Currency Carry, Momentum, and Global Interest Rate Uncertainty

Job Market Paper

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ABSTRACT

Currency carry and momentum are among the most popular investment strategies in the foreign exchange market. The carry (momentum) trade buys currencies with high-interest rates (recent returns) and sells those with low-interest rates (recent returns). Both strategies are highly profitable, but little is known on their common risk sources. This paper finds that their high returns are compensations for the risk of global interest rate uncertainty (IRU), with risk exposures explaining 92% of their cross-sectional return variations. Profitability of two strategies also weakens substantially when the global IRU risk is high. The unified explanation stems from its superior power of capturing the crashes of carry and momentum, which usually occur during bad and good market states. An intermediary-based exchange rate model confirms the negative price for the global IRU risk. Higher uncertainty tightens intermediary's financial constraints and triggers unwinding on long and short positions. High (low) carry and momentum currencies then realize low (high) returns as they are on the long (short) side of intermediary's holdings. Further empirical evidence indicates that the explanatory power for momentum extends to other asset classes, suggesting a risk-based explanation for the commonality of momentum returns.

Keywords: Cross-section of carry and momentum; risk premium; uncertainty shocks; intermediary asset pricing; momentum everywhere.

JEL Classification: E52, F31, G12, G15.

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1. Introduction

The foreign exchange (FX) market is the largest financial market in the world. The triennial survey from the Bank for International Settlements (BIS) reports that the daily FX trading volume is estimated to be $5.1 trillion as of 2016. The currency investment is also very profitable. Among the most popular currency trading strategies, the cross-section of carry and momentum trade yield average monthly excess returns of 0.58% and 0.51% respectively, during the period from January 1985 to August 2017.[1] As the FX market is very liquid with low trading costs and easy access to the short-selling, a reasonable explanation for the profitability is that their returns reflect risk compensations. However, little is known on the common risk sources underlying these two types of trade, since the existing resolutions based on the standard finance theory receive dismal performance empirically (see a review by Burnside et al., 2011).

The main contribution of this paper is to provide a unified risk-based explanation for the profitability of FX carry and momentum strategies. I find that the innovations to the global interest rate uncertainty (IRU) are negatively and significantly correlated with the returns to carry and momentum trade. To construct this global measure of uncertainty, I first estimate the monthly realized variance of the government bond yields for each of the G10 currencies. I show that the obtained interest rate uncertainty across different economies strongly co-moves with each other, with the first principal component accounting for over 60% of their variations. The global IRU is then measured as the GDP-weighted average over the individual uncertainty. After going through formal asset pricing tests by using the innovations to the global IRU as the risk factor, I show that the exposures to the global IRU risk can well explain the cross-sectional return dispersions of currency carry and momentum, with the explanatory ratios reaching 89% and 97% respectively. More specifically, I find that the top carry and momentum portfolios have lower and negative exposures (betas) to the risk of global IRU, whereas their peers at the bottom have higher and positive betas. The beta spreads are statistically significant and translate to negative and significant prices for the global IRU risk. Considering the joint cross-section of carry and momentum returns does not change the results. The cross-sectional R^2 is 92% and the Shanken t-statistic for the global IRU risk attains -2.8. Further exercises show that the main findings are robust to different measures for the global IRU, such as those based on the realized volatility or

[1] These returns are from the viewpoint of a US investor and net of transaction costs. The cross-section of carry (momentum) trade buys the basket of currencies with the highest and shorts that with the lowest interest rate differentials (realized appreciations) against USD.

the US monetary policy uncertainty index of Baker et al. (2016).

To clarify economic channels behind the findings, using the aggregate stock return as an indicator for market states, I show that periods when carry or momentum strategy experiences exceptionally low returns correspond respectively to bad and good states for the financial market. Remarkably, these periods are accompanied by large innovations to the global IRU. Thus it is the ability of global IRU shocks to capture both bad and good market states that renders the joint explanatory power for currency carry and momentum. While the role of uncertainty as a barometer for the bad states is easier to digest following a large strand of literature (see, e.g., Bloom, 2009; Brogaard and Detzel, 2015), it is less obvious why sometimes higher IRU can indicate good states for the financial market. Nevertheless, this might not be so surprising as Segal et al. (2015) document that the fluctuating growth uncertainty contains two components that are associated with positive or negative shocks to the economy. I show empirically that the innovations to the global IRU indeed provide a comprehensive measure over good and bad states for the economy and the financial markets.

The formal theoretical analysis based on a structural exchange rate model confirms that the innovations to the global IRU is a pervasive risk factor in the pricing kernel and carry a negative price of risk. The model follows the spirit of Gabaix and Maggiori (2015) and Mueller et al. (2017b) by highlighting the role of sophisticated financial intermediary as the marginal investor in the currency market. Higher global interest rate uncertainty increases the shadow price of intermediary's financial constraints and hence drives up the marginal utility of the intermediary. This renders a negative price for the global IRU risk among currency carry and momentum returns. More precisely, currencies with high (low) carry or momentum signals are on the long (short) side of intermediary's holdings in equilibrium. The reason is that higher interest rates push up intermediary's investment yields, whereas higher appreciations predict lower selling pressures by international investors in the future so that the intermediary would find them more attractive to hold today. Rising global IRU leads to position unwinding by the intermediary, but currencies with high or low carry (momentum) signals respond differently since one currency tends to depreciate (appreciate) when the intermediary holds (short-sells) less of it. Therefore, the theory is consistent with the documented negative correlations between the global IRU risk and returns to carry and momentum trade.

Further in line with the intermediary-based story, the explanatory power of the global IRU risk also presents for momentum in other asset classes. I find that the impact of the global IRU risk is quantitatively large among momentum in seven asset classes as discussed by Asness et al. (2013), in addition to the currency momentum. Almost all momentum strategies realize sizable losses when the global IRU risk becomes higher. For example, one standard deviation change of the global IRU risk is associated with a -0.39% (-0.48%) monthly loss of the momentum trade in US (UK) equity markets. The effect is similar and statistically significant for most markets. While Asness et al. (2013) employs the story of funding liquidity risk as a resolution for the commonality of momentum returns across asset classes, I show that the explanatory power of the global IRU risk is comparably much stronger in terms of both economic magnitudes and statistical significance. The cross-sectional asset pricing tests indicate that the high-minus-low spreads in IRU betas among momentum portfolios are negative and significant for most of the asset classes. The estimated risk prices from all momentum portfolios attain the same sign and significance compared with that from the FX market. Remarkably, the standard CAPM model augmented with the factor of global IRU risk even yields similar explanatory ratio on cross-sectional momentum returns, compared with the model consisting of the global momentum factor as proposed by Asness et al. (2013).

The unified explanations on currency carry and momentum based on the global IRU risk factor is attractive. First, it is a variable constructed outside the FX market, yet many competing factors are currency-based measures of systematic risk (see, e.g., Lustig et al., 2011; Corte et al., 2016). Thus the global IRU risk is unlikely to be mechanically related to the testing currency portfolios. Moreover, the time-varying domestic interest rate uncertainty should be largely exogenous to the FX market fluctuations, especially for G10 currencies that belong to the developed economies. Essentially, it is not surprising that the model based on the global interest rate uncertainty performs so well, given the critical role of monetary policy on affecting the currency markets. While the level of interest rate may matter more when explaining domestic financial markets (e.g. Maio and Santa-Clara, 2017), it is obvious that increased rate of one country can have the very limited impact on the cross-section of currency strategies. In contrast, the interest rate uncertainty, which displays strong co-movements across different countries, is more suitable for obtaining the global risk factor that governs the currency risk premia.

To corroborate the main findings, I carry out a battery of robustness checks. First, the results are invariant to using different testing procedures such as the Fama-MacBeth regression or the GMM estimation. The results are even stronger if using the factor-mimicking portfolio return as the risk factor in the test. Second, after controlling for other risk factors and measures of financial frictions, I find that the unified pricing power of the global IRU

risk on FX carry and momentum returns is not affected. The performance is also robust under different limits to arbitrage measured by the idiosyncratic volatility or skewness. Third, the currency-level study alike points to a negative and significant price of the global IRU risk. In particular, high-interest rate currencies such as the Australian Dollar (AUD) and the New Zealand Dollar (NZD) indeed have low and negative IRU betas, as opposed to low-interest rate currencies such as the Japanese Yen (JPY) and the Swiss Francs (CHF). Last but not least, the asset pricing results are robust under different subsamples covering e.g., the pre- and post-crisis periods or the developed economies.

Related literature The paper contributes to a large strand of literature towards understanding the risk sources of high returns to currency strategies. Most of the previous papers focus on the cross-section of the carry trade. Lustig and Verdelhan (2007) interpret its returns as exposures to the risk of consumption growth, and Lustig et al. (2011) further reconcile its profitability via the slope factor constructed from the carry trade portfolios. Based on the ICAPM argument, Menkhoff et al. (2012a) find that changes in the global FX volatility help explain the carry returns. Among other resolutions, Burnside et al. (2010) argue that the carry trade returns reflect a peso problem, whereas Lettau et al. (2014) and Dobrynskaya (2014) highlight the importance of downside risk. The more recent focus has been switched to understand the currency momentum. Burnside et al. (2011) and Menkhoff et al. (2012b) find that the correlation between carry and momentum returns is small, and traditional risk factors cannot explain the cross-section of momentum returns. Filippou et al. (2018) show that the global political risk can reconcile the momentum returns. Bae and Elkamhi (2017) further price the joint cross-section of carry and momentum by the risk of global equity correlation. My paper is tightly linked with all these articles. I show empirically that the risk of global interest rate uncertainty can explain the returns to currency carry and momentum strategies. The unified risk-based resolution is robust and unrelated to existing risk factors. The explanatory power is consistent with an intermediary-based asset pricing model and stems from its unique role of capturing the downturns of both strategies. An attractive feature of my resolution besides its strong performance is that the interest rate uncertainty measured directly from government bond yields is likely to be exogenous to the FX markets, compared with many competing risk factors.

This article is also related to the recent literature on studying the asset pricing implications of policy uncertainty. Besides the theoretical framework of Pástor and Veronesi (2012) and Pástor and Veronesi (2013), Brogaard and Detzel (2015) empirically evaluate the pricing of policy uncertainty in the stock market via the Economic Policy Uncertainty index of

Baker et al. (2016). Nevertheless, the discussion within the FX market is still at the infant stage, with some exceptions including, e.g., Berg and Mark (2017). In particular, my paper is closely related to Mueller et al. (2017b), who find that the profitability of the carry trade and the strategy that buys foreign currencies and short-sells the USD is significantly higher during the FOMC announcements. While they study the high-frequency behavior of these currency returns and interpret the results as compensations for the risk of US monetary policy uncertainty, my paper differs from theirs in two important perspectives. First, my paper follows more standard asset pricing test by examining and reconciling the well-known currency risk premium anomalies at the monthly frequency. Moreover, they do not study the currency momentum and further the unified risk-based explanation for the FX carry and momentum returns. I thus treat the conclusions from my paper as important complements to theirs in the sense that we both highlight the value of monetary policy uncertainty in understanding the currency risk premium, at both high- and low-frequency.

The paper is organized as follows. Section 2 describes the data and methodology. Section 3 documents the main empirical results. Section 4 discusses the economic channels behind the novel findings. Section 5 includes a battery of robustness checks, and Section 6 concludes.

2. Data and Methodology

2.1. Currency carry and momentum portfolios

The data for the spot exchange rates and one-month forward rates cover 48 countries and range from January 1985 to August 2017. The data are from the Datastream (Barclays Bank International and Reuters). I remove the Eurozone currencies after the adoption of Euro, and also remove the periods for some currencies when there are violations in the Covered Interest Rate Parities (CIP). To form the carry and momentum portfolios, I use the information from mid-level spot and forward rates, but the portfolio returns are computed by taking into account the bid-ask spreads, following e.g., Menkhoff et al. (2012b).[2]

Denote the mid-spot rate as S_t which represents units of foreign currency per unit of US dollar, and denote the one-month mid-forward rate as F_t. As the proxy for the interest rate differential between the foreign country and the US, I follow the literature by using the

[2]Details are given in the Data Appendix. The bid-ask data are also available from Reuters, and in the Internet Appendix I show how to account for transaction costs when computing portfolio returns. Note that the bid-ask spread data from Reuters are around twice the size of inter-dealer spreads, as documented by Lyons (2001).

forward discount (e.g., Lustig et al., 2011):

$$i_t^* - i_t \approx f_t - s_t, \tag{1}$$

where the small letters stand for log terms. Then the one-period log currency excess return rx_{t+1} can be computed as:

$$rx_{t+1} = i_t^* - i_t - \Delta s_{t+1} \approx f_t - s_{t+1}. \tag{2}$$

To form the carry trade portfolios, I first sort on all currencies' forward discounts at the end of each month. Then each currency is attributed to one of the quintile portfolios, where portfolio 1 (5) consists of currencies with the lowest (highest) interest rate differentials vis-à-vis the United States. To construct the momentum trade portfolios, I sort on currencies' past realized excess returns at the end of each month, where the realized quantities are computed over the past 3-month horizons.[3] Then five portfolios are formed, where the portfolio 1 (5) contains currencies with lowest (highest) realized excess returns. They are also called the *loser* and the *winner* portfolio respectively. All portfolios are rebalanced monthly, and their excess returns are computed via the equal-weighted scheme.

The first column of each panel in Table 1 reports the average monthly excess returns of carry and momentum portfolios, after taking into account the bid-ask spreads. In line with the findings in the literature, the strategy profitability is large and significant. The average monthly high-minus-low return spreads for the carry and momentum portfolios are 0.58% and 0.51%. Furthermore, the returns increase monotonically from the bottom to the top portfolios, revealing the substantial predictive power of interest rate differentials and realized currency returns on future returns. The monotonic order is also supported statistically by the test of monotonic relations (MR) following Patton and Timmermann (2010). I report in parentheses the p-values of testing the null hypothesis that the portfolio returns are monotonically increasing, which are based on all pair-wise comparisons. The null hypothesis cannot be rejected at any conventional confidence levels.

[Table 1 about here]

[3] I provide robustness checks for other horizons in the Internet Appendix.

2.2. Measuring global interest rate uncertainty

I focus on the universe of G10 currencies to construct the global measure as they play dominant roles in the FX markets. To estimate the interest rate uncertainty (IRU) for each individual currency, I rely on their daily government bond yields to obtain the monthly interest rate realized variance, similar to Cieslak and Povala (2016). The data of US 10-year bond yields are from FRED and those of other currencies are from Bloomberg.[4] Panel A of Table 2 tabulates the correlation matrix of the individual interest rate uncertainty. The large correlation coefficients point to a strong factor structure among these uncertainty measures. Indeed, the displayed outputs from the Principal Component Analysis (PCA) in Panel B show that the first principal component explains around 60%, and the first three components in total explain around 80% of the variations in the interest rate uncertainty during the entire sample. Splitting into pre- and post-crisis samples yields quite similar results, suggesting that the factor structure is not due to the presence of 2008 global financial crisis. To account for the potentially different impact of each currency's interest rate uncertainty on the global financial market, I adopt the GDP-weighted average over all individual IRU as the baseline measure for the global (IRU).[5]

[Table 2 about here]

[Figure 1 about here]

The upper panel of Figure 1 plots the level of estimated global IRU from January 1985 to August 2017, and the lower panel depicts the standardized innovations (u_t^{IRU}) obtained as the residuals from fitting an AR(1) model to the level series. The global interest rate uncertainty does indeed capture important periods corresponding to sharp changes in the international financial markets, such as the Black Monday, collapse of Long-Term Capital Management (LTCM), recent global financial crisis, and Euro-debt crisis etc. Table 3 then reports the correlation coefficients of u_t^{IRU} with the returns to currency carry, momentum, and conventional risk factors. The results are consistent with usual findings in the literature

[4]The focus on 10-year maturity is mainly due to the data availability issue as the data on other maturities are comparably shorter for many countries. The G10 currencies cover United States dollar (USD), Euro (EUR), Pound sterling (GBP), Japanese yen (JPY), Australian dollar (AUD), New Zealand dollar (NZD), Canadian dollar (CAD), Swiss franc (CHF), Norwegian krone (NOK) and Swedish krona (SEK). In particular, I use Germany 10-year bond yields as the interest rates for the Euro. The details of data availability for each economy is in the Data Appendix.

