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The Cost to Carry: Investor Uncertainty and the Currency Risk Premia

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by
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This thesis explores a risk-based explanation of carry trade returns in currency markets. We propose a two-factor model that uses investor uncertainty proxied by News Implied Volatility innovations (NVIX) and the dollar factor to explain the profitability of the carry trade strategy. This model explains 86% of the variation in currency returns. The NVIX innovations factor commands a negative risk premium of 12.9% per annum. In addition, we use NVIX's forecasting ability in carry trade returns to hedge the downside risk and improve the profitability of the carry trade strategy.

Wall Street Journal, September 17th, 1992:
"'Lira's On the Floor, Unbelievable!'; Chaos Rules Day of 'Historic' Trading."

Wall Street Journal, August 17th, 1998:
"Russian Crisis Adds Another Major Threat to Worried Global Markets."

Wall Street Journal, September 18th, 2008:
"Mounting Fears Shake World Markets as Banking Giants Rush to Raise Capital."

In September 1992, following rising unemployment and deepening recessions, Italy and the UK withdrew from the European Monetary System in order to reduce interest rates and to stimulate economic growth (Salvatore, 1996). Consequently, the pound and lira depreciated, and carry trade returns collapsed. During this time of high uncertainty, carry trade investors saw losses that surpassed 8% monthly, experiencing first-hand that the strategy is no free lunch. Similarly, the news about the Russian crisis and the 2008 financial crisis were accompanied by significant losses in carry trade returns, as shown in Figure 1. These Wall Street Journal headlines exemplify the uncontested ability of the press to capture investors' concerns about economic events, reflected in their investment decisions. Could there be a connection between investor uncertainty and carry trade returns?

In 2017, Manela and Moreira built the news implied volatility index (NVIX) as a proxy for investor uncertainty. NVIX is a text-based measure of uncertainty constructed using front-page articles of the Wall Street Journal (WSJ) from 1889 until 2016. The creation of this measure relies on the assumption that the choice of words in the business press reflects the concerns of the average investor. NVIX peaks during disasters such as stock market crashes, times of policy uncertainty, wars, and financial crises, as illustrated in Figure 2. This lends credence to the view that NVIX is a proxy for investors' uncertainty over a long horizon. Manela and Moreira (2017) find that NVIX is a powerful predictor of actual VIX which is priced in the cross-section of carry trade returns (Lustig et al., 2011). Following the assumption that markets are integrated, currency and stock market returns have the same stochastic discount factor (SDF). Thus, factors that explain stock returns should also explain currency returns. This provides motivation to study whether NVIX contains information about currency risk premia in a linear asset pricing framework. We do so in the context of one of the most popular currency strategies, namely, the carry trade.

The carry trade strategy in currency markets consists of borrowing money in low- interest currencies (funding currencies) and investing in the high-interest ones (investment currencies). The profitability of the carry trade stems from the failure of the interest rate differential between two countries should be perfectly offset by the movement in the spot exchange rate of the two currencies, so that investors cannot earn a profit. In other words, a low-interest currency should appreciate by the same amount as the interest rate differential, such that a strategy seeking to exploit the interest rate differential through investments in the two currencies would yield no returns. Several studies including Fama (1984) and Lustig and Verdelhan (2007) have shown that the UIP fails to hold empirically. The carry trade strategy has a history of high average returns and Sharpe ratios that exceed those of equity markets even after accounting for transaction costs.[1]

Critics have compared the carry trade strategy to picking up nickels in front of a steam roller (The Economist, 2007), referring to the fact that carry trade yields small gains over the long run, but it also exposes investors to significant sudden losses, as illustrated in Figure 1. Carry trades had particularly poor returns in 1998 when Russia defaulted, as well as during the financial crisis in 2008 and other events that negatively affected the markets. This suggests that the profitability of carry trade is compensating investors for their risk exposure (Fama, 1984), and has led to vast research focused on identifying risk-based explanations of carry trade profitability, discussed in more detail in the next section.

In line with the idea that carry trade returns compensate investors for risk, we propose a two-factor model that explains the cross-section of carry trade returns with two factors: a level factor proxying for investors' exposure to a basket of currencies, and a slope factor - the news implied volatility (NVIX) innovations, that proxies for investors' uncertainty. As noted by Menkhoff et al. (2012), finance theory predicts that investors care about state variables that affect their investment opportunities set. They want to hedge against unexpected changes (hereafter innovations), in market volatility because a positive volatility innovation has a detrimental effect on investors' risk-return tradeoff. In line with Menkhoff et al. (2012), we study NVIX innovations as opposed to NVIX as a state variable in levels. Our research question is: *can investor uncertainty proxied by NVIX innovations explain the carry trade risk?* Before conducting any further analysis, the relationship between our proposed factor and carry trade returns is apparent when turning NVIX innovations into a factor-mimicking portfolio, as shown in Figure 3. Carry trade returns collapse when volatility innovations spike, which coincides with adverse market events.

This thesis builds on Lustig et al. (2011), as we suggest an alternative to their two-factor model by replacing their slope factor with NVIX innovations. One limitation of Lustig et al.'s (2011) model is the scarce economic interpretation of the risk factors proposed as well as their endogeneity to the data on which they are tested. In our model, we address those limitations through NVIX's interpretability. Given

[1]The U.S. equity market had a Sharpe ratio of 0.41 from 1976 to 2010 (Burnside et al., 2011), and 0.35 from 1993 to 2015 (Dzhabarov et al., 2018), while the carry trade strategy delivered a 0.5 Sharpe ratio after accounting for transaction costs for the period from 1983 to 2009 (Lustig et al., 2011).

what type of news drives its ability to price and predict returns. Moreover, NVIX is exogenous to the data on which it is tested, namely the currency portfolios, easing the concerns that our results might be driven by endogeneity. We contribute to the existing literature by proposing a two-factor model that explains the cross-section of carry trade returns by employing an interpretable risk factor, NVIX innovations. This model unveils the underlying risk carry trade investors are exposed to, which is informative for academics and industry professionals alike. Our findings are relevant to investors wishing to achieve comparable Sharpe ratios to the equity market through carry trade. They can form strategies accounting for a well-defined risk, NVIX innovations, as well as use this factor to forecast carry trade returns.

This thesis is organized as follows: we start with a literature review of previous research that seeks to explain carry trade profitability. We then describe the testable hypotheses, the methodology, and the data. Next, we discuss the results obtained, and we check the robustness of our findings. The final part concludes.

2 Literature Review

Several papers including Burnside et al. (2007) reveal that carry trade returns cannot be explained by traditional measures of risk such as the Capital Asset Pricing Model (CAPM) (Sharpe, 1964; Lintner, 1965) or the Fama and French (1993) three-factor model. Later studies explore different risk-based approaches to carry trade profitability. These explanations include volatility risk, peso problems, liquidity risk, trade network centrality, and the persistence of interest rate differentials across countries. Lustig and Verdelhan (2007) were the first to sort currencies into portfolios based on interest rates to find explanatory factors for the cross-section of currency returns. Using annual data from 1953-2002, they show that excess returns from carry trade strategies compensate the U.S. investors for taking on more US. consumption growth risk. Low-interest currencies provide domestic investors with a hedge against domestic consumption growth risk. Burnside et al. (2011) claim that these estimates of the consumption risk premium are statistically insignificant once the standard errors are appropriately corrected, and show that linear stochastic discount factors built from conventional measures of risk fail to explain the payoffs to the carry trade, as the covariance between payoffs and conventional risk factors is not statistically significant. Using monthly data from 1976- 2009, they argue that the payoffs instead reflect a peso problem. The positive average payoff from the carry trade strategy, then, would be a compensation for rare disaster risk.

Dobrynskaya (2014) propose a global downside market factor to explain high returns to carry trade, and shows that carry trades have high downside market risk, i.e., they systematically crash in the worst states of the world, when the global stock market plunges or when a disaster occurs. Lettau et al. (2014) also find that carry trade is more correlated with the market during market downturns than it is during is 0.33, while it is only 0.02 conditional on the upstate. They show that the downside risk capital asset pricing model (DR-CAPM) prices the cross- section of currency returns. The findings of Lee and Wang (2017) are in line with the above-mentioned papers. They suggest that currencies whose changes are more sensitive to negative market jumps provide higher expected returns, such that the currency risk premium is compensation for extreme losses during periods of market turmoil.

Christiansen et al. (2011) find that the risk exposure of carry trade strategies is regime-dependent and that regimes are characterized by the level of FX volatility. In turbulent times, carry trade significantly increases its systematic risk and exposure to other risky allocations. The findings presented in the papers above are similar in nature to those found in Menkhoff et al. (2012), who argue that FX volatility innovations represent the risk that investors are being compensated for, as currencies that deliver low returns in times of unexpected high volatility earn higher returns in normal times. Previous research indicates that there is a strong link between market volatility and carry trade returns. This provides the motivation for us to further explore the impact of volatility on carry trade.

Using monthly data on currency spot and forward rates for a sample of 39 countries from 1983 until 2009, Lustig et al. (2011) identifies a two-factor model that suggests that investors load up on global risk when they invest in carry trade strategies. This model proposes a global risk factor closely related to changes in the volatility of equity markets around the world, the carry risk factor, and a country-specific level factor named “dollar”, related to the riskiness of the home country, such as a dollar risk premium for a U.S. investor. The dollar risk factor is constructed as the average of excess returns across six currency portfolios sorted on their forward discount, while the carry factor is built by taking the difference in excess returns of the first and last portfolios. Together these factors explains 80% of the variation in carry trade returns. One limitation of their paper is the scarce economic interpretation of the two factors proposed, as well as their endogeneity, as they were identified in the data itself. We address this limitation in our model by proposing an interpretable factor, NVIX, exogenous to the currency portfolios.

Further research by Menkhoff et al. (2012) builds on Lustig et al. (2011) and proposes a similar two-factor model replacing the slope factor with a global FX volatility factor. They use the same sample period as Lustig et al. (2011) but the sample is extended to include 13 additional countries. Menkhoff et al. (2012) argue that excess returns to carry trades are compensation for time-varying risk. They find a significantly negative co-movement between high-interest currencies and global FX volatility innovations, meaning that carry strategies have poor returns when exchange rate volatility is high. Investment currencies are negatively related to innovations in global FX volatility and deliver low returns in times of unexpected high volatility. FX volatility is constructed from absolute daily log returns of individual currencies averaged in the cross-section up to a monthly frequency. Therefore, volatility changes unknown. Menkhoff et al.'s (2012) paper unveils an important link between carry trade returns and volatility innovations, but the nature of the risk driving carry trade returns is still an open question. We aim to provide an answer to that question in this thesis.

3 Data

We use data on the news implied volatility measure (NVIX) developed by Manela and Moreira (2017). NVIX is a text-based measure of uncertainty constructed using front-page articles of the Wall Street Journal from 1889 until 2016 and machine learning techniques. The authors derive this news-based measure of uncertainty from the co-movement between the front-page coverage of the WSJ and the options implied volatility (VIX). NVIX is decomposed into five main categories related to disaster concerns: war, financial intermediation, government, stock markets, and natural disasters. In line with the availability of the NVIX measure, we limit our sample horizon to March 2016 for all the data used.[2]

Similar to Lustig et al. (2011), we use monthly spot and forward exchange rates in U.S. dollars starting from June 1990 to March 2016. This data was collected from Thomson Reuters and EIKON. We use a data set of 48 different currencies that varies in size across the years, including Australia, Austria, Belgium, Canada, Chile, China, Colombia, Croatia, Czech Republic, Denmark, Egypt, Euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Israel, Italy, Japan, Kuwait, Mexico, New Zealand, Norway, Peru, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, UAE, Ukraine and the UK. After 1999 we replace individual European countries with the Euro area to account for the formation of the EU and the subsequent use of the Euro as the common currency. Given that the CIP must hold for carry trade to be profitable, we follow Lustig et al. (2011) and delete several observations from our data set where there are large failures of the CIP. As a robustness check, we repeat our analysis on a smaller dataset containing the currencies of 14 developed countries: Australia, Belgium, Canada, Denmark, Euro area, France, Germany, Italy, Japan, New Zealand, Norway, Sweden, Switzerland, and the UK.

[2]While the code with ngram frequencies is available on the authors' website, one would need to connect it to newspaper articles and apply machine learning techniques to replicate the NVIX measure over a longer horizon. Due to data availability constraints, we use the NVIX measure published by Manela and Moreira (2017) with a sample horizon ending in March 2016.

This section describes the construction of the currency portfolios, the risk factors, the linear factor model for the cross-section of average currency excess returns, and the forecasting regressions.

4.1 Portfolios

Following Lustig et al. (2011), we construct six currency portfolios based on forward discounts. We denote with s the natural log of the spot exchange rate in units of foreign currency per USD, and f the natural log of the forward exchange rate in the same units. We calculate the forward discount $f_t - s_t$ of each currency at the end of period t, and we use this to allocate the currencies in our sample to each portfolio. We reallocate the currencies to portfolios on a monthly basis. The six portfolios are ranked from small to large forward discounts. Portfolio 1 contains the currencies with the smallest forward discount, which is equivalent to the lowest interest rate, while Portfolio 6 contains the currencies with the largest forward discount, equivalent to the highest interest rate.

