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From carry trades to curvy trades

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Abstract

Traditional carry trade strategies are based on differences in short-term interest rates, neglecting any other information embedded in yield curves. We derive return distributions of carry trade portfolios among G10 currencies, where the signals to buy and sell currencies are based on summary measures of the yield curve, the Nelson-Siegel factors. We find that a strategy based on the relative curvature factor, the curvy trade, yields higher Sharpe ratios and a smaller return skewness than traditional carry trade strategies. Curvy trades build less upon the typical carry currencies, like the Japanese yen and the Swiss franc, and are hence less susceptible to crash risk. In line with that, standard pricing factors of traditional carry trade returns, such as exchange rate volatility, fail to explain curvy trade returns in a linear asset pricing framework. Our findings are in line with recent interpretations of the curvature factor. A relatively high curvature signals a relatively higher path of future short-term rates over the medium-term putting upward pressure on the currency.

Keywords: currency carry trades, yield curve, Nelson-Siegel factors.

JEL-Classification: C23, C53, G11.

Non-technical summary

The forward premium puzzle has given rise to several studies that measure the economic return of portfolios including long positions in high interest rate currencies and short positions in low interest rate currencies, the so-called carry trade. According to UIP, the differential of short-term risk-free bond yields between two currencies, also known as the forward discount, equals the expected rate of depreciation of the higher yielding currency over the maturity of the interest rate. That said, high interest rate currencies are found to appreciate rather than depreciate over the short-term. Carry trades exploit the empirical failure of UIP by borrowing at low interest rates in one currency and investing into a higher yielding currency.

By trading on the relative forward discount, traditional carry trade strategies do not account for any information embedded in the respective yield curves beyond short-term interest rates. While this is an inherent feature of carry trades, it stands somewhat in contrast to a growing body of evidence which suggests that the yield curve contains some signalling power for future interest rates, the macroeconomy, and, in in particular, the exchange rate. Significant predictability of excess currency returns across a number of currencies may indeed have substantial implications for the optimal design of currency investments. Rather than exploiting the forward premium puzzle by sorting currencies into portfolios based on the relative forward discount, an alternative currency strategy could build upon trading signals derived from yield curve measures that contain some signalling power for future currency returns.

In this paper, we show that an investment strategy based on the relative curvature factor, the *curvy trade*, yields higher Sharpe ratios and lower negative return skewness than traditional carry trade strategies. By testing the predictive content of Nelson-Siegel factors for excess currency returns, we first show that the relative curvature factor has some signalling power for unexpected currency movements one to six months ahead. The lower

the domestic curvature relative to the US curvature, the higher the depreciation against the US dollar, beyond expectations implied in forward rates. Building upon this finding we sort currencies into portfolios based on the relative curvature factor, short-selling currencies with a relatively low curvature and investing into currencies with a relatively high curvature. In line with the respective trading strategies, higher economic returns of curvy trade portfolios relative to traditional carry trades strategies can be ascribed to higher returns from movements in the exchange rate that tend to off-set lower interest rate returns. The lower negative return skewness in turn reflects the different set of funding and investment currencies. Curvature trades build less upon the typical carry funding currencies, like the Japanese yen and the Swiss franc, and are hence less susceptible to crash risk. In line with that, standard pricing factors of traditional carry trade returns, such as FX volatility, fail to explain curvy trade returns in a linear asset pricing framework.

Our findings complement the literature on currency investment strategies in various forms. First, the significant predictability of exchange rates based on relative Nelson-Siegel yield curve factors in a panel of major currencies complements the existing evidence on the predictive content of relative yield curve factors for a small number of currencies against the US dollar. Second, we show that the negative skewness of the return distribution of currency investments, widely documented in the carry trade literature, is an inherent feature of the typical carry currencies. Building currency portfolios based on prospective exchange rate movements yields economic returns which are less skewed and therefore notably less subject to tail risks. In this vein, we also add to the related literature that rationalises the salient feature of negative return skewness by the stronger sensitivity of high interest rate currencies to FX volatility, and, to a lesser extent, liquidity constraints and commodity prices. With the return distribution being broadly symmetric, excess returns of curvy trade portfolios cannot be explained by standard risk factors.

1 Introduction

The forward premium puzzle has given rise to several studies that measure the economic return of portfolios including long positions in high interest rate currencies and short positions in low interest rate currencies, the so-called carry trade. According to the principle of uncovered interest rate parity (UIP), the differential of short-term risk-free bond yields between two currencies, also known as the forward discount, equals the expected rate of depreciation of the higher yielding currency over the maturity of the interest rate. That said, high interest rate currencies are found to appreciate rather than depreciate over the short-term (see, for instance, Bilson, 1981; Fama, 1984). Carry trades exploit the empirical failure of UIP by borrowing at low interest rates in one currency and investing the proceeds into a higher yielding currency.

By trading on the relative forward discount, traditional carry trade strategies do not account for any information embedded in the respective yield curves beyond short-term interest rates. While this is, by construction, an inherent feature of carry trades, it stands somewhat in contrast to a growing body of evidence which suggests that the yield curve contains some signalling power for future interest rates (Cochrane and Piazzesi, 2005; Piazzesi and Swanson, 2008; Piazzesi and Cochrane, 2009), the macro-economy (Estrella and Hardouvelis, 1991; Ang et al., 2006; Bekaert et al., 2010; Moench, 2012), and in particular the exchange rate (Chen and Tsang, 2013; Gräb and Kostka, 2018). Significant predictability of excess currency returns across a number of currencies may indeed have substantial implications for the optimal design of currency investments. Rather than exploiting the forward premium puzzle by sorting currencies into portfolios based on the relative forward discount, an alternative currency strategy could build upon trading signals derived from yield curve measures that contain some signalling power for future currency returns.

In this paper, we show that an investment strategy based on the relative curvature factor, the *curvy trade*, yields higher Sharpe ratios and lower negative return skewness than traditional carry trade strategies. By testing the predictive content of Nelson-Siegel factors for excess currency returns, we first show that the relative curvature factor has some signalling power for unexpected currency movements one to six months ahead. The lower the domestic curvature relative to the US curvature, the higher the average depreciation against the US dollar beyond UIP-implied expectations. Building upon this finding, we sort currencies into portfolios based on the relative curvature factor, short-selling currencies with a relatively low curvature and investing into currencies with a relatively high curvature. In line with the respective trading strategies, higher economic returns of curvy trade portfolios relative to traditional carry trade strategies can be ascribed to higher returns from movements in the exchange rate that tend to off-set lower interest rate returns. The lower negative return skewness in turn reflects the different set of funding and investment currencies. For instance, curvature trades build less upon the typical carry trade funding currencies, like the Japanese yen and the Swiss franc, and are hence less susceptible to crash risk. In line with that, standard pricing factors of traditional carry trade returns, such as exchange rate volatility, fail to explain curvy trade returns in a linear asset pricing framework.

Our findings complement the literature on currency investment strategies and term structure components in several ways. First, the significant predictability of exchange rates based on relative Nelson-Siegel yield curve factors when controlling for other global and country-specific predictors of exchange rates widely used in the carry trade literature (such as FX volatility, FX liquidity, commodity prices) complements the existing evidence on the predictive content of yield curve factors for a number of currencies against the US dollar (Chen and Tsang, 2013; Gräb and Kostka, 2018). In this vein, our findings also supplement the scant literature that benchmarks carry trade strategies that rely on signals from long-term interest rates and the slope of the yield curve against traditional carry trade strategies (Ang and Chen, 2010). Second, we show that the negative skewness of the return distribution of currency investments, widely documented in the carry trade literature (Lustig and Verdelhan, 2007; Brunnermeier et al., 2009), is an inherent feature of the typical carry currencies. Building currency portfolios based on prospective exchange rate movements yields return distributions which are less skewed and thus less subject to tail risks. In this way, we also add to the related literature that rationalises the salient feature of negative return skewness with the stronger sensitivity of high interest rate currencies to FX volatility, and, to a lesser extent, liquidity constraints and commodity prices (Lustig et al., 2011; Menkhoff et al., 2012; Lustig et al., 2013; Bakshi and Panayotov, 2013; Della Corte et al., 2016). With the return distribution being broadly symmetric, excess returns of curvy trade portfolios cannot be explained by observable risk factors—an assessment that is confirmed in a linear asset pricing framework.