[5]The weights are each country's world share of GDP based on the purchasing-power-parity (PPP), with the data from IMF database.

that returns to these two currency strategies are weakly correlated with popular risk factors (e.g. Burnside et al., 2011). In fact, the correlation between carry and momentum returns is close to zero, further highlighting the difficulty of establishing a unified explanation. In spite of the fact that the carry returns are significantly related with the risk of consumption growth, VIX or global FX volatility (see, e.g., Lustig and Verdelhan, 2007; Brunnermeier et al., 2008; Menkhoff et al., 2012a), none of them are significantly correlated with the momentum returns. Interestingly, the innovations in the global IRU are strongly and negatively related with both strategy returns at the 1% significance level. The negative correlations suggest that both carry and momentum returns should drop when innovations to the global IRU are high. Indeed, Figure 2 show that for the carry and two types of momentum trade (based on the past 1- and 3-month realized returns), their annualized returns decline substantially when there are large innovations to the global interest rate uncertainty. To evaluate formally the economic magnitudes of the impact of global IRU risk, I follow Brogaard and Detzel (2015) by running the following regression:

$$r_t = \alpha + \beta u_t^{IRU} + \epsilon_t, \tag{3}$$

where r_t denotes carry or momentum returns. The estimated slope coefficients are -0.43% and -0.44% respectively, indicating that one standard deviation change of u_t^{IRU} is associated with a -0.43% (-0.44%) monthly loss of the carry (momentum) trade. The effect is also statistically significant with t-statistics of -2.36 and -2.84 respectively.

[Table 3 about here]

[Figure 2 about here]

3. Empirical Results

3.1. Cross-sectional asset pricing test

In this subsection, I test the pricing power of shocks to the global interest rate uncertainty for the cross-section of carry and momentum portfolios. As the benchmark testing procedure, I use the usual two-stage Fama-MacBeth regression. At the first stage, the return sensitivity to the global IRU shocks for each portfolio i is estimated from the time-series regression:

$$rx_t^i = \alpha^i + \beta_{DOL}^i DOL_t + \beta_{IRU}^i u_t^{IRU} + \epsilon_t^i, \tag{4}$$

where DOL_t is the dollar factor constructed as the cross-sectional average of excess returns of five carry trade portfolios following Lustig et al. (2011). It can be treated analogously as the market factor in the FX market. Then at the second stage, I run the following cross-sectional regression:

$$\overline{rx}^i = \hat{\beta}_{DOL}^i \lambda_{DOL} + \hat{\beta}_{IRU}^i \lambda_{IRU} + \eta^i, \tag{5}$$

where the left-hand side is the unconditional mean of portfolio excess returns, and the first-stage estimated betas are used as the explanatory variables on the right-hand side. λ_{DOL} and λ_{IRU} are the risk prices per unit of dollar factor beta and IRU beta. Note that I do not add the intercept at the second stage regression due to the inclusion of the dollar factor (see, e.g., Menkhoff et al., 2012a).

The rest columns of Table 1 report the outcomes of first-stage time-series regression, where the standard errors of estimated betas are based on Newey and West (1987) with optimal lag selection following Andrews (1991). For both types of cross-sectional portfolios, while they load similarly on the dollar factor, their exposures to u_t^{IRU} decrease almost monotonically from the bottom to the top portfolios. The patterns are also plotted in the upper panel of Figure 3. In fact, the magnitudes of high-minus-low beta spreads are similar and also statistically significant at the 5% level. Obtaining a significant spread in betas is a pivotal check on whether the factor is priced following Kan and Zhang (1999) and Burnside (2011). The monotonic relations are statistically justified via the monotonicity test on betas following Patton and Timmermann (2010), where the p-values are reported and based on the null hypothesis that the betas are monotonically decreasing. The first-stage evidence hence sheds light on the potentially unified explanation of the currency carry and momentum returns by their exposures to the risk of global IRU.

[Figure 3 about here]

After obtaining the betas, the cross-sectional regression (5) is estimated via OLS. For test on the statistical significance of risk prices, I employ the heteroskedastic and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) with optimal lag selection following Andrews (1991) (NW), as well as those of Shanken (1992) (Sh) that further incorporate the adjustments due to the error-in-variable (EIV) problem of using first-stage estimated betas. To recognize the specific and unified pricing power, I use five carry and five momentum portfolios separately or jointly as testing assets. Panel A of Table 4 documents the results. The almost monotonically decreasing betas and increasing portfolio returns render the negative prices for the global IRU risk, with the cross-sectional R^2 of 89% and 97% respectively. The large R^2 indicates that exposures to IRU risk go a long way towards reconciling the returns to FX carry and momentum trade. Meanwhile, the magnitudes of risk prices are similar and significant under both types of standard errors. The results are invariant for the joint cross-section of carry and momentum returns, with the R^2 of 92%. To test for zero pricing errors, I further report the p-values from the χ^2-test as discussed in e.g., Cochrane (2005). The computation of χ^2 statistics are also based on the method of Newey-West (χ^2_{NW}) or Shanken (χ^2_{Sh}). From the table, the null hypothesis that all pricing errors are jointly zero cannot be rejected when separately using the carry and momentum portfolios as testing assets. This indicates close distance between the average portfolio returns and the fitted returns from Equation (5), as can be found from the lower panel of Figure 3.

[Table 4 about here]

However, the global IRU risk is a non-traded factor. To mitigate the concern of using such type of factor in the asset pricing test, as widely discussed in e.g., Kan and Zhang (1999), I construct the factor-mimicking portfolio by projecting u_t^{IRU} on ten currency portfolios:

$$u_t^{IRU} = a + b'w_t + \epsilon_t, \tag{6}$$

where w_t denotes the vector of month-t excess returns of five carry and five momentum portfolios. The correlation coefficient between the obtained factor-mimicking portfolio returns and u_t^{IRU} is 0.26. Since $u_{FMM,t}^{IRU}$ is now a traded factor, without going through any asset pricing test, the Sharpe ratio of the factor-mimicking portfolio already reflects the market price of IRU risk. Its monthly SR is -0.27 with a Newey-West t-statistic of -4.81. The magnitude of SR is even slightly larger than those of carry and momentum strategies, suggesting that the global IRU risk explains a bulk of the strategy returns. Then I follow the previous exercises by running the cross-sectional asset pricing test, using $u_{FMM,t}^{IRU}$ instead of u_t^{IRU} as the risk factor. The results are in Panel B of Table 4. The main findings are still there with large cross-sectional R^2, but now the risk prices become more significant, thanks to the usage of traded risk factor in the test that yields more accurate inference. The Shanken t-statistic reach as large as -5.0 when using the joint cross-section of currency portfolios as testing assets.

The two-stage method though is easy to implement, the pre-estimation of IRU betas is unfavorable because it introduces the error-in-variable problem when running the cross-sectional test. I thereby employ the Generalized Method of Moments (GMM) to estimate the asset pricing model in one-step directly. The analysis begins with a parametric form for the stochastic discount factor (SDF) that is linear in risk factors:

$$M_{t+1} = 1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_{IRU}u_{t+1}^{IRU}, \tag{7}$$

and the Euler equations:

$$E(M_{t+1}RX_{t+1}^{i}) = 0, \tag{8}$$

where RX_{t+1}^{i} is the excess return of testing asset i. Denote $h_t = [DOL_t - \mu_{DOL}, u_t^{IRU}]'$, then I set up the moment conditions as follows:

$$E(g_{t+1}) = E\begin{bmatrix} (1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_{IRU}u_{t+1}^{IRU})RX_{t+1}^{i} \\ DOL_{t+1} - \mu_{DOL} \\ h_{t+1}h_{t+1}' - \Sigma_{DOL,IRU} \end{bmatrix} = 0. \tag{9}$$

These moment conditions allow for the joint inference on the parameters of SDF and risk factors. In Panel C and D of Table 4, I test the pricing power of u_t^{IRU} as well as its factor-mimicking portfolio returns via GMM. The estimation is carried out by using the optimal weight matrix. To test for zero pricing errors, I display the p-values from the χ^2-test. Further to measure the model misspecification, I also report the Hansen-Jagannathan distance of Hansen and Jagannathan (1997), where the simulation based p-values following Jagannathan and Wang (1996) are in brackets. From the results I find that the estimated factor loadings for IRU risk are negative and significant with large cross-sectional R^2. The null hypothesis of zero pricing errors cannot be rejected. In fact, the Hansen-Jagannathan distances are also small and not significantly different from zero when using the raw risk factor in the test.

3.2. Alternative proxies for the global interest rate uncertainty

To mitigate the concern of data-mining, in this subsection I examine the main findings by using alternative measures for the global IRU risk. Specifically, I obtain another set of risk factors: equal-weighted average of realized variance; GDP-weighted average of realized volatility; and the US Monetary Policy Uncertainty index of Baker et al. (2016). Their index is based on the textual analysis of US newspapers and hence has the advantage of being model-free and reflecting subjective uncertainty. We shall note that although the index has the "US" name, it might still capture the global monetary policy uncertainty as the keywords it uses in the searches include European Central Bank, Bank of England, and Bank of Japan etc.[6]

The results are tabulated in Table 5 after inputing these alternative risk factors into the Fama-MacBeth cross-sectional asset pricing test. While these measures are obtained from different empirical setups or data sources, the outcomes are still in favor of the unified explanation. For example, the volatility risk (Panel B) instead of variance risk explains 93% of cross-sectional return variations. The estimated global IRU risk from the BBD MPU index (Panel C) performs even better than all other proxies, with the cross-sectional R^2 reaching 96%. The strong evidence hence points to an important prospective of the robustness that fluctuating global interest rate uncertainty indeed serves as a key risk source for FX carry and momentum returns, regardless of specific empirical measures.[7]

[Table 5 about here]

4. Inspecting the Mechanism

4.1. When carry or momentum fails

To uncover the economic channels behind the novel findings, I start from analyzing the relation between the global IRU risk and strategy returns during the states when carry or momentum trade experiences sizable losses. These are periods that are likely associated with high marginal utility states of the marginal traders and hence should matter most for the risk pricing. Previous papers such as Brunnermeier et al. (2008), Dobrynskaya (2014) and

[6]The innovations are obtained from a fitted AR(1) model for the former two proxies, and the way to extract the relevant risk factor from the BBD MPU index follows Della Corte and Krecetovs (2017) and is detailed in the Internet Appendix.

[7]In Section 5, I implement a battery of robustness checks covering other aspects of the empirical implementations.

Lettau et al. (2014) show that the carry trade fails when the market downside risk is more prominent (bad state), yet other studies on momentum such as Daniel and Moskowitz (2016) find that the momentum strategies tend to perform poorly during the market rebound (good state). Being able to capture the distinct loss behavior would be a necessary and stringent requirement for a unified risk-based explanation. To be more specific, I identify a crash of strategy from a dummy indicating whether the month-t return is below some percentile number k of the empirical distribution of strategy returns:

$$I_t = \mathbb{I}(r_t^i < percentile(r^i, k)), \tag{10}$$

where $i = C, M$ represents returns from carry and momentum trade. By using the US aggregate stock market return as an indicator for market states, the upper panel of Figure 4 plots the average market returns for each of the loss percentile defined in (10), where I experiment with the percentile numbers ranging from 10th to 50th. The striking pattern demonstrates opposite loss behavior of two strategies. Their exceptional underperformance is accompanied with significant market downturn and upturn respectively. For instance on average, when the current return from the carry (momentum) trade is worse than its lowest 10% historical returns, the aggregate stock market delivers an annualized return of -16.3% (17.3%). Similar results hold when the losses of carry or momentum trade become less severe, pointing to the stable link between strategy performance and market states.

[Figure 4 about here]

The lower panel of Figure 4 then depicts the average readings of the global IRU risk under each loss percentile. Interestingly when either carry or momentum trade suffers from large losses, the global IRU risk are obviously at high levels. The monotonically decreasing global IRU risk as the losses become less severe further confirms its role on jointly capturing the downturns of these two strategies. The pattern serves as an important basis for a risk-based resolution.[8] Combining two plots within the figure suggests that the global IRU risk tends to increase under both good and bad market states. Such implication is somewhat puzzling as many papers document that the uncertainty shocks tend to be countercyclical (see, e.g., Bloom, 2009; Brogaard and Detzel, 2015). However, this may be less surprising following the recent arguments that there are good and bad components related to the

[8]Resembling results are found for alternative currency momentum strategies such as the one based on the past one-month realized return. See the left panel of Figure IA.1.

uncertainty shocks. For example, Segal et al. (2015) documents that the fluctuating growth uncertainty contains two components associated with positive or negative shocks to the economy. Figure 5 confirms similar findings. By using alternative high-frequency measures of the economic activity such as the industrial production growth or Chicago Fed National Activity Index (CFNAI), in addition to the market return, I show that the risk of global IRU rises consistently on both tails of the economic activity. While the structural interpretation on why the global interest rate uncertainty rises is beyond the scope of the paper,[9] I find that this property is tightly linked to the unified pricing power of the global IRU risk on carry and momentum returns, after taking into account the results in Figure 4.

[Figure 5 about here]

Finally, Table 6 reports the correlation coefficients of the global IRU risk with both strategy returns under their respective crash periods. The outcomes show that under different levels of strategy losses with monthly returns dropping to as much as -5.10% (carry) and -4.84% (momentum), the global IRU risk is consistently and negatively correlated with carry and momentum returns at conventional significance levels. The strong correlations during these regimes echo the above analysis on the source of pricing power of the global IRU risk. On the other hand, the viewpoint by focusing on these crash periods also sheds light on why the risk factors motivated by standard finance theory, such as the VIX or global FX volatility (see e.g. Brunnermeier et al., 2008; Menkhoff et al., 2012a), cannot provide a unified explanation (as will be shown in Table 10). Running the same exercise with these two factors, I find that they fail to co-move with the currency momentum returns when carry trade loses money. Figure IA.1 delivers the outputs from repeating analogous exercises in the lower panel of Figure 4 using the innovations to VIX and global FX volatility. The results suggest that they are not as informative as the global IRU risk on summarizing both good and bad market states simultaneously.

[Table 6 about here]

4.2. Theoretical results

The evidence thus far calls for a well motivated theory that answers the following questions: why the global IRU risk enters the pricing kernel and carries a negative price of risk;

[9]For related discussions in the structural framework, see, e.g., Kozeniauskas et al. (2018).

why currencies with high (low) carry or momentum signals load negatively (positively) on such risk factor; and why the explanatory power mainly comes from the crashing periods of currency strategies. In this subsection, I study an intermediary-based exchange rate model following Gabaix and Maggiori (2015) and Mueller et al. (2017b) to accommodate these questions. The model shows that the strategy underperformance originates from the tightening of financial constraints of the intermediary, who serves as the marginal trader in the FX market. When the intermediary's constraint is close to bind (when either of the strategy is likely to experience sizable losses), rising global IRU will increase the shadow price of the financial constraint and the marginal utility of wealth. Hence the global IRU risk carries a negative price of risk in the pricing kernel. Meanwhile, tightened constraints lead to position unwinding by the intermediary. Such unwinding over long positions (high carry/momentum currencies) and short positions (low carry/momentum currencies) generate opposite responses at two legs at the cross-section of carry and momentum returns, leading to negative correlations between the global IRU risk and returns to carry and momentum trade.

The model setup follows Gabaix and Maggiori (2015) and Mueller et al. (2017b). There are two periods with $t = 0, 1$; and there are two countries, United States and a foreign country, each with its currency USD and FCU. The household in each country has the demand to trade the assets of the other country.[10] Under the assumption that the household only holds foreign currency to facilitate asset trading, the cross-border transactions will give rise to the supply of USD (FCU) *in exchange for* FCU (USD) in the international financial markets. For example, if the US (UK) household wants to buy (sell) the UK (US) equity, there will be the supply of USD in exchange for FCU. I denote f_t as the supply of USD and d_t as the supply of FCU. Both quantities are nominal and denominated in USD and FCU respectively, and I treat them as exogenous variables throughout the analysis. f_t and d_t are random and in particular, f_t is drawn at t from the distribution $F(\cdot)$ with the support $[\underline{f}, \bar{f}]$. At $t = 0$, there are non-defaultable bonds issued in each country under local currency, which mature at $t = 1$. R (R^*) represents the gross interest rate in the US (foreign country) between $t = 0$ and $t = 1$ that only becomes known at $t = 1$.[11] To simplify the analysis, I assume that the diagonal of the covariance matrix of (R^*, R) is (σ, σ). While more flexible form of the second moments can be adopted, I maintain this parsimonious specification. By

[10] This may be due to the search for the benefit of international diversification, or the imperfect substitutability between foreign and home assets.