4.2 Currency excess returns

The natural log of the excess return from buying foreign currency in the forward market and then selling it in the spot market after one month is given by rx:

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

This excess return can be also written as the interest rate differential minus the change in the spot rate, which results from the fact that under normal conditions, the covered interest rate parity (CIP) condition holds. According to the CIP, the forward discount is equal to the interest rate differential:

$$f_t - s_t = i_t^* - i_t, \tag{2}$$

where i_t^* and i_t are the foreign and domestic nominal risk-free rates over one month. Several papers including Tyler (1987) and more recently Akram, Rime, and Sarno (2008) provide evidence that CIP holds at daily and lower frequencies. Thus, the excess return can be written as the interest rate differential net of the depreciation rate:

$$rx_{t+1} = (i_t^* - i_t) - \Delta s_{t+1} \tag{3}$$

After constructing the six portfolios, we compute the excess returns for the individual currencies in each portfolio. All returns are mentioned in natural log form. We compute the excess return of portfolio j by taking the average of its individual

$$rx_{t+1} = \frac{1}{N}\sum_{j=1}^{N} rx_{t+1}^{j}, \tag{4}$$

where N is the number of currencies in each portfolio which varies over time.

We also compute the investor's actual realized excess return accounting for transaction costs using bid-ask quotes for spot and forward contracts. The excess return net of transaction costs is given by:

$$rx_{t+1}^{l} = f_t^{b} - s_{t+1}^{a} \tag{5}$$

The investor goes long in foreign currency at time t at the bid price f_t^b and sells the foreign currency after one period in the spot market at the price s_{t+1}^a. The net excess return can be calculated similarly for an investor going long in the domestic currency and short in the foreign currency:

$$rx_{t+1}^{s} = -f_t^{a} + s_{t+1}^{b} \tag{6}$$

4.3 Model

According to linear factor models, average returns on a cross-section of assets can be explained through their exposure to risk factors and the associated risk premia. In the arbitrage pricing theory (APT) proposed by Ross (1976), idiosyncratic movements in asset returns should not carry any risk premia, since investors can diversify idiosyncratic risk by holding portfolios. Thus, expected returns on assets are related to the assets' covariance with common components known as factors. In line with this theory, we first identify common variations in individual asset (portfolio) returns. We follow the procedure in Lustig et al. (2011) and run a principal component analysis (PCA) on the six currency portfolios to identify the existence of a common factor structure. Table 1 presents the PCA results.

The analysis reveals that two factors together capture about 79% of the common variation in the six currency portfolios' returns. The first principal component explains 60% of the common variation in portfolio returns. The loadings on this component are uniform across the six portfolios, all of them being close to 0.4. Hence, we can interpret it as a "level" factor. The second principal component explains 18% of the common variation. The loadings on this component decrease monotonically from Portfolio 1 to Portfolio 6. Therefore, we interpret it as a "slope" factor. We note that among the six principal components, only the second one exhibits a monotonic pattern in portfolio loadings, suggesting that it is the only plausible candidate risk factor that could explain the cross-section of portfolio returns. While the first component provides information about the average performance of the six returns relative to others.

In line with Lustig et al.'s (2011) findings, we identify two common factors in the cross-section of currency returns. We construct the first candidate risk factor, DOL, as the average currency excess return across the six portfolios. Lustig et al. (2011) refer to this as the "dollar" risk factor. It is the average return of the zero-cost portfolio of a U.S. investor who buys all foreign currencies available in the forward market. In other words, DOL proxies for the currency market return in USD available to a U.S. investor. This factor has a 0.99 correlation with the first principal component.

For the second candidate risk factor, $NVIX_{FM}$, we construct a tradable factor-mimicking portfolio following Breeden et al. (1989) and Ang et al. (2006). The advantage of converting NVIX innovations into a return is that we can analyze its risk price naturally. As a traded asset, the risk price of $NVIX_{FM}$ should equal the average return on the traded factor-mimicking portfolio, such that $NVIX_{FM}$ is able to price itself and the no-arbitrage condition is satisfied (Menkhoff et al., 2012).

We start from asset pricing models with time-varying risk premia, such as the dynamic risk-return trade-off of Merton (1973), which predicts a linear relationship between the expected excess returns on the market and its conditional variance. In addition, time-varying rare disaster models predict a linear relationship between expected excess returns and the variance premium, linear in the time-varying probability of a rare disaster, such as in Gabaix (2012). In line with these findings, we use the News Implied Volatility measure from Manela and Moreira (2017) at the monthly frequency to construct our factor in a linear asset pricing model.

Factors' creation

We first transform NVIX into NVIX innovations by calculating log differences. We then regress it on the six portfolio excess returns to obtain their loadings. We control for DOL, which simultaneously acts as a constant since it does not account for cross-sectional variation in portfolio returns:

$$NVIX_{t+1} = DOL_{t+1} + \beta_j rx^j_{t+1} + u_{t+1} \tag{7}$$

We define the factor-mimicking portfolio as the sum of the products of the fitted values from the regression in equation (7) and the returns of the portfolios:

$$NVIX_{FMt+1} = \sum_{i=1}^{N} \beta_j rx^j_{t+1}, \tag{8}$$

where N is the number of currency portfolios. This factor has a 0.81 correlation with the second principal component.

In addition, we construct the carry risk factor HML_{FX} from Lustig et al. (2011) as the difference between the returns on the corner portfolios, 6-1. This is simply the return on a carry trade strategy going long in the highest interest rate portfolio innovations factor VOL_{FX}, from Menkhoff et al. (2012). We calculate absolute daily log returns $|r_\tau^k|$ ($= \Delta s_\tau$) for each currency k on each day τ, and average those over all currencies on any given day. We then average the daily values up to the monthly frequency, such that the global FX volatility proxy for every month t is given by:

$$\sigma_t^{FX} = \frac{1}{T_t} \sum_{t \epsilon T_t} \left[\sum_{k \epsilon K_\tau} \left(\frac{|r_\tau^k|}{K_\tau} \right) \right], \tag{9}$$

where K_τ is the number of currencies on day τ, and T_t is the total number of days in month t. We then estimate as simple AR(1) model for the volatility level and take the residuals as the proxy for volatility innovations. Finally, we obtain the factor-mimicking portfolio VOL_{FM} following the same method described above. We regress volatility innovations on the six portfolio excess returns controlling for the DOL factor, and we sum the products of the fitted values from that regression and the returns of the portfolios.

We construct the carry and the global volatility innovations risk factors to compare our model's performance to existing models in the literature.

4.4 Cross-sectional asset pricing

This section describes the methodology used to assess whether a linear two-factor model consisting of DOL and NVIX innovations is able to price the cross-section of currency returns.

Our approach to cross-sectional asset pricing relies on a standard SDF method (Cochrane, 2005) also used in other carry trade research papers, such as Lustig et al. (2011) and Menkhoff et al. (2012). According to the no-arbitrage relation, the risk-adjusted currency excess returns satisfy the basic Euler equation:

$$E[M_{t+1} rx_{t+1}^j] = 0, \tag{10}$$

where M_{t+1} is the stochastic discount factor and rx_{t+1}^j is the excess return of each portfolio of currencies. We also assume that the stochastic discount factor M is linear in the risk factors Φ_{t+1}:

$$M_{t+1} = 1 - b(\Phi_{t+1} - \mu_\phi), \tag{11}$$

where b is the vector of factor loadings and μ_ϕ denotes the factor means. The specification of this factor model implies a beta pricing representation where expected excess returns are equal to the factor risk prices λ multiplied by the risk quantities β_j, which are obtained from the regression of portfolio excess returns on the risk factors:

$$E[rx^j] = \lambda' \beta_j, \tag{12}$$

where $\lambda = \sum_\phi b$ and $\lambda = \sum_\phi$ is the variance-covariance matrix of the factors.

Fama-Macbeth procedure and risk premia

We use a two-stage OLS estimation following Fama and MacBeth (1973) to estimate the factor prices and portfolio exposures to the two risk factors identified earlier. The Fama and MacBeth procedure is executed as follows. First, we run a time series regression of portfolio returns on the two factors and estimate the betas:

$$rx_t^j = \alpha_t^j + \beta_1^j DOL_t + \beta_2^j NVIX_{FMt} + u_{j,t} \tag{13}$$

Secondly, we run a single cross-sectional regression of average portfolio returns on the betas obtained in the first step:

$$rx_j = \lambda_{DOL}\beta_{DOL}^j + \lambda_{NVIX_{FM}}\beta_{NVIX_{FM}}^j + u_j \tag{14}$$

We do not include a constant in the second step cross-sectional regression, based on the assumption that there is no common mispricing in the cross-section of currency returns. Moreover, as noted in Lustig et al. (2011) and Menkhoff et al. (2012), DOL has no cross-sectional relation with the currency portfolios' returns, meaning that it acts as a constant in our regression. Thus, adding a constant would be redundant and could cause multicollinearity issues. In addition, we perform the second step using T cross-sectional regressions of the portfolio returns on the betas from the first step at each point in time. This method allows for time-varying risk premia. We estimate the risk premium for each factor by taking the average of the risk premia over time.

We assess whether DOL and $NVIX_{FM}$ are priced in the cross-section of currency returns by testing the significance of our factors' risk premia:

$$\mathrm{H}_0: \lambda_{DOL} = 0 \text{ and } \lambda_{NVIX_{FM}} = 0$$
$$\mathrm{H}_1: \lambda_{DOL} \neq 0 \text{ or } \lambda_{NVIX_{FM}} \neq 0$$

The test statistic is given by $\lambda/(\sigma/\sqrt{n})$, where λ is the factor risk premium, σ is the sample standard deviation, and n is the sample size. The critical value is obtained from a t-distribution with $n - 2$ degrees of freedom. We reject the null hypothesis if the absolute value of the test statistic is greater than the critical value. That would mean that the risk premia are significantly different from zero.

Pricing errors

Next, we assess how well our two-factor model is able to price the six currency portfolios. A good model would yield insignificant pricing errors, hence, we check whether the pricing errors on the six portfolios are jointly insignificant by testing the following hypotheses:

$$H_0: \alpha_1 = 0 \text{ and } \alpha_2 = 0 \text{ and } \alpha_3 = 0 \text{ and } \alpha_4 = 0 \text{ and } \alpha_5 = 0 \text{ and } \alpha_6 = 0$$
$$H_1: \alpha_1 \neq 0 \text{ or } \alpha_2 \neq 0 \text{ or } \alpha_3 \neq 0 \text{ or } \alpha_4 \neq 0 \text{ or } \alpha_5 \neq 0 \text{ or } \alpha_6 \neq 0$$

We perform the Gibbons, Ross, and Shanken (1989) (GRS) test with the test statistic given by:

$$\frac{T-N-K}{N}\left[1+\left(\frac{E(\phi)}{\sigma(\phi)}\right)^2\right]^{-1}\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}, \tag{15}$$

where T is the number of observations (months), N is the number of countries in our sample, and K is the number of factors. The critical value is given by $F_{N,T-N-K}$. $\hat{\Sigma}$ is the factor variance-covariance matrix, ϕ is the factor matrix and $\hat{\alpha}$ stands for the vector of pricing errors on the six portfolios obtained from the regressions in equation 14.

4.5 NVIX forecasting ability

Considering that $NVIX_{FM}$ proxies for investors' uncertainty and spikes during economic disasters, we expect this factor to be able to predict carry trade returns.

Stationarity

We start by checking the stationarity of our two time-series, $NVIX_{FM}$ and HML_{FX}, using the Augmented Dickey-Fuller test (ADF test). We run the following regression:

$$y_t = \alpha + \beta y_{t-1} + u_t \tag{16}$$

for both $NVIX_{FM}$ and HML_{FX} with up to 12 lags, given the monthly frequency of our data. The regression can be rewritten as:

$$\Delta y_t = y_t - y_{t-1} = \alpha + \theta_1 y_{t-1} + \theta_2 \Delta y_{t-2} + \ldots + \theta_{12}\Delta y_{12} + u_t, \tag{17}$$

where y is replaced with $NVIX_{FM}$ and HML_{FX} respectively. We then test whether the current values of our variables depend on their past values. The null and alternative hypotheses are given by:

$$H_0: \theta_1 = 0 \text{ and } \theta_2 = 0 \text{ and } \ldots \text{ and } \theta_{12} = 0$$
$$H_1: \theta_1 \neq 0 \text{ or } \theta_2 \neq 0 \text{ or } \ldots \text{ or } \theta_{12} \neq 0$$

VAR model

If we find that both series are stationary, we can estimate a Vector Autoregression (VAR) model in levels of the form:

$$\begin{aligned} NVIX_{FM_t} &= \alpha_1 + \beta_{1,1}NVIX_{FM_{t-1}} + \ldots + \beta_{1,p}NVIX_{FM_{t-p}} \\ &\quad + \phi_{1,1}HML_{FX_{t-1}} + \ldots + \phi_{1,q}HML_{FX_{t-q}} + u_{1,t} \end{aligned} \tag{18}$$

$$\begin{aligned} HML_{FX_t} &= \alpha_2 + \beta_{2,1}NVIX_{FM_{t-1}} + \ldots + \beta_{2,p}NVIX_{FM_{t-p}} \\ &\quad + \phi_{2,1}HML_{FX_{t-1}} + \ldots + \phi_{2,q}HML_{FX_{t-q}} + u_{2,t} \end{aligned} \tag{19}$$

We use the Schwarz-Bayesian (1978) Information Criterion (SBIC) to find the optimal number of lags to be used in our VAR model. The SBIC is given by:

$$\text{SBIC} = ln(\hat{\sigma}^2) + \frac{k}{T}ln(T), \tag{20}$$

where $\hat{\sigma}^2 = \frac{\sum \hat{u}_t^2}{T-k}$ is the estimated error variance, $k = p + q + 1$ is the total number of parameters estimated, and T is the sample size. According to SBIC the optimal number of lags to construct our VAR model is 1.