Finally and importantly, we offer an intuitive economic interpretation of the outperformance of curvy trade returns that is line with recent interpretations of the curvature factor. While the yield curve's level and slope may have ambiguous interpretations of underlying economic developments, let alone exchange rates, the yield curve's curvature bears an unambiguous and forward-looking interpretation (Ang and Piazzesi, 2003; Ang et al., 2006). Abstracting from term premia, the curvature factor proxies the speed at which the short-rate converges to the long-rate (at a given level and slope) and can thus be related to the stance of monetary policy with a higher curvature indicating a more hawkish outlook for monetary policy and vice versa (Gürkaynak et al., 2007; Nyholm, 2016).[1] In the same vein, Moench (2012) finds that an idiosyncratic shock to the curvature predicts an increase in short-term rates and hence a tightening of monetary policy over the quarters ahead. Also Dewachter and Lyrio (2006) interpret the curvature factor as a measure of monetary policy tightness. Hence, if the domestic curvature is higher than the foreign curvature, domestic short-term interest rates are more likely to rise in the period ahead, even beyond expectations inherent in the expectation hypothesis of the term structure (Gräb and Kostka, 2018), forcing the domestic currency to appreciate vis-à-vis the foreign currency subsequently. This interpretation is consistent with the principle of uncovered interest parity (UIP) under exchange rate stationarity, according to which the level of the exchange rate today is determined by the expectation about future short term interest rate differentials (e.g. Engel and West (2010)). In line with this narrative, our

[1] This interpretation is substantiated by the loading structure of the Nelson-Siegel curvature factor. It effectively amounts to the difference of medium-term (2 year) yields over an average of very short-term (3 months) rates and very long-term (10 year) yields (also see, Diebold and Li, 2006)

results suggest that the period of the zero lower bound has materially weighed on the forward-looking capacity of the curvature factor. With medium-term yields being close to short-term rates, the curvature bears hardly any information that stretches beyond the signals that can be derived from the slope coefficient, which, in turn, is shown to carry little predictive content for future currency excess returns. However, with monetary policy normalisation being under way, the curvature may soon regain its signalling information for future monetary policy and exchange rates.

The rest of the paper is organised as follows. Section 2 presents the analysis on the predictive content of Nelson-Siegel factors for exchange rate movements in panel regressions of G10 currencies when controlling for popular exchange rate predictors. Section 3 describes the construction of different carry trade strategies and Section 4 presents the main findings on the relevant moments of these strategies' return distributions. The link to risk factors in cross-sectional asset pricing tests is analysed in Section 5. Finally, Section 6 concludes.

2 Nelson-Siegel factors and exchange rate movements

We build on the work of Chen and Tsang (2013) and Gräb and Kostka (2018) to investigate to what extent the term structure components level, slope and curvature can help predict exchange rate excess returns in-sample. This exercise does not aim to contribute any substance to the vast literature on exchange rate forecasting, inspired by and subsequent to Meese and Rogoff (1983). Instead, we are interested in gauge the relative strength of potential trading signals with a view to designing trading strategies that could potentially exceed the economic returns from traditional carry trade strategies. In this spirit, we complement the approach by Chen and Tsang (2013) and Gräb and Kostka (2018) by investigating which of the three Nelson-Siegel factors provides the strongest signal for future exchange rate dynamics when controlling for the standard global and country-specific pricing factors of carry trade returns, such as exchange rate volatility, exchange rate liquidity, commodity prices as well as measures of exchange rate momentum and value.

As proposed by Nelson and Siegel (1987), nearly all information embedded in the yield curve can be approximated by three nearly orthogonal factors. We extract the three Nelson-Siegel factors from period-by-period OLS regressions of Equation (1) using G10 zero coupon yields at maturities from three months to ten years.[2]

$$y_t^m = L_t + S_t \left(\frac{1 - e^{\phi m}}{\phi m} \right) + C_t \left(\frac{1 - e^{\phi m}}{\phi m} - e^{\phi m} \right), \tag{1}$$

where y^m is the set of zero-coupon nominal yields on bonds with m-months residual maturity.[3] The three time-varying factors L_t, S_t, C_t capture the level (L_t), slope (S_t) and curvature (C_t) of the yield curve at each period t.[4]

We test for the ability of Nelson-Siegel factors to forecast exchange rate excess returns for return horizons h, $h \in 1, 3, 6, 12$ months, in a linear fixed-effects panel model, when adding standard pricing factors of carry trade returns to the equation.

$$\begin{aligned} s_{t+h}^{i/USD} - f_t^{i/USD} &= \alpha_i^h + \beta_1^h (L_t^i - L_t^{US}) + \beta_2^h (S_t^i - S_t^{US}) + \beta_3^h (C_t^i - C_t^{US}) \\ +\gamma_1^h \Delta\sigma_t^{FX} + \gamma_2^h &\Delta CRB_t + \gamma_3^h \Delta Liq_t + \gamma_4^h Moment_t^{i/USD} + \gamma_5^h Value_t^{i/USD} + b_t^h + \epsilon_t, \end{aligned} \tag{2}$$

where the exchange rate excess returns, $s_{t+h}^{i/USD} - f_t^{i/USD}$, are based on the difference of the logarithms of spot and forward exchange rates quoted in units of US dollar.[5] $L_t^i - L_t^{US}$, $S_t^i - S_t^{US}$, and $C_t^i - C_t^{US}$ correspond to the respective Nelson-Siegel factor differentials vis-à-vis the US. α_i and b_t are currency and year fixed effects, respectively.

Five additional exchange rate predictors are considered. The three global factors are borrowed from Bakshi and Panayotov (2013) and capture the moving three-months change in the average intra-month volatility of the daily G10 exchange rate returns ($\Delta\sigma_t^{FX}$), the

[2]Data on zero coupon yields are taken from Datastream.

[3]Following Diebold and Li (2006), ϕ, the speed of exponential decay, is set to 0.0609.

[4]As a robustness check, we also compute level, slope and curvature based on the Diebold and Li (2006) approximation, where $L_t = (y_t^{3m} + y_t^{10y})/2$, $S_t = (y_t^{10y} - y_t^{3m})$, and $C_t = 2 * y^{2y} - (y_t^{10y} + y_t^{3m})$. The correlation between the Nelson-Siegel factors and these factors is 0.93, 0.93 and 0.95, for level, slope and curvature, respectively.

[5]Data on monthly bilateral spot and forward exchange rates are taken from Barclays via Datastream.

moving three-months return of the Commodities Research Bureau's (CRB) spot commodity index (ΔCRB_t), and the average bid-ask spread of the G10 spot dollar exchange rate (ΔLiq_t). While exchange rate volatility and illiquidity are found to be associated with an appreciation of the US dollar along with other so-called safe haven currencies, higher commodity prices typically coincide with a surge in the value of currencies with higher risk premia (vis-à-vis the US dollar). Finally, the majority of the currencies in the panel have a positive risk premium vis-à-vis the dollar. We thus expect positive signs for γ_1 and γ_3 and a negative one for γ_2. In addition, inspired by Ang and Chen (2010) and Della Corte et al. (2016), we include measures of exchange rate momentum ($Moment_t^{i/USD}$) and value ($Value_t^{i/USD}$) as currency-specific predictors. The two measures correspond, respectively, to the three-months and five-year exchange rate depreciation of currency i vis-à-vis the dollar prior to month t. It is assumed that exchange rates follow their short-term trend (i.e. $\gamma_4 > 0$), but move against their long-term trend (i.e $\gamma_5 < 0$).[6]

We consider all G10 currencies vis-à-vis the US dollar, including the Australian dollar, the British pound, the Canadian dollar, the euro (Deutsche mark before 1999), the Japanese yen, the New Zealand dollar, the Norwegian krone, the Swiss franc and the Swedish krona. We use monthly end-of-period data, with the sample spanning the period from January 1991 to December 2015.[7]

The regression output of Equation (2) is presented in Table 1. The elasticity of the relative curvature factor is negative and statistically significant for predictions up to six months ahead. The coefficients of the additional regressors have the expected sign and are statistically significant in particular for shorter forecast horizons. The negative sign of the coefficient on the relative curvature factor implies that a lower curvature in country i relative to the US curvature is associated with a future depreciation of that currency vis-à-vis the US dollar. The result suggests that the curvature factor, in contrast to the other two NSFs (level and slope), may carry predictive content for exchange rate risk premia

[6]Standard errors are clustered at the currency level.

[7]Following Della Corte et al. (2016), we eliminate the following observations from our sample: Japan from May 1998 to July 1998; Norway from July 1998 to August 1998; Sweden from July 1998 to August 1998. In addition we eliminate: Norway from September 1992 to November 1992; New Zealand: February 1998; Sweden: December 1999.

one month to six months ahead. This is broadly consistent with the results by Chen and Tsang (2013) and Gräb and Kostka (2018) who also find predictive content of the relative curvature factor for the majority of the currencies under consideration. Stretching beyond their findings, our results remain robust to the addition of other popular drivers of exchange rate risk premia that have been widely exploited in the carry trade literature.

The next section explores how this statistical relationship translates into an economic one. In particular, we benchmark the performance of the curvy trade portfolios (i.e. portfolios sorted by the relative curvature) against that of traditional carry trade portfolios (i.e. portfolios sorted by the relative discount factor). For completeness, we also derive the return characteristics for currency portfolio strategies based on the relative level and slope factors.