[11] It is straightforward to make the interest rate predetermined, or make the bond risk-free as in Mueller et al. (2017b) via a three-period model. However, that complicates the analysis without changing the economic intuition.

definition, σ captures the global interest rate uncertainty and its value is known at $t = 0$.

At $t = 0$, there is a representative, risk-neutral financial intermediary called the *financier*. As in Gabaix and Maggiori (2015), the role of the financier is to accommodate the currency supply of households across countries and absorbs the excess supply of one currency against the other. That is, the market is incomplete and the households can only trade currencies with the financier. The financier enters the market with no initial capital: she takes the position of $-Q$ in USD funded by Q/e_0 units of FCU, where the exchange rate e_t is defined as the unit of USD per unit of FCU at time t. The payoff function of the financier at $t = 1$ is

$$V_1 = (\frac{e_1}{e_0} R^* - R)Q. \tag{11}$$

Moreover, the financier has limited risk-bearing capacity. She commits to the Value-at-Risk (VaR) constraint when taking currency positions. The objective at $t = 0$ for the financier is thus written as

$$\begin{aligned} \max_{Q} \qquad & E_0[V_1], \\ s.t. \qquad & P_0(V_1 \leq 0) \leq \alpha, \end{aligned} \tag{12}$$

where α is the VaR limit.[12] As the financier absorbs larger position, the VaR constraint becomes more binding, this effectively restricts the risk-taking behavior of the intermediary. The equilibrium of the economy is then defined as the financier chooses allocation Q to solve the objective, and the exchange rate adjusts such that the market clears at each period:

$$d_0 e_0 - f_0 - Q = 0, \tag{13}$$

$$d_1 e_1 - f_1 + RQ = 0. \tag{14}$$

I detail the property of the equilibrium allocation, and how it changes at the cross-section of currency carry and momentum (i.e., under different values for $E_0(R^*)$ and $E_0(d_1/d_0)$) in the following proposition. The proof is provided in the Appendix.

PROPOSITION: *If α is small enough, then the portfolio holding Q shrinks to zero as σ increases. More specifically at the cross-section of carry and momentum:*
(i) (carry) Q increases with $E_0(R^*)$.

[12] The choice of zero cutoff level does not change the model implications.

(ii) (momentum) Q *increases with* $g = 1/E_0(d_1/d_0)$.

The first part of the proposition establishes the following fact: given small VaR limit α, the financier has to reduce the risky holdings (the currency) facing higher global IRU, cause the shadow price of the VaR constraint increases. The second part indicates that the financier's choice of FCU holding depends on either the foreign interest rate, or the expected future selling pressure of the FCU (arising from expected asset trade by international investors). When the foreign interest rate level is low or the expected selling pressure for the FCU is high, the intermediary is more likely to short-sell FCU against USD, and vice versa.

On the other hand, although the use of different $E_0(R^*)$ to capture the cross-section of carry is natural, it is not obvious why the measure of expected selling pressure (g) can be used to represent the momentum in the model. I thus provide empirical evidence to justify this choice before analyzing the implications for carry and momentum. Despite the exogenously imposed relation, the economic forces behind the stage can be understood by borrowing the insights from the risk-based momentum model of Vayanos and Woolley (2013). The idea goes as follows: international investors have access to two funds that *overweight* respectively the foreign and US aggregate equity market. They are named as the FC and US fund. When FCU appreciates against USD (high momentum signal), the US fund underperforms the FC fund. Under asymmetric information between investors and fund managers, this leads to the lower belief of international investors on fund manager's efficiency. Investors then choose to withdraw from the US fund and invest in the FC fund, yet the presence of adjustment cost yields gradual flows between the funds. Hence the currency appreciation indeed should predict *negatively* the supply of FCU in exchange for USD (g). A formal integration of the exchange rate model of Gabaix and Maggiori (2015) and the momentum model of Vayanos and Woolley (2013) to endogenize such a link will be ambitious but is beyond the scope of the current paper.

As for the empirical justification, I rely on the monthly country-level cross-border equity transactions with US, with data available from the Treasury International Capital (TIC) system. They are direct empirical counterparts to construct d_t (see, e.g., Hau and Rey, 2005; Dumas et al., 2016). Specifically, I treat the sum of foreign purchases of US equity from US households and US sales of foreign equity to foreign households as the proxy for the supply of foreign currency in exchange for USD.[13] I then test the above mentioned *cross-sectional predictability* via two standard methods: portfolio formation and currency-level

[13] However, the raw data is denominated in USD. To match the definition of d_t and change the denomination to local currency, I multiply them by within-month average FX rates (computed from daily mid-spot rates).

Fama-MacBeth regression. To ensure robustness of the findings, I choose different window sizes to compute currency realized log returns ($-\Delta s_{t-j:t}$), and different forecasting horizons (h) to evaluate the predictability. Consistent with the previous notations, higher $-\Delta s_{t-j:t}$ represents foreign currency appreciation against USD. The left part of each panel in Table 7 reports the portfolio-level results. By construction, they are simply the currency momentum portfolios similar to those considered before. I find that when moving from the loser to the winner portfolio, the future growth of foreign currency supply declines almost monotonically. The high-minus-low differences are negative and many of them are significant at least at 10% level. Switching to the right panel, I report the average slope coefficient and R^2 from the following Fama-MacBeth cross-sectional regression, under different j and h:

$$\log d^i_{t+h} - \log d^i_t = b_{0,t} + b_t(-\Delta s^i_{t-j:t}) + \epsilon^i_{t+1}, \qquad i = 1, 2, \cdots N_t, \tag{15}$$

where N_t is the number of countries with available data at month-t. The currency-level results also point to the negative and significant predictive power of currency returns on future changes in currency supply. The effects are even stronger under many situations, with the Newey-West t-statistic as large as -2.82.[14]

[Table 7 about here]

With the evidence in hand, it is now possible to incorporate both carry and momentum into the model via a parsimonious way. Based on the Proposition, high carry and momentum currencies correspond to higher $E_0(R^*)$ and g, then the intermediary is more likely to hold these currencies ($Q > 0$). On the other hand, low carry and momentum currencies tend to be shorted ($Q < 0$). Therefore, the position unwinding under higher global IRU leads to opposite responses from high and low carry (momentum) currencies: unwinding of the long (short) positions yields lower (higher) returns, which naturally translates to the negative comovements of carry and momentum returns with the global IRU risk.

4.3. Pricing momentum in other asset classes

Another testable implication from the intermediary-based story is that the global IRU risk should also price other asset classes, because the financial intermediary is likely to be the marginal investor in many financial markets (Adrian et al., 2014; He et al., 2017).

[14] Note that to remove the impact of outliers in equity flow data, I truncate the time series used to compute these statistics at the 10% level, for both portfolio-level and Fama-MacBeth exercises.

This is especially the case for the momentum since Asness et al. (2013) documents that momentum returns are correlated across asset classes. They argue that this stylized fact is hardly consistent with behavioral theories, which serve as the main workhorse to interpret the momentum anomalies. They further find that the commonality of momentum returns might be due to the funding liquidity risk. Intuitively, the global IRU risk should be closely related to the funding liquidity risk, as is clear from the theoretical model in the previous subsection. Hence I test whether the pricing power of the global IRU risk also presents among other momentum anomalies. Meanwhile, extending the universe of testing assets also serves as a more stringent test following the suggestions of Lewellen et al. (2010).

I focus on three momentum portfolios within each of the seven asset classes as covered by Asness et al. (2013): US equities, UK equities, Europe equities, Japan equities, Equity indices, Fixed income, and Commodities.[15] I also obtain the global momentum strategy returns as the cross-sectional weighted average of momentum returns across asset classes. To evaluate the quantitative relevance of the global IRU risk, for each momentum strategy returns I run the time-series regression (3) and Table 8 reports the results. Consistent with Asness et al. (2013), almost all momentum strategies earn positive returns except from the fixed income market. The slope coefficients on the global IRU risk are unambiguously negative and many of them are statistically significant, as long as the momentum is profitable. In terms of the economic magnitudes, for example, one standard deviation change of the global IRU risk lowers the monthly momentum returns from UK equities and commodities by 0.48% and 0.64%. Then I add the measure of funding liquidity risk based on the TED spread as in Asness et al. (2013) into the regression. While the results are roughly consistent with their findings, the impact of funding liquidity risk is comparably small. This might imply that it is the global IRU risk instead of the funding liquidity risk which accounts for the commonality of momentum returns.

[Table 8 about here]

Then I run the two-stage cross-sectional asset pricing test over these momentum portfolios, where I consider a two-factor model consisting of the market factor (CAPM) and the global IRU risk. Table 9 first reports the portfolio returns and estimated CAPM and global IRU betas from the first-stage time-series regression. The high-minus-low spreads in IRU betas are negative and many of them are significant. The bottom right corner of the table then displays the estimated price for the global IRU risk from the second-stage

[15] The data are obtained from the website of AQR Capital.

cross-sectional regression, by pooling 21 momentum portfolios together. In line with the results from the currency momentum, the risk price is also negative and statistically significant among other momentum returns. Figure 6 further displays the pricing error plots generated by this asset pricing model. For comparison, I plot the same fits from alternative models including the CAPM, CAPM augmented with the risk of TED spread, and with the global momentum factor of Asness et al. (2013). Not surprisingly, the classical CAPM fails to capture the momentum returns, with a cross-sectional R^2 being close to zero. Adding the funding liquidity risk does indeed improve the performance. However, it still underperforms the model that incorporates the global momentum factor, which by construction should explain the cross-section of momentum returns. Interestingly, the model based on the global IRU risk reaches almost similar level of R^2 compared with that including the global momentum factor. This cross-sectional evidence together with that from the time-series test in Table 8 strongly suggests that the exposures to the global IRU risk go a long way towards understanding the commonality of momentum returns across asset classes.

[**Table 9 about here**]

[**Figure 6 about here**]

5. Robustness Checks

In this section, I carry out a battery of robustness checks to ensure that the main empirical findings are invariant to alternative setups or implementations. Some of the results are listed in the Internet Appendix.

5.1. Asset pricing test including other factors

It is important to ensure that the new findings are unrelated to existing explanations. I thus test whether the inclusion of other risk factors can attenuate the explanatory power of IRU risk by running the asset pricing test with the dollar factor, global IRU risk, and the control variables. I consider two types of controls, where the first type contains other measures of financial frictions, and the second includes commonly used currency risk factors. The inclusion of the former type is necessary to ensure that the usefulness of IRU risk is not subsumed by other measures of financial frictions, given their similar roles in theory.

To be more specific, I consider five measures of financial frictions: VIX and TED spread of Brunnermeier et al. (2008), bond liquidity factor of Fontaine and Garcia (2011), betting against beta factor of Frazzini and Pedersen (2014), and intermediary's capital ratio of He et al. (2017).[16] For currency risk factors, I use the global FX volatility of Menkhoff et al. (2012a), FX liquidity factor of Karnaukh et al. (2015), the recently proposed global equity correlation of Bae and Elkamhi (2017),[17] and the slope factors (high-minus-low returns) from carry and momentum portfolios. Table 10 reports the results of asset pricing test of the three-factor model via Fama-MacBeth regression, by using the joint cross-section of carry and momentum portfolios as testing assets. For comparison, I also display the outcomes from a model without using the IRU risk. While these competing risk factors fail to jointly reconcile the carry and momentum returns, as manifested by the low R^2, the explanatory power of the global IRU risk is unaffected by adding in those controls. Moreover, despite the significant risk prices for many control variables, partly due to the success of explaining carry returns, their magnitudes of risk prices decrease substantially after adding in the global IRU risk. Thus the evidence removes the concern that the information in the global IRU risk is subsumed by other risk factors.

[Table 10 about here]

5.2. G10 carry and currency-level asset pricing

I evaluate whether the newly documented return-beta relation exists among some well-known high or low interest rate currencies, such as the Australian Dollar (AUD) or Japanese Yen (JPY). Panel A of Table 11 reports the excess returns and IRU betas after sorting G10 currencies on their forward discounts. Interestingly, the return-beta relation found from portfolio-level analysis also translates to G10 currencies. High interest rate currencies such as AUD and NZD own the lowest negative IRU betas, whereas low interest rate currency such as JPY and CHF possess the highest IRU betas.

On the other hand, as widely discussed in e.g., Ang et al. (2017), forming portfolios for asset pricing test may destroy the information due to the shrinkage of cross-sectional beta dispersions. I thus study the pricing power of IRU risk at the country-level carry and

[16] Since the leverage ratio of Adrian et al. (2014) is only available at the quarterly frequency, and He et al. (2017) show that their factor is the reciprocal of that of Adrian et al. (2014). I mainly focus on the monthly factor of He et al. (2017). Quarterly results using the leverage ratio are similar and available upon request.

[17] The replicated series is plotted in Figure IA.2.

momentum trade. First, the conditional currency excess return for currency i is defined as

$$crx^i_{t+1} = c^i_t rx^i_{t+1}, \tag{16}$$

where I consider two ways of incorporating the conditional information:

$$c^i_{1,t} = \begin{cases} \text{sign}(f^i_t - s^i_t), \\ \text{sign}(rx^i_t). \end{cases} \qquad c^i_{2,t} = \begin{cases} \text{sign}(f^i_t - s^i_t - \text{med}(f_t - s_t)), \\ \text{sign}(rx^i_t - \text{med}(rx_t)). \end{cases} \tag{17}$$

The first specification of sign functions follows Burnside et al. (2011) and Filippou et al. (2018), and the second type is as in Della Corte and Krecetovs (2017), which represents the sign of deviations from the cross-sectional median. These conditional returns are from the managed long-short strategies on individual currencies based on their carry or momentum signals. Since the panel of currency-level data is unbalanced, I follow Della Corte and Krecetovs (2017) by using the Fama-MacBeth regression to estimate risk prices. Panel B of Table 11 displays the results, where Newey-West standard errors are based on the estimated series of risk prices, adjusted for the EIV problem of betas following Shanken (1992). The outcomes point to the negative and almost significant pricing of the global IRU risk also at the currency-level.

[Table 11 about here]

5.3. Subsample analysis

In this subsection, I assess the performance under a variety of subsamples over time and countries, whose results are in Table 12. I first examine the performance of the global IRU risk during the pre- and post-crisis sample, which are gapped by the period from July 2007 to April 2010. The 2008 global financial crisis brings dramatic changes to the financial markets and hence it is useful to evaluate the consistent pricing power of the global IRU risk before and after the crisis. The carry and momentum trade implemented over the full universe of currencies remain profitable in the pre-crisis (post-crisis) sample, with the monthly excess returns of 0.50% and 0.46% (0.83% and 0.58%). Going through the asset pricing tests, I find that the explanatory power of the global IRU risk is similar in both subsamples, with the cross-sectional R^2 reaching 81% and 85% respectively. The risk prices are also negative and statistically significant.

Existing papers typically find that the momentum trade is not profitable among developed countries (see, e.g., Karnaukh, 2016; Filippou et al., 2018). I thus study how the pricing performance varies over carry and momentum returns by restricting the sample to include only 21 developed economies.[18] I find that although the carry trade is still profitable, the profit from momentum strategy is indeed close to zero. Conforming to this fact, the pricing power of the global IRU risk persists among carry portfolios, and the feeble momentum returns is naturally accompanied with weak price of the global IRU risk.

As for other subsamples, I construct them by excluding the periods of extreme market events that may be important to the FX market, such as the 1997 Asian financial crisis, 2008 global financial crisis, as well as the Euro-debt crisis.[19] The pricing ability of the global IRU risk remains hardly affected for these samples. Finally in Figure IA.3, I plot the estimated IRU betas under all considered subsamples above for both carry and momentum portfolios. It is clear that these betas still decline almost monotonically within the cross-section of carry and momentum portfolios, justifying the robust role of the global IRU risk as a unified explanation for these two currency strategies.

