-RATE	USDNOK Curncy	11.6	11.7	11.7	11.6
USD-SEK X-RATE	USDSEK Curncy	11.2	11.3	11.4	11.1
Russian Ruble SPOT (TOM)	USDRUB Curncy	12.7	12.8	12.9	11.8
USD-SGD X-RATE	USDSGD Curncy	5.6	5.7	5.8	4.9
USD-KRW X-RATE	USDKRW Curncy	10.3	10.3	10.2	8.9
USD-TWD X-RATE	USDTWD Curncy	5.3	5.5	5.6	3.7
USD-TRY X-RATE	USDTRY Curncy	13.8	14.1	14.3	13.2
Bonds					
US ULTRA BOND CBT Jun21	WNM1 Comdty	13.1	13.1	9.3	13.0
US LONG BOND(CBT) Jun21	USM1 Comdty	10.1	10.0	10.0	9.9
US 10yr Ultra Fut Jun21	UXYM1 Comdty	6.6	6.6	2.3	5.7
US 10YR NOTE (CBT)Jun21	TYM1 Comdty	5.6	5.5	5.5	5.4
US 5YR NOTE (CBT) Jun21	FVM1 Comdty	3.5	3.4	3.4	3.3
US 2YR NOTE (CBT) Jun21	TUM1 Comdty	1.2	1.2	1.1	1.1
CAN 10YR BOND FUT Jun21	CNM1 Comdty	7.0	6.6	6.6	6.0
EURO-BUND FUTURE Jun21	RXM1 Comdty	5.6	5.5	5.5	5.5
EURO-BOBL FUTURE Jun21	OEM1 Comdty	2.9	2.9	2.9	3.0
EURO-SCHATZ FUT Jun21	DUM1 Comdty	1.0	1.0	1.0	0.9
LONG GILT FUTURE Jun21	G M1 Comdty	7.1	7.0	6.9	6.7
Euro-BTP Future Jun21	IKM1 Comdty	8.1	7.9	7.7	8.2
JPN 10Y BOND(OSE) Jun21	JBM1 Comdty	2.7	2.7	2.7	2.4

Tables A2.2: Descriptive statistics: Securities instruments list per asset class and annualised mean and standard deviation of FVA and VS excess returns.

The table presents the securities instruments list per asset class and annualised mean and standard deviation of FVA and VS excess returns ($r_{t+1}^{FVA} = (SVOL_{t+1}^{1} - FVOL_{t,1}^{1})/SVOL_{t}^{1}$ and $r_{t+1}^{VS} = (VOL_{t+1}^{1} - SVOL_{t}^{1})/VOL_{t}^{1}$ where $SVOL_{t}^{1}$ and $FVOL_{t,1}^{1}$ are time t, 1-month implied volatility and 1-month forward volatility with 1-month maturity) as well as carry ($C_{t}^{FVA} = (SVOL_{t}^{1} - FVOL_{t,1}^{1})/SVOL_{t}^{1}$ and $C_{t}^{VS} = (VOL_{t}^{1} - SVOL_{t}^{1})/VOL_{t}^{1}$ where VOL_{t}^{1} is time t, 1-month realised volatility) for the sample duration that runs from February 2006 to April 2021.

