U.S. Equity Tail Risk and Currency Risk Premia*

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This Version: November 2019

Abstract

We find that an option-based U.S. equity tail risk factor is priced in the cross section of currency returns. Currencies highly exposed to this factor offer a low risk premium because they hedge against U.S. tail risk. In a reduced-form model, we show that a long-short portfolio that buys currencies with high U.S. equity tail beta and shorts those with low tail beta extracts the global component embedded in the U.S. tail risk factor. Inspired by the model, we construct a novel global tail risk factor from currency returns. This factor along with the dollar factor explains a large portion of the cross-sectional variation in the currency carry and momentum portfolios and outperforms other popular models.

JEL Classification: G12, G15, F31
Keywords: Global tail risk; Currency returns; Carry trade; Currency momentum.

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1. Introduction

This paper studies the pricing implications of U.S. equity tail risk in the cross section of currency excess returns. The size and international linkages of the U.S. economy have substantial implications for the global economy. The U.S. is, after all, the largest economy in the world, according to the World Economic Outlook report published by the IMF in 2019. In terms of trade linkages, the U.S. is the most important export destination for one-fifth of all countries in the world, according to the 2018 World Bank's Global Economic Prospects report, and most of the international goods trade is invoiced in U.S. dollars (Goldberg and Tille (2008)). Several recent studies show that, as a consequence of trade and financial linkages, movements in U.S. equity markets have important implications for the pricing of international assets. For instance, Rapach, Strauss, and Zhou (2013) find evidence that U.S. stock returns have a leading role in the predictability of international stock returns, while non-U.S. stock returns have almost no additional predictability. Aït-Sahalia, Cacho-Diaz, and Laeven (2015) show that most equity markets tend to reflect U.S. equity jumps quickly, while statistical evidence for the reverse transmission is much less pronounced. Bollerslev, Marrone, Xu, and Zhou (2014) and Londono (2015) find that the U.S. equity variance risk premium has predictive power for international stock returns.

In this paper, we build on the intuition that, if a currency appreciates with respect to the U.S. dollar when U.S. equity tail risk increases, this currency is essentially a hedge against U.S. tail risk, which makes the currency more attractive to investors and, therefore, reduces its expected returns. To motivate our empirical analysis, we propose a stylized reduced-form model to assess the pricing implications of global and country-specific risks in the cross section of currency returns. We show that if a country's tail risk factor contains a global component, exposures of foreign currencies to this tail risk should matter in the cross section of currency returns. In particular, the model implies that a long-short portfolio that buys currencies with high tail beta and shorts those with low tail beta extracts the global component embedded in a country's local tail risk factor, irrespective of the reference currency.

We construct a U.S. equity tail risk factor based on the innovation to the left jump tail measure in Bollerslev and Todorov (2011); that is, the compensation demanded by investors to hedge extreme negative events in U.S. equity markets. The tail risk factor is closely related to the return of a protective put (married put) strategy, which is frequently used as a hedge against tail risk by institutional investors, and hence is a tradable factor. Our option-implied tail factor has several features that differentiate it from other related factors in the exchange rate literature. First, it can be measured at high frequency with forward-looking information extracted from traded option prices, even though large-magnitude downside market states occur infrequently. Therefore, it differs from measures of realizations of downside U.S. equity market events (Lettau, Maggiori, and Weber (2014)), downside global equity market events (Dobrynskaya (2014)), and high frequency currency jumps (Lee and Wang (2018)). Second, our tail risk factor does not only contain information about the probability of left-tail jump events, such as in Lu and Murray (2018), but also about investors' beliefs of the potential jump size. Third, our tail risk factor is a tradable factor and can be regarded as the log return of a synthetic trading strategy. Prevailing tail measures are typically constructed as either realized jumps or option-implied jumps, which cannot be replicated by self-financing portfolios. Fourth, our tail risk measure captures the risk related to the time-varying nature of jump tails, which differentiates if from the risk-neutral third moment in Gao, Lu, and Song (2018) and the measure of systematic jumps in returns in Begin, Dorion, and Gauthier (2019). Lastly, our measure also differs from currency volatility measures, such as the foreign exchange (FX) volatility factor in Menkhoff et al. (2012a) and the currency variance risk premium in Londono and Zhou (2017), because our tail-risk factor focuses on large unfavorable stock market events.

Our paper makes two main empirical contributions to the literature. In our first contribution, we find that the U.S. tail risk factor carries a negative price of risk in the cross section of currency returns. In particular, using data for 37 currencies (in units of foreign currency per U.S. dollar) between January 1990 and April 2018, we show that the future returns of quintile currency portfolios sorted on U.S. tail betas decrease monotonically. A portfolio that longs the top quintile and shorts the bottom quintile generates a significantly negative average excess return of -4.73% (-4.57) per year in the sample of all (developed markets) currencies with a Sharpe ratio of -0.7 (-0.6). These return spreads cannot be explained by the dollar risk factor or by the FX volatility factor and remain robust after controlling for changes in the VIX.

Moreover, consistent with the implications of our model that the cross-sectional pricing implications hold irrespective of the reference currency, we find that U.S. tail risk is also priced in the cross section of U.K. pound- and Japanese yen-denominated currencies. The high-minus-low return spread is -4.62% and -4.69% for U.K. investors and Japanese investors in the universe of all currencies, and -4.72% and -4.69% in the universe of developed markets' currencies, confirming that the U.S. tail risk has a global nature.

Motivated by the intuition from the model and by the empirical evidence for the cross-sectional implications of the U.S. tail factor, in our second contribution, we construct a global tail factor using the high-minus-low return spread of the tail-beta-sorted currency portfolios. We use this factor along with the dollar risk factor to conduct asset pricing tests on the currency carry and momentum portfolios. We find that high interest rate currencies have a negative exposure to the global tail factor and thus deliver low returns in times of increased tail risk. Currency winners; that is, currencies that appreciate with respect to the U.S. dollar in the past month, have lower tail beta than currency losers.

Currency losers provide a hedge by yielding higher returns during high tail risk periods and thus have lower returns on average. These results suggest that excess returns to carry trade and momentum strategies can be partially understood as compensation for global tail risk.

A factor model with the global tail factor and the dollar risk factor outperforms popular models that explain the cross section of currency carry and momentum portfolios, such as the CAPM, the downside-risk CAPM, and a currency model with the dollar risk factor and the FX volatility risk factor. Our evidence suggests that the cross-sectional explanatory power of our model can be attributed almost exclusively to the global tail factor. Moreover, the global tail factor has significant pricing power in the cross section of carry and momentum currency portfolios after controlling for the carry factor in Lustig, Roussanov, and Verdelhan (2011), the FX volatility factor in Menkhoff, Sarno, Schmeling, and Schrimpf (2012a), the global disaster risk factor in Gao, Lu, and Song (2018), the dollar carry and global dollar risk factor in Verdelhan (2018), and innovations in the VIX.

This paper contributes to three branches of the literature. First, this paper contributes to the literature on crash risk in currency markets. Brunnermeier, Nagel, and Pedersen (2008) find that high interest rate differentials predict negative skewness of currency returns and conclude that carry trade returns bear currency-specific crash risk. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) and Jurek (2014) study the contribution of crash risk to carry trade using the returns on "hedged carry trade" with currency options. In a parametric model, Chernov, Graveline, and Zviadadze (2018) find strong evidence for the existence of jumps in returns as well as in volatilities for each currency. Unlike these studies, which center the attention on country-specific crash risks, our paper focuses on the pricing of systematic tail risk in the cross section of currency returns. There are several papers on the importance of systematic disaster risk in currency markets. Farhi and Gabaix (2015) show that an exchange rate model with global disaster risk can reproduce the forward premium puzzle. Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2015) find empirical evidence that disaster risk accounts for a considerable amount of the carry trade risk premium. Our paper differs from these papers that account for systematic disaster risk in two main aspects. First, we study the global component in the U.S. equity tail risk factor and show that our construction can better identify the global tail risk factor. Second, we examine the pricing of these factors in the cross section of currency returns and the extent to which the global tail risk factor explains the cross section of currency strategy returns, such as carry and momentum.