Granger causality

We then test for Granger causality to see if past values of the two factors contain information that helps predict their future values. We test the following VAR(1) model:

$$\begin{aligned} NVIX_{FM_t} &= \alpha_1 + \beta_{1,1}NVIX_{FM_{t-1}} \\ &\quad + \phi_{1,1}HML_{FX_{t-1}} + u_{1,t} \end{aligned} \tag{21}$$

$$\begin{aligned} HML_{FX_t} &= \alpha_2 + \beta_{2,1}NVIX_{FM_{t-1}} \\ &\quad + \phi_{2,1}HML_{FX_{t-1}}u_{2,t} \end{aligned} \tag{22}$$

We perform an F-test for with the test statistic given by:

$$\frac{SSR_R - SSR_U}{SSR_U} * \frac{T-k}{q} \sim F(q, T-k), \tag{23}$$

where q is the number of lags, k is the number of estimated parameters, T is the sample size, SSR_R and SSR_U are the sum squared residuals from the restricted and unrestricted regressions. The unrestricted regressions are as presented in the VAR(1) model, while in the restricted ones we regress lagged values of the factors on themselves only. *F(q,T-k)* is the critical value. The VAR(1) model allows us to examine Granger causality in both directions. However, since NVIX is a text-based measure exogenous to carry trade returns, we are only interested in one causality

$$\mathrm{H}_0 : \beta_{2,1} = 0$$
$$\mathrm{H}_1 : \beta_{2,1} \neq 0$$

We then check for autocorrelation in the residuals of the VAR model with the Ljung-Box test to assess the fit of our model. If the residuals are not autocorrelated, the model has a good fit. The test statistic is given by:

$$Q = T(T+2) \sum_{k=1}^{m} \frac{\hat{\tau}_k^2}{T-k} \sim \chi^2(m), \tag{24}$$

where T is the sample size, τ_k is the estimated autocorrelation of the series at lag k, and m is the number of lags being tested. $\chi^2(m)$ is the critical value. We test whether the correlation coefficients are significantly different from zero with the following hypotheses:

$$\mathrm{H}_0 : \tau_1 = 0 \text{ and } \tau_2 = 0 \text{ and ... and } \tau_m = 0$$
$$\mathrm{H}_1 : \tau_1 \neq 0 \text{ or } \tau_2 \neq 0 \text{ or ... or } \tau_m \neq 0$$

Forecasting ability

Finally, we use our results from the previous steps to estimate future values of carry trade returns using past values of $NVIX_{FM}$. We use a rolling window method with a window size of 18 months to obtain portfolio loadings on NVIX innovations as a state variable, and then we create the factor mimicking portfolio $NVIX_{FM}$. We then use one lag of $NVIX_{FM}$ to estimate one carry trade return at each point in time, moving the time window one step ahead, such that we use 18 months of data at a time. We use this window size due to the monthly frequency of our data and to guard against major market downturns or upturns distorting the results.Including 18 observations in each window enables more accurate estimates since the effects of long-lasting economic events, such as the 2008-2009 financial crisis, are balanced with observations from "normal" market states.

After estimating the carry trade returns, we assess the forecasting accuracy of our model using a measure closely correlated with profitability, namely the percentage of correct sign predictions:

$$\%\text{ correct sign predictions} = \frac{100}{N} \sum_{t-1}^{N} z_{t+s} \quad \text{where } z_{t+s} = \begin{cases} 1 & \text{if } y_{t+s} E(y_{t+s} | \Omega_t) > 0 \\ 0 & \text{otherwise} \end{cases} \tag{25}$$

carry trade returns over our sample period. We test the following hypotheses:

$$H_0: \mu_{HML_{FX}} - \mu_{HML_{FX\ forecasted}} = 0$$
$$H1: \mu_{HML_{FX}} - \mu_{HML_{FX\ forecasted}} \neq 0$$

We repeat the analysis described above for VOL_{FM} to assess its ability to forecast carry trade returns.

4.6 Strategies conditional on NVIX

Upon establishing NVIX's ability to forecast carry trade returns, we design two augmented carry trade strategies conditional on $NVIX_{FM}$. We then compare the returns from these strategies with the standard carry trade returns, as well as with strategies conditional on VOL_{FM}. For the first strategy, we implement the following rule at each period *t*: if our model predicts a negative carry trade return at time *t*, we close the carry trade position and receive an excess return of zero at $t + 1$. Otherwise, we implement the carry trade as usual. For the second strategy, we implement a combination of two rules. First, we follow Cenedese et al. (2014) and at each period *t*, if the NVIX innovations factor from *t-1* to t is "high", we close the carry trade position and receive an excess return of zero at *t+1*. Otherwise, we implement the carry trade strategy as usual. A "high" NVIX innovations factor means that it is higher than its median value up to that point. Secondly, we implement the rule from the first augmented strategy: at each period *t*, if our forecasting model predicts a negative carry trade return at time *t*, we close the carry trade position and receive an excess return of zero at $t + 1$. Otherwise, we implement the carry trade as usual. We use the first 18 months to estimate the factor loadings for the creation of the NVIX innovations factor-mimicking portfolio, adding one more observation at each point in time as we move forward. We perform the same two strategies using VOL_{FM} for comparison. These strategies are meant to limit the downside risk of the carry trade and improve its profitability.

5 Results

5.1 Returns to currency portfolios for a U.S. investor

This section presents evidence that a U.S. investor in forward currency markets can earn significant excess returns and a Sharpe ratio higher than the one in equity markets. Table 2 presents the properties of the six currency portfolios from the perspective of a U.S. investor. We report the depreciation rate Δs^j, the forward costs, and the log excess return to high-minus-low trade strategies given by $rx^j - rx^1$ for each portfolio j. All the reported numbers are annualized, and the returns and standard deviations are reported in percentage points.

We first note that the UIP condition does not hold in the data. According to the UIP, the average depreciation rate of each portfolio should perfectly offset its corresponding average forward discount, resulting in zero log excess returns across all portfolios. However, empirically, that is not the case. Forward discounts are consistently larger than the depreciation rates for portfolios 3-6 while being smaller for the first two portfolios. High-interest rate currencies do not depreciate as much as predicted by the UIP, but instead, appreciate. The opposite is true for the low-interest rate currencies. Hence, investors are able to generate significant excess returns by investing in long-short strategies, such as the carry trade, as shown in the lower panels of Table 2. These results hold after accounting for transaction costs as well.

By construction, there is a perfect monotonic pattern in forward discounts across the six portfolios. We also observe an almost monotonic pattern in the excess returns of these portfolios. Portfolio 1 has a negative forward discount of -6.22%, which indicates that the foreign currencies in that portfolio are expected to appreciate on average by that amount. However, the appreciation rate is significantly lower, resulting in an excess return of -6.72%[3]. Similarly, Portfolio 6 has a positive forward discount of 14.95%, indicating an expected average depreciation rate of the same amount. However, the currencies in Portfolio 6 depreciate by a significantly lower amount, resulting in a positive excess return of 8.63%. Consequently, there is a large spread between the corner portfolios' returns equal to 15.35%. At the same time, the dispersion in standard deviation across portfolios is significantly lower, resulting in a Sharpe ratio of 1.31.

Finally, the last two panels, labeled "High-minus-Low", present the returns to zero-cost strategies going long in the high-interest rate portfolios and short in the low-interest rate portfolios. The standard errors reported in brackets indicate that all the returns on these high-minus-low strategies are statistically significantly different from zero at the 1% confidence level. Moreover, they are economically significant, all being above 6% in annual terms. The carry trade strategy that goes long in the last portfolio and short in the first portfolio yields 15.35% annually before transaction costs and a net return of 13.04%. This results in Sharpe ratios above 1, remarkably higher than the Sharpe ratio of the U.S. equity market during roughly the same period, which was only 0.35 from 1993 to 2015 (Dzhabarov et al., 2018).

[3] By construction, the excess return is equal to the forward discount minus the spot change. The discrepancy in our numbers is the result of merging two databases of spot and forward rates, due to data availability issues. Each database reports slightly different quotes than the other. Therefore, there is a slight discrepancy between the excess return and the difference between the forward discount and the spot change.

Table 3 reports the asset pricing results obtained from the single cross-sectional regression and the FMB procedure on the six currency portfolios. The table reports the market risk prices λ of the two factors and the adjusted R^2. The Newey-West corrected standard errors are reported in brackets. The market price of $NVIX_{FM}$ is -12.91% per year, meaning that an asset with a beta of 1 earns a -12.91% risk premium per year. The standard errors indicate that this risk price is statistically significantly different from zero at the 1% confidence level. The negative risk price suggests that portfolio returns which covary positively with NVIX innovations and thus provide a hedge against this risk will have a lower risk premium, while those that negatively covary with NVIX innovations will earn a higher risk premium. The market price of DOL, our second risk factor, is -0.69% and statistically insignificant. This is not surprising as this factor does not help explain any of the cross-sectional variations in portfolio returns. The adjusted R^2 is 87%, indicating a good cross-sectional fit. The results hold in the sample of developed countries as well. We obtain the same results using a single cross-sectional regression and the FMB procedure.

5.3 Time-series regressions

Table 4 reports the results of the time-series regressions of our two-factor model on the six portfolios. The intercept is reported in annual terms. First, we note that the loadings on the dollar factor are all close to 1 across the six portfolios, indicating that this factor does not help explain the variation in portfolio returns. This is not a surprising result given the construction of this factor. Nevertheless, the dollar factor helps to explain the average level of excess returns across portfolios. Next, we observe that the loadings on $NVIX_{FM}$ are monotonically decreasing from Portfolio 1 to 6. Low-interest rate portfolios are positively exposed to NVIX innovations, while high-interest rate portfolios are negatively exposed to this risk factor. In other words, when NVIX innovations increase, such as in times of market turmoil, low-interest-rate currencies' returns also increase, providing a hedge against this risk. On the other hand, high-interest-rate currencies' returns decrease when NVIX innovations increase.

Given that high-interest-rate currencies perform particularly poorly during times of market turmoil, investors demand high returns to invest in these currencies. By contrast, low-interest-rate currencies provide a hedge against periods of unexpected high volatility; hence, investors are willing to invest in these currencies at low returns. This explains the pattern in the excess returns of the six currency portfolios observed in Table 2. To further exemplify how some currencies act as a hedge while others are perceived as risky, we look at individual currencies. Figure 3 shows that NVIX innovations reached a peak of 13% monthly return on October 31st, 2008, during the height of the financial crisis. Carry trade, on the other hand, had a monthly return of -5%. The Japanese Yen (JPY), a common funding currency, saw a return of 7%, the Indonesian Rupee (IDR) had the lowest return of -14% in the same period. Regressions of NVIX innovations on these currencies reveal that the JPY loads positively on NVIX innovations with a beta of 0.2, while the IDR loads negatively with a beta of -0.37. Hence, JPY acted as a hedge during the financial crisis, while the return on IDR crashed, confirming the risk-return relationship presented earlier.

We note from the standard errors reported in brackets in Table 4 that both factors in the time-series regressions are statistically significantly different from zero at the 1% level. The high reported adjusted R^2 confirms the good fit of this two-factor model. Finally, we assess the performance of our two-factor model by checking the statistical significance of the pricing errors from the time-series regressions. We perform a GRS test and we fail to reject the null that the pricing errors are jointly insignificant. Figure 4 provides a graphic illustration of our two-factor model's fit. It plots the realized portfolio excess returns and the model-predicted excess returns on the six currency portfolios. The pricing errors are given by the deviations from the 45° line. We note that the model predicts portfolio returns fairly well, as most of the returns are very close to the line, or on the line itself.

5.4 Comparison with other risk factors in currency markets

In this section we draw a comparison between our two-factor model and other existing factors that price the cross-section of currency returns. We note that our proposed risk factor, $NVIX_{FM}$ is highly correlated with other existing risk factors in currency markets. $NVIX_{FM}$ has a -0.77 correlation with the carry risk factor HML_{FX}, proposed by Lustig et al. (2011), and a 0.95 correlation with the portfolio-mimicking global volatility factor, VOL_{FM}, proposed by Menkhoff et al. (2012). The main advantage of $NVIX_{FM}$ compared to these other factors, is that it is exogenous to the test assets and it has an economic meaning as discussed in the previous section. We investigate whether the explanatory power of our proposed model is comparable to existing two-factor models: the dollar and carry factor model proposed by Lustig et al. (2011), and the dollar and global volatility innovations model proposed by Menkhoff et al. (2012). The results are presented in Table 5, 6, and 7.

We first consider the carry factor HML_{FX}. The risk prices λ in Table 5 Panel I show that HML_{FX} commands a risk premium of 12.95% per year, very close in absolute value to the risk premium associated with $NVIX_{FM}$, of -12.91% per year. These two models appear to be the closest in terms of risk premia and factor loadings. They provide similar results with an opposite sign due to the way these factors are constructed. It is worth noting that if $NVIX_{FM}$ is built using NVIX levels instead of innovations, the factor would closely follow the carry risk factor, as shown in Figure 5. The two factors move together with roughly the same magnitude; hence, the underlying information driving $NVIX_{FM}$ could be the same driving force behind the carry factor proposed by Lustig et al. (2011). Looking at the R^2 of the time-series a better fit in Portfolios 1, 4, and 6, compared to the dollar-NVIX model (Table 4). This is not surprising since the carry factor is constructed directly from the tested assets and there is a mechanical relationship between the two, particularly with the corner portfolios that were directly used in the factor construction. Next, we run a horse race between the carry and NVIX factors. The results are reported in Table 6. HML_{FX} subsumes $NVIX_{FM}$ in the time-series regressions on the corner portfolios, while both stay significant in the remaining regressions. Once again, this is hardly surprising considering the mechanical relationship between those portfolios and the carry risk factor. However, the persistence of $NVIX_{FM}$'s significance in most of the portfolios confirms it as a strong risk factor in the cross-section of currency returns.

Next, we consider the global volatility innovations factor, VOL_{FM}. The high correlation between $NVIX_{FM}$ and VOL_{FM} once again suggests that the two factors might be driven by the same underlying economic forces. However, as shown in Table 7 Panel II, the risk price associated with VOL_{FM} of only -1.2% in annual terms is significantly lower than the -12.91% associated with $NVIX_{FM}$. Since both factors proxy for volatility innovations, they share the same pattern in factor loadings and they both entail a negative risk premium. The reported R^2 suggests that the dollar-NVIX model does a better job of explaining currency returns compared to the dollar-VOL model.