3 Carry trade construction

We take the perspective of a US investor. Funding currencies are sold against the US dollar, and the US dollar proceeds are invested into a third currency. The resulting exposure is neutral with respect to the dollar. We follow Bakshi and Panayotov (2013) in that all carry trade strategies are symmetric, i.e. the number of funding currencies is equal to the number of investment currencies in each portfolio, where a portfolio consists of k currencies, $(1 \leq k \leq 4)$.[8]

Following the literature, we take into account transactions costs, distinguishing between bid and ask spreads in order to work with net portfolio returns. For our analysis of the standard characteristics of symmetric carry trade strategies (Section 4) we take account of each month's long and short trades' transaction costs with full portfolio turnover. In the asset pricing exercises (Section 5) we instead follow Menkhoff et al. (2012) and deduct the bid-ask spread from excess returns depending on whether the currency was in the same

[8]Using symmetric portfolios consisting of k currencies has the advantage of explicitly testing whether results are robust across portfolios consisting of a different number of investment and carry currencies.

portfolio in the previous month and whether it remains there in the following month.[9] We adjust the returns of the short portfolio for the transaction costs of selling the particular (e.g. low interest rate) currency. Net returns of the long portfolio are adjusted for the transaction costs of buying a respective (e.g. high interest rate) currency.[10]

The return on a currency that remains in the same (either short or long) portfolio in $t-1$, t and $t+1$ is given by:

$$rx_{t+1} = \frac{F_t}{S_{t+1}} - 1, \tag{3}$$

and determined by mid-rates in both the forward and spot market.

For a currency that enters a new portfolio in t, a bid-rate F_t^b in the forward market applies for long portfolios, while an ask-rate F_t^a applies for short portfolios. Equivalently, an ask-rate in the spot market S_{t+1}^a applies for a currency that exits a long portfolio in $t+1$, while a bid-rate in the spot market S_{t+1}^b applies for a currency that exits a short portfolio. Table 2 provides a complete overview of currency excess returns construction.

We sort currencies into short and long portfolios based on the signals derived from the relative forward discount (traditional carry trade strategy), as well as based on relative level, slope and curvature factors as described in Equation (1). The signs of the respective elasticities derived in Table 1 are suggestive of strategies to sell a relatively low level, low slope and low curvature currencies and to buy relatively high level, high slope and high curvature currencies.

[9] We find that the results of cross-sectional asset pricing regressions are generally robust to transaction costs with full portfolio turnover as in Lustig et al. (2011) as well as for returns without transaction costs.

[10] Following, the presentation of Menkhoff et al. (2012), for the cross-sectional asset pricing exercise, we use long returns for all portfolios regardless of whether they are funding or investment currencies.

4 Characteristics and predictability of carry trade and curvy trade return distributions

4.1 Curvy trades yield higher Sharpe ratios

We first consider the equally-weighted carry trade strategies based on the standard sorting, using forward discounts. Over the full sample, spanning the time period from January 1991 to December 2015, the annualised average returns of this strategy range between 1.26 percent for the $k = 1$ currency baskets and 2.34 percent for the $k = 3$ currency baskets (see Table 3). The standard deviations and corresponding Sharpe ratios range between 7.09 and 13.35 percent and 0.09 and 0.27, respectively.

Notably higher annualized returns and Sharpe ratios can be achieved with curvy trade portfolios. Their Sharpe ratios range between 0.36 and 0.56 with the highest Sharpe ratio for the $k = 1$ currency baskets. This finding stands in contrast with the standard result in the literature that the Sharpe ratio of *traditional* carry trade strategies gradually increases with the number of currencies in the basket—up to a certain threshold—, reflecting a monotonous decline in the portfolios' return volatility (see, for instance, Bakshi and Panayotov, 2013).

Finally, the results presented in Table 3 suggest that portfolios sorted by the relative level and slope factors yield lower Sharpe ratios than forward discount and curvature sorted portfolios, reflecting both low returns and high return volatility. The remainder of the paper will therefore focus on the properties of the curvature sorted, curvy trade, portfolios using the traditional carry trade strategy as the benchmark.

4.2 Lower negative return skewness

A common finding in the carry trade literature is the negative skewness of carry trade returns, reflecting that returns of typical carry trade currency pairs (e.g. AUD/JPY) are subject to negative tail risks (see, for instance, Brunnermeier et al., 2009; Bekaert and Panayotov, 2015). In line with the literature, we find substantial negative skewness in the traditional carry trade return distribution; and we find that the skewness becomes less negative the more currency pairs are included in a carry trade, ranging between -1.34 for strategy $k = 1$ and -0.35 for strategy $k = 4$. For the curvy trade, there is no such negative skewness in the return distribution of all but one strategy, while the negative skewness of the $k = 1$ currency basket is smaller than that of any of the traditional carry trade strategies. The positive (or less negative) skewness of the curvature trade returns is also illustrated in Figure 1 which plots the mean returns of the curvature and forward discount sorted currency strategies for $k = 1$ to $k = 4$. Figure 1 highlights that downward spikes in annual returns are much less frequent for curvy trades, vividly illustrating the disappearance of negative return skewness as an inherent feature of currency investment strategies.

4.3 Different set of funding and investment currencies

What are the main funding/investment currencies in curvy trades? Table 4 illustrates that the set of funding currencies used in curvy trades is materially different from those used for traditional carry trades. The Japanese yen and the Swiss franc are the standard funding currencies when currencies are sorted into short portfolios based on their forward discount vis-à-vis the US dollar. The Norwegian krone and the Deutsche mark are, by contrast, very rarely used as the short leg of traditional carry trades. This pattern reverses for the curvy trade signal: the Swiss franc becomes much less important as a funding currency, while the Norwegian krone and the Deutsche mark are frequently sorted into short portfolios. Also the relative frequency of currencies sorted into long portfolios is materially different across the two signals (see Table 5). Interestingly, the British pound and, albeit to a lesser extent, the Swiss franc turn into frequently used investment currencies when portfolios are based on the curvature signal. Overall, the curvature signal leads to a more evenly distributed ranking of currencies.

4.4 Time consistency and out-performance of short positions

The remarkable performance of the curvy trade strategy raises the question whether this result has been driven by few outlier years or specific episodes, for instance the financial crisis period. Figure 2 depicts the development of annual Sharp ratios throughout the sample period (from 1991 to 2015). It shows that the curvature trade has a very limited number of sharp downward or upward spikes, implying that the finding of higher Sharpe ratios is rather robust over time. That said, the curvy trade underperforms the traditional carry trade with respect to the last five years of the sample. This underperformance of curvy trades since 2010 coincides with the so-called zero or effective lower bound period, i.e. the years when the main policy rates of major central banks around the world had been close to zero. Coupled with forward guidance policies on the future path of short-term risk-free rates, the yield curve flattened materially up to medium-term maturities in several economies in our sample (e.g. US, euro area, Japan, UK). With medium-term yields being close to short-term rates, the curvature bears hardly any information that stretches beyond the signals that can be derived from the slope coefficient, which has been shown to carry little predictive information for future currency excess returns (see Table 1). This suggests that the zero lower bound period has materially weighed on the forward-looking capacity of the curvature factor when it comes to forecasting currency risk premia. However, with a number of rate hikes having taken place in the US, and a solid global growth momentum paving the way towards monetary policy normalisation for other major central banks, the curvature may regain its signalling information for future monetary policy.

Finally, the out-performance of those curvy trade strategies which use a relatively low number of currency pairs in each portfolio is particularly driven by the relative out-performance of the short positions. Figure 3 shows that the short positions of curvy trade strategies building on few currency pairs yield substantially higher mean returns and positive return skewness, relative to any of the traditional carry trade short portfolios.

4.5 Standard predictors of carry trade returns fail to explain performance of the curvature trade

Having established that curvy trades yield significantly higher payoffs relative to traditional (i.e. forward discount sorted) carry trade strategies, we next turn to the question whether standard predictors of carry trade payoffs continue to hold true for curvy trades. Menkhoff et al. (2012) have shown that carry trade payoffs are negatively related to volatility in global foreign exchange markets. At times of elevated volatility, high-yielding currencies tend to depreciate, thus delivering low returns. High-yielding currencies therefore offer a currency risk premium to compensate investors for crash risk (see, for instance, Brunnermeier et al., 2009; Burnside et al., 2011; Lustig et al., 2011; Farhi et al., 2015). A similar interpretation has been put forward by Della Corte et al. (2016) who relate currency risk premia to global imbalances, arguing that debtor countries' currencies offer a premium to compensate investors' willingness to finance current account deficits, precisely because these currencies tend to depreciate at times of heightened financial market volatility.

To investigate potential drivers of the curvature trade, we follow Bakshi and Panayotov (2013) and consider regressions of the form

$$rx_{t+1}^{k} = \beta_0 + \beta_1 \Delta\sigma_t^{FX} + \beta_2 \Delta CRB_t + \beta_3 \Delta Liq + \epsilon_t, \tag{4}$$

where rx_{t+1}^{k} is the carry trade and curvy trade return for month $t+1$ in portfolios with k short and long currencies; σ_t^{FX} is volatility in foreign exchange markets, ΔCRB_t corresponds to changes in a commodity prices index, and Liq is a measure of liquidity in financial markets (see Section 2 for more details).