This paper also contributes to a second branch of the literature on explaining the excess return of currency carry trade and momentum. Several studies show that different variables can explain the excess return of the carry trade returns; for example, U.S. consumption risk in Lustig and Verdelhan (2007); innovations to FX volatility in Menkhoff, Sarno, Schmeling, and Schrimpf (2012a); U.S. equity downside risk in Lettau, Maggiori, and Weber (2014); global long-run consumption news in Colacito, Croce, Gavazzoni, and Ready (2018); and global imbalances in Della Corte, Riddiough, and Sarno (2016). Filippou, Gozluklu, and Taylor (2018) show that the winner portfolio in the currency momentum strategy is compensated for the exposure to the global political risk of those currencies. The variables in the aforementioned papers have difficulties explaining the returns of carry and momentum strategies simultaneously. Our paper shows that the global tail risk factor and the dollar risk factor are able to explain a large portion of the cross-sectional variation in both currency carry and momentum portfolios.

Finally, this paper contributes to the literature on the pricing implications across asset classes and across geographical markets. In particular, our paper is related to a branch of the literature on the role of U.S.-specific shocks and global shocks in the pricing of currency returns. Lustig, Roussanov, and Verdelhan (2014) link the return of the dollar carry strategy to U.S.-specific business cycle variations. Verdelhan (2018) shows that the global component of the dollar factor, which is calculated as the average of the appreciation rates of a set of currencies with respect to the U.S. dollar, explains a large portion of the variation in bilateral exchange rates. Another branch of this literature links developments in stock markets with currency returns. Hau and Rey (2006) find that currency returns are related to the relative performance of equity returns across countries. Londono and Zhou (2017) find that the U.S. equity variance risk premium is a useful predictor of currency returns. We contribute to these branches of the literature by showing that U.S. tail risk does not only contain U.S.-specific shocks, but also has a global component that is relevant for an international investor. This global component has pricing implications for the cross section of currency returns.

The remainder of the paper proceeds as follows. In Section 2, we propose a theoretical framework to understand the role of country-specific and global tail risks in the pricing of cross-sectional currency returns. Section 3 introduces the data used for the empirical exercises. In the empirical part of the paper, we consider the U.S. as the home country and investigate the pricing of U.S. tail risk for the cross section of currency returns. Section 4 shows the main empirical results and robustness checks regarding the pricing of U.S. tail risk in the cross section of currency excess return. Section 5 discusses the construction of the global tail risk factor and the results for the asset pricing tests on carry and momentum portfolios. We conclude in Section 6.

2. Domestic and Global Tail Risks and the Cross Section of Currency Returns

In this section, we introduce a model to illustrate the implications of country-specific and global tail risks in the cross sectional variation of currency returns. We then propose a novel equity tail risk factor used to capture the global component in the U.S. (domestic) tail risk.

2.1. A Stylized Factor Model of Currency Returns

We assume a factor model for the log nominal stochastic discount factor (SDF) in each country k, denoted by $m_{k,t+1}$. Specifically, we assume that the log nominal SDF is driven by a country-specific factor u_k, a global factor u_g, and a tail factor $Tail_k$:

$$-m_{k,t+1} = i_{k,t} + a_{k,t} + \gamma_k u_{k,t+1} + \delta_k u_{g,t+1} + \lambda_k Tail_{k,t+1}, \tag{1}$$

where i_k represents the risk-free interest rate of country k; a_k is a constant such that $E_t[e^{m_{k,t+1}}] = e^{i_{k,t}}$; $u_{k,t+1}$ and $u_{g,t+1}$ capture country-specific and global shocks; and $Tail_{k,t+1}$ captures shocks related to the time-varying jump tails.[1] The three shocks (or factors), $u_{k,t+1}$, $u_{g,t+1}$, and $Tail_{k,t+1}$, are independently distributed.

We further assume that the tail risk of country k contains a systematic component, the global tail risk factor $Tail^{global}_{t+1}$, and a country-specific component, $Tail^{local}_{k,t+1}$, as follows:

$$Tail_{k,t+1} = \zeta_k Tail^{global}_{t+1} + Tail^{local}_{k,t+1}, \tag{2}$$

where ζ_k is country k's loading on the global tail risk factor.

Assuming complete markets, the log change in the nominal exchange rate between the home country and any foreign country k, Δfx_k, is equal to the difference of the log pricing kernels of the two countries (see, for instance, Backus, Foresi, and Telmer (2001)). That is,

$$\Delta fx_{k,t+1} = m_{t+1} - m_{k,t+1}, \tag{3}$$

[1] $u_{k,t+1}$ and $u_{g,t+1}$ could be any country-specific and global factors that drive currency returns, as indicated in Lustig et al. (2011); however, as our stylized model only serves an illustrative purpose, we use this general specification to include these factors without specifying their fundamental nature.

where m and m_k denote the log nominal SDF of the domestic country and any foreign country k, respectively. The exchange rate is expressed in units of foreign currency per domestic currency; for instance, per U.S. dollars. In the remainder of this paper, we take the perspective of a U.S. investor and regard the U.S. as the home country. To keep the notation simple, we omit the home country subscript j and write the currency rate $fx_{jk,t+1}$ as $fx_{k,t+1}$ when no confusion is caused. Thus, an increase in fx_k denotes an appreciation of the home currency with respect to the foreign currency.

In the model, the log change in excess currency returns is given by

$$\begin{aligned} rx_{k,t+1} =& \Delta fx_{k,t+1} + i_t - i_{k,t} \\ =& a_{k,t} - a_t + \gamma_k u_{k,t+1} - \gamma u_{t+1} + \lambda_k Tail_{k,t+1} - \lambda Tail_{t+1} + (\delta_k - \delta) u_{g,t+1}, \\ =& a_{k,t} - a_t + \underbrace{(\gamma_k u_{k,t+1} + \lambda_k Tail^{local}_{k,t+1})}_{\text{foreign country shocks}} - \underbrace{(\gamma u_{t+1} + \lambda Tail^{local}_{t+1})}_{\text{home country shocks}} \\ & + \underbrace{(\lambda_k \zeta_k - \lambda\zeta) Tail^{global}_{t+1} + (\delta_k - \delta) u_{g,t+1}}_{\text{global shocks}}. \end{aligned} \tag{4}$$

If country-specific shocks for the foreign and the home country are diversifiable, only global shocks will be priced in the cross section of currency returns. Intuitively, if a currency appreciates with respect to the U.S. dollar when the global tail risk increases, this currency is essentially a hedge against global tail risk, which makes the currency more attractive to investors and yields lower expected returns.

Since $Tail^{global}$ is not directly observable empirically, we instead focus on the conditional beta of currency excess return to the domestic tail factor $Tail$, which has a global component. In the model, the corresponding conditional beta of the currency excess return on the U.S. tail-risk factor ($Tail$), $\beta_{Tail,k,t}$, is

$$\beta_{Tail,k,t} = \frac{\mathrm{cov}_t(rx_{k,t+1}, Tail_{t+1})}{\mathrm{var}_t(Tail_{t+1})} = \frac{\zeta(\lambda_k\zeta_k - \lambda\zeta)\mathrm{var}_t(Tail^{global}_{t+1}) - \lambda \mathrm{var}_t(Tail^{local}_{t+1})}{\mathrm{var}_t(Tail_{t+1})}. \tag{5}$$

If the tail risk of the home country, $Tail_t$, is not exposed to the global tail component ($\zeta = 0$ in Equation (2) for the home country), $\beta_{Tail,k,t}$ is equal to $-\lambda$ for all foreign currencies. However, if $\zeta \neq 0$, the conditional beta of foreign currency k varies across currencies for different exposures of the home country's tail factor to the global tail factor, ζ.

Meanwhile, the conditional beta of the currency excess return on the global tail risk factor, $\beta^{global}_{Tail,k,t}$, is

$$\beta^{global}_{Tail,k,t} = \frac{\text{cov}_t(rx_{k,t+1}, Tail^{global}_{t+1})}{\text{var}_t(Tail^{global}_{t+1})} = \frac{(\lambda_i \zeta_i - \lambda\zeta)\text{var}_t(Tail^{global}_{t+1})}{\text{var}_t(Tail^{global}_{t+1})}. \tag{6}$$

Comparing Equation (6) with Equation (5), we can see that sorting currencies by $\beta_{Tail,k,t}$ is equivalent to sorting them by $\beta^{global}_{Tail,k,t}$. Hence, when $\beta^{global}_{Tail,k,t}$ is not observable, $\beta_{Tail,k,t}$ can be used as a proxy for $\beta^{global}_{Tail,k,t}$, as long as $\zeta \neq 0$.