Finally, we run a horse race between $NVIX_{FM}$ and VOL_{FM}, the results are reported in Table 7 Panel III. $NVIX_{FM}$ stays significant in almost every regression, being insignificant in the time-series regression on Portfolio 5, while VOL_{FM} is subsumed by $NVIX_{FM}$ in the first portfolio regression. These results reveal that both factors contain information that helps explain currency returns, and that $NVIX_{FM}$ is a strong factor even when compared to other existing risk factors.

5.5 Forecasting regression and the augmented carry trade strategy

In order to examine $NVIX_{FM}$'s ability to forecast carry trade returns we construct a VAR(1) model as described in the Methodology section. We perform an F-test to check whether $NVIX_{FM}$ Granger causes HML_{FX}, and we obtain an F-statistic of 3.14, failing to reject the null that there is no Granger causality. We confirm the lack of autocorrelation in the residuals of our forecasting model with a Ljung-Box test and we use a rolling window of 18 months to forecast carry trade returns. Figure 6 presents the plot of the forecasted returns and the realized carry trade returns from 1990 until 2016. The average forecasted returns are 13.34% in annual terms, while the average realized returns are 13.85%. We fail to reject the null that there is a statistically significant difference in the two average returns. Our model correctly predicts the sign for 65% of the returns over our sample period, with a RMSE of 2.97%, signifying a good fit of the forecasting model.

the carry trade position at each period t when our model predicts a negative carry trade return in the next period. Otherwise, we keep the carry trade position unchanged. Figure 7 presents the results. This strategy yields 15.16% in annual terms compared to 13.85% earned by the original carry trade strategy. The increase of 1.31% in annual terms is statistically significantly different from zero at the 1% confidence level. We create the second augmented carry trade strategy such that we close the carry trade position at each period t if our forecasting model predicts a negative carry trade return in the next period, and if the NVIX innovations factor is higher than its median value up to that point in time. Otherwise, we keep the carry trade position unchanged. This strategy yields 15.62% in annual terms, an increase of 1.75% annually compared to the classic carry trade strategy. This is a statistically significant result at the 1 % level.

Finally, we perform the same analysis using the VOL_{FM} factor from Menkhoff et al. (2012). Given the information criteria obtained, we use a VAR(2) model to assess whether VOL_{FM} Granger causes HML_{FX}. We obtain an F-statistic of 4.54, and we fail to reject the null hypothesis that VOL_{FM} Granger causes HML_{FX}. We use VOL_{FM} to forecast carry trade returns, and we note that this model is able to correctly predict the sign for 56% of the returns over our sample period. This is an inferior performance compared to the model containing NVIX innovations. We build the two augmented carry trade strategies as before, based on VOL_{FM}'s ability to forecast carry trade returns. The first strategy yields 11.64% in annual terms, lower than the classic carry trade return. The second strategy yields 14.01% annually, which is slightly higher than the classic carry trade return, but lower than the return obtained from an augmented carry trade strategy involving NVIX innovations. We conclude that augmented carry trade strategies conditional NVIX innovations yield superior returns to the classic carry trade strategy, as well as to strategies conditional on other risk factors in the literature, namely, VOL_{FM}.

5.6 NVIX decomposition

The news-implied volatility index developed by Manela and Moreira (2017) can be decomposed into five main categories related to disaster concerns: war, financial intermediation, government, stock markets, and natural disasters. We use this decomposition to investigate which components explain most of the variation in currency returns. The results are presented in Table 8. Panel I reports the adjusted R^2 for regressions of NVIX as a state variable on each of those components. We note that Securities Markets (SM) and Financial Intermediation (I) exhibit the strongest ability to explain NVIX. Together, these two components explain 64% of the news-implied volatility measure. In other words, information relating to securities markets and financial intermediation are the two main sources of volatility, which is further priced in currency markets. Hence, we repeat our previous time-series and cross-sectional instead of the entire factor. We first transform this new factor into innovations by taking log differences, and then we obtain the loadings of the six portfolios on it such that we can create a new factor-mimicking portfolio, hereafter called $NVIX_{ISM}$. This factor has a 0.84 correlation with $NVIX_{FM}$ and a -0.70 correlation with HML_{FX}.

We run time-series regressions using the dollar factor and $NVIX_{ISM}$ on the six currency portfolios and obtain the factor loadings, presented in Table 8 Panel III. We notice an almost monotonic pattern in the factor loadings on $NVIX_{ISM}$, as before, decreasing from Portfolio 1 to 6. All factor loadings are statistically significant and the adjusted R^2 is fairly high, suggesting a good fit of the model. We conduct a GRS test to assess whether the pricing errors resulting from this model are jointly different from zero. We fail to reject the hypothesis that the pricing errors are jointly insignificant. We note that the loadings on $NVIX_{ISM}$ are significantly lower than the loadings on $NVIX_{FM}$, since we are not using the complete measure of volatility anymore, creating a measurement error. As the expected return on each portfolio is fixed in the data and the loadings are smaller, the estimated risk premium is inflated by construction. Indeed, in Panel II, we observe a risk premium of -24.15% in annual terms, which is also statistically significantly different from zero at the 1% level.

Despite the inflated risk premium, this NVIX decomposition analysis confirms that volatility driven by information related to securities markets and financial intermediation is able to price the cross-section of currency returns. Hence, the risk for which carry trade investors are compensated is proxied mainly by the uncertainty about securities markets and financial intermediation. This may provide further evidence that markets are integrated and risk factors from the stock markets are priced in currency markets.

6 Robustness

In this section we provide more evidence to support the findings presented earlier. In addition to the robustness checks presented in this section, we conduct an analysis using a sample of 14 developed countries and present the results in the Appendix.

6.1 Beta-sorted portfolios

Following Lustig et al. (2011), we show that sorting currencies on forward discounts truly measure their exposure to our proposed risk factor. We regress each currency's monthly log excess return on $NVIX_{FM}$ controlling for the dollar factor, which also acts as a constant, using an 18-month rolling window. We obtain the loadings of each currency on $NVIX_{FM}$ at every point in time t and we use these loadings to allocate the currencies into six portfolios, such that Portfolio 1 contains the currencies with the lowest factor loadings, and Portfolio 6 contains the currencies with the highest factor loadings on $NVIX_{FM}$. The summary statistics are reported in Table 9.

Portfolio 1 to 6. Similarly, we observe an almost monotonically decreasing pattern in the excess returns of the six portfolios. The spread between the corner portfolios is 13.26% compared to a 15.35% spread obtained from the sorting on forward discounts. From our previous analysis, the currencies with the highest forward discount had a negative risk exposure to $NVIX_{FM}$, while the currencies with the lowest forward discount had a positive risk exposure to this factor. Hence, the pattern observed in Table 9 is consistent with our previous findings.

We confirm that sorts based on forward discounts and sorts based on betas are related. Forward discounts indeed convey information about the riskiness of individual currencies, as noted by Lustig et al. (2011). The pre-formation betas reported at the bottom of Table 9 present the average loadings of the currencies in each portfolio after being sorted. The post-formation betas are the factor loadings of each currency portfolio on $NVIX_{FM}$. Currencies that covary negatively with $NVIX_{FM}$ are riskier and provide higher excess returns, while those that covary positively with our risk factor act as a hedge, therefore earning lower returns. This analysis confirms the robustness of our findings.

6.2 Split-sample analysis

Since we transform NVIX innovations into a factor-mimicking portfolio using the test assets, and the dollar factor is obtained from the test assets themselves, we conduct a robustness check to guard against results driven by the construction of our factors. We follow Lustig et al. (2011) and run a split-sample analysis and we show that our results are not driven by a mechanical relation between our risk factors and the six currency portfolios. The results are presented in Table 10 and 11. We sort our sample of 48 currencies alphabetically and split it into two sub-samples of 24 currencies each. We sort currencies based on forward discounts into four portfolios instead of six. This is due to the small number of currencies in each sample and the missing observations that further shrink our sub-samples of currencies at each point in time. We first check whether the portfolios in each sample share a common factor structure. We compute the correlation coefficients between the time-series of portfolio excess returns in one sample and their corresponding portfolio excess returns in the second sample. The correlation coefficients vary between 0.51 and 0.62, suggesting the existence of a common factor structure. In other words, if one portfolio has a poor performance in the first sample, we should observe that its counterpart in the second sample exhibits a poor performance as well. We use one sample to create the risk factors, and the other sample to construct test assets and to estimate the factor loadings and risk premia with a single cross-sectional regression. We then repeat the analysis, reversing the samples.

We find that DOL and $NVIX_{FM}$ built from currencies' returns that are not included in the test assets are still able to price the cross-section of currency as shown by the p-values reported at the bottom of Panel I and II in Table 10. The risk premium for $NVIX_{FM}$ remains significant, while the dollar risk premium is insignificant, confirming our previous results. The pattern in the factor loadings is strictly monotonic for one of the samples as shown in Panel I, while almost monotonic for the other.

We note that the $NVIX_{FM}$ risk premium is significantly smaller for the sample presented in Table 11, Panel I. This is due to the way we split the samples. Sample 1 happens to contain higher return currencies, while the second sample has lower return currencies. Since the factor loadings on $NVIX_{FM}$ are roughly the same across the two samples, the difference in returns mechanically translates into a lower risk premium for $NVIX_{FM}$. Moreover, as we estimate the risk factors only on part of our sample, we introduce a measurement error. This shrinks the factor loadings as in the case of the dollar factor in Table 10, which again, by construction leads to an inflated risk premium as shown in Table 11, Panel II. Nevertheless, we obtain a monotonic pattern in the factor loadings and we confirm overall the previously obtained results. We show that the two identified common risk factors indeed explain returns in currency markets and that our results are not mechanically driven.

6.3 Country-level analysis

As a last robustness check of our results, we test our model at the country level. As noted by Lo and MacKinlay (1990), we may destroy some information when creating portfolios of currencies, leading to data-snooping biases and smaller dispersion of the betas. To mitigate this concern, we use individual currencies as test assets for our two-factor model containing DOL and $NVIX_{FM}$. Following Lustig et al. (2011), we do not account for transaction costs proxied by the bid-ask spread as we do not know *a priori* whether investors take long or short positions in each particular currency. To obtain consistent results we use the same two factors as before, which were constructed accounting for transaction costs. The results of the country-level analysis are reported in Table 12.

We obtain a highly significant risk premium on $NVIX_{FM}$ of -23.2% in annual terms, and a statistically insignificant risk premium on the dollar factor of 0.07% per year. Since we are not sorting the currencies into portfolios, there is more noise in the data resulting in an inflated risk premia. The adjusted R^2 is 51.3%. Overall, our country-level analysis is consistent with the portfolio-level results, confirming that DOL and $NVIX_{FM}$ are able to explain returns in currency markets.

This thesis provides evidence that investor uncertainty proxied by NVIX innovations is a priced risk in the cross-section of currency returns. We show that investor uncertainty constructed as a factor-mimicking portfolio commands a strong negative risk premium of 12.91%. High values of NVIX innovations are associated with periods of market downturn. Hence, currencies that covary negatively with NVIX innovations are riskier and earn a higher risk premium. Currencies that covary positively with this risk factor act as a hedge for investors and they trade at a lower risk premium. A two-factor model consisting of the dollar factor and NVIX innovations explains 86.75% of the cross-sectional variation in returns in the global currency market and 78.91% in the developed market. We construct a VAR(1) forecasting model and use its predictive power to improve the profitability of the carry trade strategy. By hedging the downside risk of the carry trade we obtain 15.61% average returns per year compared to the 13.87% yielded by the classic carry trade strategy. Therefore, carry trade investors can use NVIX's forecasting ability to hedge carry trade risk, and earn superior returns. We use the NVIX decomposition to find that uncertainty about financial intermediation and securities markets is the main driver of the risk premia in currency markets. This risk explains 63.55% of the variation in NVIX and 93.55% of the variation in the cross-section of currency returns.

Our results are in line with the findings in existing literature, such as Menkhoff et al. (2012) who show that global volatility innovations are priced in the cross-section of currency returns. This thesis contributes to standing literature by offering an economic interpretation of the carry trade risk. Going forward, it would be interesting to disentangle the specific words that matter the most in the creation of the NVIX innovations factor for currency returns. The factor used in this thesis was initially created as a proxy for investor uncertainty in the stock market. Therefore, identifying the words that matter for currency returns would enable the creation of a stronger NVIX factor tailored specifically for the currency market.

Finally, more recent research focused on explanations of the carry trade returns based on permanent differences in countries' characteristics. For instance, Richmond (2019) argues that trade network centrality is the economic source of exposure to global risk that drives international asset prices. Countries that are more central in the global trade network have lower interest rates and currency risk premia, while those that are more peripheral have higher interest rates and currency risk premia. Ready et al. (2017) argue that countries that produce commodity goods have currencies that depreciate in times of market downturn and command a higher risk premia, while countries that produce final goods experience the opposite. These papers suggest that some currencies are fundamentally riskier than others. Hence, a next step for our research would be to check whether the results presented in this thesis hold when accounting for various characteristics presented in the literature.