	FVA Returns		FVA Carry		VS Returns		VS Carry	
Equities	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**
ISHARES MSCI EMERGING MARKET	-34.8%	81.8%	-38.5%	44.0%	-76.4%	117.3%	-87.6%	88.9%
ISHARES MSCI MEXICO ETF	-27.4%	78.1%	-32.1%	40.3%	-68.4%	127.4%	-81.0%	82.6%
ISHARES MSCI BRAZIL ETF	-6.5%	73.7%	-11.6%	36.0%	-59.7%	133.6%	-75.7%	78.5%
ISHARES CHINA LARGE-CAP ETF	-12.6%	67.5%	-18.1%	31.7%	-14.5%	96.7%	-45.0%	70.0%
VANECK RUSSIA ETF	-33.4%	81.1%	-37.0%	34.7%	-43.1%	136.4%	-64.7%	77.2%
ISHARES MSCI SOUTH KOREA ETF	-32.1%	75.1%	-33.8%	31.0%	-49.9%	116.4%	-67.5%	72.8%
ISHARES MSCI INDIA ETF	-52.4%	131.2%	-53.4%	58.4%	-77.4%	193.0%	-93.8%	135.8%
ISHARES MSCI SOUTH AFRICA ET	-15.6%	76.2%	-22.7%	40.9%	-52.6%	115.6%	-73.3%	88.1%
AEX-Index	-21.6%	97.8%	-27.0%	34.0%	-78.7%	123.9%	-88.4%	88.3%
CAC 40 INDEX	-17.9%	82.1%	-24.8%	35.6%	-67.7%	118.1%	-84.8%	92.4%
DAX INDEX	-32.2%	81.0%	-36.4%	31.2%	-63.4%	109.3%	-81.8%	85.3%
HANG SENG INDEX	-25.4%	79.0%	-32.3%	39.5%	-57.3%	90.0%	-70.7%	66.3%
NIKKEI 225	-26.7%	103.9%	-36.3%	54.2%	-52.1%	131.7%	-77.4%	91.2%
FTSE 100 INDEX	-36.4%	87.4%	-39.6%	34.1%	-61.1%	115.3%	-76.8%	83.0%
SWISS MARKET INDEX	-30.8%	86.5%	-37.3%	39.3%	-61.5%	126.8%	-79.3%	86.0%
S&P 500 INDEX	-41.2%	89.7%	-47.5%	33.9%	-92.6%	151.3%	-98.0%	118.9%
NASDAQ 100 STOCK INDX	-37.6%	80.6%	-43.7%	33.4%	-83.4%	125.4%	-95.1%	103.9%
Euro Stoxx 50 Pr	-19.8%	85.4%	-28.2%	38.7%	-73.1%	117.5%	-87.4%	89.9%