Tail-beta sorted portfolios are useful to extract the global component of any domestic tail risk factor. Specifically, we define the long-short portfolio of buying high tail-beta currencies and shorting low tail-beta currencies as Global Tail,

$$\text{Global Tail}_{t+1} = \frac{1}{N_{H_\beta}} \sum_{k \in H_\beta} rx_k - \frac{1}{N_{L_\beta}} \sum_{k \in L_\beta} rx_k,$$

where N_{H_β} and N_{H_β} denote the number of currencies in the high (H_β) and low (L_β) tail-beta portfolios, respectively. Note that the tail beta given by Equation (6) does not depend on global or country-specific diffusion shocks. Therefore, in the limit when $N \longrightarrow \infty$, the high-beta and low-beta currency baskets are likely to share the same average diffusion exposures as well as country-level tail risks. As a result, the long-short portfolio return is dominated by the global tail risk component. When $N \to \infty$, the global component of the tail risk factor is thus:

$$\lim_{N\to\infty} \text{Global Tail}_{t+1} = (\bar{\beta}_t^{H_\beta} - \bar{\beta}_t^{L_\beta}) Tail_{t+1}^{global}. \tag{7}$$

Therefore, the long-short tail-beta portfolio can isolate the global tail component from the purely country-specific tail risk factor.

An interesting implication of our framework is that the long-short portfolio in Equation (7) can be constructed for currency excess returns expressed in any currency (that is, assuming a different home country). For example, to calculate the global tail factor, we could consider the cross section of currency-m denominated currencies instead of the USD-denominated currencies. In principle, the long-short beta portfolio with any base currency should isolate the global tail factor.

An alternative way of constructing a global tail risk factor in the literature is to aggregate the tail risk factor of individual currencies, such as in Rafferty (2012) and Gao, Lu, and Song (2018). Suppose we are able to extract the tail risk from currency returns. This alternative global tail, denoted as $\overline{\text{Global Tail}}$, is calculated as the sum of tail risk in all currencies:

$$\begin{aligned}\overline{\text{Global Tail}} &\equiv \sum_{k=1}^{n} (\lambda_k Tail_{k,t+1}) - n\lambda Tail_{t+1} \\ &= (\sum_{k=1}^{n} \lambda_k \zeta_k - n\lambda\zeta)(Tail_{t+1}^{global}) + (\sum_{k=1}^{n} \lambda_k - n\lambda)(Tail_{t+1}^{local}).\end{aligned} \tag{8}$$

Unlike our Global Tail factor, which, by construction, has a positive exposure to $Tail^{global}$ at all times, the exposure to $Tail^{global}$ in $\overline{\text{Global Tail}}$, $(\sum_{k=1}^{n} \lambda_k \zeta_k) - n\lambda\zeta$, could be positive, negative, or even null. If any of the parameters λ_k, λ, ζ_k, or ζ is time-varying, whether this exposure is consistently positive or negative cannot be guaranteed. Our Global Tail factor is, therefore, a cleaner measure of $Tail^{global}$ than $\overline{\text{Global Tail}}$.

To sum up, our framework suggests that if the tail factor of the home country has a global component, the conditional exposure (beta) of foreign currency excess returns to this risk factor varies across countries. Moreover, each country's conditional beta can be used as a proxy for the country's currency exposure to the global tail factor, which is unobserved. Therefore, our framework also implies that a long-short tail-beta-sorted currency portfolio has a positive exposure to the global tail factor and can be used as a proxy for the global tail factor.

2.2. The Tail Risk Factor

Our model assumes the existence of a tail risk factor with the potential to contain information about global tail risk in the pricing kernel of each country. In this subsection, we introduce our measure for the tail risk factor. Motivated by the literature providing empirical evidence that exposure to market tail (jump) risk is priced in the cross section of stock returns (see Cremers, Halling, and Weinbaum (2015), Lu and Murray (2018), and Atilgan et al. (2019), among others), our factor is an equity tail factor.

Because large jumps in equity returns are difficult to pin down, as these rarely occur over a finite sample and may suffer from the peso-type problem, we propose an option-implied equity tail risk factor. Specifically, our equity tail risk factor is based on the tail measure proposed by Bollerslev and Todorov (2011), which is calculated from short maturity deep out-of-money options.

The option-implied left jump tail measure in Bollerslev and Todorov (2011), LT^Q, is defined as[2],

$$LT_t^Q(T,k) \equiv \frac{P_t(T,K)}{S_t} \approx \mathbb{E}_t^Q[(k - e^{J_T \Delta N_T})^+], \tag{9}$$

where $P_t(T,K)$ is the price of a deep out-of-the-money put option with strike price K and maturity T, S_t is the current stock price, $k = \frac{K}{e^{i(t,T)}S_t}$ denotes the moneyness of the option, and $J_t \Delta N_t$ represents jumps in the log stock price process. Jumps are the product of J_t, the jump amplitude at time t, and ΔN_t, which equals 1 if a jump occurs and 0 otherwise. As in Bollerslev and Todorov (2011), we assume that, at most, one jump can occur before the option expires. We denote the risk-neutral conditional probability of a jump at time t by q_t; that is,

$$\Delta N_T = \begin{cases} 1 & \text{with probability } q_t \text{ from } t \text{ to } T, \\ 0 & \text{with probability } 1 - q_t \text{ from } t \text{ to } T. \end{cases} \tag{10}$$

Potentially, the jump process, N_t, could be specified as a non-homogeneous Poisson process with intensity ν_t. In that case, q_t is equal to $\nu e^{-\nu}$.

Since the put option would only be in the money if $\Delta N_T = 1$, the left tail measure LT^Q in Equation (9) can be further expressed as

$$LT_t^Q(T,k) = \mathbb{E}_t^Q\left[\mathbb{E}_t^Q[(k - e^{J_T \Delta N_T})^+ | \Delta N_T]\right] = q_t(k - \mathbb{E}_t^Q[e^{J_T}]). \tag{11}$$

The intertemporal capital asset pricing model (ICAPM) of Merton et al. (1973) suggests that risk premia are associated with the conditional covariances between asset returns and innovations in state variables that describe the time-variation of the investment

[2] In an extensive Monte Carlo simulation study designed to investigate the finite sample accuracy of the approximations of LT^Q, Bollerslev and Todorov (2011) show that the error involved in approximating LT^Q through Equation (9) is trivial for options and empirical settings designed to mimic those of the actual data.

opportunities. In the spirit of the ICAPM, if the time-varying left jump tail risk affects investors utility, the change of the left jump tail LT_t^Q in Equation (11) is a potential pricing factor:

$$\Delta LT_{t+1}^Q(T,k) = k(q_{t+1} - q_t) - (q_{t+1}\mathbb{E}_{t+1}^Q[e^{J_T}] - q_t\mathbb{E}_t^Q[e^{J_T}]). \tag{12}$$

This factor captures two important aspects of time-varying jump risk. The first term on the right hand side of Equation 12 is the change in the risk-neutral jump probability—not the jump intensity itself, but the change of the jump intensity.[3] This probability differs from the risk-neutral third moment contributed by jumps in Gao, Lu, and Song (2018) and the systematic jumps in index returns in Begin, Dorion, and Gauthier (2019). The second term on the right hand side of Equation (12) is also related to changes in the expected jump amplitude. If the risk-neutral expectation of jump sizes does not change over time, i.e., $\mathbb{E}_{t+1}^Q[e^{J_T}] = \mathbb{E}_t^Q[e^{J_T}]$, $\Delta LT_{t+1}^Q(T,k)$ only captures changes in jump intensity. Otherwise, it also captures the change in investors' beliefs of the jump magnitude. This feature differentiates our factor from the measure in Lu and Murray (2018), which only depends on the stochastic driver of jump intensity but not on the change in jump sizes.