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FIGURES

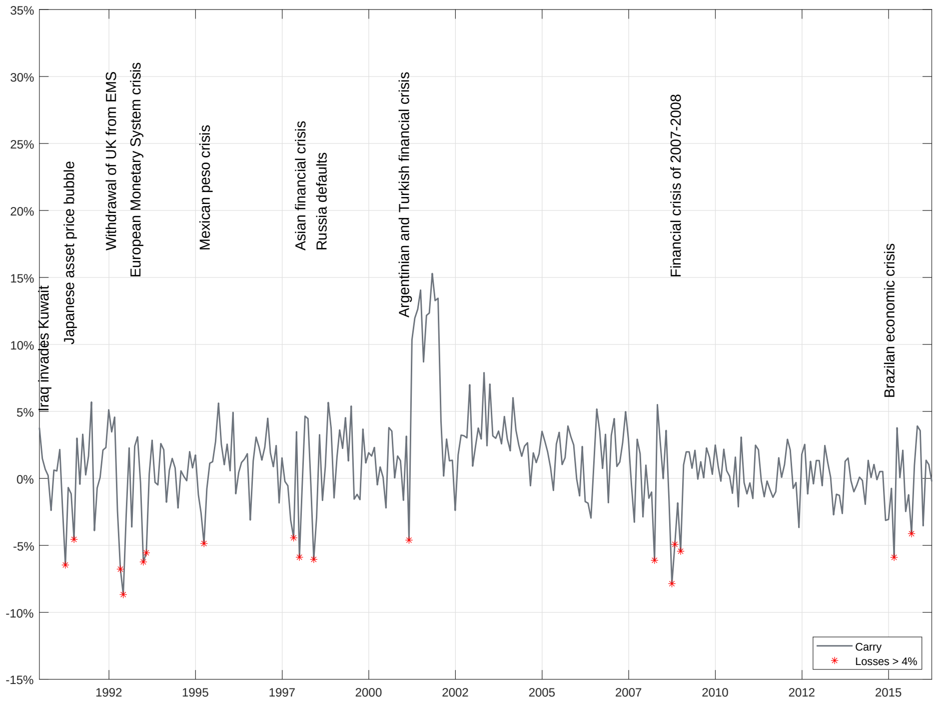

Figure 1: Carry trade returns 1990-2018. The figure shows monthly carry trade returns for the period 1990-2018 and several events that coincided with those returns.

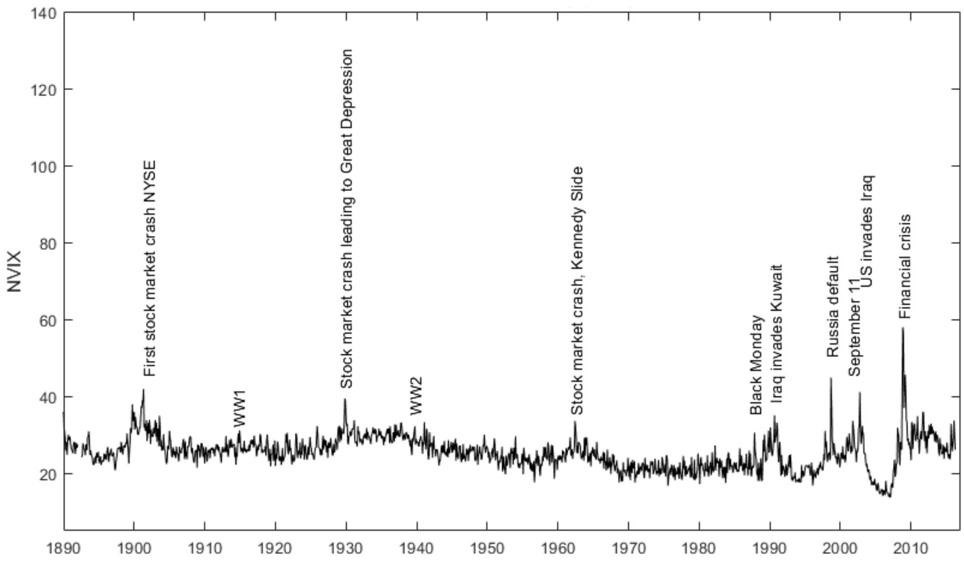

Figure 2: News Implied Volatilty (NVIX). The figure shows the NVIX measure (Manela and Moreira, 2017) for the period 1890-2016, and events coinciding with spikes in NVIX.

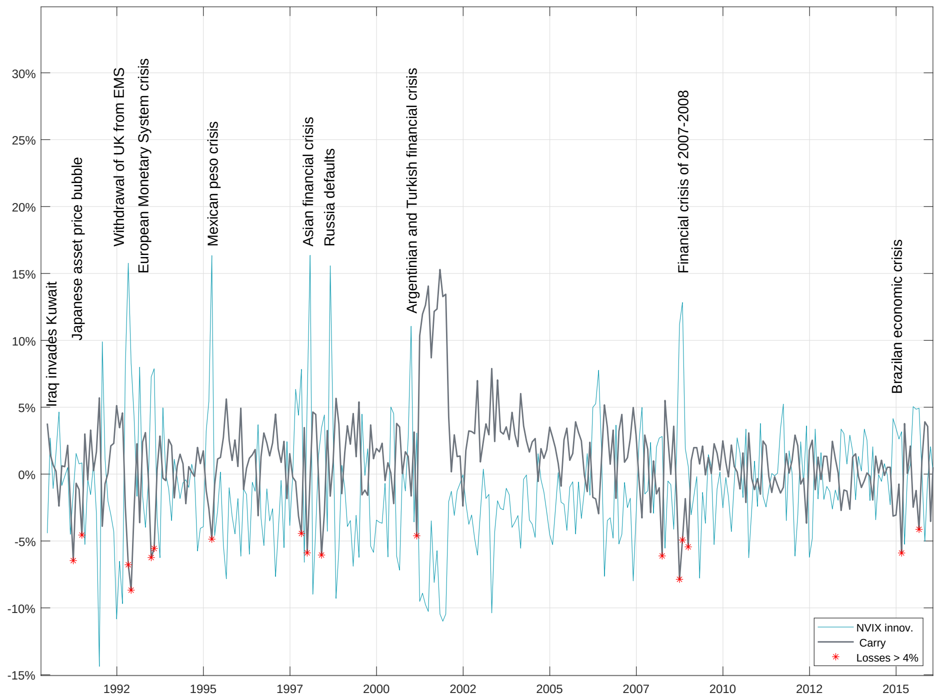

Figure 3: NVIX Innovations and Carry trade returns, 1990-2016. The figure shows returns for carry trade and NVIX innovations as a factor-mimicking portfolio from Jun 1990 - Mar 2016 and several events that coincided with strong negative carry trade returns and positive spikes in NVIX innovations.

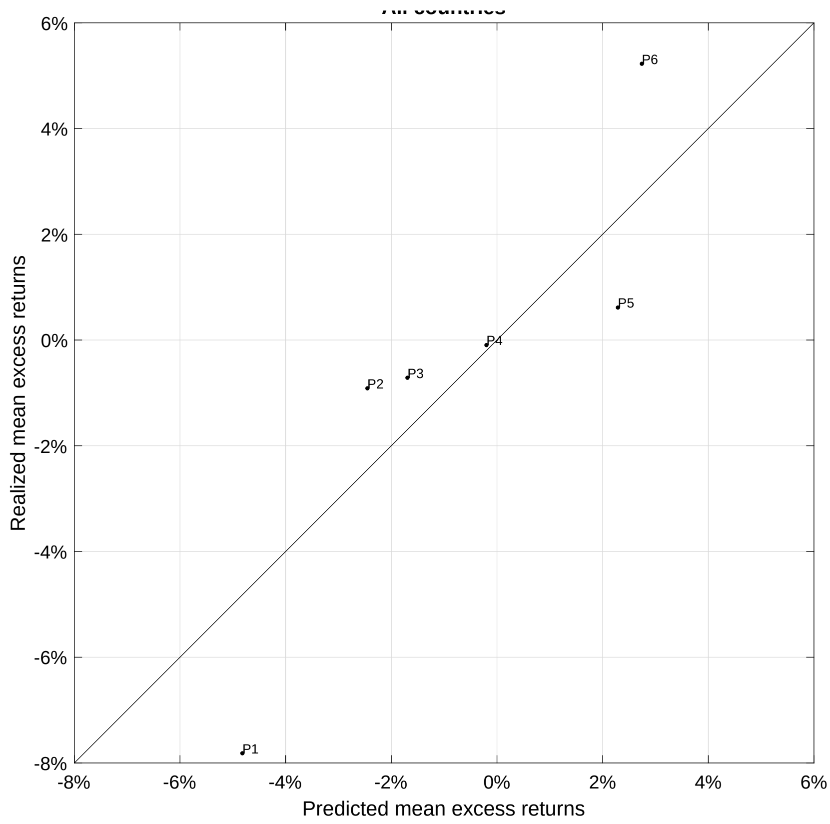

Figure 4: Pricing error plot. This figure show pricing errors for asset pricing models with Dollar and NVIX Innovations as risk factors. Returns are annualized.

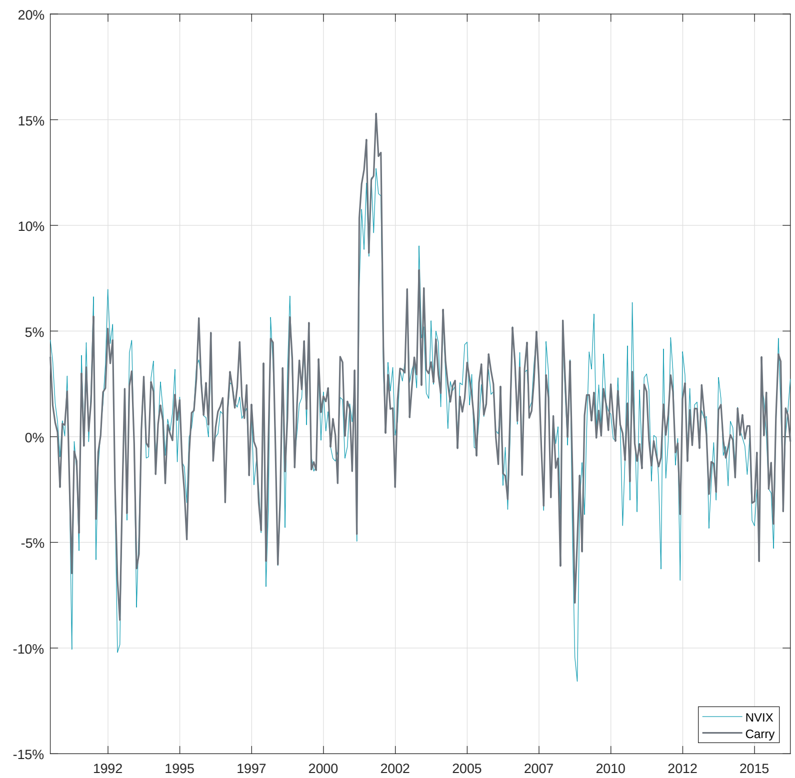

Figure 5: NVIX in levels and Carry trade returns. The figure shows monthly returns for carry trade and NVIX in levels during 1990-2016.

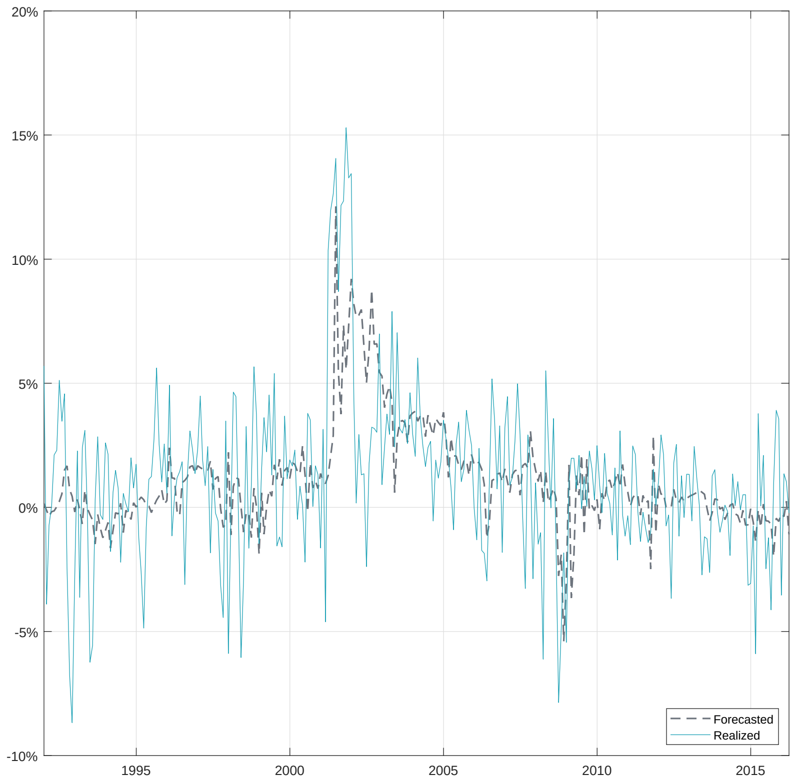

Figure 6: Forecasted carry trade strategy. The figure shows monthly returns for carry trade and for the forecasted carry trade strategy using NVIX innovations.