The results are presented in Table 6. We can confirm earlier findings of the predictability of traditional carry trade returns (columns 1 to 4). Increases in volatility are significantly related to lower carry trade returns across all portfolios, i.e. with $1 \leq k \leq 4$. Similarly, an increase in commodity prices explains significantly higher carry payoffs across portfolios.

However, standard factors fail to predict curvy trade returns (columns 5 to 8 of Table 6). The results thus tentatively suggest that curvy trade returns cannot be interpreted as a compensation for risk.

The subsequent section takes a deeper look into any risk-based explanations of carry trade payoffs.

5 Cross-sectional asset pricing

We deploy a standard linear asset pricing framework to test whether the cross-sectional variation of returns across our curvy trade portfolios can be reconciled with the existence of any type of risk premium paid for higher curvature currencies. Arbitrage pricing theory (Ross, 1976) states that portfolio returns can be modelled as a linear function of factors, with factor coefficients representing the portfolio's exposure to the respective factor. We first apply asset pricing tests for traditional carry trade strategies to assess whether we can replicate the asset pricing results of Lustig et al. (2011) and Menkhoff et al. (2012). Based on these findings we then search for a risk-based explanation for returns generated by sorting currencies on their curvature signal.

5.1 Set-up of cross-sectional asset pricing tests

First, we assess the capability of the volatility risk factor—as established by Menkhoff et al. (2012)—to price the returns in the cross-section of portfolios.[11] Portfolio returns are represented by their long returns, i.e. the return incurred by buying the foreign currency against the dollar in the forward market and selling it in the spot market at the end of the month, such that returns can be compared across portfolios.

[11] In their cross-sectional analysis using different factors, Lustig et al. (2011) argue for the use of geometric excess returns ($rx_{t+1} = \frac{F_t}{S_{t+1}} - 1$) in order to avoid needing the assumption of joint log-normality of excess returns and the pricing kernel. We carry out our analysis also for excess returns in logs, confirming the results obtained with geometric returns.

To assess whether there is a linear relationship between factor loadings and the size of the forward discount or curvature represented by a particular portfolio, we allocate currencies into three portfolios (instead of two). At each point in time, they are composed of the three currencies with the lowest (PF1), medium (PF2) and highest (PF3) forward discounts / curvature (relative to the US) in the G10 sample.[12,13] Portfolio excess returns are then computed as an equally weighted average of the currencies' returns within each portfolio.

5.1.1 Principal component analysis

Figure 4 presents mean portfolio returns for both sorting strategies (left: carry trades; right: curvy trades). In both strategies, portfolio returns are monotonically increasing in the size of their average forward discount and relative curvature.[14]

To examine the relationship with risk factors established in the literature, we motivate the choice of risk factors by carrying out a principal component analysis as in Lustig et al. (2011). Table 7 reports the loadings of the three principal components of the three portfolio returns as well as their correlation with other popular carry trade factors for both sorting strategies. Panel I.A replicates the findings of Lustig et al. (2011) for the traditional carry trade portfolios applied to the sample of G10 currencies. First, loadings on the first principal component are very similar across portfolios. It is moreover highly correlated with the average exchange rate return vis-a-vis the dollar, the so-called dollar factor (DOL). Second, loadings on the second principal component increase monotonically across portfolios with a negative loading on portfolio 3 and a positive loading on portfolio

[12]Given that we have only nine currencies in bilateral terms against the US dollar, we cannot create five portfolios as is standard in the literature.

[13]In our sample, transaction costs change excess returns significantly once currencies have been sorted into portfolios. We see this by looking at the frequency of portfolio switches per currency. Specifically, for forward discount sorting, we find that currencies switch between 12 (JPY) and 59 (CAD) times in our sample spanning a total of 300 months. For the curvature sorting, currencies switched portfolios in the range of 54 (GBP) to 129 (NOK). The allocation of currencies into portfolios thus shows more variation over time when using curvature sorting. Transaction costs thus matter more for the portfolio returns.

[14]Aside from the different accounting of transaction costs, these mean returns for portfolios 1 (low forward discount/curvature) and 3 (high forward discount/curvature) are equivalent to the statistics on short and long trades, respectively, of strategy $k = 3$ presented in Section 3. The long returns of portfolio 1 are negative reflecting that it is profitable to sell the currencies included in this portfolio.

1. It is therefore highly correlated with the total carry trade return, approximated by the difference between PF3 and PF1 (HML) (corresponding to a long position in PF3 and a short position in PF1). We also find a correlation of 0.29 between principal component 2 and the innovations in FX volatility (VOL), confirming that the cross-section of portfolio returns in traditional carry trades is associated to the portfolios' varying degrees of risk-sensitivity.

Turning to curvy trade portfolios (Panel II), the first principal component explains 83% of variation, suggesting that dollar returns may matter a little more for this strategy. Curvy trade portfolios also exhibit a trend in loadings from negative to positive for the second principal component. The latter explains less variation (9%) than in the case of forward discount sorted portfolios. While the DOL and HML factor again correlate highly with principal components 1 and 2 (0.99 and 0.93 respectively), the volatility risk factor (VOL), that Menkhoff et al. (2012) show to matter for forward discount sorted portfolios, does not exhibit a notable correlation with any of the principal components.

5.2 Asset Pricing Tests

We now examine more thoroughly if curvy trade returns can be explained by global risk factors. Throughout the analysis, we use the dollar risk factor DOL as the first risk factor. This factor represents the average returns from buying an equally weighted basket of currencies against the dollar. The second risk factor is innovations in exchange rate volatility (VOL).[15]

In a standard no-arbitrage relationship the return adjusted for risk is zero, so that the Euler condition

$$E[M_{t+1}Rx^i_{t+1}] = 0 \tag{5}$$

[15]We employ the definition of Bakshi and Panayotov (2013) for the level of volatility, constructed as the square root of the sum of squares of daily log changes in the spot rate, averaged across currencies. The VOL risk factor is then constructed in the same way as Menkhoff et al. (2012) as the residual from an AR(1) model of the level of volatility.

is satisfied. The stochastic discount factor M is linear in the pricing factors h:

$$M_t = 1 - b(h_t - \mu_h) \tag{6}$$

where μ_h are factor means and b denotes a vector of stochastic discount factor loadings, implying a beta pricing model

$$E[Rx_t^i] = \lambda_t' \beta^i, \tag{7}$$

with risk factor prices λ where $\lambda = \sum_{hh} b$ and $\sum_{hh} = E(h_t - \mu_h)(h_t - \mu_h)'$ is the risk factor variance-covariance matrix. We estimate λ and β from the stochastic discount factor representation using the generalised method of moments (GMM) by Hansen (1982).

In addition, we use the traditional two-stage OLS Fama-MacBeth procedure (Fama and MacBeth, 1973) to retrieve portfolio betas and risk prices for each factor in the beta-pricing representation. The first stage is a time-series regression of excess returns $E[Rx_t^i]$ on risk factors h_t and a constant with a separate regression for each portfolio i. This procedure generates time-independent factor exposures β^i. In the second stage, we run T cross-sectional regressions (one for each time period t) of excess returns on the exposures β^i estimated in the first stage. The estimated portfolio-independent coefficients $\hat{\lambda}_t$ are averaged across time periods to retrieve factor risk prices $\hat{\lambda} = \frac{1}{T}\sum_{t=1}^{T} \hat{\lambda}_t$. We do not include a constant in the second stage which rules out the possibility of over- or underpricing.[16]

5.2.1 Forward discount sorted currencies

The left-hand side of Table 8 reports the results of asset pricing regressions on portfolios sorted by forward discount. Panel I shows the risk prices obtained from GMM and Fama-MacBeth regressions (second stage).[17] We report p-values for a χ^2 test on the pricing

[16]As mentioned in Menkhoff et al. (2012), using a constant instead of the DOL factor in the second stage yields very similar results as the DOL factor only contains explanatory power in the time-series. In line with the constant loading of the second principal component across portfolios, the DOL factor has little explanatory power in the cross-section. Any mis-pricing essentially occurs in the DOL coefficient.

[17]To account for the errors-in-variables problem of estimating the risk price λ using factor exposures β^i estimated in the first stage, we provide standard errors with the Shanken (1992) correction. We additionally report Newey-West (1987) standard errors (using data-driven optimal lag selection according

errors. Panel II reports the exposures and constants from the first stage Fama-MacBeth regressions. The corresponding Newey-West standard errors are shown in parentheses.

We find support for the results of Lustig et al. (2011) insofar as the HML^{FD} risk factor is positive and highly significant in explaining cross-sectional variation (Table 9). As HML^{FD} is a traded factor, the risk price is equal to the mean of HML^{FD} level returns. A portfolio with an exposure (beta) of 1 to HML^{FD} risk will thus earn a premium of 4.14% per annum. The same is true for the DOL risk price, which is unsurprisingly insignificant.