Notice that ΔLT^Q in Equation (12) is not a traded factor. However, because the price of a short maturity OTM put option is small compared with the index price, $LT_t^Q(T,k)$

[3]Time-varying jump intensity is a well-documented phenomenon in the literature. For example, Bates (1991) finds significant time variation in the conditional expectations of jumps in aggregate stock market returns. Santa-Clara and Yan (2010) and Christoffersen, Jacobs, and Ornthanalai (2012) find substantial time variation in the jump intensity process. Bollerslev and Todorov (2011) show that the shapes of the nonparametrically estimated jump tails vary significantly over time.

is approximately equal to $\log(1 + LT_t^Q(T,k))$, which leads to

$$\begin{aligned}\Delta LT_{t+1}^Q(T,k) &\approx \log(LT_{t+1}^Q(T,k)+1) - \log(LT_t^Q(T,k)+1) \\ &= \log(\frac{P_{t+1}+S_{t+1}}{S_{t+1}}) - \log(\frac{P_t+S_t}{S_t}) \\ &= \log(\frac{P_{t+1}+S_{t+1}}{P_t+S_t}) - \log(\frac{S_{t+1}}{S_t}) \\ &\equiv Tail_{t+1}, \end{aligned} \tag{13}$$

which is our definition of the Tail risk factor. To gain intuition, our tail factor can be considered as the difference between the log returns of the put-protected stock portfolio, which buys the stock and an OTM put option on the stock at the same time, and those of the underlying stock. In other words, the tail factor can be approximately regarded as the log return of a synthetic trading strategy in which the investor invests 1 dollar in the put-option protected underlying index and shorts 1 dollar in the stock index. The Tail factor is positive if the price of the OTM put option increases compared with the underlying index price, which implies increased investors' desire to hedge against large stock price drops within the next month.

3. Data

This section describes the construction of our equity tail factor and the exchange rate data used to calculate currency excess returns.

3.1. Construction of the U.S. Equity Tail Risk Factor

To construct the U.S. equity tail factor introduced in Section 2.2, we obtain historical prices for S&P 500 index options and for the S&P 500 index from the Chicago Board

Options Exchange (CBOE) from 1990 to 2018.[4] To calculate the equity tail factor, we deviate from Bollerslev and Todorov (2011) in two important aspects. First, we only use prices of options that are actually traded. Thus, our measure is not dependent on the particular choice of the interpolation method. Second, our tail factor can be interpreted as the return of a self-financing portfolio. To achieve this, we roll options on the settlement day by considering the payoff of the old option and by buying a new option on that day.[5] On the roll day of each month, which is normally the third Friday of that month, we select a 5% OTM put option with the first available strike price below the 95% of the closing price of the S&P 500 index.[6] We track the price change of that put option until maturity and then roll the option on the roll date in the next month.

Because options' expiration dates are not at the end of each month, we first construct the tail factor at the daily frequency and then convert it to a monthly frequency. On each trading day excluding roll dates, daily $Tail_t$ is calculated as in Equation (13). On the third Friday of every month, the old put option settles and a new 5% OTM monthly put option will be subsequently selected. The Tail factor on roll dates is calculated as:

$$Tail_{t+1} = \log(\frac{P_{t+1,settle} + S_{t+1}}{P_t + S_t}) - \log(\frac{S_{t+1}}{S_t}), \tag{14}$$

where $P_{t+1,settle} = \max(0, K - S_{t+1,settle})$ and $S_{t+1,settle}$ is the settlement value on that day, and we use the closing price of S&P 500 index as the settlement value.

[4]Equity index options in the U.S. have a much longer history than index options in other markets. In particular, while S&P index options began to trade in 1983 and the data are available from 1990 from the CBOE, FTSE 100 index options and EURO STOXX 50 index are available for a shorter sample, starting in 2000 and 2006, respectively.

[5]According to Bollerslev and Todorov (2011), in which no rolling occurs, the price of the put option for the day one week away from settlement is interpolated from option prices that settle next month, while the price of the put option for the previous day is the option price that settles this month.

[6]There is a trade-off between the moneyness and the liquidity of put options. To capture the jumps in equities, deep OTM put options are preferred. However, deep OTM options typically have little trading volume. Therefore, we choose OTM put options with a moneyness of 95%. We have also constructed the Tail factor using 90% moneyness put options as a robustness check for our main empirical findings, and these results are reported in Section 5.3.

Table 1 shows a set of summary statistics for our tail factor. For comparison, we also show summary statistics for a set of U.S. equity- and currency-related factors used throughout the paper. In particular, we calculate the excess return of the S&P 500 index (MKT), monthly innovations in the VIX index (ΔVIX), the dollar risk factor in Lustig et al. (2011) (DOL), the carry trade risk factor in Lustig, Roussanov, and Verdelhan (2011) (CARRY), and the change in volatility of the foreign exchange market (ΔFXvol), which is calculated following Menkhoff, Sarno, Schmeling, and Schrimpf (2012a). All factors are considered at a monthly frequency.

The $Tail$ factor is, on average, negative with mean -0.09%, suggesting that investors are willing to pay a premium to buy the tail factor. Compared with the VIX innovation, the $Tail$ factor has, on average, a less negative mean and lower volatility, but it displays much higher skewness and kurtosis. In panel B of Table 1, we show the correlation among all factors. The tail risk factor is negatively correlated with the excess stock market return (-0.61) and positively correlated with the VIX innovation (0.43). Correlations between $Tail$ and the dollar and carry factors are negative with coefficients -0.29 and 0.16, respectively. Finally, the correlation between $Tail$ and the innovation in currency volatility is relatively small and positive (0.18).

Figure 1 plots the time series of the S&P 500 return and the $Tail$ factor for the sample period running from February 1990 to April 2018. As can be seen from the figure, the $Tail$ factor tends to have extremely positive spikes around episodes of large negative jumps in the time series of S&P 500 returns.

In unreported result, we find evidence that the U.S. tail factor is likely to have a global component that affects the pricing of global equities. In particular, we find that the U.S. equity tail factor significantly predicts aggregate stock market returns for several advanced economies after controlling for the 3-month Treasury bill rate, the log country dividend yield, and the lagged U.S. stock market return. The predictability of U.S. $Tail$

is significant for the following countries' stock returns: the U.S., France, Germany, Japan, the U.K., Switzerland, Italy, and the Netherlands.

3.2. Spot and Forward Exchange Rates

We obtain spot and one-month forward exchange rates with respect to the U.S. dollar from Barclays Bank International (BBI) and WM/Reuters via DataStream. Spot and forward rates used for the empirical exercises are end-of-the-month data and are quoted as foreign currency units per U.S. dollar. Our exchange rate data spans the period from December 1989 to April 2018. The exchange rate database from WM/Reuters only starts in 1993. Therefore, observations for the period before 1993 are obtained from BBI.

Our sample consists of 37 currencies from the following countries (and regions in the case of the euro area): Australia, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, the euro area, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Israel, Japan, Kuwait, Malaysia, Mexico, New Zealand, Norway, the Philippines, Poland, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Sweden, Switzerland, Taiwan, Thailand, and the U.K.. Note that we do not include the 10 countries that adopted the euro in 1999.[7] We remove the rest of the euro-area countries after their adoption of the euro. Following Lustig et al. (2011), we also remove the observations that display large failures of covered interest rate parity: Malaysia from the end of August 1998 to the end of June 2005 and Indonesia from the end of December 2000 to the end of May 2007. We also consider a subsample of currencies that includes only the following developed markets: Australia, Canada, Denmark, the euro area, Hong Kong, Israel, Japan, New Zealand, Norway, Singapore, South Korea, Sweden, Switzer-

[7]These countries are: Austria, Belgium, Finland, France, Germany, Italy, Ireland, the Netherlands, Portugal, and Spain. Because our exchange rate sample starts in 1990 and the sample for our equity tail index starts even later, there are few observations for these countries' currencies after 1990. In addition, these countries' currencies typically comoved greatly before they were officially replaced by the euro.

land, and the U.K.. This reduced sample allows us to assess the robustness of our results to issues like liquidity and tradability.

The monthly excess return for holding foreign currency k, from the perspective of a U.S. investor, is calculated as follows:

$$rx_{k,t} = (i_{k,t-1} - i_{t-1}) - (fx_{k,t} - fx_{k,t-1}) \approx f_{k,t-1} - fx_{k,t}, \tag{15}$$

where f and fx denotes the logarithm of the forward and spot exchange rates, respectively.

4. Evidence for the Relation Between U.S. Tail Risk and the Cross Section of Currency Returns

The model in Section 2 suggests that if the tail factor of the home country has a global component, excess returns of foreign currencies would have different exposures to this tail risk factor. Moreover, the return of a portfolio that is long in the high tail beta currencies and short in the low beta currencies isolates the global component of the home country's tail factor. In this section, we test these implications by considering the U.S. as the home country and using the equity tail factor introduced in Section 2.2 and calculated in Section 3.1.