[Table 12 about here]

5.4. Additional robustness exercises

In the Internet Appendix, I report more results covering other aspects of robustness concern. First, I evaluate the asset pricing performance on the momentum portfolios formed over different window sizes, or formed by sorting on realized changes in log spot rates instead of excess returns. The latter exercise is an important check since Menkhoff et al. (2012b) show that there is a carry component within the momentum portfolios when sorting on excess instead of simple returns. Table IA.1 and IA.2 show that although the performance is slightly weaker for one-month momentum, with the joint cross-sectional R^2 now reduces to 86%, the main conclusions are largely unchanged: the high-minus-low beta spreads are significant and the global IRU risk carries negative prices of risk.

Since the currency momentum may be tightly linked to the limits to arbitrage (e.g. Menkhoff et al., 2012b), I test whether the role of IRU risk may be different for currencies with different limits to arbitrage. Following Filippou et al. (2018), at each month and for each

[18] The detailed classification is in the Data Appendix.

[19] To avoid specific dating of these crisis periods, I simply remove the data from Jan 1997 to Dec 1998, from July 2007 to April 2010, and from Jan 2011 to Dec 2012 respectively.

currency, I compute the idiosyncratic volatility (idvol) and skewness (idskew) that serve as two measures for the limits to arbitrage.[20] Then I run double sort by first forming two groups of currencies based on their idiosyncratic volatility or skewness, and within each group, I form three momentum portfolios. Table IA.3 and IA.4 report the IRU betas of these portfolios and the results of asset pricing test. Whereas the profitability of FX momentum is generally higher among the currencies with stronger limits to arbitrage, the high-minus-low spreads in IRU betas are significant across these two groups of momentum portfolios. Also, compared with the baseline asset pricing results, the magnitudes of most of the cross-sectional R^2 are still large. Therefore, the main empirical findings in this paper are unlikely driven by the limits to arbitrage.

6. Conclusion

This paper documents the importance of the risk of global interest rate uncertainty on accounting for the returns to FX carry and momentum trade. Empirically by using the GDP-weighted average of G10 currencies' interest rate realized variance as the measure for the global interest rate uncertainty, I show that the return sensitivities of currency carry and momentum portfolios to the global IRU shocks are almost monotonically decreasing from the bottom to the top portfolios. The high-minus-low beta spreads are negative and statistically significant. These risk exposures explain 89% and 97% of the cross-sectional variations in mean returns of carry and momentum portfolios respectively. The negative and significant correlations between the global IRU risk and returns to carry and momentum trade are robust to other proxies for the global IRU, such as the realized volatility or the US monetary policy uncertainty index of Baker et al. (2016). The explanatory power remains significant under a variety of settings and robustness checks, and the global IRU risk is also priced in momentum across other asset classes.

The economic reason behind the empirical success is the strong co-movements of the global IRU risk with both strategy returns during their downturns. Existing studies find that the crash behavior of carry and momentum differ substantially, which exacerbates the difficulty of reconciling these returns in a unified way. I show that the global IRU risk outperforms the commonly used risk factors such as the VIX or the global FX volatility on achieving this task. It is significantly and negatively correlated with both strategy returns under their respective crash periods. This channel is also consistent with an intermediary-

[20]The computation method follows Filippou et al. (2018) and is in the Internet Appendix.

based exchange rate model featuring the financial intermediary with limited risk-bearing capacity, in the spirit of Gabaix and Maggiori (2015) and Mueller et al. (2017b). When the intermediary's constraint is close to bind, i.e., when either of the strategy is likely to experience losses, rising global IRU will increase the shadow price of intermediary's financial constraint, leading to position unwinding by the intermediary. Such unwinding over long positions (high carry/momentum currencies) and short positions (low carry/momentum currencies) generate opposite responses and hence the negative correlations between the global IRU risk and returns to carry and momentum.

Appendix A. Data Appendix

The full dataset of currencies covers 48 countries from January 1985 to August 2017, within which the classification of developed economies includes 21 countries: Australia, Austria, Belgium, Canada, Denmark, Euro, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. The 27 developing economies cover Brazil, Bulgaria, Croatia, Cyprus, Czech Republic, Egypt, Hong Kong, Hungary, Iceland, India, Indonesia, Israel, Kuwait, Malaysia, Mexico, Philippines, Poland, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Taiwan, Thailand, and Ukraine. The series for the euro start from January 1999 and I exclude the Eurozone currencies after that date. Due to the large failures of covered interest rate parity, the following observations are removed from the sample: South Africa from July 1985 to August 1985, Malaysia from August 1998 to June 2005, Indonesia from December 2000 to May 2007.

The final dates of all G10 daily interest rate data are as of August 2017, but the starting months vary over countries and are listed in the following table.

Currency	Starting month
AUD	November 1999
CAD	July 1989
CHF	March 2007
DEM/EUR	August 1990
GBP	January 1992
JPY	April 1989
NOK	March 2007
NZD	November 1999
SEK	January 2007
USD	January 1985

Other data include the daily FX returns, which are used to obtain global FX volatility and correlation following Menkhoff et al. (2012a) and Mueller et al. (2017a). The daily bid-ask spot and forward rates are used to construct the global FX liquidity measure following Karnaukh et al. (2015). Finally, the TED spread and the VIX are downloaded from FRED, whose samples start from January 1986 and January 1990 respectively.

Appendix B. Proof

Appendix B.1. Proof of Proposition

In equilibrium, the VaR constraint is binding due to the linear payoff function of the financier. When Q is positive, we have:

$$P_0(R^* e_1 \leq R e_0) = \alpha. \tag{B.1}$$

If f_1 is with the distribution function of $F(\cdot)$ and is independent of R and R^*, then (B.1) can be expressed as

$$\int_{\underline{f}}^{\bar{f}} P_0(RQ + \frac{(f_0 + Q)d_1 R}{R^* d_0} \geq z)dF(z) = \alpha. \tag{B.2}$$

Suppose that after the uncertainty shock to R and R^*, the distribution function $P_0(\cdot)$ changes to $\hat{P}_0(\cdot)$. Due to the optimal behavior of the intermediary, Q will adjust to $\hat{Q}$ so that the following equation holds

$$\int_{\underline{f}}^{\bar{f}} \hat{P}_0(R\hat{Q} + \frac{(f_0 + \hat{Q})d_1 R}{R^* d_0} \geq z)dF(z) = \alpha. \tag{B.3}$$

Then I rely on the property of uncertainty shock as derived by e.g. Diamond and Stiglitz (1974) for the proof. The idea is that the uncertainty shock moves the probability mass towards the tails of the distribution, without the change in the mean. Hence given z and Q, denote the joint c.d.f of R^* and R before and after positive uncertainty shock as $G(\cdot|z;Q)$ and $\hat{G}(\cdot|z;Q)$, then there exist two threshold values $\bar{r}^*$ and $\bar{r}$ such that

$$1 - \hat{G}(R^*, R|z;Q) > 1 - G(R^*, R|z;Q), \text{ if } R^* < \bar{r}^* \text{ and } R > \bar{r}. \tag{B.4}$$

(B.4) in fact amounts to the following inequality when $RQ + \frac{(f_0+Q)gR}{R^*} > \bar{r}Q + \frac{\bar{r}}{\bar{r}^*}g(f_0 + Q)$

$$\int_{\underline{f}}^{\bar{f}} \hat{P}_0(RQ + \frac{(f_0 + Q)gR}{R^*} \geq z)dF(z) > \int_{\underline{f}}^{\bar{f}} P_0(RQ + \frac{(f_0 + Q)gR}{R^*} \geq z)dF(z), \tag{B.5}$$

as long as the VaR limit α is small enough such that[21]

$$\bar{r}Q + \frac{\bar{r}}{\bar{r}^*}g(f_0 + Q) \leq \underline{f}. \tag{B.6}$$

Now suppose that higher uncertainty by contradiction does not dampen the intermediary's risk-taking, that is, $\hat{Q} \geq Q$, then we have

$$\alpha = \int_{\underline{f}}^{\bar{f}} \hat{P}_0(R\hat{Q} + \frac{(f_0 + \hat{Q})gR}{R^*} \geq z)dF(z) \geq \int_{\underline{f}}^{\bar{f}} \hat{P}_0(RQ + \frac{(f_0 + Q)gR}{R^*} \geq z)dF(z). \tag{B.7}$$

Due to (B.5), the last term of (B.7) satisfies

$$\int_{\underline{f}}^{\bar{f}} \hat{P}_0(RQ + \frac{(f_0 + Q)gR}{R^*} \geq z)dF(z) > \int_{\underline{f}}^{\bar{f}} P_0(RQ + \frac{(f_0 + Q)gR}{R^*} \geq z)dF(z) = \alpha, \tag{B.8}$$

where the equality at the right-hand side reflects the optimality condition before the uncertainty shock. Hence we obtain the contradiction.

Similar proof can be derived for the equilibrium $Q < 0$, where two threshold values are

[21] The inequality arises from the obvious fact that Q becomes lower when α decreases.

obtained such that $R > \bar{r}$ and $R^* > \frac{R}{\bar{r}}\bar{r}^*$, and when α is small enough such that

$$\bar{r}Q + \frac{\bar{r}}{\bar{r}^*}g(f_0 + Q) \geq \bar{f}. \tag{B.9}$$

Then to prove for the cross-sectional properties, note that Equation (B.2) can be further expressed as

$$\int_{\underline{f}}^{\bar{f}} \int_{\underline{R}}^{\bar{R}} P_0(R^* \leq \frac{(f_0 + Q)d_1 r}{(z - rQ)d_0})dG(r)dF(z) = \alpha. \tag{B.10}$$

Hence Q increases with $E_0(R^*)$ when $Q > 0$, since the threshold value in the parenthesis has to increase so as the maintain the equality. Similarly, one can find that Q increases with $E_0(R^*)$ also when $Q < 0$.

Meanwhile, one can also rewrite the Equation (B.2) as

$$\int_{\underline{f}}^{\bar{f}} \int_{\underline{R}}^{\bar{R}} P_0(\frac{d_1}{d_0} \geq \frac{R^*(z - rQ)}{(f_0 + Q)r})dG(r)dF(z) = \alpha. \tag{B.11}$$

Hence Q decreases with $E_0(d_1/d_0)$ when $Q > 0$, since the threshold value in the parenthesis has to increase so as the maintain the equality. Similarly, one can find that Q decreases with $E_0(d_1/d_0)$ also when $Q < 0$.

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Table 1. Statistics of currency carry and momentum portfolios

The table reports the statistics for the currency carry and momentum portfolios. Carry portfolios are obtained by sorting on the forward discounts, and momentum portfolios are obtained by sorting on the realized excess returns over the previous 3-month period. All portfolios are rebalanced monthly, and the reported average monthly excess returns (in percentage) are net of transaction costs. Exposures to the risk of global IRU are computed from Equation (4). The R^2 of these regressions are listed in the last column of each panel. Standard errors are in parentheses and based on Newey and West (1987) with optimal lag selection following Andrews (1991). The excess returns, IRU betas and monthly Sharpe ratios (SR) of high-minus-low portfolios are also reported. The monotonicity of portfolio excess returns and IRU betas are tested via the monotonic relation (MR) test of Patton and Timmermann (2010), where the p-values are reported in parentheses based on all pair-wise comparisons. The null hypotheses for the tests are the monotonically increasing returns and decreasing betas respectively. The sample period is from January 1985 to August 2017.

	Panel A: Carry			Panel B: Momentum		
	$r^e(\%)$	β_{DOL}	β_{IRU}	$r^e(\%)$	β_{DOL}	β_{IRU}
L	-0.22	0.87	0.22	-0.10	1.02	0.22
	(0.12)	(0.04)	(0.07)	(0.15)	(0.08)	(0.08)
2	0.05	0.91	0.06	-0.02	0.99	0.10
	(0.11)	(0.03)	(0.05)	(0.12)	(0.05)	(0.05)
3	0.22	1.01	-0.09	0.17	1.02	-0.07
	(0.12)	(0.03)	(0.07)	(0.12)	(0.04)	(0.10)
4	0.21	1.06	0.04	0.23	0.98	-0.05
	(0.13)	(0.03)	(0.06)	(0.12)	(0.04)	(0.05)
H	0.36	1.16	-0.23	0.41	1.00	-0.22
	(0.17)	(0.06)	(0.13)	(0.14)	(0.07)	(0.10)
HML	0.58		-0.44	0.51		-0.44
	(0.16)		(0.18)	(0.15)		(0.16)
SR	0.21			0.17		
MR	(0.93)		(0.97)	(1.00)		(0.92)

Table 2. Interest rate uncertainty of G10 currencies

Panel A reports the correlation coefficients of interest rate uncertainty for G10 currencies. For each economy, the interest rate uncertainty is estimated as the monthly realized variance of 10-year government bonds, computed from daily bond yields. Panel B reports the output from the principal component analysis on the correlation matrix of G10 interest rate uncertainty. The pre-crisis sample is from January 1985 to June 2007, and the post-crisis sample ranges from May 2010 to August 2017. Reported are the percentage of the total variance explained by each of the first three principal components.

Panel A: Correlation										
	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK	USD
AUD	1.00									
CAD	0.71	1.00								
CHF	0.78	0.75	1.00							
EUR	0.57	0.43	0.54	1.00						
GBP	0.56	0.53	0.59	0.57	1.00					
JPY	0.11	0.35	0.35	0.13	0.33	1.00				
NOK	0.67	0.64	0.61	0.70	0.55	0.18	1.00			
NZD	0.72	0.61	0.64	0.46	0.45	0.18	0.48	1.00		
SEK	0.73	0.72	0.69	0.76	0.71	0.16	0.75	0.61	1.00	
USD	0.71	0.39	0.69	0.54	0.38	0.10	0.50	0.59	0.60	1.00

Panel B: Principal component analysis			
	Full sample	Pre-crisis	Post-crisis
First	59.9	54.1	59.9
Second	10.9	11.7	11.8
Third	8.3	8.7	7.8
Total	79.1	74.5	79.5

Table 3. Correlation analysis

The table reports the correlation coefficients of returns to currency carry, momentum, global *IRU* risk, and other risk factors. These risk factors include the innovations to VIX, TED spread and global FX volatility; US consumption growth; NBER recession dummy, Fama-French small-minus-big (SMB) and high-minus-low (HML) factors. Significance of correlations is only displayed for quantities related to carry and momentum returns, where *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels. The sample period is from January 1985 to August 2017.

	VIX	TED spread	Global FX vol	US growth	NBER recession	SMB	HML	Global IRU	Carry	Momentum
VIX	1.00									
TED spread	0.22	1.00								
Global FX vol	0.35	0.11	1.00							
US growth	-0.02	-0.01	0.06	1.00						
NBER recession	0.12	0.03	0.14	-0.29	1.00					
SMB	-0.21	-0.06	0.01	0.09	0.05	1.00				
HML	0.09	0.08	0.01	-0.08	-0.07	-0.27	1.00			
Global IRU	0.47	0.20	0.20	0.04	0.10	-0.10	0.01	1.00		
Carry	-0.26***	-0.05	-0.35***	-0.09*	-0.01	0.06	-0.07	-0.16***	1.00	
Momentum	0.01	-0.07	0.04	0.02	0.01	0.02	-0.05	-0.15***	0.03	1.00

Table 4. Cross-sectional asset pricing test

The table reports the results of asset pricing test for the two-factor model containing the dollar factor and the global IRU risk (u_t^{IRU}), or its factor-mimicking portfolio returns ($u_{FMM,t}^{IRU}$). The factor-mimicking portfolio is constructed by projecting u_t^{IRU} on the return space of five carry and five momentum portfolios. Panel A and B display the test results via Fama-MacBeth regression, where I report the estimated risk prices, cross-sectional OLS R^2, the heteroskedastic and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) with optimal lag selection following Andrews (1991) (NW), and the Shanken-adjusted standard errors of Shanken (1992) (Sh). The p-values of χ^2-test on the null hypothesis that the pricing errors are jointly zero are also reported. Panel C and D display the test results via the GMM estimation, where I report the estimated factor loadings in the SDF model (7) by using the optimal weight matrix in the estimation. The Newey-West standard errors are in parentheses. I also report the p-values from the χ^2-test, and the estimated Hansen-Jagannathan distances and their p-values, which are obtained via simulation following Jagannathan and Wang (1996). The testing assets are the carry, momentum or their joint cross-sectional portfolios. The sample period is from January 1985 to August 2017.