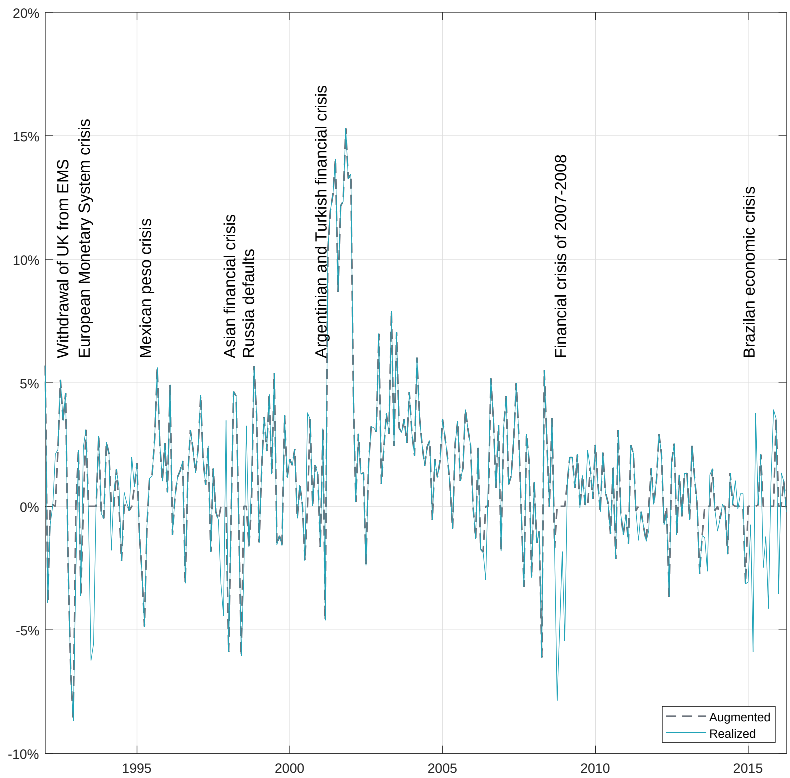

Figure 7: Augmented carry trade strategy. The figure shows monthly returns for carry trade and for the augmented carry trade strategy using NVIX innovations.

TABLES

Table 1: Principal components

All Countries

Portfolio	1	2	3	4	5	6
1	0.40	0.83	0.38	0.08	-0.05	0.08
2	0.33	0.10	-0.33	-0.11	0.56	-0.67
3	0.35	0.07	-0.49	-0.49	-0.62	-0.01
4	0.39	-0.11	-0.22	-0.15	0.49	0.72
5	0.46	-0.22	-0.21	0.80	-0.23	-0.02
6	0.49	-0.49	0.64	-0.27	-0.06	-0.16
% Var.	60.38	18.29	8.57	5.85	4.17	2.74

This table reports the coefficients of a principal component analysis on the six currency portfolios sorted on forward discounts. The last row reports (in %) the share of the total variance explained by each common factor.

Table 2: Currency Portfolios

Portfolio	1	2	3	4	5	6
			Spot change: Δs^j			
Mean	0.42	-0.27	0.38	0.83	1.97	6.48
Std	6.57	6.91	7.54	7.40	8.95	9.70
			Forward Discount: $f^j - s^j$			
Mean	-6.22	-0.34	0.65	1.85	4.22	14.95
Std	6.80	0.34	0.34	0.37	0.55	3.08
			Excess Return: rx^j (without b-a)			
Mean	-6.72	-0.25	0.22	1.11	2.33	8.63
Std	9.72	6.81	7.50	7.41	8.89	10.09
SR	-0.69	-0.04	0.03	0.15	0.26	0.85
			Net Excess Return: $rx^j{}_{\text{net}}$ (with b-a)			
Mean	-7.82	-0.91	-0.72	-0.10	0.61	5.23
Std	9.91	6.79	7.52	7.41	8.97	10.03
SR	-0.79	-0.13	-0.10	-0.01	0.07	0.52
			High-minus-Low: $rx^j - rx^1$ (without b-a)			
Mean		6.47	6.94	7.83	9.04	15.35
Std		8.42	9.13	9.47	10.37	11.58
SR		0.77	0.76	0.83	0.87	1.32
			High-minus-Low: $rx^j{}_{\text{net}} - rx^1{}_{\text{net}}$ (with b-a)			
Mean		6.90	7.10	7.72	8.43	13.04
		[0.49]	[0.53]	[0.55]	[0.60]	[0.66]
Std		8.59	9.31	9.61	10.55	11.66
SR		0.80	0.76	0.80	0.80	1.12

This table reports the average change in log spot exchange rates Δs^j, the average log forward discounts $f_t - s_{t+1}$, the average log excess return $rx^j{}_{\text{net}}$ and rx_{t+1} (with and without bid-ask spreads), and the average return on the long-short strategy $rx^j{}_{\text{net}} - rx^1{}_{\text{net}}$ and $rx^j - rx^1$ (with and without bid-ask spreads), for each portfolio j. All numbers are annualized and reported in percentage points. Standard errors are reported in brackets. The table reports Sharpe ratios for excess returns, computed as ratios of means to standard deviations (both annualized). The first portfolio contains currencies with the lowest interest rate, the last portfolios contains currencies with the highest interest rate.

Table 3: Asset pricing - U.S. investor

Dollar and NVIX Innovations Risk Prices

$$rx_j = \lambda_{DOL}\beta^j_{DOL} + \lambda_{NVIX_{FM}}\beta^j_{NVIX_{FM}} + u_j$$

	λ_{DOL}	$\lambda_{\text{NVIX}_{\text{FM}}}$	R^2
SCSR	-0.69	-12.91	86.75
	[2.33]	[2.70]	
FMB	-0.69	-12.91	
	[1.51]	[3.73]	
Mean	**-0.62**	**-11.98**	

This table reports results from a single cross-sectional regression *SCSR* and Fama-MacBeth asset pricing procedures. Parameter estimates and R^2 are reported in percentages. Newey-West-corrected standard errors are reported in brackets.

Table 4: Factor Betas

Dollar and NVIX Innovations

$$rx^j_t = \alpha^j_t + \beta^j_1 DOL_t + \beta^j_2 NVIX_{FMt} + u_{j,t}$$

	All Countries					
Portfolio	$\alpha^j{}_0$	$\beta^j{}_{\text{DOL}}$	$\beta^j{}_{\text{NVIX}_{\text{FM}}}$	R^2	F-stat	*P-value*
1	-3.37	1.13	0.31	68.00		
	[1.52]	[0.15]	[0.09]			
2	1.34	0.90	0.14	77.80		
	[0.79]	[0.07]	[0.04]			
3	0.84	0.93	0.08	64.80		
	[0.96]	[0.06]	[0.03]			
4	0.07	0.95	-0.04	74.80		
	[0.79]	[0.06]	[0.02]			
5	-1.53	1.02	-0.23	84.80		
	[0.84]	[0.04]	[0.02]			
6	2.65	1.06	-0.27	77.70		
	[1.12]	[0.05]	[0.03]			
All					0.30	100%

This table reports the intercepts, factor loadings and adjusted R^2 from regressing the six currency portfolios on a two-factor model consisting of the Dollar factor DOL and the portfolio-mimicking NVIX Innovations $NVIX_{\text{FM}}$. Intercepts are annualized. Newey-West-corrected standard errors are reported in brackets. The F-statistic and the p-value come from the GRS test of the pricing errors.

Table 5: Asset pricing - Dollar and Carry two-factor model

Panel I: Risk Prices

$$rx_j = \lambda_{DOL}\beta^j_{DOL} + \lambda_{HML_{FX}}\beta^j_{HML_{FX}} + u_j$$

	λ_{DOL}	$\lambda_{\text{HML}_{\text{FX}}}$	R^2
SCSR	-0.63	12.95	99.64
	[1.30]	[2.29]	
FMB	-0.63	12.95	
	[1.51]	[3.20]	
Mean	**-0.62**	**13.04**	

Panel II: Factor Betas

$$rx^j_t = \alpha^j_t + \beta^j_1 DOL_t + \beta^j_2 HML_{FXt} + u_{j,t}$$

Portfolio	$\alpha^j{}_0$	$\beta^j{}_{\text{DOL}}$	$\beta^j{}_{\text{HML}_{\text{FX}}}$	R^2	F-stat	*P-value*
1	0.11	1.10	-0.56	86.80		
	[0.83]	[0.07]	[0.09]			
2	0.43	0.85	-0.06	68.50		
	[0.90]	[0.07]	[0.07]			
3	0.29	0.90	-0.04	62.20		
	[0.99]	[0.06]	[0.06]			
4	-0.63	0.95	0.09	76.10		
	[0.83]	[0.05]	[0.03]			
5	-0.30	1.10	0.12	71.30		
	[1.09]	[0.06]	[0.03]			
6	0.11	1.10	0.44	87.10		
	[0.83]	[0.07]	[0.09]			
All					0.02	100%

This table reports the results from an analysis of Lustig et al.'s carry factor HML_{FX}. Panel I reports results from a single cross-sectional regression *SCSR* and Fama-MacBeth asset pricing procedures. Factor risk prices and factor means are annualized. R^2 are reported in percentages. Panel II reports the intercepts, factor loadings and adjusted R^2 from regressing the six currency portfolios on a two-factor model consisting of the Dollar factor DOL and the HML_{FX}. Intercepts are annualized. Newey-West-corrected standard errors are reported in brackets. The F-statistic and the p-value come from the GRS test of the pricing errors.

Table 6: Horse race between the Carry and NVIX Innovations factors

$$rx_t^j = \alpha_t^j + \beta_1^j DOL_t + \beta_2^j HML_{FXt} + \beta_3^j NVIX_{FMt} + u_{j,t}$$

Portfolio	$\alpha^j{}_0$	$\beta^j{}_{\text{DOL}}$	$\beta^j{}_{\text{HML}_{\text{FX}}}$	$\beta^j{}_{\text{NVIX}_{\text{FM}}}$	R^2
1	0.14	1.09	-0.58	-0.03	86.80
	(.85)	(<.001)	(<.001)	(.21)	
2	0.10	0.92	0.21	0.26	82.80
	(.86)	(<.001)	(<.001)	(<.001)	
3	0.10	0.94	0.12	0.15	66.10
	(.91)	(<.001)	(<.001)	(<.001)	
4	-0.68	0.96	0.12	0.04	76.20
	(.37)	(<.001)	(<.001)	(<.08)	
5	0.19	1.00	-0.29	-0.40	90.30
	(.74)	(<.001)	(<.001)	(<.001)	
6	0.14	1.09	0.42	-0.03	87.10
	(.85)	(<.001)	(<.001)	(.21)	

This table reports the factor loadings and R^2 from a horse race between the Carry and NVIX Innovations factors. The six currency portfolios are regressed on a three-factor model consisting of the Dollar factor, the Carry factor and NVIX Innovations. These OLS regressions are run with an intercept. P-values are reported in brackets. All intercepts are annualized.

Table 7: Dollar and Volatility Innovations two-factor model

Panel I: Factor betas

$$rx_t^j = \alpha_t^j + \beta_1^j DOL_t + \beta_2^j VOL_{FMt} + u_{j,t}$$

Portfolio	$\alpha^j{}_0$	$\beta^j{}_{\text{DOL}}$	$\beta^j{}_{\text{VOL}_{\text{FM}}}$	R^2	F-stat	*P-value*
1	-3.84	1.22	4.04	66.50		
	[1.51]	[0.15]	[1.01]			
2	0.76	0.92	1.39	73.00		
	[0.81]	[0.06]	[0.37]			
3	1.44	1.00	1.93	70.80		
	[0.89]	[0.06]	[0.42]			
4	-0.28	0.91	-0.94	76.40		
	[0.76]	[0.05]	[0.27]			
5	-1.32	0.95	-3.17	85.50		
	[0.82]	[0.03]	[0.29]			
6	3.24	1.00	-3.26	74.70		
	[1.18]	[0.05]	[0.32]		0.36	100%

Table 7 continued on next page

Panel II: Factor risk prices

$$rx_j = \lambda_{DOL}\beta^j_{DOL} + \lambda_{VOL_{FM}}\beta^j_{VOL_{FM}} + u_j$$

	λ_{DOL}	$\lambda_{\text{VOL}_{\text{FM}}}$	R^2
SCSR	-0.68	-1.20	69.63
	[0.97]	[0.32]	
Mean	**-0.62**	**-0.80**	

Panel III: Horse race between the NVIX Innovations and Volatility Innovations factors

$$rx^j_t = \alpha^j_t + \beta^j_1 DOL_t + \beta^j_2 NVIX_{FMt} + \beta^j_3 VOL_{FMt} + u_{j,t}$$

Portfolio	$\alpha^j{}_0$	$\beta^j{}_{\text{DOL}}$	$\beta^j{}_{\text{NVIX}_{\text{FM}}}$	$\beta^j{}_{\text{VOL}_{\text{FM}}}$	R^2
1	-3.40	1.15	0.27	0.63	67.90
	(<.01)	(<.001)	(<.001)	(.50)	
2	1.57	0.79	0.49	-4.81	83.50
	(<.01)	(<.001)	(<.001)	(<.001)	
3	0.35	1.18	-0.66	10.32	86.60
	(.53)	(<.001)	(<.001)	(<.001)	
4	0.33	0.81	0.37	-5.67	81.50
	(.60)	(<.001)	(<.001)	(<.001)	
5	-1.42	0.96	-0.06	-2.42	85.60
	(.04)	(<.001)	(.17)	(<.001)	
6	2.56	1.11	-0.41	1.93	78.00
	(<.001)	(<.001)	(<.001)	(.01)	

This table show results from an analysis of Menhoff et al.'s Volatility Innovations factor. Panel I reports intercepts, factors loadings and R^2 from time-series regressions of the currency portfolios' excess returns on a two-factor model consisting of the dollar factor DOL and the factor-mimicking Volatility Innovations VOL_{FM}. Intercepts are annualized. The F-statistic and the p-value come from the GRS test of the pricing errors. Newey-West standard errors are reported in square brackets. Panel II reports results from a single cross-sectional regression *SCSR*. Factor risk prices and factor means are annualized. Panel III reports the results from a horse race between the factor-mimicking NVIX Innovations $NVIX_{\text{FM}}$ and the factor-mimicking Volatility Innovations VOL_{FM}. All R^2's are adjusted and reported in percentages.