4.1. Currency Portfolios Sorted by U.S. Tail Exposures

To assess whether the U.S. tail risk is priced in the cross section of currency returns, we sort currencies into five portfolios depending on their lagged U.S. tail betas. To do so, we estimate the following regression for each currency's monthly excess return, rx_i, on the U.S. equity tail factor, Tail, using the following rolling window of 60 months:

$$rx_{i,t} = \alpha_i + \beta_{Dol,i}\text{DOL}_t + \beta_{Mkt,i}\text{MKT}_t + \beta_{Tail,i}\text{Tail}_t + \varepsilon_{i,t}, \tag{16}$$

where we control for the Dollar (DOL) factor and the U.S. stock market return (MKT). The Dollar factor (DOL), proposed by Lustig, Roussanov, and Verdelhan (2011), is the equally-weighted cross-sectional average of foreign currency excess returns with respect to the U.S. Dollar. This factor corresponds to the return of a strategy that borrows money in the U.S. and invests it in global money markets outside of the U.S.. Lustig, Roussanov, and Verdelhan (2011) find that the DOL factor is highly correlated with the first principal component of all currency returns and accounts for a large fraction of the cross-sectional variation in currency excess returns. We include the DOL factor to proxy for the global diffusion shocks, $u_{g,t}$ in Equation (4). MKT is the return of the S&P 500 index, which captures U.S.-specific shocks and serves as a proxy for u_t in Equation (4).

Figure 2 shows the time series of the tail betas for each of the quintile portfolios for all the currencies in the sample and for those of developed markets, in panels A and B, respectively. During almost the whole sample, the bottom quintile portfolio (P1 or tail-prone portfolio) has negative betas, while the top quintile portfolio (P5 or tail-resistant portfolio) has positive betas. The figure shows that there is substantial time variation in all portfolios' tail betas and in the dispersion among the betas of the five portfolios. In particular, soon after the Asian crisis of the late 1990s and the 2008 global financial crisis, the gap between the beta of the lowest quintile portfolio and that of the highest quintile portfolio increases. The increase in the gap during crises suggests that the distinct hedging potential against U.S. equity tail risk of tail-prone and tail-resistant currencies strengthens during market downturns.

Table 2 reports the descriptive statistics of the tail-beta-sorted portfolios. Panel A reports the statistics for all the currencies in our sample. The average excess return shows a decreasing trend from portfolio 1 to portfolio 5. Thus, investing in currencies with high tail betas—those that provide a hedge against U.S. tail risk—yields a significantly lower return than investing in low tail-beta currencies. As a consequence, the high-minus-low portfolio (H-L) yields an average annual return of -4.7%, which is statistically significant at the 5% confidence level, and has a Sharpe ratio as large as -0.7. The return of the H-L portfolio comes from the long component of the portfolio as well as from its short component. The mean excess returns of the long (P5) and short (P1) portfolios are comparable in magnitude, especially for the subsample of developed market currencies. The pre-formation tail betas show a symmetric pattern, with the average beta of portfolio 1 equal to -0.4 and that of portfolio 5 equal to 0.4, suggesting that some currencies co-move with the U.S. equity tail risk while some have hedging potential against this risk.[8]

We separate the currency excess returns into interest rate differentials, or pre-formation forward discount, labeled "pre-FD", and exchange rate returns, labeled "FX return". Both FX return and forward discount display a decreasing trend from portfolio 1 to portfolio 5, suggesting that tail beta is related to both components in currency excess returns. A decreasing forward discount pattern across portfolios suggests that countries in which currencies have high exposure to U.S. tail risk typically have higher interest rates than the U.S., implying that portfolios sorted on tail-beta share some similarities with the carry trade portfolios. The result shows that the spread of the FX returns in the H-L portfolio accounts for more than half of the total returns.

In addition, we observe that the excess return of the portfolio in the pre-formation month (RX(-1,0)) decreases from portfolio 1 to portfolio 5, suggesting that currencies

[8] In unreported results, we calculate cumulative returns for the carry, momentum, and tail strategies, and we find that during the period of 1997-2002 (Asian crisis) and 2008 (global financial crisis), the long-short tail strategy accumulates large positive returns, as opposed to the decrease in carry and momentum returns, which suggests that the long-short tail-beta-sorted portfolio return is countercyclical.

with low tail beta coincide with the "winner" currencies in the momentum portfolio. Hence, our results indicate that U.S. equity tail-beta sorted portfolios bear both features of carry and momentum portfolios.

Panel B of Table 2 reports the descriptive statistics for the subsample of currencies from developed markets. For this subsample of currencies, the high-minus-low tail-beta portfolio yields a significant annual return of -4.6%. The Sharpe ratio for this portfolio is -0.56. The results show that the tail-beta anomaly is robust when we only consider developed markets, suggesting that our results are not driven by currencies in emerging markets and their associated sovereign risks.

We explore two robustness checks for our empirical results thus far. First, because the U.S. equity tail factor is constructed from OTM put returns, it contains information about both volatility and jump risk. As shown in Andersen, Bondarenko, Todorov, and Tauchen (2015), short-maturity deep OTM put options load mostly on negative jumps and have hardly any exposure to the diffusive volatility. However, the U.S. tail factor might still be partially attributed to equity volatility risk. In fact, Lustig et al. (2011) show that the equity volatility risk factor has explanatory power for the cross section of currency excess returns. To address this issue, we add the innovation of the VIX index, ΔVIX, to the individual currency regressions to control for their exposures to volatility risk. We run the following regression:

$$rx_{i,t} = \alpha_i + \beta_{Dol,i}\mathrm{DOL}_t + \beta_{Mkt,i}\mathrm{MKT}_t + \beta_{\mathrm{VIX},i}\Delta\mathrm{VIX}_t + \beta_{Tail,i}\mathrm{Tail}_t + \varepsilon_{i,t}. \tag{17}$$

Then, we follow the same procedure as in the benchmark results and sort currency excess returns into five quintiles according to the estimated regression coefficient $\hat{\beta}_{Tail,i}$. Table A1 shows the statistics of these portfolios when we use the sample of all currencies. The high-minus-low (H-L) returns remain significantly negative with substantial contribution from exchange rate changes. The Sharpe ratios of this tail-beta sorting strategy are only slightly smaller in magnitude than those reported in Table 2.

Second, one may argue that, to capture the jump risk with large magnitude, we could construct the U.S. tail factor using put options with moneyness deeper than 95%. In Table A2, we use put options with moneyness 90% to construct the tail factor. To do so, we follow the same methodology as in Section 3.1 but, on the roll day each month, we select one short-maturity put option with moneyness smaller than 95% and closest to 90%. Compared with 95% put options, 90% put options have less open interest and less trading volume. Table A2 reports the beta-sorted portfolios with respect to this alternative tail factor. As in the benchmark results, average currency portfolio returns decrease from portfolio 1 to portfolio 5, and the long-short strategy results in a significantly negative annualized return of -4.05% and a Sharpe ratio of -0.6.

4.2. Economic Determinants of Tail Betas

To further understand the heterogeneity in currencies' exposures to U.S. tail risk, we explore the potential drivers of tail betas. In particular, we consider the following five hypotheses inspired by the literature. First, countries with tail-resistant currencies may be larger in economic capacity than those with tail-prone currencies, as they are better hedges against consumption risk. Following Hassan (2013), we use each country's GDP share of the aggregate GDP for all countries in the sample to characterize the country's relative size (source: IMF). Second, tail-prone currencies are likely to be commodity currencies, which typically appreciate in "good" times and depreciate in "bad" times. To measure the extent to which a currency is a commodity currency, we consider the basic export ratio, which is calculated as the ratio of net exports of basic goods minus net exports of complex goods to total trade (source: Wharton Research Data Service (WRDS), kindly provided by the authors of Ready et al. (2017)). Third, countries with tail-prone currencies might have high international currency exposure. We use the measure of aggregate foreign currency exposure (FXAGG) in Bénétrix et al. (2015), which is defined as

$$\text{FXAGG}_{i,t} = \omega_{i,t}^{A} s_{i,t}^{A} - \omega_{i,t}^{L} s_{i,t}^{L}, \tag{18}$$

where $\omega_{i,t}^{A}$ ($\omega_{i,t}^{L}$) is the share of foreign assets (liabilities) denominated in foreign currencies, $s_{i,t}^{A}$ ($s_{i,t}^{L}$) is the share of foreign assets (liabilities) in the sum of foreign assets and foreign liabilities (source: Philip Lane's website). Fourth, countries that are more central in the global trade network might be more resistant to U.S. tail risk. To account for this, we include the measure of trade network centrality suggested by Richmond (2019), which is defined as the export-share-weighted average of bilateral trade intensities (source: Robert Richmond's website). Finally, high-inflation currencies might have larger tail beta. Londono and Zhou (2017) find that high-inflation currencies depreciate more than low-inflation currencies following an increase in the world currency variance risk premium. Inflation data, calculated as the percentage change in CPI, is obtained from the World Economic Outlook database.