	Carry			Momentum			Carry+Momentum		
				Panel A: Fama-MacBeth					
	λ_{DOL}	λ_{IRU}	R^2	λ_{DOL}	λ_{IRU}	R^2	λ_{DOL}	λ_{IRU}	R^2
	0.13	-1.16	0.89	0.13	-1.19	0.97	0.13	-1.18	0.92
(NW)	(0.11)	(0.34)		(0.11)	(0.33)		(0.11)	(0.28)	
(Sh)	(0.11)	(0.53)		(0.11)	(0.52)		(0.11)	(0.42)	
χ^2_{NW}	[0.14]			[0.66]			[0.05]		
χ^2_{Sh}	[0.51]			[0.88]			[0.60]		
				Panel B: Fama-MacBeth using factor-mimicking portfolio					
	λ_{DOL}	λ_{IRU}	R^2	λ_{DOL}	λ_{IRU}	R^2	λ_{DOL}	λ_{IRU}	R^2
	0.13	-0.30	0.89	0.13	-0.31	0.97	0.13	-0.30	0.92
(NW)	(0.11)	(0.08)		(0.11)	(0.08)		(0.11)	(0.06)	
(Sh)	(0.11)	(0.08)		(0.11)	(0.08)		(0.11)	(0.06)	
χ^2_{NW}	[0.14]			[0.66]			[0.05]		
χ^2_{Sh}	[0.17]			[0.69]			[0.08]		
				Panel C: GMM					
	b_{DOL}	b_{IRU}	R^2	b_{DOL}	b_{IRU}	R^2	b_{DOL}	b_{IRU}	R^2
coef	0.05	-1.24	0.87	0.05	-1.57	0.87	0.04	-1.52	0.76
s.e.	(0.04)	(0.58)		(0.04)	(0.62)		(0.03)	(0.49)	
χ^2-test	[0.36]			[0.89]			[0.49]		
HJ-dist	0.13			0.07			0.19		
	[0.28]			[0.80]			[0.34]		
				Panel D: GMM using factor-mimicking portfolio					
	b_{DOL}	b_{IRU}	R^2	b_{DOL}	b_{IRU}	R^2	b_{DOL}	b_{IRU}	R^2
coef	0.04	-0.30	0.87	0.04	-0.31	0.96	0.04	-0.33	0.91
s.e.	(0.03)	(0.07)		(0.03)	(0.09)		(0.03)	(0.06)	
χ^2-test	[0.20]			[0.73]			[0.19]		
HJ-dist	0.13			0.07			0.19		
	[0.00]			[0.04]			[0.00]		

Table 5. Asset pricing tests with alternative measures for global IRU risk

The table reports the results of asset pricing test by using three alternative measures for the global IRU risk based on: equal-weighted average of realized variance; GDP-weighted average of realized volatility; and the US Monetary Policy Uncertainty index of Baker et al. (2016). In each panel, I first report the estimated IRU betas of carry and momentum portfolios together with their Newey-West standard errors. Then I display the results of asset pricing test via the Fama-MacBeth cross-sectional regression, where I report the estimated risk prices, cross-sectional OLS R^2, the heteroskedastic and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) with optimal lag selection following Andrews (1991) (NW), and the Shanken-adjusted standard errors of Shanken (1992) (Sh). The p-values of χ^2-test on the null hypothesis that the pricing errors are jointly zero are also reported. The testing assets are the carry, momentum or their joint cross-sectional portfolios. The sample period is from January 1985 to August 2017.

	Panel A: Equal-weighted average of realized variance					
	L	2	3	4	H	HML
β^C_{IRU}	0.24	0.05	-0.10	0.04	-0.24	-0.48
	(0.06)	(0.05)	(0.07)	(0.06)	(0.12)	(0.16)
β^M_{IRU}	0.24	0.13	-0.08	-0.07	-0.24	-0.48
	(0.07)	(0.04)	(0.09)	(0.06)	(0.09)	(0.14)
λ^C_{IRU}	-1.08	R^2	0.90		χ^2_{Sh}	[0.48]
(Sh)	(0.46)					
λ^M_{IRU}	-1.05	R^2	0.97		χ^2_{Sh}	[0.91]
(Sh)	(0.42)					
λ^{C+M}_{IRU}	-1.06	R^2	0.93		χ^2_{Sh}	[0.59]
(Sh)	(0.36)					
	Panel B: GDP-weighted average of realized volatility					
	L	2	3	4	H	HML
β^C_{IRU}	0.19	0.10	-0.11	0.01	-0.19	-0.38
	(0.08)	(0.05)	(0.06)	(0.06)	(0.13)	(0.18)
β^M_{IRU}	0.15	0.09	-0.02	-0.06	-0.17	-0.32
	(0.11)	(0.06)	(0.09)	(0.05)	(0.11)	(0.20)
λ^C_{IRU}	-1.27	R^2	0.90		χ^2_{Sh}	[0.52]
(Sh)	(0.57)					
λ^M_{IRU}	-1.61	R^2	0.99		χ^2_{Sh}	[0.99]
(Sh)	(0.83)					
λ^{C+M}_{IRU}	-1.41	R^2	0.93		χ^2_{Sh}	[0.78]
(Sh)	(0.56)					
	Panel C: BBD MPU index					
	L	2	3	4	H	HML
β^C_{IRU}	0.18	0.05	-0.04	-0.04	-0.16	-0.34
	(0.07)	(0.05)	(0.04)	(0.06)	(0.09)	(0.15)
β^M_{IRU}	0.21	0.10	-0.04	-0.07	-0.19	-0.40
	(0.10)	(0.06)	(0.06)	(0.05)	(0.10)	(0.17)
λ^C_{IRU}	-1.64	R^2	0.98		χ^2_{Sh}	[0.97]
(Sh)	(0.90)					
λ^M_{IRU}	-1.29	R^2	0.98		χ^2_{Sh}	[0.99]
(Sh)	(0.57)					
λ^{C+M}_{IRU}	-1.42	R^2	0.96		χ^2_{Sh}	[0.63]
(Sh)	(0.56)					

Table 6. Comovements with risk factors when carry or momentum fails

The table reports the correlation coefficients of the risk of global IRU, VIX, global FX volatility and returns to carry (r_t^C) and momentum (r_t^M) trade, computed over different crashing periods for two strategies. The crash periods are identified as the months when current strategy returns are below the k-th percentile of the empirical distribution of strategy returns. The average monthly strategy returns during the crash periods and the significance of correlations are also reported, where *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels. The sample period is from January 1985 to August 2017.

Percentile (k)	< 10	< 20	< 30	< 40	< 50
			Panel A: When carry fails		
$Corr(u_t^{IRU}, r_t^C)$	-0.29^{*}	-0.26^{**}	-0.27^{***}	-0.28^{***}	-0.24^{***}
$Corr(u_t^{IRU}, r_t^M)$	-0.38^{**}	-0.31^{***}	-0.24^{***}	-0.20^{**}	-0.18^{**}
$Corr(u_t^{VIX}, r_t^C)$	-0.09	-0.13	-0.18^{*}	-0.22^{***}	-0.22^{***}
$Corr(u_t^{VIX}, r_t^M)$	-0.03	0.01	-0.02	0.01	-0.01
$Corr(u_t^{FXVOL}, r_t^C)$	-0.17	-0.31^{***}	-0.37^{***}	-0.41^{***}	-0.42^{***}
$Corr(u_t^{FXVOL}, r_t^M)$	0.24	0.25^{**}	0.23^{**}	0.24^{***}	0.21^{***}
$E(r_t^C)(\%)$	-5.10	-3.38	-2.49	-1.86	-1.38
			Panel B: When momentum fails		
$Corr(u_t^{IRU}, r_t^C)$	-0.39^{**}	-0.36^{***}	-0.33^{***}	-0.30^{***}	-0.29^{***}
$Corr(u_t^{IRU}, r_t^M)$	-0.38^{***}	-0.38^{***}	-0.37^{***}	-0.33^{***}	-0.30^{***}
$Corr(u_t^{VIX}, r_t^C)$	-0.37^{**}	-0.30^{***}	-0.30^{***}	-0.31^{***}	-0.28^{***}
$Corr(u_t^{VIX}, r_t^M)$	$-0.31*$	-0.17	-0.09	-0.06	-0.06
$Corr(u_t^{FXVOL}, r_t^C)$	-0.33^{**}	-0.25^{**}	-0.29^{***}	-0.27^{***}	-0.29^{***}
$Corr(u_t^{FXVOL}, r_t^M)$	-0.23	-0.23^{**}	-0.27^{***}	-0.30^{***}	-0.28^{***}
$E(r_t^M)(\%)$	-4.84	-3.44	-2.67	-2.13	-1.67

Table 7. Cross-sectional predictability of foreign currency supply by currency returns The table reports the results of using currency returns to predict future supply of foreign currency in exchange for USD. For each country, $-\Delta s_{t-j:t}$ is the currency return (vis-à-vis USD) between month $t-j$ to t, $\log d_{t+h} - \log d_t$ is the log change of country's equity purchases from US between month t to $t+h$, which served as the proxy for the growth of foreign currency supply. The forecasting horizon h ranges from one- to three-month. Panel A to C correspond to the results for $j = 1$, 3 and 6. The left part of each panel reports the time series average of $\log d_{t+h} - \log d_t$ for portfolios formed by sorting on currency return $-\Delta s_{t-j:t}$ at the end of month-t, and the right part displays the average slope coefficients from the currency-level Fama-MacBeth cross-sectional regression (15). Reported R^2 is the time-series average of cross-sectional R^2 from the regressions. All t-statistics are reported in the parentheses and based on the standard errors of Newey and West (1987) with the optimal lag selection of Andrews (1991). The sample period is from January 1985 to August 2017.

	Portfolio approach						Fama-MacBeth	
	L	2	3	4	H	HML	b	$R^2(\%)$
Panel A: MOM11 ($-\Delta s_{t-1:t}$ on $\log d_{t+h} - \log d_t$)								
$h = 1$	1.84	2.35	1.41	1.20	0.80	-1.53	-0.27	3.57
(t)	(1.99)	(2.40)	(1.69)	(1.53)	(1.04)	(-1.46)	(-1.61)	
$h = 2$	3.84	3.49	2.60	2.04	2.84	-1.65	-0.11	3.71
(t)	(3.51)	(2.98)	(2.43)	(1.85)	(2.80)	(-1.52)	(-0.59)	
$h = 3$	6.05	5.00	4.51	4.48	3.51	-2.87	-0.33	4.21
(t)	(4.77)	(3.65)	(3.56)	(3.39)	(3.00)	(-2.58)	(-1.63)	
Panel B: MOM31 ($-\Delta s_{t-3:t}$ on $\log d_{t+h} - \log d_t$)								
$h = 1$	0.79	3.81	2.31	0.88	0.52	-0.09	-3.75	3.89
(t)	(0.91)	(4.29)	(2.66)	(0.99)	(0.66)	(-0.65)	(-1.17)	
$h = 2$	2.34	5.25	4.30	1.20	1.51	-1.16	-0.23	4.19
(t)	(2.15)	(4.44)	(3.99)	(1.00)	(1.48)	(-0.99)	(-2.18)	
$h = 3$	4.77	6.98	5.68	3.44	2.82	-2.33	-0.29	4.58
(t)	(3.50)	(5.54)	(4.51)	(2.62)	(2.33)	(-1.74)	(-2.25)	
Panel C: MOM61 ($-\Delta s_{t-6:t}$ on $\log d_{t+h} - \log d_t$)								
$h = 1$	2.35	1.12	2.65	1.65	0.31	-2.49	-0.09	4.70
(t)	(2.75)	(1.42)	(3.32)	(2.04)	(0.38)	(-2.50)	(-1.61)	
$h = 2$	4.07	3.80	3.78	2.88	1.31	-2.92	-0.15	4.37
(t)	(3.40)	(3.53)	(3.43)	(2.48)	(1.25)	(-2.39)	(-2.11)	
$h = 3$	6.00	5.22	4.16	4.76	3.11	-3.43	-0.24	4.92
(t)	(4.30)	(4.36)	(3.37)	(3.48)	(2.43)	(-2.54)	(-2.82)	

Table 8. Momentum everywhere and global IRU risk

The table reports the results of time-series regression (3) by projecting momentum returns in different asset classes on the global IRU risk or the funding liquidity risk, proxied by the innovations to the TED spread. All t-statistics are reported in the parentheses and based on the standard errors of Newey and West (1987) with the optimal lag selection of Andrews (1991). The sample period is from January 1985 to August 2017.

	$E(r_t^{MOM})$(%)	β_{IRU}(%)	β_{TED}(%)	β_{IRU}(%)
US equities	0.31	-0.39	-0.23	-0.44
	(1.38)	(-2.34)	(-1.08)	(-2.62)
UK equities	0.64	-0.48	-0.39	-0.41
	(2.59)	(-3.19)	(-1.68)	(-2.28)
Europe equities	0.41	-0.20	-0.25	-0.18
	(1.84)	(-1.44)	(-1.40)	(-1.22)
Japan equities	0.15	-0.39	0.16	-0.46
	(0.52)	(-2.18)	(0.65)	(-2.01)
Equity indices	0.49	-0.45	-0.07	-0.54
	(3.11)	(-1.54)	(-0.41)	(-2.01)
Fixed income	-0.01	0.02	-0.04	-0.04
	(-0.02)	(0.21)	(-0.46)	(-0.49)
Commodities	0.73	-0.64	0.10	-0.75
	(2.68)	(-2.69)	(0.33)	(-2.57)
Global Mom	0.34	-0.30	-0.12	-0.33
	(3.01)	(-3.52)	(-1.43)	(-4.12)

Table 9. Pricing momentum returns across asset classes

The table reports the results of cross-sectional asset pricing test using the asset pricing model with the market factor and the global *IRU* risk. The test is done via the Fama-MacBeth regression, where I report the first-stage estimated betas for each asset class, and the second-stage estimated risk price by pooling 21 momentum portfolios together. I also report the cross-sectional OLS R^2, the t-statistics based on the heteroskedastic and autocorrelation consistent (HAC) standard errors pf Newey and West (1987) with optimal lag selection following Andrews (1991), or based on the Shanken-adjusted standard errors of Shanken (1992) (Sh). I impose zero intercept in the second-stage regression. The sample period is from January 1985 to August 2017.