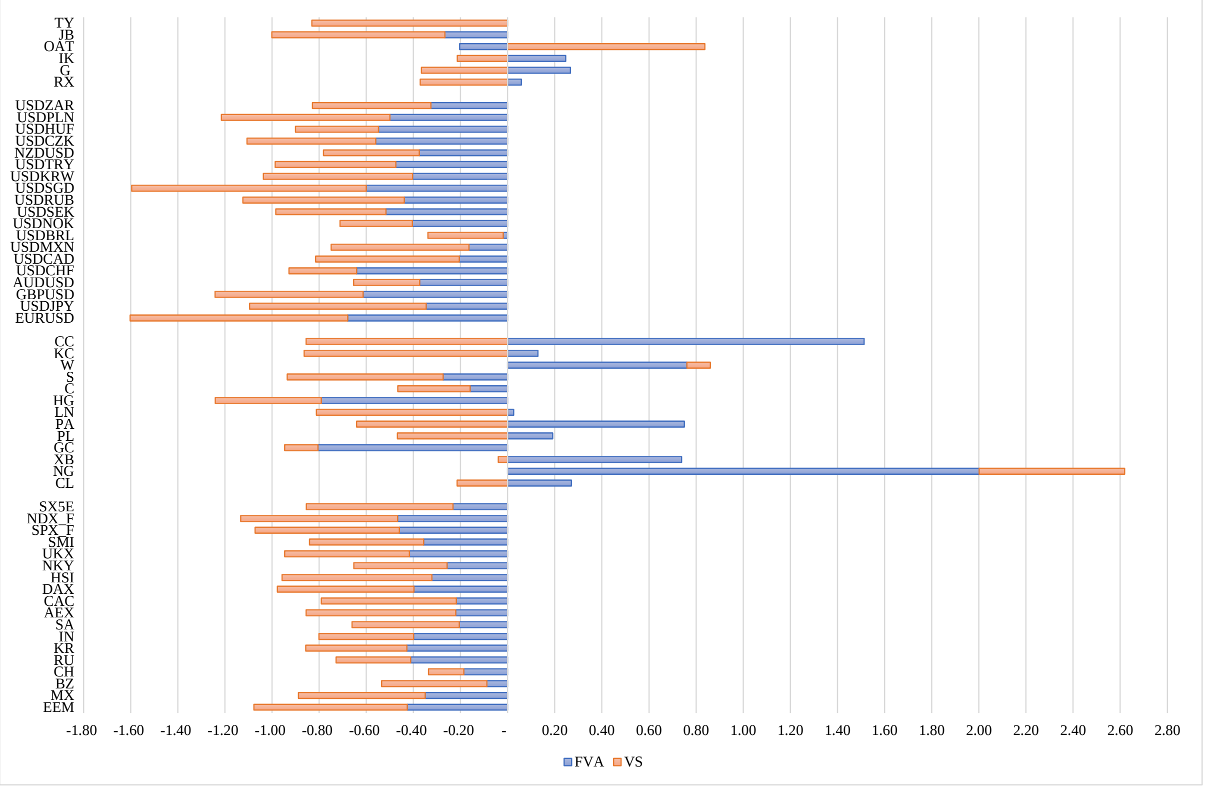
	FVA Returns		FVA Carry		VS Returns		VS Carry	
Commodities	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**
NYMEX Light Sweet Crude Oil Fu	27.6%	101.6%	17.3%	40.9%	-26.9%	125.8%	-57.4%	79.9%
NYMEX Henry Hub Natural Gas Fu	135.9%	67.9%	101.3%	57.9%	51.3%	83.1%	-3.5%	75.5%
NYMEX Reformulated Gasoline Bl	68.8%	93.1%	62.4%	47.7%	-5.5%	138.4%	-49.6%	81.0%
COMEX Gold 100 Troy Ounces Fut	-61.8%	76.8%	-63.0%	44.6%	-13.3%	94.5%	-50.6%	77.8%
NYMEX Platinum Future	16.5%	86.2%	14.1%	41.3%	-55.3%	118.1%	-71.9%	90.7%
NYMEX Palladium Future	51.8%	69.0%	31.4%	32.8%	-64.9%	101.3%	303.1%	190.0%
LME Nickel Future	1.9%	75.8%	-12.3%	43.3%	-76.4%	94.2%	-83.2%	77.4%
COMEX Copper Future	-68.5%	86.6%	-68.9%	57.6%	-39.7%	88.3%	-60.7%	72.6%
CBOT Corn Future	-11.4%	71.6%	-38.4%	64.6%	-33.1%	107.7%	-69.2%	86.4%
CBOT Soybean Future	-17.5%	64.0%	-31.0%	46.1%	-58.3%	88.1%	-75.2%	83.6%
CBOT Wheat Future	46.4%	61.0%	26.8%	44.2%	7.7%	77.7%	-31.5%	71.4%
NYBOT CSC C Coffee Future	7.4%	57.7%	0.2%	32.8%	-69.2%	80.1%	-78.2%	76.7%
NYBOT CSC Cocoa Future	68.5%	45.3%	59.7%	34.0%	-67.6%	79.1%	-79.5%	78.3%