Table 3 presents panel regression results of currency tail betas on the potential explanatory variables. All specifications include time fixed effects. The data sample for this table is smaller than in all other tables because we merge datasets from various sources, as discussed above. The final sample consists of 22 currencies, 12 of which are from developed markets and 10 from emerging markets, from 1999 to 2012. The results for the full sample of currencies show that currencies in countries with lower basic export ratio; that is, those that specialize in producing final goods instead of basic goods, are more resistant to U.S. tail risk. Currencies in countries with higher international currency exposure (FXAGG) are significantly more prone to U.S. tail risk. Trade network centrality is also a significant driver of heterogeneity in currencies' exposures to U.S. tail risk. In particular, a one-standard-deviation increase in trade network centrality significantly increases a country's currency tail beta by 0.48. Inflation and country size (GDP share) are not significant drivers of the heterogeneity in the exposures to U.S. tail risk.

The developed market sample shows similar results: basic export ratio and FXAGG significantly explain tail betas with negative signs, while centrality significantly explains tail betas with a positive sign. By contrast, only centrality can significantly explain tail betas in the emerging market currencies. One possible explanation for this result is that emerging countries are not well integrated into the global financial market.

4.3. Can FX Factors Explain the Tail-Beta Sorted Portfolios?

Next, we explore how the tail-beta sorted portfolios are related to well-established common factors in currency markets. To do so, we regress the returns of each portfolio on the Dollar and FX volatility factors. The FX volatility factor proposed by Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) is the equally-weighted cross-sectional average of the realized volatility of foreign currency excess returns with respect to the U.S. Dollar. The Dollar and FX volatility factors can be regarded as measures associated with the first- and second-order moments of global currency returns.

We run time-series regressions of the excess returns of each tail-beta portfolio, $p_{j,t}$, on the Dollar factor (DOL) and the innovation of the FX volatility factor (ΔFXvol), as follows:

$$p_{j,t} = \alpha_j + \beta_{1,j}\text{DOL}_t + \beta_{2,j}\Delta\text{FXvol}_t + \epsilon_{j,t}. \tag{19}$$

The regression results are reported in Table 4. Whether we consider portfolios constructed from all currencies or those from developed markets (Panels A and B, respectively), the coefficients associated with ΔFXvol or DOL do not exhibit monotonic trends. For both samples of currencies, $\hat{\alpha}_j$'s display a decreasing pattern from portfolio 1 to portfolio 5, indicating that the difference in excess returns across portfolios is not explained by these two currency factors. In addition, the $\hat{\alpha}_j$'s of the high-minus-low portfolios are negative and statistically significant. The tail-beta sorting strategy generates an annual alpha of -4.8% and -4.6% for the sample with all currencies and for that with only developed markets, respectively, both statistically significant. While the currency factors explain a good amount of the time-series variation for each portfolio, they hardly capture any time series variation in the high-minus-low portfolios, with a 1.9% R^2 for the sample with all currencies and a 1.2% R^2 for the sample with only developed markets. Our results then demonstrate that the dollar and the FX volatility factors cannot explain the cross section of tail-beta sorted portfolios.[9]

4.4. Alternative Reference Currencies

The intuition from the model in Section 2 suggests that if the tail factor of the home country has a global component, the tail-beta-sorted portfolios uncover that global component even if the cross section of currencies are not denominated in the home currency. We estimate the tail beta in the cross section of pound-denominated or yen-denominated currency returns and sort the currencies into five quintiles. The results are shown in Tables A3 and A4 for the pound and the yen, respectively. The results from the point of view of a U.S. investor remain robust if we consider other reference currencies. That is, the return of the H-L portfolio is negative and significant for both reference currencies, and these results hold when we consider the full sample and that with only the currencies of developed markets.

[9] In unreported results, we find that the dollar and carry factors cannot explain a large portion of the cross section of tail-beta sorted portfolios either.

Table A5 reports the correlation matrix of tail-beta-sorted long short returns constructed from different base currencies for the full sample (Panel A) and the developed-market sample (Panel B). Tail-beta-sorted return spreads are highly correlated among different base currencies, irrespective of the sample of currencies. In both the all-currency sample or the developed-market sample, the pairwise correlation of the Global Tail factor for the different base currencies is around 0.9 and can be as high as 0.99. This table shows that the construction of the Global Tail factor is robust to the choice of the home currency. In the remainder of the paper, we consider the Global Tail Factor constructed from the cross section of currency returns with the U.S. as the home currency.

5. The Price of Global Tail Risk in the Cross Section of Currency Excess Returns

As shown in Section 2, a long-short portfolio that buys currencies with high U.S. equity tail beta and shorts those with low tail beta extracts the global component embedded in the U.S. tail risk. In this section, we test the asset pricing performance of this novel global tail risk factor in the cross section of currency excess returns; in particular, its ability to explain carry and momentum currency portfolios.

5.1. Carry and Momentum Portfolios

We construct five monthly rebalanced carry trade portfolios following Lustig, Roussanov, and Verdelhan (2011) and other studies in the recent currency literature.[10] At the end of each month, we sort the currencies in our sample into five portfolios based on their forward discount rates; that is, the differences between the forward FX rate and the

[10] See, for instance, Bakshi and Panayotov (2013), Daniel et al. (2017), and Bekaert and Panayotov (2019).

spot FX rate. Sorting on forward discount rates is equivalent to sorting on interest rate differentials since covered interest parity holds closely, as shown by Akram et al. (2008), among others. Portfolio 1 contains the bottom quintile of currencies with the lowest interest rate differentials relative to the U.S. and portfolio 5 contains the top quintile of currencies with the highest interest rate differentials. The high-minus-low return of the carry portfolios is referred to as the CARRY factor in the literature, and it corresponds to borrowing in the money markets of low interest rate countries and investing it in the money markets of high interest rate countries.

Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) find that currencies with higher returns in the past month have, on average, higher returns in the next month(s). Following this intuition, we construct five momentum portfolios by sorting the currencies in our sample based on one-month-lagged excess returns. We assign the bottom 20% of all currencies with the lowest lagged excess returns to portfolio 1 (loser portfolio) and the top 20% of all currencies with the highest lagged excess returns to portfolio 5 (winner portfolio).

We present the summary statistics of the carry and momentum portfolios, in panels A and B, respectively, for all the currencies in our sample in Table 5. As shown in panel A and consistent with previous studies (e.g., Burnside et al. (2011), Lustig et al. (2011), among others), the carry strategy delivers a sizable average excess return of 6.6% annually, with a Sharpe ratio of 0.76. Average returns monotonically increase when moving from portfolio 1 to portfolio 5. The carry returns are skewed to the left, suggesting the presence of crash scenarios in this strategy. As shown in panel B and consistent with the evidence in Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) and Filippou and Taylor (2017), the momentum strategy in the all currencies universe also generates considerable excess returns of 7.6% per year.

5.2. Explaining Carry and Momentum Portfolio Returns Using the Global Tail Factor

As suggested in the literature (see, for instance, Verdelhan (2018)), carry returns are mainly exposed to global shocks rather than to country-specific shocks. Moreover, inspired by the evidence in Table 2, which shows that portfolios with high tail risk beta have low interest rate differentials and low currency returns in the past month, we conjecture that the global component of the U.S. tail risk factor might help us understand the risk-return profile of carry trade and momentum strategies in the currency market.

We test the pricing power of the tail-beta-sorted return spread or Global Tail for the cross-section of carry and momentum portfolios. We run the standard two-stage Fama-MacBeth regression. In the first stage, we run the following time-series regression of the excess returns of each currency portfolio, p_i:

$$p_{i,t} = \alpha_i + \beta_{Dol,p_i}\text{DOL}_t + \beta_{GTail,p_i}\text{Global Tail}_t + \varepsilon_{i,t}, \tag{20}$$

where "Global Tail" is the H-L return of the tail-beta sorted portfolios. We control for DOL, the dollar risk factor, following standard practice.