	L	M	H	HML	L	M	H	HML
	US equities				UK equities			
Return (%)	0.55	0.62	0.86	0.31	0.24	0.81	0.88	0.64
	(2.02)	(2.99)	(3.48)	(1.38)	(0.68)	(3.23)	(3.00)	(2.59)
CAPM beta	0.94	0.75	0.83	-0.11	1.15	0.87	0.93	-0.23
	(14.50)	(20.79)	(15.91)	(-1.29)	(15.29)	(20.21)	(18.55)	(-2.98)
IRU beta	0.15	-0.28	-0.33	-0.48	0.00	-0.34	-0.66	-0.66
	(1.07)	(-1.84)	(-2.03)	(-2.32)	(0.02)	(-1.86)	(-3.32)	(-3.22)
	Europe equities				Japan equities			
Return (%)	0.59	0.82	1.00	0.41	0.23	0.27	0.39	0.15
	(1.77)	(3.06)	(3.50)	(1.84)	(0.63)	(0.87)	(1.14)	(0.52)
CAPM beta	1.13	0.93	0.92	-0.21	0.97	0.89	0.86	-0.11
	(10.16)	(12.97)	(13.49)	(-2.44)	(10.72)	(11.80)	(9.31)	(-1.42)
IRU beta	-0.05	-0.14	-0.41	-0.36	0.88	0.39	0.40	-0.48
	(-0.26)	(-0.79)	(-2.12)	(-2.22)	(3.70)	(1.65)	(1.64)	(-2.47)
	Equity indices				Fixed-income			
Return (%)	0.30	0.63	0.78	0.49	0.33	0.23	0.32	-0.01
	(1.10)	(2.54)	(2.99)	(3.11)	(3.79)	(2.67)	(3.62)	(-0.02)
CAPM beta	0.86	0.80	0.81	-0.05	0.01	0.00	0.01	0.01
	(12.65)	(20.67)	(18.29)	(-0.75)	(0.23)	(0.02)	(0.56)	(0.44)
IRU beta	-0.34	-0.26	-0.83	-0.48	0.00	-0.04	0.03	0.02
	(-2.44)	(-1.94)	(-4.40)	(-1.78)	(0.04)	(-0.46)	(0.19)	(0.29)
	Commodities				Pricing test with 21 portfolios			
Return (%)	-0.04	0.09	0.69	0.73	Risk price			-0.51
	(-0.17)	(0.40)	(2.56)	(2.68)	NW (t)			(-2.53)
CAPM beta	0.33	0.30	0.27	-0.07	Sh (t)			(-2.27)
	(4.38)	(3.78)	(2.18)	(-0.87)				
IRU beta	0.44	0.22	-0.25	-0.69	R^2			0.44
	(2.08)	(1.38)	(-1.09)	(-2.97)				

Table 10. Robustness: Pricing power of IRU risk under controls

The table reports the results of asset pricing test on the joint cross-section of currency carry and momentum portfolios, by including other control variables in addition to the global IRU risk. Panel A contains the controls measuring the financial frictions: VIX and TED spread, the bond liquidity factor of Fontaine and Garcia (2011), betting against beta factor of Frazzini and Pedersen (2014), and intermediary's capital ratio of He et al. (2017). Panel B contains the commonly used currency risk factors: the global FX volatility of Menkhoff et al. (2012a), FX liquidity factor of Karnaukh et al. (2015), global equity correlation of Bae and Elkamhi (2017), and the high-minus-low returns of carry and momentum portfolios respectively. The test is done via Fama-MacBeth regression, where I report the estimated risk prices, cross-sectional OLS R^2, the heteroskedastic and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) with optimal lag selection following Andrews (1991) (NW), and the Shanken-adjusted standard errors of Shanken (1992) (Sh). The p-values of χ^2-test on the null hypothesis that the pricing errors are jointly zero are also reported. The sample period is from January 1985 to August 2017.

Panel A: Other measures of financial frictions										
X	VIX		TED		Bond liquidity		BAB		Capital ratio	
λ_X	-0.68	-0.49	-1.84	-0.35	-0.90	0.32	1.76	-0.29	0.49	0.24
(NW)	(0.22)	(0.21)	(0.49)	(0.51)	(0.40)	(0.37)	(0.56)	(0.45)	(0.23)	(0.23)
(Sh)	(0.27)	(0.31)	(1.01)	(0.76)	(0.53)	(0.56)	(1.13)	(0.74)	(0.25)	(0.32)
λ_{IRU}		-1.08		-1.06		-0.98		-1.19		-1.06
(NW)		(0.25)		(0.26)		(0.25)		(0.28)		(0.32)
(Sh)		(0.37)		(0.38)		(0.37)		(0.45)		(0.45)
R^2	0.33	0.87	0.53	0.87	0.09	0.87	0.32	0.94	0.37	0.91
χ^2_{NW}	[0.00]	[0.03]	[0.00]	[0.04]	[0.00]	[0.05]	[0.00]	[0.06]	[0.01]	[0.11]
χ^2_{Sh}	[0.02]	[0.44]	[0.73]	[0.45]	[0.02]	[0.52]	[0.37]	[0.66]	[0.05]	[0.56]

Panel B: Other currency risk factors										
X	FX Vol		FX liquidity		GEC		HML_{carry}		HML_{mom}	
λ_X	-0.46	-0.30	-0.74	-0.02	-0.81	-0.14	0.19	0.21	0.19	0.18
(NW)	(0.17)	(0.17)	(0.35)	(0.34)	(0.37)	(0.38)	(0.05)	(0.05)	(0.05)	(0.05)
(Sh)	(0.19)	(0.25)	(0.44)	(0.53)	(0.47)	(0.59)	(0.05)	(0.06)	(0.05)	(0.05)
λ_{IRU}		-1.15		-1.18		-1.20		-1.15		-1.13
(NW)		(0.28)		(0.28)		(0.28)		(0.32)		(0.36)
(Sh)		(0.42)		(0.43)		(0.44)		(0.48)		(0.53)
R^2	0.32	0.93	0.20	0.92	0.26	0.93	0.45	0.92	0.55	0.92
χ^2_{NW}	[0.00]	[0.04]	[0.00]	[0.04]	[0.00]	[0.04]	[0.00]	[0.05]	[0.00]	[0.03]
χ^2_{Sh}	[0.00]	[0.52]	[0.00]	[0.53]	[0.01]	[0.55]	[0.00]	[0.53]	[0.00]	[0.43]

Table 11. Robustness: Currency-level asset pricing

The table reports the results of currency-level asset pricing. Panel A reports the forward discounts, excess returns and IRU betas of G10 currencies (excl. USD). Panel B reports the estimated risk prices from the Fama-MacBeth regression by using the conditional currency excess returns of individual currencies. $C1$ is based on the conditional excess return that is defined as the raw excess return multiplied by the sign function of lagged interest rate differential or realized excess return, and $C2$ uses the sign function of the deviation from the cross-sectional median of lagged interest rate differential or realized excess return (detailed in Equation (17)). The Newey-West HAC standard errors are in parentheses with the optimal lag selection following Andrews (1991), and adjusted for the EIV problem of betas following Shanken (1992). The sample period is from January 1985 to August 2017.

	Panel A: G10 currency		
	Forward discount	Excess return	IRU beta
CHF	-1.92	0.02	0.41
JPY	-1.25	0.14	0.23
DEM/EUR	-0.35	0.14	0.10
CAD	0.63	0.08	-0.15
SEK	1.18	0.15	0.06
GBP	1.45	0.18	0.04
NOK	1.65	0.21	-0.02
NZD	2.55	0.25	-0.34
AUD	3.44	0.45	-0.25

	Panel B: Conditional currency returns			
	$C1$		$C2$	
	λ_{DOL}	λ_{IRU}	λ_{DOL}	λ_{IRU}
Carry	3.93	-0.18	2.37	-0.35
(NW)	(1.51)	(0.21)	(1.37)	(0.18)
MOM	-9.99	-0.58	-2.69	-0.22
(NW)	(5.93)	(0.21)	(3.97)	(0.19)
Carry+MOM	3.18	-0.40	2.14	-0.26
(NW)	(1.56)	(0.16)	(1.39)	(0.14)

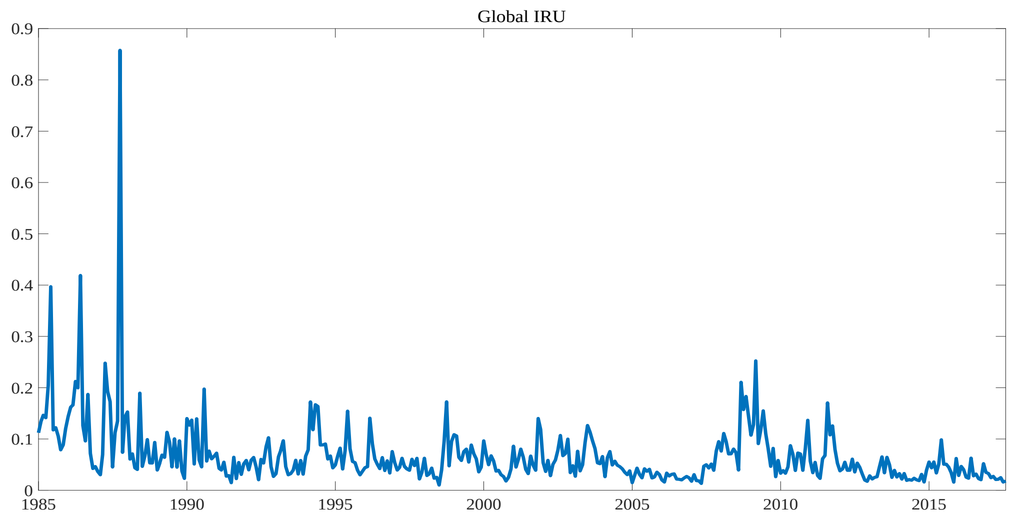
Table 12. Robustness: Subsample analysis

The table reports the returns to carry and momentum trade, and results of asset pricing test under different subsamples for the joint cross-section of carry and momentum portfolios. For the subsample that only includes 21 developed economies, results are reported separately for carry and momentum. The test is done via the Fama-MacBeth cross-sectional regression, where I report the estimated risk prices, cross-sectional OLS R^2, the heteroskedastic and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) with optimal lag selection following Andrews (1991) (NW), and the Shanken-adjusted standard errors of Shanken (1992) (Sh). The p-values of χ^2-test on the null hypothesis that the pricing errors are jointly zero are also reported in brackets. The sample period is from January 1985 to August 2017.

	r^{carry}(%)	r^{mom}(%)	λ_{DOL}	λ_{IRU}	R^2	χ^2_{NW}	χ^2_{Sh}
Pre-crisis (Jan 1985 to June 2007)	0.50	0.46	0.26	-0.90	0.81	19.46	11.80
(NW)	(0.19)	(0.18)	(0.12)	(0.30)		[0.01]	[0.16]
(Sh)			(0.12)	(0.38)			
Post-crisis (May 2010 to August 2017)	0.83	0.58	-0.24	-0.57	0.85	8.25	2.65
(NW)	(0.35)	(0.28)	(0.21)	(0.21)		[0.41]	[0.95]
(Sh)			(0.21)	(0.36)			
Developed economies (carry)	0.30		0.16	-0.60	0.79	2.48	1.82
(NW)	(0.16)		(0.12)	(0.34)		[0.48]	[0.61]
(Sh)			(0.12)	(0.39)			
Developed economies (momentum)		0.08	0.16	-0.07	0.03	2.06	2.04
(NW)		(0.14)	(0.12)	(0.25)		[0.56]	[0.56]
(Sh)			(0.12)	(0.25)			
Excl. periods of Asian financial crisis	0.66	0.49	0.18	-1.13	0.91	14.47	6.46
(NW)	(0.16)	(0.15)	(0.11)	(0.25)		[0.07]	[0.60]
(Sh)			(0.11)	(0.37)			
Excl. periods of 08 global financial crisis	0.58	0.51	0.13	-1.00	0.89	18.99	9.61
(NW)	(0.17)	(0.16)	(0.11)	(0.26)		[0.01]	[0.29]
(Sh)			(0.11)	(0.36)			
Excl. periods of Euro-debt crisis	0.59	0.56	0.13	-1.24	0.91	17.44	7.05
(NW)	(0.17)	(0.16)	(0.11)	(0.29)		[0.03]	[0.53]
(Sh)			(0.11)	(0.45)			

Figure 1. Global interest rate uncertainty and its innovations

The upper panel plots the level of global interest rate uncertainty, computed as the GDP-weighted realized variance of 10-year government bond yields of G10 currencies. The lower panel plots the standardized innovations u_t^{IRU}, obtained from fitting an AR(1) model to the level series. The sample period is from January 1985 to August 2017.



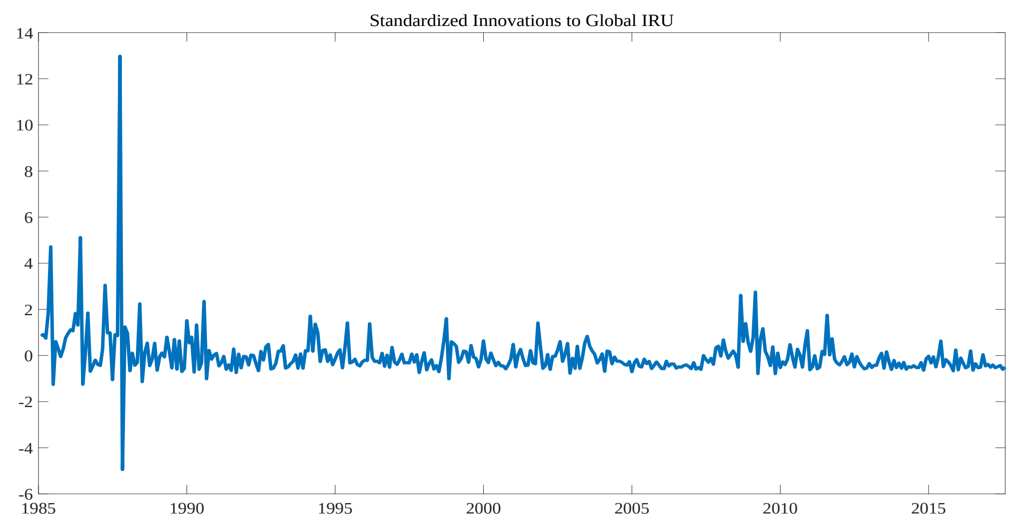


Figure 2. Carry and momentum returns conditional on global IRU risk

The figure plots the performance of carry (left panel) and momentum (right two panels) strategy conditional on four quartiles of the empirical distribution of innovations to the global IRU. The momentum trade are based on either one-month (middle panel) or three-month (right panel) formation window. The sample period is from January 1985 to August 2017.

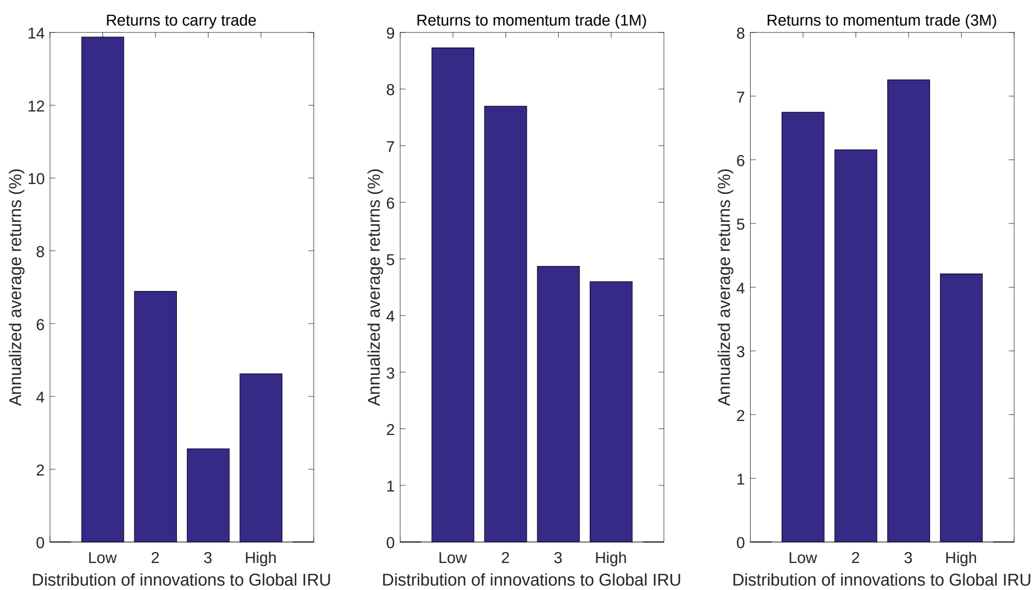


Figure 3. Global IRU betas and pricing error plots

The upper panel plots the sensitivities of carry and momentum portfolio returns to the risk of global uncertainty (IRU betas), which are estimated from Equation (4). The lower panel plots the portfolio mean returns and fitted returns from the asset pricing model containing the dollar factor and the global IRU risk, estimated over carry and momentum portfolio separately. The sample period is from January 1985 to August 2017.