	FVA Returns		FVA Carry		VS Returns		VS Carry	
Currencies	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**
EUR-USD OPT VOL 1M	-38.8%	57.1%	-41.7%	32.2%	-69.1%	74.8%	-77.0%	64.6%
USD-JPY OPT VOL 1M	-22.7%	65.8%	-28.6%	35.7%	-77.6%	103.5%	-87.2%	76.6%
GBP-USD OPT VOL 1M	-40.0%	65.3%	-49.7%	42.5%	-56.9%	90.5%	-72.6%	76.8%
AUD-USD OPT VOL 1M	-26.1%	70.0%	-28.9%	27.6%	-27.7%	98.8%	-48.7%	61.7%
USD-CHF OPT VOL 1M	-36.5%	57.0%	-39.1%	29.4%	-51.2%	178.5%	-71.6%	75.4%
USD-CAD OPT VOL 1M	-13.1%	63.7%	-14.6%	26.4%	-55.9%	91.8%	-67.6%	61.3%
USD-MXN OPT VOL 1M	-15.4%	94.1%	-24.3%	33.7%	-77.3%	132.2%	-86.8%	76.8%
USD-BRL OPT VOL 1M	-1.7%	91.1%	-11.8%	43.7%	-39.1%	122.3%	-64.6%	77.3%
USD-NOK OPT VOL 1M	-24.4%	60.4%	-27.1%	25.0%	-35.9%	116.8%	-54.5%	65.2%
USD-SEK OPT VOL 1M	-26.4%	51.2%	-28.7%	26.3%	-37.9%	80.9%	-51.3%	62.7%
USD-RUB OPT VOL 1M	-38.3%	87.4%	-43.2%	27.3%	-94.3%	137.5%	-96.4%	100.0%
USD-SGD OPT VOL 1M	-40.2%	67.1%	-44.3%	30.8%	-91.0%	91.4%	-95.0%	77.2%
USD-KRW OPT VOL 1M	-36.2%	89.9%	-39.1%	35.4%	-90.0%	142.1%	-95.0%	86.9%
USD-TRY OPT VOL 1M	-50.2%	105.8%	-58.1%	37.0%	-79.4%	155.0%	-86.4%	134.1%
NZD-USD OPT VOL 1M	-23.1%	61.5%	-26.7%	29.4%	-33.0%	81.1%	-51.7%	61.7%
USD-CZK OPT VOL 1M	-32.5%	58.0%	-36.1%	31.7%	-54.3%	99.4%	-67.7%	74.3%
USD-HUF OPT VOL 1M	-33.6%	61.2%	-35.7%	26.4%	-29.4%	83.4%	-40.5%	60.5%
USD-PLN OPT VOL 1M	-30.4%	60.8%	-31.5%	27.2%	-72.1%	100.8%	-78.0%	78.0%
USD-ZAR OPT VOL 1M	-21.8%	67.0%	-25.9%	24.7%	-46.3%	92.1%	-65.7%	66.0%

Bonds	FVA Returns		FVA Carry		VS Returns		VS Carry	
	Mean	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**
EURO-10YR BUND Future	3.7%	64.4%	-7.9%	34.1%	-35.6%	95.8%	-67.9%	80.0%
10YR GILT Future	14.9%	56.1%	15.4%	44.5%	-46.3%	126.6%	-70.1%	107.4%
EURO-10YR BTP Future	43.9%	177.7%	18.1%	48.0%	-44.1%	206.0%	-73.7%	85.8%
EURO-10YR OAT Future	-14.6%	72.0%	-13.1%	38.3%	194.2%	232.0%	-12.0%	97.1%
JPN 10Y BOND Future	-28.7%	107.9%	-25.2%	50.9%	-93.2%	126.9%	-96.7%	104.3%
US 10YR NOTE Future	17.3%	63.9%	2.1%	35.1%	-60.6%	73.0%	-77.9%	78.0%

Figure A2.1: Sharpe ratios of spot and forward volatility premia for the securities instruments list grouped by asset class.

The figure presents Sharpe ratios of spot and forward volatility premia for the securities instruments list grouped by asset class. The Sharpe ratio is derived using the annualised mean and standard deviation of FVA and VS excess returns ($r^{FVA}_{t+1} = (SVOL^1_{t+1} - FVOL^1_{t,1})/SVOL^1_t$ and $r^{VS}_{t+1} = (VOL^1_{t+1} - SVOL^1_t)/VOL^1_t$ where $SVOL^1_t$ and $FVOL^1_{t,1}$ are time t, 1-month implied volatility and 1-month forward volatility with 1-month maturity) for the sample duration that runs from February 2006 to April 2021.



References

Acharya, Viral v., and Lasse Heje Pedersen, 2005, Asset pricing with liquidity risk, *Journal of Financial Economics* 77, 375–410.

Aït-Sahalia, Yacine, Mustafa Karaman, and Loriano Mancini, 2020, The term structure of equity and variance risk premia, *Journal of Econometrics* 219, 204–230.

Asness, Clifford S., Tobias J. Moskowitz, and Lasse Heje Pedersen, 2013, Value and Momentum Everywhere, *The Journal of Finance* 68, 929–985.

Baba Yara, Fahiz, Martijn Boons, and Andrea Tamoni, 2021, Value Return Predictability across Asset Classes and Commonalities in Risk Premia, *Review of Finance* 25, 449–484.