Having obtained estimates of the coefficients associated with the dollar factor and Global Tail, $\hat{\beta}_{Dol,p_i}$ and $\hat{\beta}_{GTail,p_i}$, respectively, in a second stage, we run the following cross-sectional regression:

$$\bar{p}_i = \hat{\beta}_{Dol,p_i}\lambda_{Dol} + \hat{\beta}_{GTail,p_i}\lambda_{GTail} + \eta_i, \tag{21}$$

where the dependent variable $\bar{p}_i$ is the time-series average of the excess return of portfolio i; the first stage estimators, $\hat{\beta}_{Dol,p_i}$ and $\hat{\beta}_{GTail,i}$ are used as explanatory variables; λ_{Dol} and λ_{GTail} are the risk prices of the dollar and tail factors, respectively; and η_i is the pricing error of portfolio i. Following Lettau et al. (2014), we calculate the cross-section R^2 as:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} \hat{\eta}_i^2}{\sum_{i=1}^{N} \bar{p}_i^2}. \tag{22}$$

After estimating the parameters from the second-stage regression, we calculate the model-predicted excess return as $\hat{\bar{p}}_i = \hat{\beta}_{Dol,p_i}\hat{\lambda}_{Dol} + \hat{\beta}_{GTail,p_i}\hat{\lambda}_{Tail}$ and the root mean squared error (RMSE) as $\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\bar{p}_{i,t} - \hat{\bar{p}}_{i,t})^2}$.

To compare the relative cross-sectional pricing performance of a specification with the dollar and global tail factors, we also consider a CAPM, a downside risk CAPM (DR-CAPM), and a FX factor model. Following Lettau et al. (2014), we define the DR factor as the market excess return when this return is one standard deviation below its mean. We implement the DR-CAPM estimation as in Lettau et al. (2014).[11] Following Menkhoff et al. (2016), we include DOL and ΔFXvol in the FX factor model.[12]

Table 6 reports the results for the second-stage Fama-Macbeth regressions for carry and momentum portfolios, in panels A and B, respectively. Note that since we do not include a constant in the second-stage cross-sectional regressions, R^2s can become negative for badly fitted models. We find that the CAPM model and the DOL model fail to explain the cross section of carry or momentum returns with insignificant prices of market risk and low R^2. Turning to the DR-CAPM model, contrary to the theoretical prediction that the price of downside risk should be positive, we find a negative price of downside risk when pricing both carry and momentum portfolios. Interestingly, however, when we use the same sample as in Lettau et al. (2014); that is, from January 1974 to March 2010, we are able to replicate their findings for the positive and significant price of downside

[11]Note that since the price of market risk is restricted to be equal to its sample average, as in Lettau et al. (2014), the estimates of the price of market risk do not have standard errors.

[12]As Lewellen, Nagel, and Shanken (2010) point out, a majority of the time series and cross sectional variation of carry portfolios can be mechanically explained by the carry factor. Hence, we do not consider the carry factor as an explanatory variable.

risk.[13] The FX model gives the best performance among all four models considered in pricing the carry portfolios. It is also the second best with respect to cross-section fit of the momentum portfolios. Nevertheless, the estimated price of risk for ΔFXvol in the momentum portfolios is significantly positive, as opposed to the negative value in the carry portfolios.

In the model with the dollar and global tail risk factors, the price of Global Tail is significantly negative in both carry and momentum portfolios. This result is consistent with the theoretical prediction and with the negative average return of tail-beta-sorted portfolios reported in Section 4.1. Compared with the regression using DOL alone (third column), we find that adding the Global Tail factor increases the cross-section pricing performance substantially. Thus, the cross-sectional explanatory power of our model can be attributed almost exclusively to the Global Tail factor.

While there are many studies that manage to explain the cross section of carry and momentum portfolios separately, relatively fewer models successfully capture the joint cross section of carry and momentum portfolios. In Table 7, we further investigate the pricing performance of the Global Tail factor in the joint cross section of currency carry and momentum portfolios. We show that our model achieves the highest R^2 and the lowest RMSE among its competitors. Similar to the results in Table 6, estimated risk premiums for Global Tail are negative and highly statistically significant. This result is an important achievement of our model, as factors that are priced in portfolios sorted by a single characteristic do not necessarily explain joint portfolios. For instance, the FX model, which performs well in pricing the carry portfolios, hardly explains any variation when considering carry and momentum portfolios jointly.

Figure 3 plots the model predicted returns against the sample returns for the joint

[13] The downside risk, which is the truncated stock market return, is pro-cyclical by construction and should earn a positive risk premium. In contrast, the global tail risk factor spikes during economic downturns and drops in economic booms and should, therefore, have a negative price of risk.

cross-section of carry and momentum portfolios. The left panel shows the asset pricing performance for the FX factor model (DOL+ΔFXvol), while the right panel shows the performance of our model (DOL+Global Tail). As can be seen in the left panel, the momentum portfolios even display a slightly negative relation between fitted and realized excess returns for the FX model. Since the price of risk of ΔFXvol in carry and momentum portfolios have opposite signs, when we try to jointly explain carry and momentum portfolios, the FX model under-prices the carry portfolios to adapt to the momentum portfolios. In contrast, the consistency of the negative prices of risk of the Global Tail factor in carry and momentum portfolios guarantees the fit of the model with Global Tail in the joint cross section of carry and momentum. Indeed, as we observe in the right panel of Figure 3, all carry and momentum portfolios lie around the 45-degree line, with visibly fewer outliers than those in the FX panel.

The asset pricing results in this section shed new light to understand currency anomalies; in particular, carry and momentum strategies. Existing literature relates carry returns to individual currency's crash risk. The hypothesis is that higher interest rate currencies are more likely to crash and they are compensated for higher risk premium. However, the empirical evidence in the literature is mixed. Burnside et al. (2011) find that most of the carry returns are gone once we hedge the crash risk in individual currencies, while Jurek (2014) finds that currency-level crash risk only accounts for a small fraction of carry returns using similar methodology. We argue that exposure to the global tail risk is a potential explanation for currency anomalies. For instance, higher interest rate currencies provide investors with higher returns because they have larger exposure to the global tail risk.

5.3. Robustness Tests for Asset Pricing Tests

We now conduct a series of robustness tests for the results on the pricing of the Global Tail risk. First, to assess the additional explanatory power of Global Tail for currency returns, we consider the following control risk factors: the carry trade risk factor (CARRY) in Lustig et al. (2011), the innovations in global FX volatility (ΔFXvol) in Menkhoff et al. (2012a), the innovations in the index of global ex ante tail risk concerns (ΔGRIX) in Gao et al. (2018), the dollar carry in Lustig et al. (2014), and the global Dollar in Verdelhan (2018). CARRY and ΔFXvol are factors shown in the literature to explain the cross-section of currency carry returns. ΔGRIX is the option-implied global tail risk concerns constructed across different asset classes, which shares similar economic information as our Global Tail factor. We include the Dollar carry to capture U.S.-specific business cycle variations. We also include the Global Dollar to capture the global aspect of the Dollar factor, which may have substitutionary or complementary information to our Global Tail factor. Lastly, we consider ΔVIX, the change in S&P 500 option-implied volatility, to control for the explanatory power of equity volatility risk.

We run the Fama-Macbeth regression with the aforementioned factors as control variables, one at a time, with the joint cross-section of 12 carry and momentum portfolios as test assets, and the results are summarized in Table 8. The estimates of the price of risk of the Global Tail factor are negative and highly statistically significant irrespective of the control variable and range from -2.05 to -2.52. The regressions with CARRY or Dollar Carry as additional factors explain the highest variation in the cross section of carry and momentum portfolios, with an R^2 of 83% and 85%, respectively. In addition, CARRY and Dollar Carry are the only two significant variables in the regression across all control variables considered. Interestingly, the price of risk for ΔFXvol changes from the statistically significant value reported in Table 7 to insignificant when considered jointly with Global Tail. Moreover, The FX model with DOL and ΔFXvol delivers a cross sectional R^2 of -10% in Table 7, which increases to 80% after adding the Global Tail factor.

Second, to alleviate the concern that there are too few portfolios in the asset pricing tests in the FX market (see Lewellen et al. (2010)), we also consider 12 portfolios for each strategy—6 portfolios constructed from all currencies including the long-short portfolio and 6 portfolios constructed from developed-market currencies. Tables A6 and A7 report the regression results including developed market currency portfolios as test assets. In line with the results in Tables 6 and 7, the estimated risk premiums for Global Tail are negative and highly statistically significant. Moreover, our model achieves the highest R^2 and the lowest RMSE among its competitors when pricing momentum and the joint cross-section of carry and momentum portfolios.