Table 8: NVIX Analysis

Panel I: NVIX decomposition

$$NVIX_t = \alpha_t^j + \beta^j Component_{j,t} + u_{j,t}$$

Components	R^2
War	0.23
Natural Disaster	1.94
Government	2.73
Securities Markets (SM)	45.41
Financial Intermediation (I)	47.01
I & SM	63.55
All components	**99.99**

Panel II: Factor Risk Prices

$$rx_j = \lambda_{DOL}\beta_{DOL}^j + \lambda_{NVIX_{ISM}}\beta_{NVIX_{ISM}}^j + u_j$$

	λ_{DOL}	$\lambda_{\mathrm{NVIX_{ISM}}}$	R^2
SCSR	-0.59	-24.15	93.55
	[0.84]	[2.18]	
FMB	-0.59	-24.15	
	[1.50]	[6.56]	
Mean	**-0.62**	**-23.65**	

Panel III: Factor Betas

$$rx_t^j = \alpha_t^j + \beta_1^j DOL_t + \beta_2^j NVIX_{ISMt} + u_{j,t}$$

Portfolio	$\alpha^j{}_0$	$\beta^j{}_{\mathrm{DOL}}$	$\beta^j{}_{\mathrm{NVIX_{ISM}}}$	R^2	F-stat	*P-value*
1	-4.67	0.91	0.11	54.90		
	[2.42]	[0.13]	[0.02]			
2	1.28	0.78	0.07	77.30		
	[0.79]	[0.04]	[0.01]			
3	1.76	0.82	0.08	72.70		
	[0.89]	[0.04]	[0.01]			
4	0.53	0.96	0.00	74.30		
	[0.83]	[0.06]	[0.01]			
5	-0.72	1.20	-0.09	77.20		
	[1.01]	[0.05]	[0.01]			
6	1.82	1.33	-0.18	88.40		
	[0.81]	[0.04]	[0.01]			
All					0.31	100%

This table reports the results from an analysis of NVIX. Panel I reports adjusted R^2 (in percent) from regressing each of the components on the NVIX level factor. Panel II reports results from a single cross-sectional regression *SCSR*, and the Fama-MacBeth asset pricing procedure. A constant is not included in the second-step FMB procedure. Newey-West-corrected standard errors are reported in brackets. Excess returns are annualized and take into account bid-ask-spreads. Panel III reports results from two-factor regressions of currency portfolios on the Dollar factor DOL and the portfolio-mimicking decomposed NVIX, consisting of Intermediation and Securities Market $NVIX_{\mathrm{ISM}}$. This decomposed NVIX is created by adding together Intermediation and Securities Market in levels, then turning it into a portfolio-mimicking factor. The panel shows intercepts, factors loadings and R^2 from time-series regressions of the portfolios' excess returns on the factors. Intercepts are annualized. The F-statistic and the p-value come from the GRS test of the pricing errors.

Table 9: Beta-Sorted Currency Portfolios

Portfolio	1	2	3	4	5	6
			Spot change: Δs^j			
Mean	3.05	1.38	1.58	1.45	1.33	1.59
Std	9.89	6.08	6.16	4.05	7.47	8.20
			Discount: $f^j - s^j$			
Mean	8.67	3.27	1.14	1.89	1.44	-3.71
Std	3.19	1.23	1.25	1.06	0.64	7.00
			Excess Return: rx^j (without b-a)			
Mean	6.88	1.82	0.20	1.17	0.14	-6.38
Std	10.78	6.01	6.20	3.80	7.55	12.06
SR	0.64	0.30	0.03	0.31	0.02	-0.53
			High-minus-Low: $rx^j - rx^6$ (without b-a)			
Mean	13.26	8.20	6.58	7.55	6.52	
	[0.99]	[0.69]	[0.85]	[0.69]	[0.61]	
Std	13.42	11.83	14.60	11.76	10.39	
SR	0.79	0.69	0.45	0.64	0.63	
			Pre-formation β			
Mean	-0.39	-0.09	-0.03	0.02	0.14	0.40
Std	0.15	0.06	0.05	0.03	0.06	0.32
			Post-formation β			
Estimate	-0.50	-0.70	-0.60	0.11	0.13	1.56
s.e	[0.16]	[0.04]	[0.05]	[0.12]	[0.16]	[0.34]

This table reports the average change in log spot exchange rates Δs^j, the average log forward discounts $f_t - s_t$, the average log excess return rx^j(without bid-ask spreads), and the average return on the long-short strategy $rx^j - rx^1$ (without bid-ask spreads), for each portfolio j. All numbers are annualized and reported in percentage points. Standard errors are reported in brackets. The table reports Sharpe ratios for excess returns, computed as ratios of means to standard deviations (both annualized). Portfolios are constructed by sorting currencies into six portfolios based on slope coefficients β_t^i. The slope coefficients are obtained by regressing currency i log excess return on the Dollar factor DOL, and NVIX Innovations $NVIX_{FM}$ on an 18-period moving window that ends in period $t-1$. The first portfolio contains currencies with the lowest βs, the last portfolio contains currencies with the highest βs. Post-formation betas are found by taking the average of the beta loadings in each portfolio j. Post-formation betas are calculated by regressing each portfolio on a two-factor model consisting of DOL, and NVIX Innovations $NVIX_{FM}$.

Table 10: Split-sample Factor Betas

Panel I: Sample 1 factors tested on sample 2 portfolios

$$rx_t^j = \alpha_t^j + \beta_1^j DOL_{t,s1} + \beta_2^j NVIX_{t,s1} + u_{j,t}$$

Portfolio	$rx^j{}_{\text{net,s2}}$	α	DOL	$NVIX_{\text{FM}}$	R^2	F-stat	P-value
1	-6.25	-6.66	0.81	0.26	24.40		
	[10.41]	[2.93]	[0.09]	[0.09]			
2	0.28	-0.73	0.70	0.09	46.80		
	[6.79]	[1.16]	[0.04]	[0.07]			
3	1.53	-0.56	0.73	-0.10	48.70		
	[7.91]	[1.32]	[0.06]	[0.07]			
4	4.29	0.99	0.77	-0.32	48.50		
	[9.67]	[1.67]	[0.08]	[0.07]			
All						0.58	94.48%

Panel II: Sample 2 factors tested on sample 1 portfolios

$$rx_t^j = \alpha_t^j + \beta_1^j DOL_{t,s2} + \beta_2^j NVIX_{t,s2} + u_{j,t}$$

Portfolio	$rx^j{}_{\text{net,s1}}$	α	DOL	$NVIX_{\text{FM}}$	R^2	F-stat	P-value
1	-2.21	0.29	0.68	0.23	57.70		
	[7.48]	[1.24]	[0.08]	[0.04]			
2	-0.01	3.53	0.72	0.33	67.70		
	[8.06]	[1.31]	[0.08]	[0.03]			
3	1.28	0.79	0.81	-0.05	41.00		
	[8.57]	[1.49]	[0.12]	[0.05]			
4	9.52	6.00	1.00	-0.34	50.90		
	[8.57]	[2.15]	[0.11]	[0.07]			
All						0.78	76.27%

This table shows the results from a split-sample analysis. We divide the alphabetically sorted countries into two samples, consisting of 24 countries each. We then sort the currencies in each sub-sample into 4 portfolios, by their forward discounts. Factors constructed in each sample are then tested on portfolios in the opposite sample. The results in Panel I show sample 2 portfolios regressed on factors from sample 1, while Panel II shows sample 1 portfolios regressed on factors from sample 2. The two panels report annualized portfolio net excess returns (s1 = Sample 1, s2 = Sample 2), intercepts, factors loadings and R^2 from time-series regressions of the 4 portfolios' excess returns on the factors. Intercepts are annualized. The F-statistic and the P-value come from the GRS test of the pricing errors.

Table 11: Split-sample Risk Prices

Panel I: Sample 1 Factor Risk Prices

$$rx_j = \lambda_{DOL,1}\beta^j_{DOL,1} + \lambda_{NVIX_{FM},1}\beta^j_{NVIX_{FM},1} + u_j$$

	λ_{DOL}	$\lambda_{\mathrm{NVIX_{FM}}}$	R^2
SCSR	0.43	-6.98	53.10
	[1.59]	[2.64]	
FMB	0.43	-6.98	
	[1.84]	[1.76]	
Mean	**2.14**	**-5.20**	

Panel II: Sample 2 Factor Risk Prices

$$rx_j = \lambda_{DOL,2}\beta^j_{DOL,2} + \lambda_{NVIX_{FM},2}\beta^j_{NVIX_{FM},2} + u_j$$

	λ_{DOL}	$\lambda_{\mathrm{NVIX_{FM}}}$	R^2
SCSR	2.55	-11.26	85.31
	[1.30]	[2.36]	
FMB	2.55	-11.26	
	[1.79]	[2.57]	
Mean	**-0.03**	**-10.59**	

This table shows the results from a split-sample analysis. We divide the alphabetically sorted countries into two samples, consisting of 24 countries each. We then sort the currencies in each sub-sample into 4 portfolios, by their forward discounts. Factors constructed in each sample are then tested on portfolios in the opposite sample. Panel I and II reports results from a single cross-sectional regression *SCSR*, and the Fama-MacBeth asset pricing procedure. A constant is not included in the second-step FMB procedure. Newey-West-corrected standard errors are reported in brackets. Excess returns are annualized and take into account bid-ask-spreads.

Table 12: Country-level analysis

$$rx_j = \lambda_{DOL}\beta_{DOL} + \lambda_{NVIX_{FM}}\beta_{NVIX_{FM}} + u_j$$

	λ_{DOL}	$\lambda_{\text{NVIX}_{\text{FM}}}$	R^2
SCSR	0.07	-23.19	51.32
	[0.72]	[3.02]	
Mean	**0.89**	**-14.69**	

This table shows a country-level analysis of the dollar and NVIX factors from a single cross-sectional regression *SCSR*. The table reports the market prices of the factors, their standard errors and adjusted R^2. All moments are annualized, R^2 is reported in percent. The results from the *SCSR* are obtained from regressing the two factors on the individual countries's monthly returns and using these betas for a single cross-sectional regression of average country returns on the dollar and NVIX factor, including the factors themselves.

APPENDIX

A1 Developed countries

We repeat the analysis of NVIX innovations on a sample of 14 developed countries. The results are presented in tables A1 to A4 and Figure A1. The PCA analysis in table A1 finds that a level and a slope factor together explain 80% of the variation in currency returns. Table A2 shows that there is a monotonic increase in portfolio monthly returns, sorted by forward discounts, and a strictly monotonic increase in monthly returns for high-minus-low strategies. Table A3 confirms that the NVIX innovations factor is priced in the cross-section of currency returns, with an annual risk premium of -6.12%, highly statistically significantly different from zero at the 1% level. Table A4 presents the NVIX factor loadings on the six currency portfolios. We observe a monotonic decrease from Portfolio 1 to 6. Figure A1 shows the pricing errors, these are statistically insignificantly different from zero at the 1% level. All these results are consistent with the results from the full sample analysis. We repeat the analysis using Lustig et al.'s (2011) two-factor model consisting of DOL and HML_{FX}, on the sample of developed countries in Table A5. Portfolio 1 and 6 have a higher R^2 for Lustig et al.'s model compared to the model consisting of DOL and NVIX innovations, while the remaining portfolios have a worse fit. These results are identical to the full sample analysis results. Additionally, we perform a horse race between HML_{FX} and NVIX innovations on the six currency portfolios, results are presented in Table A6. The factor loadings of NVIX innovations on Portfolio 1 and 6 are statistically insignificantly different from zero at the 10% level, while the remaining portfolios are significantly different from zero at the 1% level, consistent with the full sample results.

Table A1: Principal components

Developed Countries

Portfolio	1	2	3	4	5	6
1	0.32	0.60	-0.53	-0.23	-0.44	-0.08
2	0.34	0.38	0.80	0.17	-0.27	-0.07
3	0.40	0.28	-0.08	0.04	0.80	-0.34
4	0.40	-0.01	0.01	-0.15	0.18	0.88
5	0.44	-0.51	0.12	-0.66	-0.13	-0.29
6	0.51	-0.40	-0.25	0.68	-0.21	-0.08
% Var.	70.05	10.43	7.79	4.62	3.89	3.23

This table reports the coefficients of a principal component analysis on the six currency portfolios sorted on forward discounts, for developed countries. The last row reports (in %) the share of the total variance explained by each common factor.

Table A2: Currency Portfolios

Portfolio	1	2	3	4	5	6
	Developed Countries					
	Δs^j					
Mean	-2.05	0.67	0.95	0.12	1.25	-0.58
Std	9.09	9.39	9.42	9.10	10.52	11.61
	Forward Discount: $f^j - s^j$					
Mean	-1.95	-0.33	0.06	0.75	1.95	3.65
Std	0.59	0.47	0.49	0.55	0.62	0.84
	Excess Return: rx^j (without b-a)					
Mean	0.08	-1.00	-0.89	0.63	0.71	4.21
Std	9.15	9.44	9.44	9.15	10.51	11.56
SR	0.01	-0.11	-0.09	0.07	0.07	0.36
	Net Excess Return: $rx^j{}_{net}$ (with b-a)					
Mean	-0.63	-1.63	-1.50	-0.08	-0.17	3.01
Std	9.15	9.44	9.44	9.15	10.52	11.58
SR	-0.07	-0.17	-0.16	-0.01	-0.02	0.26
	High-minus-Low: $rx^j - rx^1$ (without b-a)					
Mean		-1.08	-0.96	0.55	0.63	4.14
Std		9.46	7.57	8.14	10.46	10.16
SR		-0.11	-0.13	0.07	0.06	0.41
	High-minus-Low: $rx^j{}_{net} - rx^1{}_{net}$ (with b-a)					
Mean		-1.01	-0.87	0.55	0.45	3.63
		[0.54]	[0.43]	[0.46]	[0.59]	[0.58]
Std		9.45	7.57	8.14	10.47	10.17
SR		-0.11	-0.12	0.07	0.04	0.36

This table reports the average change in log spot exchange rates Δs^j, the average log forward discounts $f_t - s_t$, the average log excess return $rx^j{}_{net}$ and rx_{t+1} (with and without bid-ask spreads), and the average return on the long-short strategy $rx^j{}_{net} - rx^1{}_{net}$ and $rx^j - rx^1$ (with and without bid-ask spreads), for each portfolio j. All numbers are annualized and reported in percentage points. Standard errors are reported in brackets. The table reports Sharpe ratios for excess returns, computed as ratios of means to standard deviations (both annualized). The first portfolio contains currencies with the lowest interest rate, the last portfolios contains currencies with the highest interest rate.