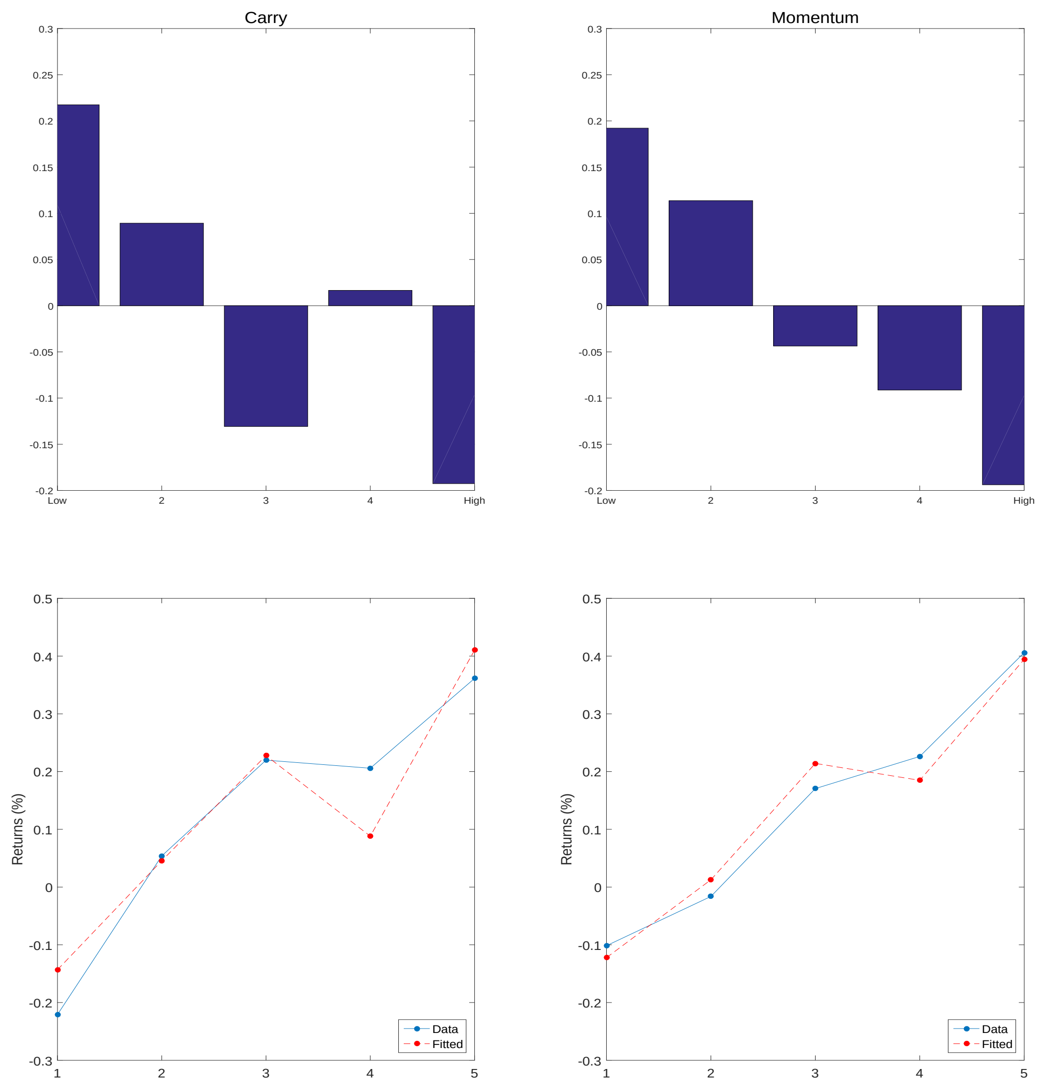
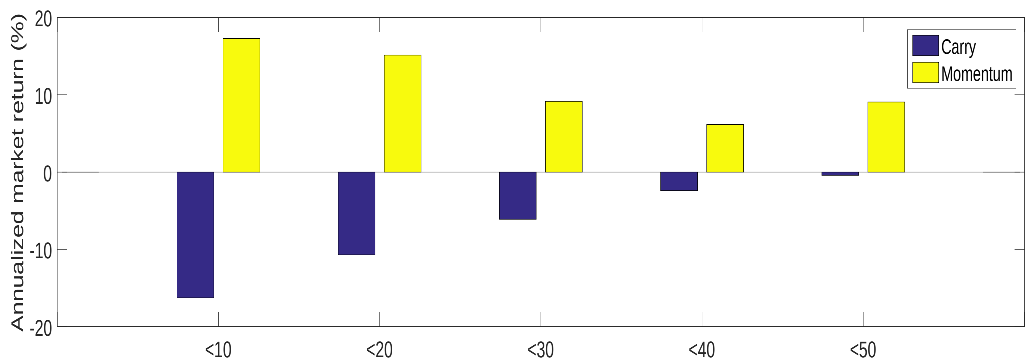


Figure 4. Market states and global IRU risk when carry or momentum fails

The upper (lower) panel plots the average of US aggregate stock returns (innovations to the global interest rate uncertainty) when currency carry or momentum strategy experiences sizable losses as defined in Equation (10). The sample period is from January 1985 to August 2017.



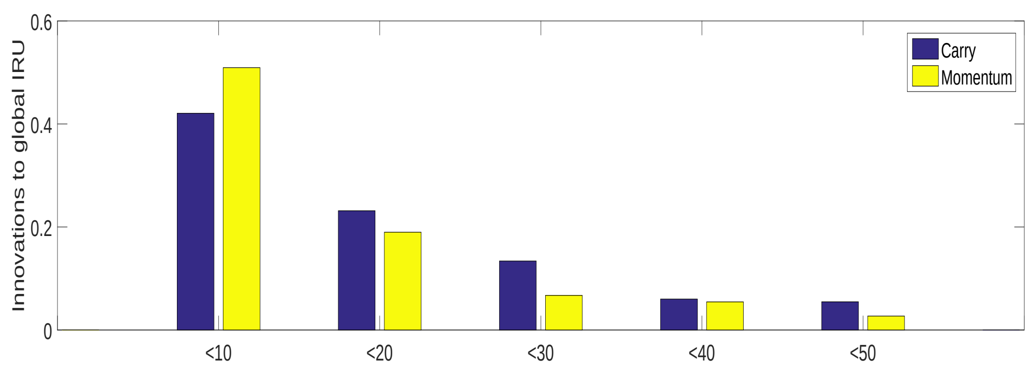


Figure 5. Global IRU risk during bad and good states

The figure plots the average of innovations to the global interest rate uncertainty when the economy is in bad or good states contemporaneously. The measure of the economic activity is the US industrial production growth, the Chicago Fed National Activity Index (CFNAI), and the aggregate market returns. The definition of bad or good states follows similarly the Equation (10). The sample period is from January 1985 to August 2017.

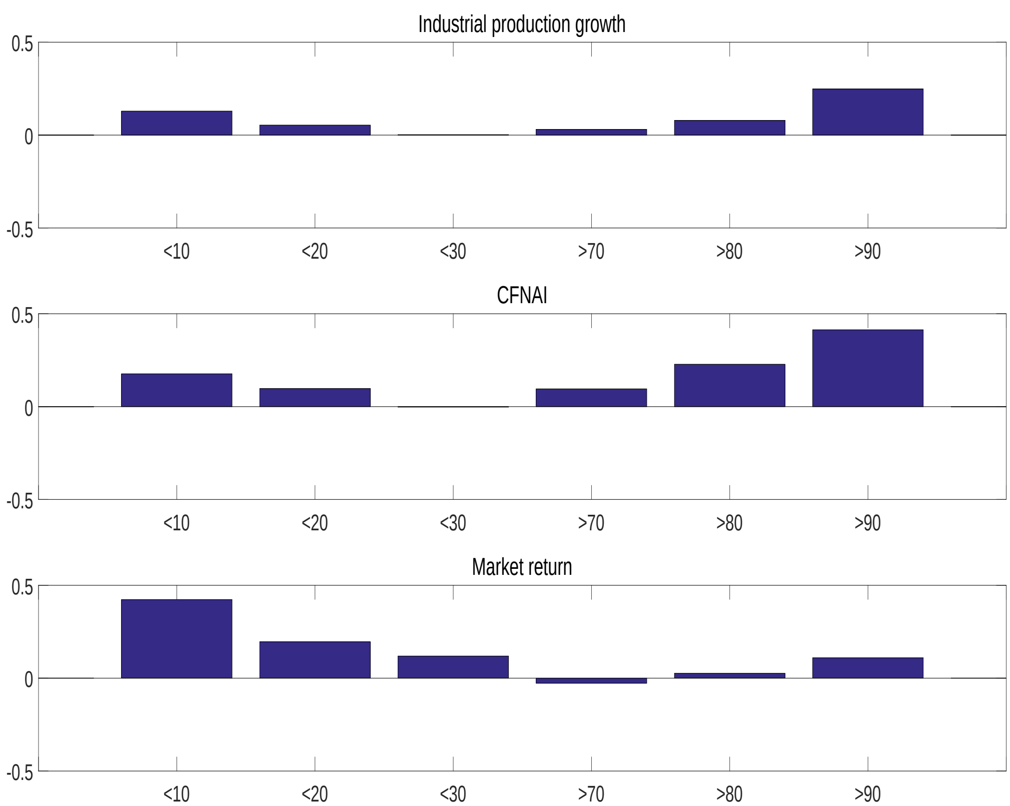
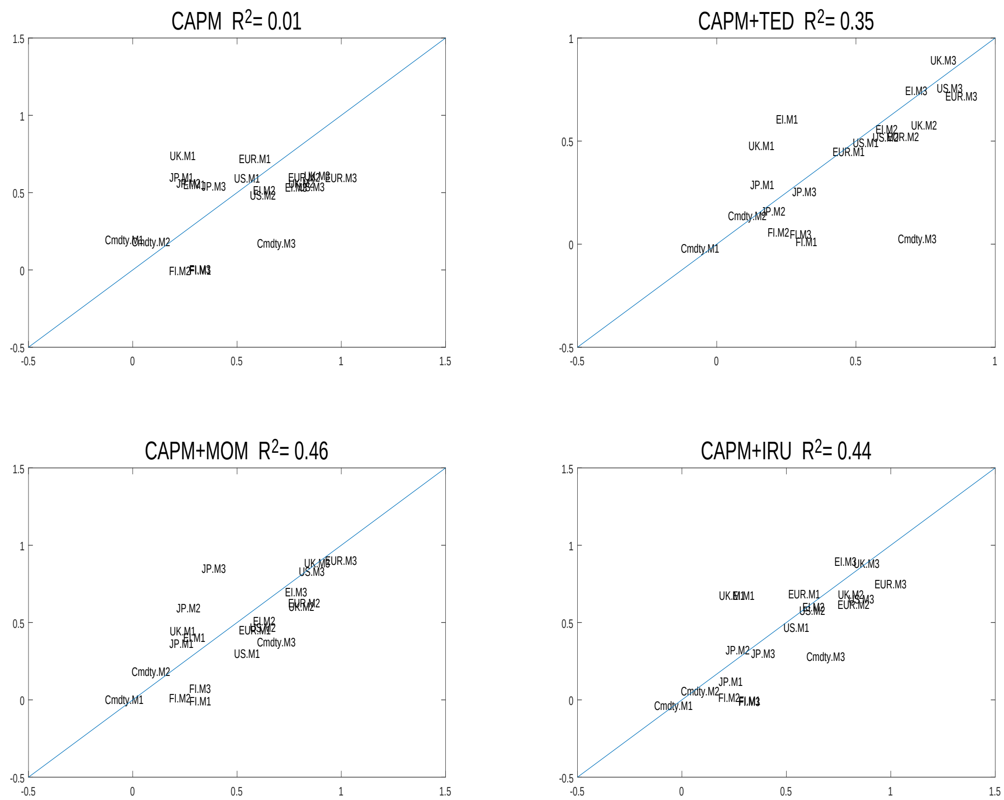


Figure 6. Pricing error plots for momentum everywhere

The figure contains the scatter plots between average portfolio excess returns and the fitted excess returns from the asset pricing model described in each panel. The model is estimated via the two-stage Fama-MacBeth regression. Zero intercept is imposed when running the second-stage cross-sectional regression. The sample period is from January 1985 to August 2017.



Internet Appendix to "Currency Carry, Momentum, and Global Interest Rate Uncertainty" (not for publication)

A. Adjustment for transaction costs, calculation of idiosyncratic volatility and skewness

Following Menkhoff et al. (2012b) and many others, at the end of month $t+1$, and for currency i, if it leaves the sorted portfolio that is formed at month t after $t+1$, then the *net* excess return for the lowest portfolio (the portfolio being shorted) is computed as

$$rx^s_{t+1} = f^a_t - s^b_{t+1}, \tag{IA.1}$$

where the superscripts a and b represent the ask and bid prices. For the long portfolios above the bottom one, the net excess returns are

$$rx^l_{t+1} = f^b_t - s^a_{t+1}. \tag{IA.2}$$

On the other hand, if currency i does not leave the current portfolio, then the excess returns are computed as

$$rx^s_{t+1} = f^a_t - s_{t+1}, \quad rx^l_{t+1} = f^b_t - s_{t+1}. \tag{IA.3}$$

To compute two measures of the limits to arbitrage for each currency i, I follow Filippou et al. (2018) by first extracting the residual series from the following asset pricing model

$$rx^i_t = \alpha^i + \beta^i_1 DOL_t + \beta_2 HML_{carry,t} + \epsilon_{i,t}, \tag{IA.4}$$

where DOL_t and $HML_{carry,t}$ are the daily dollar factor and the slope factor from carry trade portfolios. This asset pricing model is proposed by Lustig et al. (2011), and the regression is estimated by using daily data within each month. Then the currency i's idiosyncratic volatility and skewness at month-T are computed as

$$IV_{i,T} = \sqrt{\frac{\sum_{j=1}^{N_T} \hat{\epsilon}^2_{i,d}}{N_T}}, \quad IS_{i,T} = \frac{\sum_{j=1}^{N_T} \hat{\epsilon}^3_{i,d}}{N_T (IV_{i,T})^3}, \tag{IA.5}$$

where N_T denotes the number of daily returns available during month-T.

B. Extracting risk factor from the BBD MPU index

The US Monetary Policy Uncertainty (MPU) index built by Baker et al. (2016) is constructed as the scaled frequency counts of articles that discuss US monetary policy uncertainty, from hundreds of US daily newspapers covered by Access World News. To obtain their shocks as the risk factor, I follow Della Corte and Krecetovs (2017) by first computing the simple change in MPU level:

$$\Delta MPU_t = MPU_t - MPU_{t-1}. \tag{IA.6}$$

However, ΔMPU_t is highly correlated with changes in other category-specific BBD policy uncertainty indexes,[22] which confound the identification of shocks. I thus run the following orthogonalization:

$$\Delta MPU_t = \alpha + \sum_j \beta_j \Delta EPU_{j,t} + u_t^{MPU}, \tag{IA.7}$$

where $EPU_{j,t}$ denotes the BBD policy uncertainty index of category-j, and u_t^{MPU} denotes the orthogonal MPU shocks used in the paper. For variables on the right-hand side of Equation (IA.7), I consider four categories that cover Taxes; Fiscal and government spending; Sovereign debt; and National security. The selection follows their relevance for FX markets (see, e.g., Kumhof and Van Nieuwerburgh, 2007; Della Corte et al., 2016) and results are not sensitive to other choices.

C. Supplementary results

[22]In addition to the uncertainty over monetary policy, Baker et al. (2016) also builds the policy uncertainty indexes for the categories such as the fiscal policy, sovereign debt, etc.

Table IA.1. Statistics of alternative momentum portfolios

The table reports the statistics for the currency momentum portfolios, which are obtained by sorting on the realized excess returns over the previous 1- and 6-month periods. Alternatively, I form the momentum portfolios by sorting on the changes in log spot rates over the previous 1-, 3- and 6-month periods. All portfolios are rebalanced monthly, and the average monthly excess returns (in percentage) are net of transaction costs. The exposures to the risk of global IRU are computed from Equation (4). The standard errors are in parentheses and based on Newey and West (1987) with optimal lag selection following Andrews (1991). The returns and IRU betas of high-minus-low portfolios are also reported. The monotonicity of portfolio excess returns and IRU betas are tested via the monotonic relation (MR) test of Patton and Timmermann (2010), where the p-values are reported based on either five portfolios (brackets) or all pair-wise comparisons (parentheses). The null hypotheses for the tests are the monotonically increasing returns and decreasing betas respectively. The sample period is from January 1985 to August 2017.