The left-hand side of Panel II shows why the average currency excess return against the dollar has no explanatory power and turns out insignificant in the cross-section. Each portfolio has a beta of 1 with respect to this factor. Although the exposure to DOL risk β_{DOL} does not explain returns in the cross-section, the risk factor is important and highly significant in the first stage of Fama-MacBeth for determining the level of excess returns. We observe that exposures to HML^{FD} risk, by construction, have opposite signs in the highest and lowest forward discount sorted portfolios. Specifically, we see a monotonic trend across portfolios from -0.52 in portfolio 1 to 0.48 in portfolio 3, which aligns with the principal component 2 loadings and serves to explain the cross-sectional variation. The estimate for portfolio 2 is unsurprisingly estimated with less precision. The alpha estimates are insignificant and the null that alphas are jointly zero is not rejected.[18]

We find a significant negative coefficient for volatility innovations, providing support for the finding by Menkhoff et al. (2012) that volatility explains the cross-sectional variation of portfolio returns. Two factors explain almost all variation in the cross-section of three portfolios. Portfolios that co-move positively with volatility innovations, i.e. those that perform well in times of heightened global exchange rate volatility (insuring against the risk), earn a lower risk premium on their portfolio. Those that experience lower returns in times of high volatility therefore earn, on average, a positive premium. Such currencies are generally found in portfolio 3. In Panel II, we find the same monotonic decline of

to Andrews (1991) (see chapter 12.2 of Cochrane, 2005).

[18]Because we have a linear combination of factors, this imposes the following properties on the coefficients for orthogonal factors: $\alpha^3 = \alpha^1$, $\beta^3_{DOL} = \beta^1_{DOL}$ and $\beta^3_{HML} - \beta^1_{HML} = 1$. We observe this in our results.

betas from portfolio 1 through to portfolio 3 that is reported by Menkhoff et al. (2012), with a time-series fit of 70% or more in each portfolio. Volatility betas range from 6.47 in portfolio 1 to -5.08 in portfolio 3 and are statistically significant. In line with expectation, the co-variance of portfolio excess returns with DOL returns is generally close to 1 and statistically significant. We do however pick up significant coefficients on the constant term for portfolio 1 and 3, which seems to pick up the divergences from $\beta_{DOL} = 1$ for portfolio 1 and 3.

5.2.2 Curvature sorted currencies

Table 8 also reports the results of using these risk factors for pricing curvy trade portfolios. Given the loadings of the first and second principal component, we are again interested in a risk-based explanation using DOL as a level factor and VOL as a slope factor. Given the very low correlation of the second principal component and the risk factor VOL established in the principal component analysis, we do not expect VOL to price portfolio returns in the cross-section. This is also what we find. Global exchange rate volatility innovations have a negative but insignificant risk price. The corresponding χ^2 statistic strongly rejects the hypothesis of pricing errors equal to zero. In the first stage regressions, we find very different exposures to volatility risk across portfolios, however none of these are significant and they do not display a monotonic trend. Additionally, we observe that the $\chi^2(\alpha)$ statistic strongly rejects the null hypothesis of intercepts jointly being zero. Clearly, such a linear asset pricing model does not sufficiently explain the variation in the cross-sectional or the time series dimension, and we consequently find significant over- and underpricing in portfolios 3 and 1. At the same time, dollar returns work much in the same way as for other asset pricing tests, with highly significant exposures close to 1 and an insignificant cross-sectional estimate.

In addition, we run regressions with the high-minus-low factor, HML, as the second risk factor (Table 9). The returns of 4.06% per annum are highly significant. Given the nature of how the risk factor is constructed, this should again not be surprising. Especially when the sample restricts the number of portfolios to three, two out of three portfolios (the first and last portfolio) are by default highly exposed to the risk factor. The estimated exposure for portfolio 2 however generates significant support for an interpretation as a slope factor, as the exposures display a monotonic trend ranging from -0.47 to 0.53.

The DOL factor is qualitatively and quantitatively very similar to the case of forward discount sorting, both in terms of the highly significant exposures in the time-series dimension as well as the insignificant risk price and inability to price returns in the cross-section.

The results of the cross-sectional asset pricing tests are consistent with the findings of the principal component analysis. Returns generated by curvature sorting of currencies cannot be reconciled with risk-based explanations. The risk factors brought forward by existing studies on the carry trade neither correlate with the principal component nor explain the cross-section of returns in a linear asset pricing model. This is also the case for factors such as liquidity and commodity indices discussed in the context of carry trade predictability (Bakshi and Panayotov, 2013).[19]

5.2.3 Factor-mimicking portfolio and beta sorting

We carry out some additional analyses to generate further confirmation of the cross-sectional pricing ability. We construct a factor-mimicking portfolio for the non-traded VOL factor and create portfolios based on beta sorting.

We follow Menkhoff et al. (2012) to generate a factor-mimicking portfolio of the VOL factor. Volatility innovations are regressed on a constant and the excess returns in each portfolio. Using the estimated vector of coefficients b, we generate returns of the factor-mimicking portfolio as $Rx_{t+1}^{FMP} = \hat{b}' Rx_{t+1}^{i}$. By generating a traded factor for VOL, we can interpret the risk price on the factor mimicking portfolio in the same way as other traded factors like DOL.

[19] Further asset pricing results using risk factors ΔCRB and ΔLiq, as employed in the predictive regressions by Bakshi and Panayotov (2013), are available upon request. These factors are equally unable to price the cross-section of curvature sorted portfolios.

The left-hand side of Table 10 replicates the cross-sectional regressions for forward discount sorted portfolios. The weights assigned in constructing the factor mimicking portfolio are 0.0077 (PF1), -0.0026 (PF2), and -0.0062 (PF3). As expected, the loading on portfolio 1 is positive, and there is a monotonic trend towards a negative loading for portfolio 3. As Menkhoff et al. (2012) point out, this not only generates a high correlation of the factor mimicking portfolio VOL_{fmp} with the second principal component (0.90) but also with a high-minus-low factor (0.98). Pricing portfolio excess returns with the factor mimicking portfolio thus strongly supports the previous findings.[20]

The right-hand side of Table 10 shows the results for the same exercise applied to the curvature sorted portfolios. The weights are -0.0031 (PF1), 0.0033 (PF2) and -0.0036 (PF3). While exposures to VOL risk are significant, they are not monotonically trending. In addition, the risk price for the factor-mimicking portfolio is insignificant. This confirms the inability to reconcile curvature sorted portfolio returns with common risk interpretations.

Next, we turn to generating portfolios based on factor betas. Sorting currencies based on each currency's exposure to VOL should generate further evidence for the previous findings. The exposure is estimated from a regression of each currency's excess returns on the factor and a constant in rolling 36 month windows. The highest betas enter portfolio 3, while portfolio 1 contains the lowest betas. Portfolios are re-balanced every 6 months. Excess returns are based on log returns without bid-ask spread. We report descriptive statistics for portfolios sorted according to VOL betas in Table 11. We find that sorting on the exposures to risk factor VOL creates a monotonic decline in portfolio returns from portfolio 1 to 3. The explanation is that high beta currencies which hedge against volatility risk earn a lower mean return (Menkhoff et al., 2012). We thus see the lowest returns for those currencies least exposed to volatility risk (portfolio 3). The pre- and post-formation forward discounts show that the portfolios generated from VOL betas have similar characteristics to the traditional carry trade, for which the highest forward

[20] The significant negative risk price of -0.03% per annum is for a beta of 1. Given that the betas are large, this is simply a result of scaling in the volatility measure.

discount currencies enter the first portfolio with the highest returns. Sorting on volatility risk is thus similar to sorting on the forward discount. Pre- and post-formation curvature interestingly also indicate a monotonic trend, which would point towards some similarities between sorting on VOL and sorting on curvature. However, in particular the difference between pre-formation curvatures in portfolio 1 and 2 is small, thereby providing support for the statistical insignificance of the negative coefficient on volatility risk obtained in the cross-sectional pricing regression.

6 Conclusion

Recent advances in the literature on term structure models suggest that the term structure components, level, slope and curvature, may contain some predictive information for financial markets in general, and exchange rate movements in particular. We build upon this finding and test whether carry trade portfolios where the signals to buy and sell currencies are derived from signals by relative yield curve factors, yield different return distributions relative to traditional carry trade strategies. We find that a currency investment strategy based on the relative curvature factor, the curvy trade, yields higher Sharpe ratios than traditional carry trade strategies. Moreover, we find that the negative skewness of carry trade returns does not apply to the curvy trades. The skewness of returns of traditional carry trade portfolios reflects the characteristics of typical funding and investment currencies. This is also confirmed in a linear asset pricing framework which finds that curvature sorted carry trade portfolios do not reconcile with risk-based explanations. We offer an intuitive economic explanation of the strong relationship between the relative curvature factor and future exchange rates that is in line with recent interpretations of the yield curve; a relatively high curvature signals a relatively higher path of future short-term rates, putting upward pressure on the currency.