Table A3: Asset pricing - U.S. investor

Dollar and NVIX Innovations Risk Prices

$$rx_j = \lambda_{DOL}\beta^j_{DOL} + \lambda_{NVIX_{FM}}\beta^j_{NVIX_{FM}} + u_j$$

	Developed Countries		
	λ_{DOL}	$\lambda_{\mathrm{NVIX_{FM}}}$	R^2
SCSR	-0.11	-6.12	78.91
	[2.43]	[2.39]	
FMB	-0.11	-6.12	
	[1.74]	[4.20]	
Mean	**-0.17**	**-6.09**	

This table reports results from a single cross-sectional regression *SCSR* and Fama-MacBeth asset pricing procedures. Parameter estimates and R^2 are reported in percentages. Newey-West-corrected standard errors are reported in brackets.

Table A4: Factor Betas

Dollar and NVIX Innovations

$$rx^j_t = \alpha^j_t + \beta^j_1 DOL_t + \beta^j_2 NVIX_{FMt} + u_{j,t}$$

	Developed Countries					
Portfolio	$\alpha^j{}_0$	$\beta^j{}_{\mathrm{DOL}}$	$\beta^j{}_{\mathrm{NVIX_{FM}}}$	R^2	F-stat	*P-value*
1	0.60	0.95	0.17	68.10		
	[1.09]	[0.04]	[0.02]			
2	-0.62	0.98	0.14	65.80		
	[1.07]	[0.05]	[0.02]			
3	-0.47	1.11	0.14	84.90		
	[0.70]	[0.03]	[0.01]			
4	-0.33	0.95	-0.07	82.30		
	[0.80]	[0.03]	[0.01]			
5	-1.44	0.90	-0.23	88.40		
	[0.67]	[0.03]	[0.01]			
6	2.26	1.12	-0.15	83.50		
	[0.96]	[0.04]	[0.02]			
All					0.48	94.26%

This table reports the intercepts, factor loadings and adjusted R^2 from regressing the six currency portfolios on a two-factor model consisting of the Dollar factor DOL and the portfolio-mimicking NVIX Innovations $NVIX_{\mathrm{FM}}$. Intercepts are annualized. Newey-West-corrected standard errors are reported in brackets. The F-statistic and the p-value come from the GRS test of the pricing errors.

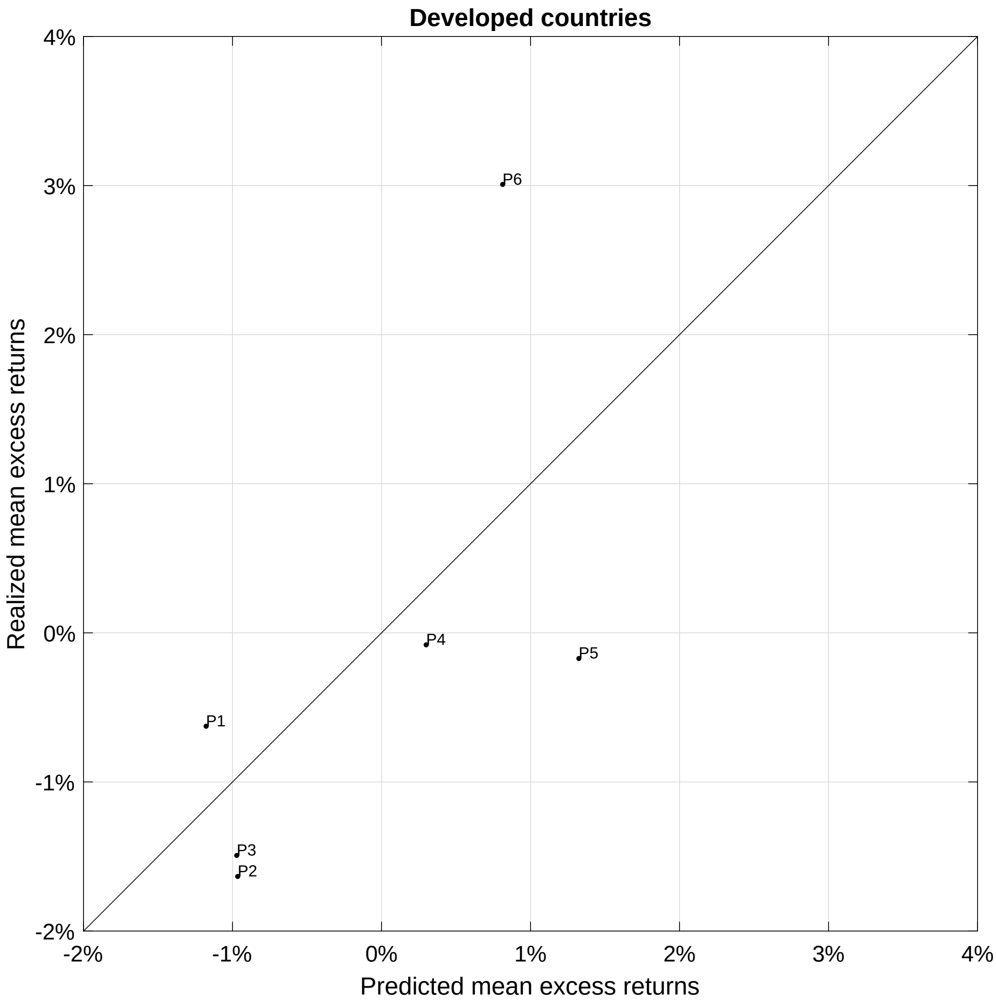

Figure A1: Pricing error plot. This figures show pricing errors for asset pricing models with Dollar and NVIX Innovations as risk factors for developed countries. Returns are annualized.

Table A5: Asset pricing - Dollar and Carry two-factor model

Panel I: Risk Prices

$$rx_j = \lambda_{DOL}\beta^j_{DOL} + \lambda_{HML_{FX}}\beta^j_{HML_{FX}} + u_j$$

	Developed Countries		
	λ_{DOL}	$\lambda_{\text{HML}_{\text{FX}}}$	R^2
SCSR	-0.13	3.56	66.74
	[2.16]	[2.18]	
FMB	-0.13	3.56	
	[1.74]	[2.21]	
Mean	**-0.17**	**3.63**	

Table A5 continued on next page

Panel II: Factor Betas

$$rx_t^j = \alpha_t^j + \beta_1^j DOL_t + \beta_2^j HML_{FXt} + u_{j,t}$$

	Developed Countries					
Portfolio	$\alpha^j{}_0$	$\beta^j{}_{\text{DOL}}$	$\beta^j{}_{\text{HML}_{\text{FX}}}$	R^2	F-stat	*P-value*
1	1.51	1.04	-0.54	86.30		
	[0.70]	[0.03]	[0.03]			
2	-1.20	0.90	-0.08	58.10		
	[1.16]	[0.06]	[0.04]			
3	-0.98	1.04	-0.09	77.60		
	[0.91]	[0.04]	[0.03]			
4	0.00	0.99	0.02	80.40		
	[0.83]	[0.04]	[0.03]			
5	-0.84	0.97	0.23	74.00		
	[1.11]	[0.05]	[0.04]			
6	1.51	1.04	0.46	91.40		
	[0.70]	[0.03]	[0.03]			
All					0.40	97.54%

This table reports the results from an analysis of Lustig et al.'s carry factor HML_{FX}. Factor risk prices and factor means are annualized. R^2 are reported in percentages. Panel I reports results from a single cross-sectional regression *SCSR* and Fama-MacBeth asset pricing procedures. Panel II reports the intercepts, factor loadings and adjusted R^2 from regressing the six currency portfolios on a two-factor model consisting of the Dollar factor DOL and the HML_{FX}. Intercepts are annualized. Newey-West-corrected standard errors are reported in brackets. The F-statistic and the p-value come from the GRS test of the pricing errors.

Table A6: Horse race between the Carry and NVIX Innovations factors

$$rx_t^j = \alpha_t^j + \beta_1^j DOL_t + \beta_2^j HML_{FXt} + \beta_3^j NVIX_{FMt} + u_{j,t}$$

	Developed Countries				
Portfolio	$\alpha^j{}_0$	$\beta^j{}_{\text{DOL}}$	$\beta^j{}_{\text{HML}_{\text{FX}}}$	$\beta^j{}_{\text{NVIX}_{\text{FM}}}$	R^2
1	1.50	1.04	-0.54	0.00	86.20
	(.03)	(<.001)	(<.001)	(.76)	
2	-0.96	0.94	0.20	0.21	68.00
	(.37)	(<.001)	(<.001)	(<.001)	
3	-0.75	1.08	0.17	0.19	86.40
	(.28)	(<.001)	(<.001)	(<.001)	
4	-0.12	0.97	-0.12	-0.11	83.20
	(.87)	(<.001)	(<.001)	(<.001)	
5	-1.18	0.92	-0.16	-0.28	89.50
	(.08)	(<.001)	(<.001)	(<.001)	
6	1.50	1.04	0.46	0.00	91.40
	(.03)	(<.001)	(<.001)	(.76)	

This table reports the factor loadings and R^2 from a horse race between the Carry and NVIX Innovations factors. The six currency portfolios are regressed on a three-factor model consisting of the Dollar factor, the Carry factor and NVIX Innovations. These OLS regressions are run with an intercept. P-values are reported in brackets. All intercepts are annualized.

A2 Horse race

Table A7 shows a horse race between HML_{FX} and $NVIX_{ISM}$ on the full sample of currencies. The results show that the $NVIX_{ISM}$ factor is statistically significantly different from zero at the 1% level for all portfolios, performing better in the horse race against HML_{FX} than NVIX innovations. Table A8 shows a horse race between HML_{FX}, NVIX innovations, and VOL_{FM} on the full sample of currencies. The results show that the NVIX innovations factor is statistically significantly different from zero at the 1% level for all portfolios, while VOL_{FM} is statistically significantly different from zero at the 5% level for the corner portfolios, and at the 1% level for the rest of the portfolios. This result indicates that NVIX innovations is a strong factor in explaining currency returns, remaining significant even when controlling for other factors.

Table A7: Horse race between the Carry and the $NVIX_{ISM}$ factors

$$rx_t^j = \alpha_t^j + \beta_1^j DOL_t + \beta_2^j HML_{FXt} + \beta_3^j NVIX_{ISMt} + u_{j,t}$$

Portfolio	$\alpha^j{}_0$	$\beta^j{}_{\mathrm{DOL}}$	$\beta^j{}_{\mathrm{HML_{FX}}}$	$\beta^j{}_{\mathrm{NVIX_{ISM}}}$	R^2
1	0.27	1.23	-0.76	-0.11	91.70
	(.65)	(<.001)	(<.001)	(<.001)	
2	0.26	0.72	0.16	0.12	80.70
	(.68)	(<.001)	(<.001)	(<.001)	
3	0.06	0.71	0.26	0.16	80.30
	(.93)	(<.001)	(<.001)	(<.001)	
4	-0.71	0.88	0.19	0.06	78.40
	(.32)	(<.001)	(<.001)	(<.001)	
5	-0.14	1.23	-0.09	-0.11	77.80
	(.87)	(<.001)	(<.01)	(<.001)	
6	0.27	1.23	0.24	-0.11	91.90
	(.65)	(<.001)	(<.001)	(<.001)	

This table reports the factor loadings and R^2 from a horse race between the Carry and $NVIX_{ISM}$ factors. The six currency portfolios are regressed on a three-factor model consisting of the Dollar factor, the Carry factor and $NVIX_{ISM}$. These OLS regressions are run with an intercept. P-values are reported in brackets. All intercepts are annualized.

Table A8: Horse Race between the Carry, NVIX Innovations and Volatility Innovations factors

$$rx_t^j = \alpha_t^j + \beta_1^j DOL_t + \beta_2^j HML_{FXt} + \beta_3^j NVIX_{FMt} + \beta_4^j VOL_{FMt} + u_{j,t}$$

	All Countries					
Portfolio	$\alpha^j{}_0$	$\beta^j{}_{\text{DOL}}$	$\beta^j{}_{\text{HML}_{\text{FX}}}$	$\beta^j{}_{\text{NVIX}_{\text{FM}}}$	$\beta^j{}_{\text{VOL}_{\text{FM}}}$	R^2
1	0.10	1.13	-0.59	-0.13	1.40	87.00
	(.89)	(<.001)	(<.001)	(<.01)	(.02)	
2	0.26	0.79	0.22	0.64	-5.09	89.20
	(.58)	(<.001)	(<.001)	(<.001)	(<.001)	
3	-0.21	1.18	0.09	-0.59	10.20	87.40
	(.71)	(<.001)	(<.001)	(<.001)	(<.001)	
4	-0.50	0.82	0.14	0.47	-5.85	83.24
	(.43)	(<.001)	(<.001)	(<.001)	(<.001)	
5	0.25	0.95	-0.28	-0.25	-2.05	90.90
	(.65)	(<.001)	(<.001)	(<.001)	(<.001)	
6	0.10	1.13	0.41	-0.13	1.40	87.30
	(.89)	(<.001)	(<.001)	(<.01)	(.02)	

This table reports the factor loadings and R^2 from a horse race between the Carry, NVIX Innovations and Volatility Innovations factors. The six currency portfolios are regressed on a four-factor model consisting of the Dollar factor, the Carry factor, NVIX Innovations and Volatility Innovations. These OLS regressions are run with an intercept. P-values are reported in brackets. All intercepts are annualized.