	Mom 1-1		Mom 6-1		Mom 1-1 (spot)		Mom 3-1 (spot)		Mom 6-1 (spot)	
	r^e	β_{IRU}	r^e	β_{IRU}	r^e	β_{IRU}	r^e	β_{IRU}	r^e	β_{IRU}
L	-0.15	0.21	-0.07	0.27	-0.01	0.12	0.05	0.17	0.15	0.20
	(0.14)	(0.08)	(0.15)	(0.09)	(0.14)	(0.08)	(0.15)	(0.08)	(0.16)	(0.09)
2	0.12	0.10	0.08	0.08	0.03	0.19	-0.01	0.07	-0.02	0.12
	(0.12)	(0.07)	(0.12)	(0.07)	(0.13)	(0.06)	(0.12)	(0.08)	(0.12)	(0.07)
3	0.12	-0.04	0.13	-0.06	0.12	-0.04	0.16	0.00	0.14	-0.03
	(0.13)	(0.06)	(0.12)	(0.06)	(0.13)	(0.06)	(0.12)	(0.06)	(0.12)	(0.05)
4	0.21	-0.14	0.15	-0.05	0.15	-0.08	0.20	-0.04	0.16	-0.08
	(0.12)	(0.08)	(0.12)	(0.06)	(0.13)	(0.07)	(0.13)	(0.05)	(0.12)	(0.07)
H	0.39	-0.12	0.41	-0.26	0.32	-0.13	0.25	-0.17	0.24	-0.23
	(0.13)	(0.09)	(0.14)	(0.10)	(0.13)	(0.09)	(0.13)	(0.10)	(0.13)	(0.09)
HML	0.54	-0.34	0.47	-0.53	0.33	-0.25	0.20	-0.34	0.09	-0.43
	(0.14)	(0.15)	(0.15)	(0.17)	(0.14)	(0.16)	(0.15)	(0.16)	(0.15)	(0.16)
MR	[0.97]	[1.00]	[1.00]	[0.99]	[0.99]	[0.99]	[0.48]	[0.93]	[0.39]	[0.81]
	(0.97)	(0.98)	(1.00)	(0.95)	(0.99)	(0.89)	(1.00)	(0.54)	(1.00)	(0.79)

Table IA.2. Asset pricing test of alternative momentum portfolios

The table reports the results of asset pricing test for the two-factor model containing the dollar factor and the global IRU risk (u_t^{IRU}). The testing assets are three types of currency momentum portfolios (or joint with carry portfolios), which are obtained by sorting on the realized excess returns over the previous 1- and 6-month periods, or by sorting on the realized log changes in spot rates over the past 1-month. Panel A displays the results using Fama-MacBeth regression, where I report the estimated risk prices, cross-sectional OLS R^2, the heteroskedastic and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) with optimal lag selection following Andrews (1991) (NW), and the Shanken-adjusted standard errors of Shanken (1992) (Sh). The p-values of χ^2-test on the null hypothesis that the pricing errors are jointly zero are also reported. Panel B displays the results of test via the GMM estimation, where I report the estimated factor loadings in the SDF model (7) by using the optimal weight matrix in the estimation. The Newey-West standard errors are in parentheses. I also report the the p-values from the χ^2-test, and the estimated Hansen-Jagannathan distance and its p-values, which are obtained via simulation. The sample period is from January 1985 to August 2017.

	Momentum 1-1			Momentum 6-1			Momentum 1-1 (spot)		
				Panel A: Fama-MacBeth					
	λ_{DOL}	λ_{IRU}	R^2	λ_{DOL}	λ_{IRU}	R^2	λ_{DOL}	λ_{IRU}	R^2
	0.14	-1.17	0.77	0.14	-0.86	0.93	0.13	-0.84	0.74
(NW)	(0.11)	(0.33)		(0.11)	(0.29)		(0.11)	(0.38)	
(Sh)	(0.11)	(0.51)		(0.11)	(0.39)		(0.11)	(0.49)	
χ^2_{NW}	[0.01]			[0.61]			[0.17]		
χ^2_{Sh}	[0.22]			[0.79]			[0.40]		
				Joint with carry					
	0.13	-1.36	0.86	0.13	-1.09	0.87	0.13	-1.20	0.83
(NW)	(0.11)	(0.31)		(0.11)	(0.31)		(0.11)	(0.27)	
(Sh)	(0.11)	(0.51)		(0.11)	(0.45)		(0.11)	(0.42)	
χ^2_{NW}	[0.00]			[0.00]			[0.02]		
χ^2_{Sh}	[0.21]			[0.20]			[0.47]		
				Panel B: GMM					
	b_{DOL}	b_{IRU}	R^2	b_{DOL}	b_{IRU}	R^2	b_{DOL}	b_{IRU}	R^2
coef	0.03	-0.90	0.72	0.04	-0.86	0.88	0.03	-0.50	0.60
s.e.	(0.04)	(0.57)		(0.03)	(0.39)		(0.03)	(0.45)	
χ^2-test	[0.23]			[0.81]			[0.26]		
HJ-dist	0.16			0.07			0.11		
	[0.03]			[0.52]			[0.31]		
				Joint with carry					
coef	0.03	-1.05	0.80	0.03	-1.23	0.85	0.03	-0.80	0.74
s.e.	(0.04)	(0.50)		(0.04)	(0.41)		(0.04)	(0.44)	
χ^2-test	[0.13]			[0.27]			[0.22]		
HJ-dist	0.28			0.22			0.22		
	[0.01]			[0.08]			[0.04]		

Table IA.3. ***IRU*** **betas of FX momentum under different limits to arbitrage**

The table reports the statistics for the currency momentum portfolios under different limits to arbitrage. I run double sort based on currency's idiosyncratic volatility (or skewness) and realized excess returns over the past 1-, 3- and 6-month horizons to obtain 2×3 portfolios. All portfolios are rebalanced monthly, and the average monthly excess returns (in percentage) are net of transaction costs. The exposures to the risk of global IRU are computed from Equation (4). The standard errors are in parentheses and based on Newey and West (1987) with optimal lag selection following Andrews (1991). The returns and IRU betas of high-minus-low portfolios are also reported. The sample period is from January 1985 to August 2017.

	Low idvol		High idvol		Low idskew		High idskew	
	r^e	β_{IRU}	r^e	β_{IRU}	r^e	β_{IRU}	r^e	β_{IRU}
				Panel A: Mom 1-1				
L	0.03	0.21	-0.07	0.11	0.04	0.24	-0.08	0.05
	(0.12)	(0.08)	(0.15)	(0.09)	(0.14)	(0.08)	(0.15)	(0.08)
2	0.11	0.01	0.25	-0.03	0.09	0.01	0.21	-0.07
	(0.12)	(0.06)	(0.14)	(0.07)	(0.13)	(0.06)	(0.12)	(0.07)
H	0.23	-0.04	0.33	-0.23	0.29	-0.11	0.29	-0.21
	(0.12)	(0.09)	(0.15)	(0.11)	(0.15)	(0.11)	(0.13)	(0.09)
HML	0.22	-0.25	0.41	-0.36	0.24	-0.35	0.37	-0.26
	(0.13)	(0.15)	(0.15)	(0.17)	(0.15)	(0.17)	(0.14)	(0.15)
				Panel B: Mom 3-1				
L	-0.17	0.19	-0.01	0.14	0.04	0.24	-0.05	0.09
	(0.13)	(0.09)	(0.17)	(0.10)	(0.14)	(0.08)	(0.15)	(0.09)
2	0.14	-0.02	0.08	0.03	0.14	-0.03	0.11	0.00
	(0.12)	(0.05)	(0.14)	(0.08)	(0.12)	(0.11)	(0.12)	(0.06)
H	0.28	-0.09	0.42	-0.22	0.23	-0.11	0.47	-0.21
	(0.12)	(0.07)	(0.15)	(0.08)	(0.14)	(0.07)	(0.13)	(0.07)
HML	0.46	-0.28	0.42	-0.36	0.19	-0.35	0.52	-0.31
	(0.14)	(0.14)	(0.15)	(0.15)	(0.13)	(0.14)	(0.14)	(0.14)
				Panel C: Mom 6-1				
L	-0.01	0.19	-0.00	0.30	0.16	0.37	-0.03	0.04
	(0.13)	(0.09)	(0.17)	(0.10)	(0.15)	(0.08)	(0.14)	(0.08)
2	0.14	0.01	0.11	-0.09	0.13	-0.10	0.13	-0.07
	(0.12)	(0.05)	(0.14)	(0.06)	(0.12)	(0.07)	(0.12)	(0.06)
H	0.27	-0.08	0.29	-0.21	0.16	-0.11	0.38	-0.25
	(0.12)	(0.09)	(0.16)	(0.11)	(0.13)	(0.09)	(0.14)	(0.09)
HML	0.28	-0.29	0.32	-0.54	0.01	-0.47	0.41	-0.29
	(0.14)	(0.16)	(0.16)	(0.17)	(0.15)	(0.16)	(0.15)	(0.15)

Table IA.4. Pricing FX momentum under different limits to arbitrage

The table reports the results of asset pricing test for the two-factor model containing the dollar factor and the global IRU risk factor (u_t^{IRU}). The testing assets are momentum portfolios within each group of limits to arbitrage, formed by running double sorts on idiosyncratic volatility (skewness) and realized currency excess returns over the past 1-, 3- and 6-month horizons. The test is done via the Fama-MacBeth regression, where I report the estimated risk prices, cross-sectional OLS R^2, the heteroskedastic and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) with optimal lag selection following Andrews (1991) (NW), and the Shanken-adjusted standard errors of Shanken (1992) (Sh). The p-values of χ^2-test on the null hypothesis that the pricing errors are jointly zero are also reported. The sample period is from January 1985 to August 2017.

	Low idvol			High idvol			Low idskew			High idskew		
Panel A: Mom 1-1												
	λ_{DOL}	λ_{IRU}	R^2	λ_{DOL}	λ_{IRU}	R^2	λ_{DOL}	λ_{IRU}	R^2	λ_{DOL}	λ_{IRU}	R^2
	0.17	-0.69	0.63	0.09	-1.06	0.79	0.17	-0.63	0.80	0.03	-1.41	0.88
(NW)	(0.12)	(0.45)		(0.11)	(0.40)		(0.11)	(0.39)		(0.12)	(0.54)	
(Sh)	(0.13)	(0.54)		(0.12)	(0.58)		(0.12)	(0.46)		(0.15)	(0.93)	
χ^2_{NW}	2.97			2.22			1.01			2.32		
	(0.08)			(0.14)			(0.31)			(0.13)		
χ^2_{Sh}	2.00			1.05			0.72			0.78		
	(0.16)			(0.31)			(0.40)			(0.38)		
Panel B: Mom 3-1												
	λ_{DOL}	λ_{IRU}	R^2	λ_{DOL}	λ_{IRU}	R^2	λ_{DOL}	λ_{IRU}	R^2	λ_{DOL}	λ_{IRU}	R^2
	0.14	-1.60	0.98	0.14	-1.17	1.00	0.16	-0.54	0.96	0.11	-1.75	0.99
(NW)	(0.12)	(0.47)		(0.11)	(0.39)		(0.11)	(0.37)		(0.11)	(0.41)	
(Sh)	(0.14)	(0.87)		(0.12)	(0.59)		(0.12)	(0.42)		(0.13)	(0.83)	
χ^2_{NW}	0.76			0.01			0.16			0.17		
	(0.38)			(0.90)			(0.69)			(0.68)		
χ^2_{Sh}	0.21			0.01			0.12			0.04		
	(0.64)			(0.94)			(0.72)			(0.84)		
Panel C: Mom 6-1												
	λ_{DOL}	λ_{IRU}	R^2	λ_{DOL}	λ_{IRU}	R^2	λ_{DOL}	λ_{IRU}	R^2	λ_{DOL}	λ_{IRU}	R^2
	0.21	-0.92	0.92	0.12	-0.49	0.81	0.15	-0.01	-0.27	0.02	-1.46	1.00
(NW)	(0.12)	(0.50)		(0.11)	(0.29)		(0.11)	(0.27)		(0.12)	(0.50)	
(Sh)	(0.13)	(0.68)		(0.11)	(0.33)		(0.11)	(0.27)		(0.15)	(0.88)	
χ^2_{NW}	1.05			1.21			0.26			0.00		
	(0.31)			(0.27)			(0.61)			(0.95)		
χ^2_{Sh}	0.56			0.97			0.26			0.00		
	(0.45)			(0.32)			(0.61)			(0.97)		

Figure IA.1. Risk factors when carry or one-month momentum fails

The figure plots the average of innovations to the global interest rate uncertainty, VIX and global FX volatility when currency carry or momentum strategy experiences sizable losses as defined in Equation (10). The momentum strategy is based on sorting the past one-month realized returns. The sample period is from January 1985 to August 2017.

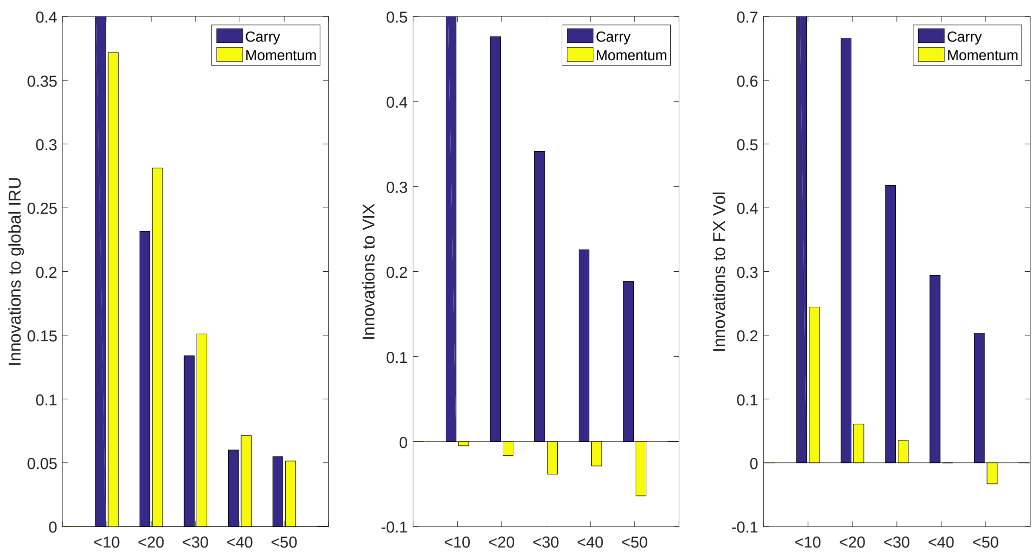


Figure IA.2. Time-series plot of global equity correlation

The figure plots the replicated series of global equity correlation of Bae and Elkamhi (2017). The sample period is from January 1985 to August 2017.

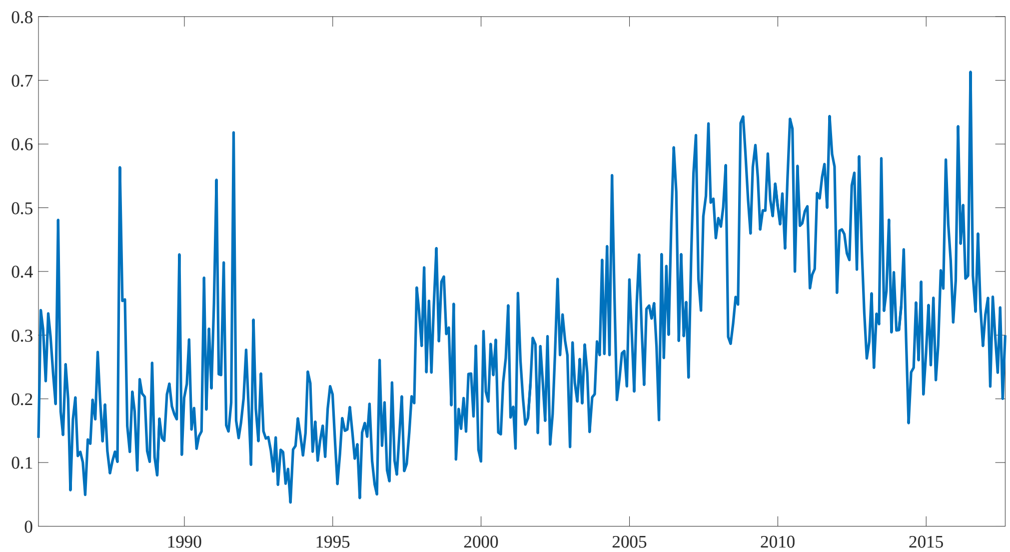


Figure IA.3. ***IRU* betas under subsamples**

The figure plots the betas of carry and momentum portfolio returns to the global *IRU* risk, estimated from Equation (4) by using data from different subsamples. The overall sample period is from January 1985 to August 2017.