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A Tables

Table 1: In-sample predictions of FX returns—including standard predictors

	(1) 1 month	(2) 3 months	(3) 6 months	(4) 12 months
dCRB	-0.05	-0.17***	0.06*	0.10***
	(-1.46)	(-7.58)	(2.02)	(5.49)
dLiq3	-8.09***	18.76***	10.59***	-11.89**
	(-3.94)	(3.80)	(4.07)	(-2.50)
Volatility_FX	0.02***	0.00*	-0.03***	0.03***
	(4.37)	(1.89)	(-5.96)	(4.89)
Moment	0.00	-0.06***	-0.04***	-0.03
	(0.01)	(-6.06)	(-4.47)	(-1.39)
Value	-0.03***	-0.02***	-0.02***	-0.00
	(-4.62)	(-4.15)	(-3.49)	(-0.64)
Level	-0.12	0.03	-0.35	0.64
	(-0.12)	(0.04)	(-0.46)	(0.80)
Slope	-1.20*	-0.42	-0.55	-1.15
	(-1.86)	(-0.76)	(-1.00)	(-1.53)
Curvature	-1.17*	-0.64*	-0.82*	0.14
	(-1.93)	(-1.85)	(-1.91)	(0.32)
Observations	2772	2748	2721	2667
R^2	0.09	0.12	0.09	0.08

t statistics in parentheses
Robust standard errors.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Excess returns Rx_{t+1}

Funding portfolios			Investment portfolios		
	remains in $t+1$	exits in $t+1$		remains in $t+1$	exits in $t+1$
remains in t	$S_{t+1}/F_t - 1$	$S^b_{t+1}/F_t - 1$	remains in t	$F_t/S_{t+1} - 1$	$F_t/S^a_{t+1} - 1$
enters in t	$S_{t+1}/F^a_t - 1$	$S^b_{t+1}/F^a_t - 1$	enters in t	$F^b_t/S_{t+1} - 1$	$F^b_t/S^a_{t+1} - 1$

Notes: The table provides an overview of currency excess returns construction.

Table 3: Return distributions of carry trade strategies

Sorting	**k**	**Mean annual**	**Stdev annual**	**Skewness monthly**	**Kurtosis monthly**	**Sharpe ratio**
Forward discount	1	1.26	13.35	-1.34	6.99	0.09
	2	1.83	10.44	-1.20	6.14	0.18
	3	2.34	8.61	-0.76	5.19	0.27
	4	1.58	7.09	-0.35	5.02	0.22
Level	1	1.34	14.36	-0.69	5.25	0.09
	2	0.16	11.00	-0.80	5.64	0.01
	3	0.22	7.88	-0.55	4.49	0.03
	4	-0.40	6.58	-0.49	3.89	-0.06
Slope	1	3.11	11.67	-0.13	3.74	0.27
	2	1.10	8.91	-0.38	4.82	0.12
	3	0.57	7.69	-0.39	5.93	0.07
	4	-0.13	6.60	-0.14	5.05	-0.02
Curvature	1	6.67	11.99	-0.23	3.81	0.56
	2	2.95	8.13	0.17	3.80	0.36
	3	2.64	6.70	0.01	3.93	0.39
	4	2.25	6.20	0.29	4.63	0.36

Notes: The table reports the return distributions of the different carry trade strategies, where k corresponds to the number of currencies in each portfolio (long and short portfolios).

Table 4: Frequency of currencies used as *funding* currencies by carry trade strategies

Sorting	**k**	**AUD**	**CAD**	**CHF**	**DEM**	**GBP**	**JPY**	**NOK**	**NZD**	**SEK**
Forward discount	1	0	1	83	0	1	213	0	0	2
	2	8	18	263	5	2	280	1	6	17
	3	24	81	272	47	57	293	25	15	86
	4	36	177	285	62	93	293	78	34	142
Curvature	1	18	11	19	28	61	124	16	9	15
	2	41	44	59	116	72	163	51	27	29
	3	90	73	103	172	92	186	90	44	53
	4	136	108	133	213	111	206	132	76	89

Notes: The table reports the number of times a currency is used as a funding currency in each currency trade strategy.

Table 5: Frequency of currencies used as *investment* currencies by carry trade strategies

Sorting	k	AUD	CAD	CHF	DEM	GBP	JPY	NOK	NZD	SEK
Forward discount	1	67	13	12	30	21	12	49	138	50
	2	147	16	12	112	50	13	75	195	69
	3	214	26	13	214	88	13	92	247	80
	4	256	39	14	242	161	15	182	264	114
Curvature	1	32	30	44	30	54	47	41	71	35
	2	67	61	76	36	110	63	55	125	89
	3	109	109	106	51	146	72	98	163	127
	4	142	156	133	72	171	85	145	200	178

Notes: The table reports the number of times a currency is used as an investment currency in each currency trade strategy.

Table 6: In-sample predictions of carry trade excess returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Forward discount				Curvature factor		
k	1	2	3	4	1	2	3	4
dCRB	0.13^{**}	0.06^{+}	0.04^{+}	0.02	-0.03	-0.00	-0.01	0.01
	(2.07)	(1.55)	(1.40)	(0.91)	(-1.04)	(-0.11)	(-0.21)	(0.31)
Volatility FX	-0.02^{+}	-0.02^{**}	-0.02^{**}	-0.02^{***}	-0.01	-0.01^{+}	-0.00	-0.00
	(-1.44)	(-2.32)	(-2.27)	(-2.63)	(-1.07)	(-1.48)	(-0.68)	(-0.88)
dLiq3	10.36^{*}	4.99	0.40	2.67	2.26	6.66	7.15	4.85
	(1.85)	(0.46)	(0.03)	(0.27)	(0.29)	(0.77)	(0.63)	(0.59)
Constant	0.00	0.00	0.00^{+}	0.00	0.00^{***}	0.00^{***}	0.00^{**}	0.00^{+}
	(0.55)	(0.65)	(1.34)	(1.23)	(3.91)	(3.44)	(2.28)	(1.45)
Observations	290	290	290	290	290	290	290	290

t statistics in parentheses

Newey-West standard errors.

$^{+}$ $p < 0.2$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Principal components

	A. Portfolio returns			B. FX returns			C. Interest returns		
Panel I: Forward Discount									
	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3
PF 1	0.54	0.82	0.17	0.54	0.82	0.17	0.59	−0.21	−0.78
PF 2	0.61	−0.24	−0.76	0.61	−0.24	−0.76	0.58	−0.56	0.59
PF 3	0.58	−0.52	0.63	0.58	−0.51	0.63	0.56	0.80	0.21
% Var	78.98	14.98	6.04	78.79	15.01	6.20	75.15	14.09	10.75
corr(DOL)	0.99	−0.02	0.02	0.99	−0.02	0.02	0.11	−0.03	0.04
corr(HML)	0.31	−0.92	0.25	0.31	−0.92	0.25	0.02	0.06	0.04
corr(VOL)	−0.13	0.29	−0.02	−0.14	0.29	−0.03	0.11	−0.02	−0.03
Panel II: Curvature									
	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3
PF 1	0.58	−0.48	0.66	0.58	−0.43	0.69	0.60	−0.05	−0.80
PF 2	0.58	−0.32	−0.75	0.58	−0.37	−0.72	0.57	−0.68	0.46
PF 3	0.57	0.82	0.09	0.57	0.82	0.04	0.56	0.73	0.38
% Var	82.78	9.48	7.73	82.68	9.41	7.91	65.23	19.14	15.63
corr(DOL)	0.99	0.01	0.00	0.99	0.01	0.00	0.11	0.10	0.05
corr(HML)	0.05	0.93	−0.35	0.06	0.90	−0.42	−0.05	0.18	0.09
corr(VOL)	−0.14	−0.06	−0.10	−0.15	−0.06	−0.10	0.11	−0.06	−0.11

The table shows factor loadings obtained from a principal component analysis on portfolio returns. Panel I reports for portfolios with currencies sorted by forward discount, Panel II for curvature sorting. The fourth row in each panel displays the percentage of variance explained by each factor. The following three rows display the correlation of the principal component with risk factors discussed in the literature. Section A reports principal components for portfolio returns, Section B and C report them for FX returns and interest returns alone.