Baltas, Nick, 2017, Optimizing Cross-Asset Carry, *Factor Investing* (Elsevier).

Baz, Jamil, Nicolas M Granger, Campbell R. Harvey, Nicolas le Roux, and Sandy Rattray, 2015, Dissecting Investment Strategies in the Cross Section and Time Series, *SSRN Electronic Journal*.

Britten-Jones, Mark, and Anthony Neuberger, 2000, Option Prices, Implied Price Processes, and Stochastic Volatility, *The Journal of Finance* 55, 839–866.

Campbell, John Y., Stefano Giglio, Christopher Polk, and Robert Turley, 2018, An intertemporal CAPM with stochastic volatility, *Journal of Financial Economics* 128, 207–233.

Carr, Peter, and Liuren Wu, 2009, Variance Risk Premiums, *Review of Financial Studies* 22, 1311–1341.

CBOE, 2014, The CBOE Volatility Index – VIX, .

Cheng, Ing-Haw, 2019, The VIX Premium, *The Review of Financial Studies* 32, 180–227.

Della Corte, Pasquale, Roman Kozhan, and Anthony Neuberger, 2021, The cross-section of currency volatility premia, *Journal of Financial Economics* 139, 950–970.

Demeterfi, Kresimir, Emanuel Derman, Michael Kamal, and Joseph Zou, 1999, A Guide to Volatility and Variance Swaps, *The Journal of Derivatives* 6, 9–32.

Dew-Becker, Ian, Stefano Giglio, Anh Le, and Marius Rodriguez, 2017, The price of variance risk, *Journal of Financial Economics* 123, 225–250.

Fallon, William, James Park, and Danny Yu, 2015, Asset Allocation Implications of the Global Volatility Premium, *Financial Analysts Journal* 71, 38–56.

Hamdan, Rayann, Fabien Pavlowsky, Thierry Roncalli, and Ban Zheng, 2016, A Primer on Alternative Risk Premia, *SSRN Electronic Journal*.

Henriksson, Roy D., and Robert C. Merton, 1981, On Market Timing and Investment Performance. II. Statistical Procedures for Evaluating Forecasting Skills, *The Journal of Business* 54, 513.

Johnson, Travis L., 2017, Risk Premia and the VIX Term Structure, *Journal of Financial and Quantitative Analysis* 52, 2461–2490.

Knauf, Stephane, 2003, Making money from FX volatility, *Quantitative Finance* 3, C48–C51.

Koijen, Ralph S.J., Tobias J. Moskowitz, Lasse Heje Pedersen, and Evert B. Vrugt, 2018, Carry, *Journal of Financial Economics* 127, 197–225.

Korajczyk, Robert A., and Ronnie Sadka, 2008, Pricing the commonality across alternative measures of liquidity, *Journal of Financial Economics* 87, 45–72.

Kozhan, Roman, Anthony Neuberger, and Paul Schneider, 2013, The Skew Risk Premium in the Equity Index Market, *Review of Financial Studies* 26, 2174–2203.

Lettau, Martin, Matteo Maggiori, and Michael Weber, 2013, Conditional Risk Premia in Currency Markets and Other Asset Classes, *SSRN Electronic Journal*.

Lustig, Hanno, Nikolai Roussanov, and Adrien Verdelhan, 2011, Common Risk Factors in Currency Markets, *Review of Financial Studies* 24, 3731–3777.

Martin, Ian, 2017, What is the Expected Return on the Market?*, *The Quarterly Journal of Economics* 132, 367–433.

Menkhoff, Lukas, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf, 2012, Carry Trades and Global Foreign Exchange Volatility, *The Journal of Finance* 67, 681–718.

Moskowitz, Tobias J., Yao Hua Ooi, and Lasse Heje Pedersen, 2012, Time series momentum, *Journal of Financial Economics* 104, 228–250.

Nagel, Stefan, 2014, The Liquidity Premium of Near-Money Assets.

Todorov, Viktor, 2010, Variance Risk-Premium Dynamics: The Role of Jumps, *Review of Financial Studies* 23, 345–383.