Table 8: Cross-sectional asset pricing—DOL and VOL factors

	Forward discount sorting				*Curvature* sorting			
Panel I: Factor Prices								
GMM		DOL	VOL	R^2		DOL	VOL	R^2
b		−0.00	−0.69	99.87		−0.00	−0.85	14.12
		(0.00)	(0.48)			(0.01)	(2.13)	
λ		0.89	−0.33			0.83	−0.41	
		(1.70)	(0.21)			(1.74)	(0.57)	
FMB	χ^2	DOL	VOL	R^2	χ^2	DOL	VOL	R^2
λ		0.89	−0.33	99.87		0.83	−0.41	14.12
	[0.89]	(1.58)	(0.14)		[0.00]	(1.58)	(0.35)	
(Sh)	[0.90]	(1.58)	(0.15)		[0.01]	(1.58)	(0.41)	
(NW)	[0.90]	(1.59)	(0.21)		[0.04]	(1.58)	(0.62)	
Panel II: Factor Betas								
	α	DOL	VOL	R^2	α	DOL	VOL	R^2
1	−2.23	0.84	6.47	69.76	−1.80	0.98	−0.65	83.00
	(0.77)	(0.07)	(1.87)		(0.78)	(0.04)	(1.97)	
2	0.56	1.01	−1.39	86.43	−0.40	0.98	1.95	83.60
	(0.61)	(0.02)	(0.83)		(0.68)	(0.02)	(2.23)	
3	1.67	1.16	−5.08	84.34	2.20	1.04	−1.30	82.02
	(0.95)	(0.06)	(1.67)		(0.85)	(0.04)	(1.36)	
$\chi^2(\alpha)$	6.73				9.26			
	[0.08]				[0.03]			

The table reports the results of stochastic discount factor and Fama-MacBeth cross-sectional asset pricing with two factors for returns on three forward discount sorted portfolios and three curvature sorted portfolios. Returns are adjusted for transaction costs and are annualised. Panel I reports results of the stochastic discount factor representation estimated in GMM. We show both SDF parameter estimates and risk prices with standard errors in parentheses. The table also reports the second stage of Fama-MacBeth, the cross-sectional regressions. In parentheses, OLS, Shanken corrected and Newey-West standard errors are reported. We test for the null hypothesis that pricing errors are jointly zero (test statistic χ^2) and display the resulting p-values in brackets. R^2 is reported in percentage points. We do not include a constant in the second stage regressions of Fama-MacBeth. Panel II reports the results of the first stage regressions, the time series regressions within each portfolio which yield the factor loadings β. These regressions include a constant α. Heteroskedasticity and autocorrelation consistent standard errors (Newey-West with optimal lag selection according to Andrews (1991)) are shown in parentheses.

Table 9: Cross-sectional asset pricing—DOL and HML factors

	Forward discount sorting				*Curvature* sorting			
Panel I: Factor Prices								
GMM		DOL	HML	R^2		DOL	HML	R^2
b		-0.00	0.00	97.75		0.00	0.01	99.61
		(0.00)	(0.00)			(0.00)	(0.01)	
λ		0.89	4.14			0.80	4.06	
		(1.57)	(1.70)			(1.58)	(1.33)	
FMB	χ^2	DOL	HML	R^2	χ^2	DOL	HML	R^2
λ		0.89	4.14	97.75		0.80	4.06	99.61
	[0.56]	(1.58)	(1.72)		[0.83]	(1.58)	(1.32)	
(Sh)	[0.57]	(1.58)	(1.72)		[0.83]	(1.58)	(1.32)	
(NW)	[0.59]	(1.58)	(1.72)		[0.83]	(1.59)	(1.33)	
Panel II: Factor Betas								
	α	DOL	HML	R^2	α	DOL	HML	R^2
1	-0.18	1.00	-0.52	95.94	0.07	1.01	-0.47	96.05
	(0.35)	(0.01)	(0.01)		(0.39)	(0.01)	(0.02)	
2	0.36	1.00	0.05	86.52	-0.15	0.97	-0.06	83.58
	(0.69)	(0.02)	(0.02)		(0.78)	(0.03)	(0.03)	
3	-0.18	1.00	0.48	97.58	0.07	1.01	0.53	96.50
	(0.35)	(0.01)	(0.01)		(0.39)	(0.01)	(0.02)	
$\chi^2(\alpha)$	0.32				0.05			
	[0.96]				[0.99]			

The table reports the results of stochastic discount factor and Fama-MacBeth cross-sectional asset pricing regressions using two factors, DOL and HML. The left half of the table reports results for portfolios with currencies sorted according to the forward discount, the right half uses curvature to sort currencies into 3 portfolios. Panel I and Panel II are otherwise structured like Table 8 and Table 10.

Table 10: Cross-sectional asset pricing: Factor-mimicking portfolios

	Forward discount sorting				*Curvature* sorting			
Panel I: Factor Prices								
GMM		DOL	VOL_{fmp}	R^2		DOL	VOL_{fmp}	R^2
b		-0.00	-0.69	99.87		-0.00	-0.85	14.12
		(0.00)	(0.48)			(0.01)	(1.91)	
λ		0.89	-0.03			0.83	-0.01	
		(1.56)	(0.01)			(1.59)	(0.01)	
FMB	χ^2	DOL	VOL_{fmp}	R^2	χ^2	DOL	VOL_{fmp}	R^2
λ		0.89	-0.03	99.87		0.83	-0.01	14.12
	[0.89]	(1.58)	(0.01)		[0.00]	(1.58)	(0.01)	
(Sh)	[0.89]	(1.58)	(0.01)		[0.00]	(1.58)	(0.01)	
(NW)	[0.89]	(1.59)	(0.01)		[0.00]	(1.58)	(0.01)	
Panel II: Factor Betas								
	α	DOL	VOL_{fmp}	R^2	α	DOL	VOL_{fmp}	R^2
1	-0.02	1.09	76.39	99.01	-1.98	0.81	-49.78	84.72
	(0.18)	(0.01)	(0.85)		(0.76)	(0.05)	(9.07)	
2	0.08	0.95	-16.43	87.55	0.14	1.51	150.29	99.92
	(0.69)	(0.02)	(3.32)		(0.05)	(0.00)	(0.63)	
3	-0.06	0.96	-59.96	95.07	1.84	0.68	-100.51	88.26
	(0.52)	(0.02)	(2.47)		(0.71)	(0.05)	(8.44)	
$\chi^2(\alpha)$	0.02				8.64			
	[1.00]				[0.03]			

The table reports the results of stochastic discount factor and Fama-MacBeth cross-sectional asset pricing regressions using two factors, DOL and a factor mimicking portfolio for volatility, VOL_{fmp}. The factor-mimicking portfolio is generated by regressing the VOL factor on portfolio returns. The resulting coefficients are used as weights for summing up portfolio returns into a portfolio mimicking the VOL factor. The left half of the table reports results for portfolios with currencies sorted according to the forward discount, the right half uses curvature to sort currencies into 3 portfolios. Panel I and Panel II are otherwise structured like Table 8.

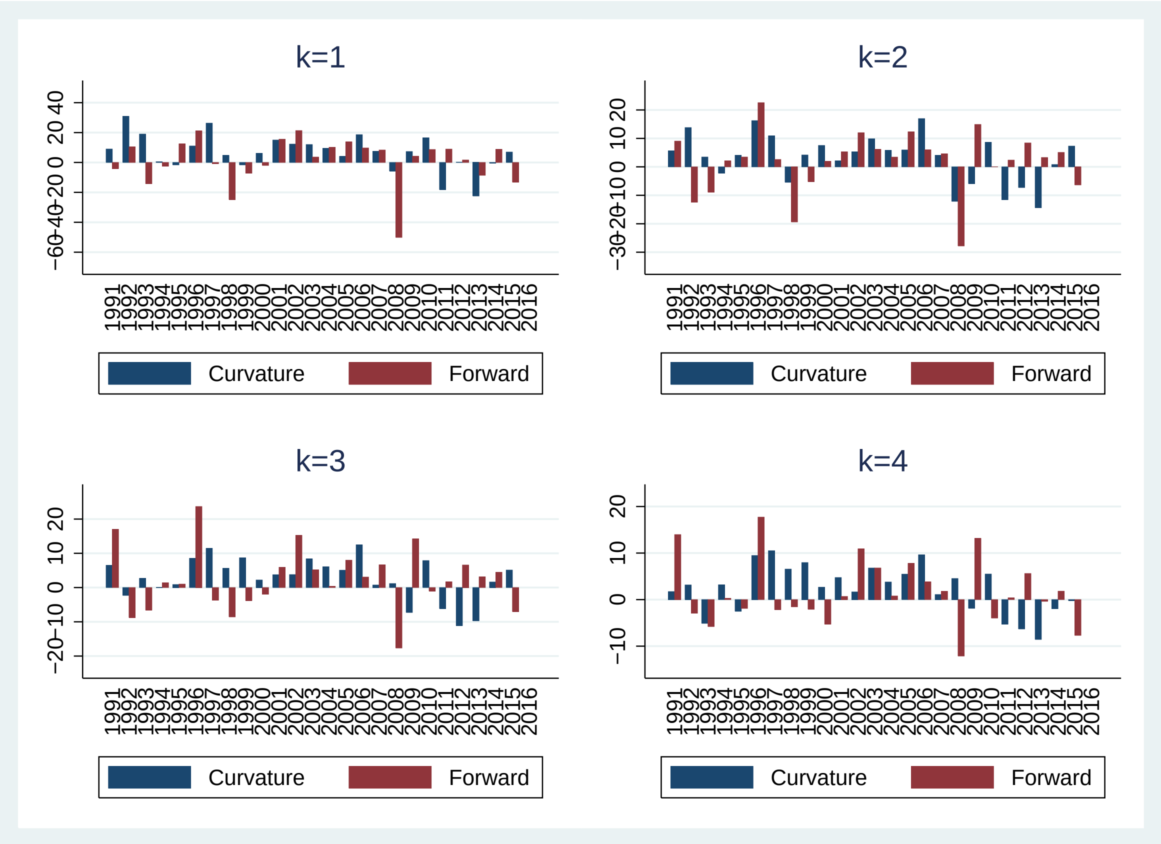
Table 11: Beta sorted portfolios: Descriptive Statistics

	VOL		
	1	2	3
RX (Mean)	1.66	0.16	−0.08
IR (Mean)	1.61	0.46	−0.73
FX (Mean)	0.05	−0.30	0.65
pre-f. beta	−16.45	−5.35	6.88
post-f. beta	−17.21	−7.19	0.18
pre-f. FD	1.78	0.23	−0.50
post-f. FD	1.60	0.48	−0.72
pre-f. curv	0.53	0.46	−0.08
post-f. curv	0.68	0.34	−0.04

*The table displays descriptive statistics for portfolios sorted according to their exposure (β) to the VOL factor. Excess returns are based on log returns without bid-ask spread. We report mean portfolio returns, mean FX and interest rate returns, pre- and post-formation betas, as well as pre- and post-formation means of the variables we used to sort currencies in previous tables. Pre-formation and post-formation curvature are scaled up (*1000) for easier comparison amongst portfolios.*

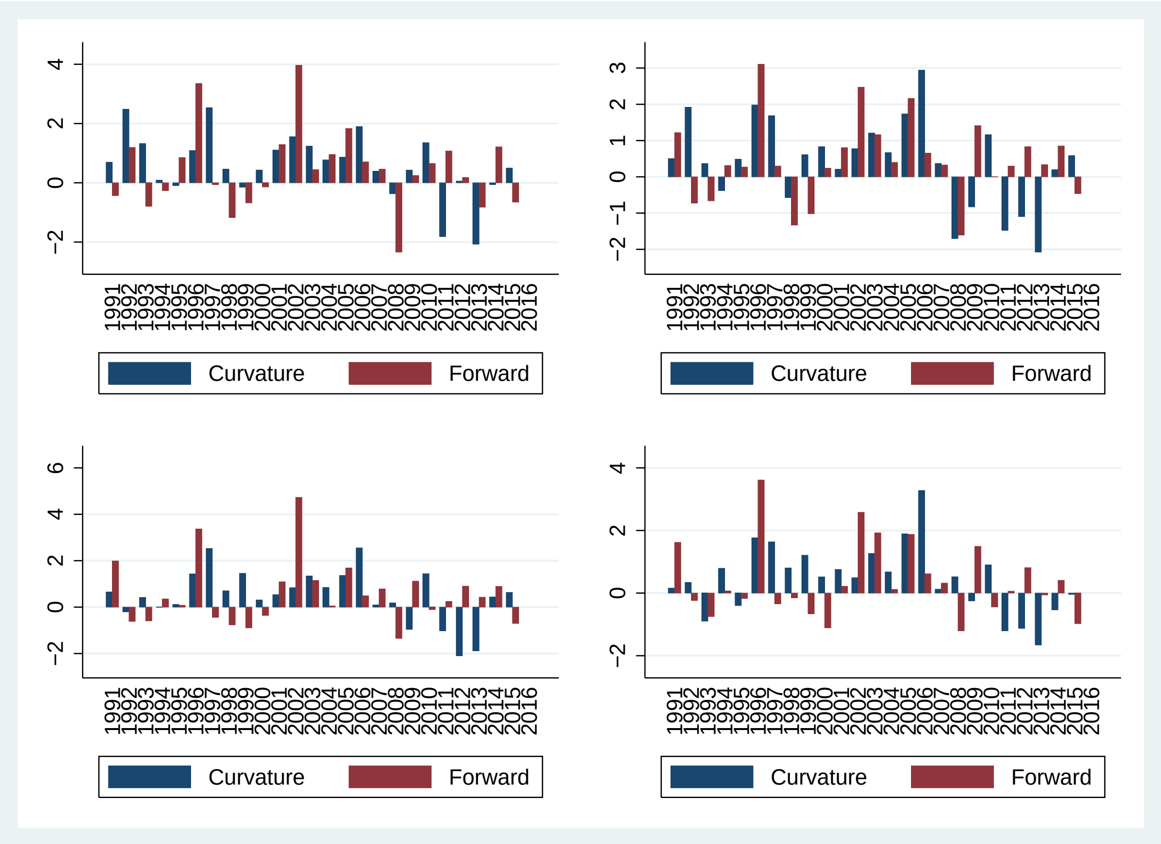
B Figures

Figure 1: Mean returns over time



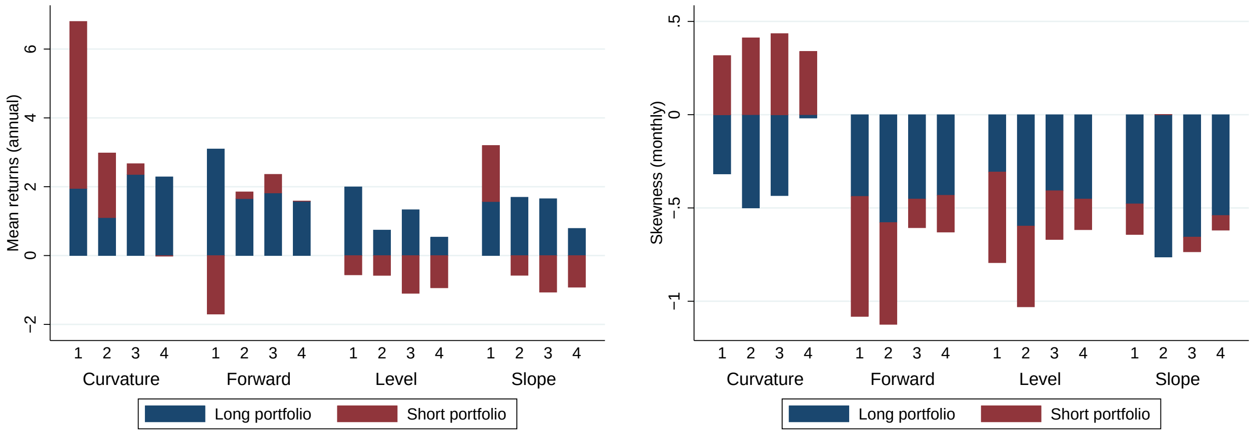
The figure plots the mean returns of the curvature and forward discount sorted currency strategies for $k = 1$ to $k = 4$, where k corresponds to the number of currencies in each portfolio (long and short portfolios).

Figure 2: Sharpe ratios over time



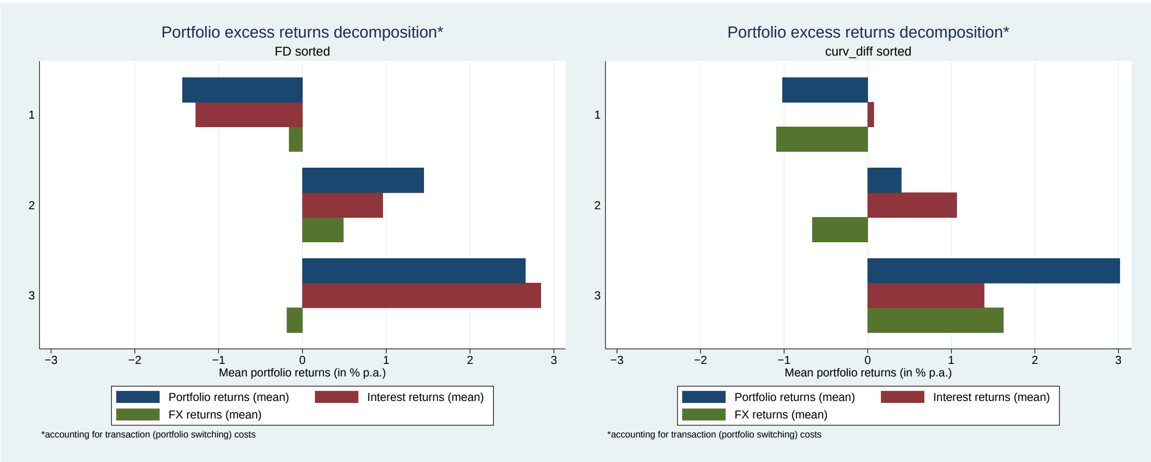
Notes: The figure plots the Sharpe ratios of the curvature and forward discount sorted currency strategies for $k = 1$ to $k = 4$, where k corresponds to the number of currencies in each portfolio (long and short portfolios).

Figure 3: Mean returns and skewness of portfolios



The figure plots mean returns and skewness for each currency strategy for $k = 1$ to $k = 4$, where k corresponds to the number of currencies in each portfolio (long and short portfolios).

Figure 4: Decomposition of portfolio returns



Notes: The figure plots the portfolio returns, decomposed into interest rate and exchange rate (FX) returns, for forward discount (left-hand panel) and curvature sorted (right-hand panel) currency strategies.

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