Furthermore, to improve the power of the asset pricing tests, we include the 12 Tail-beta-sorted portfolios constructed from the full sample and developed-market sample in addition to the carry and momentum portfolios. Table A8 reports the pricing results of our model and the competing models for the extended set of test assets. The significance of the Global Tail factor remains.

Third, following the intuition in Lewellen et al. (2010), we impose restrictions on the risk premia. Specifically, in Table A9, we report the pricing results of our model and the competing models with the restriction that the price of global tail risk λ_{Gtail} is equal to the sample mean of the global tail risk factor, -0.39. In this case, the estimator $\hat{\lambda}_{Gtail}$ does not have a standard error. We use the dollar factor, ΔFXvol, and Global Tail as explanatory variables. Restricting the price of global tail risk produces conservative estimates of cross-sectional fitness, compared to the estimation without restrictions. However, comparing Table A9 with Table 6 and Table 7, we observe that the R^2 increases after adding Global tail with the parameter restriction. For instance, the R^2 of the DOL+ΔFXvol model is 6.6% when explaining carry and momentum portfolios jointly (see Table A7), and it increases to 37.56% after adding Global Tail with the parameter restriction. Overall, the results in Table A9 show that the Global Tail factor provides explanatory power in addition to ΔFXvol after restricting the price of Global Tail risk.

6. Conclusion

This paper studies the pricing of U.S. equity tail risk in the cross section of currency returns. Our work sheds light on the pricing of global risk factors in currency markets and, more specifically, on the relation between sources of tail risk emanating from stock markets and their pricing implications for currencies.

We find that the U.S. tail risk factor bears a negative price of risk: Currencies with higher exposure to U.S. tail risk have significantly lower returns than currencies with lower exposure to this factor. In a reduced-form model, we show that the U.S. tail risk factor is priced in the cross section of currency returns when it has a global component. We also show that the return of a portfolio that buys high tail-beta currencies and shorts low tail-beta currencies can isolate the global component of the U.S. tail risk factor. We refer to this return spread as Global Tail risk. Empirically, this global factor can simultaneously explain a large portion of the cross section of carry and momentum returns and outperforms other popular models.

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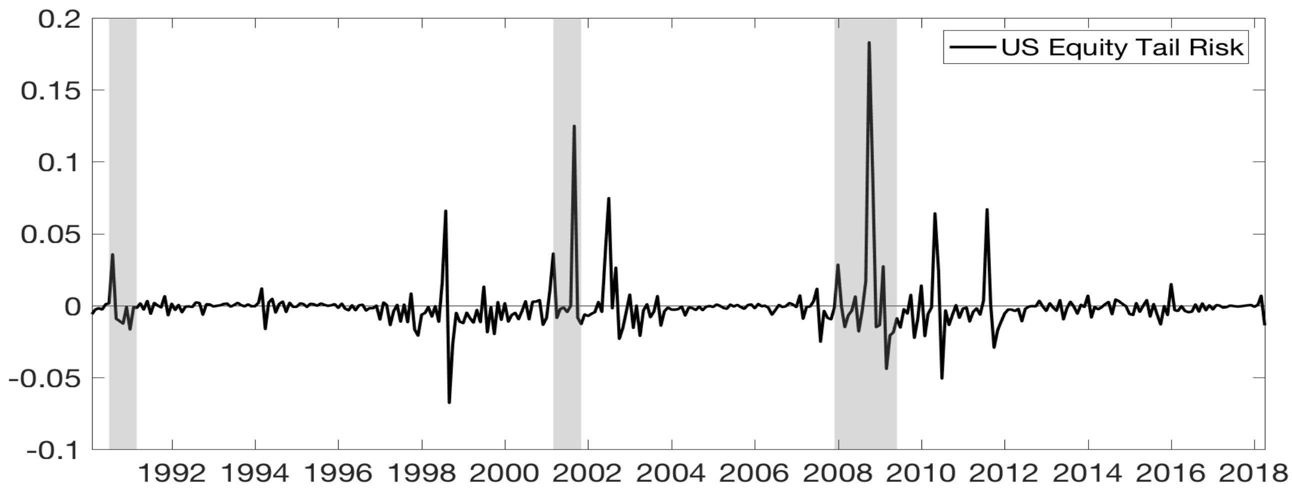
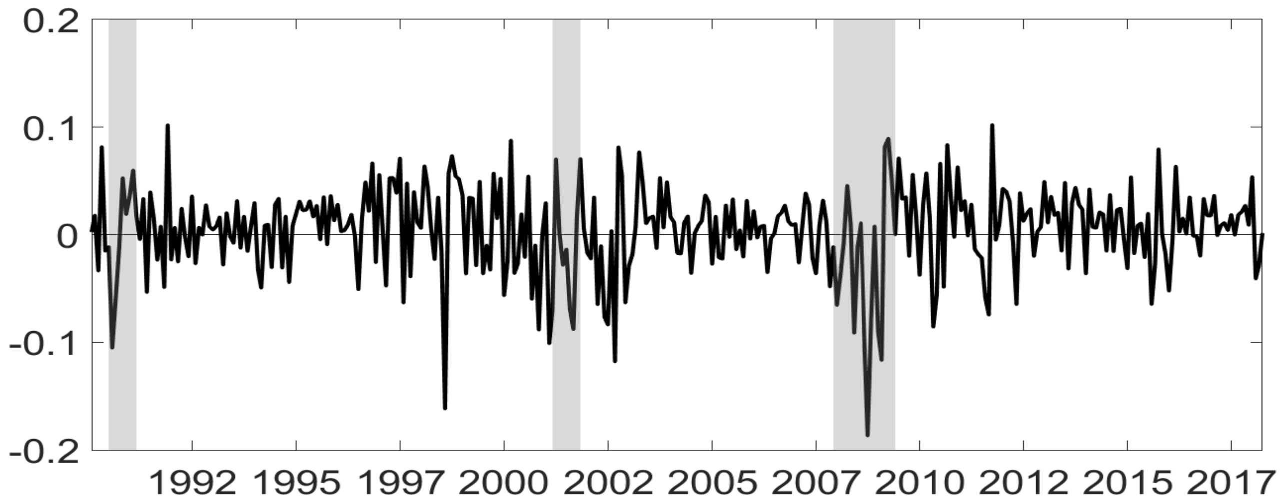
Figure 1: Time Series of the U.S. Equity Tail Risk Factor and S&P 500 Returns

A. U.S. Equity Tail Risk



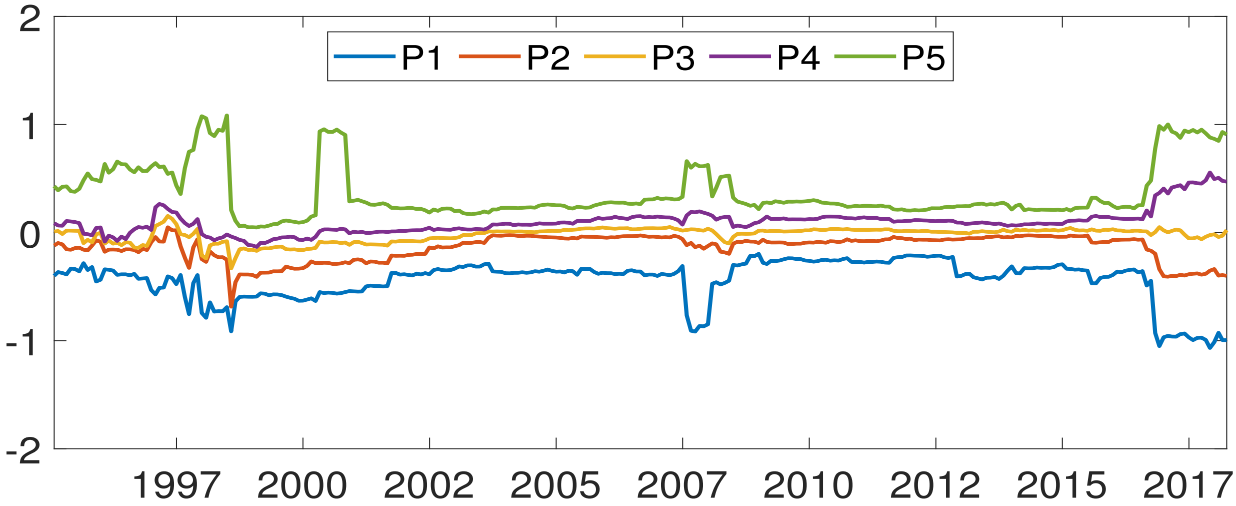
B. S&P 500 Index Return



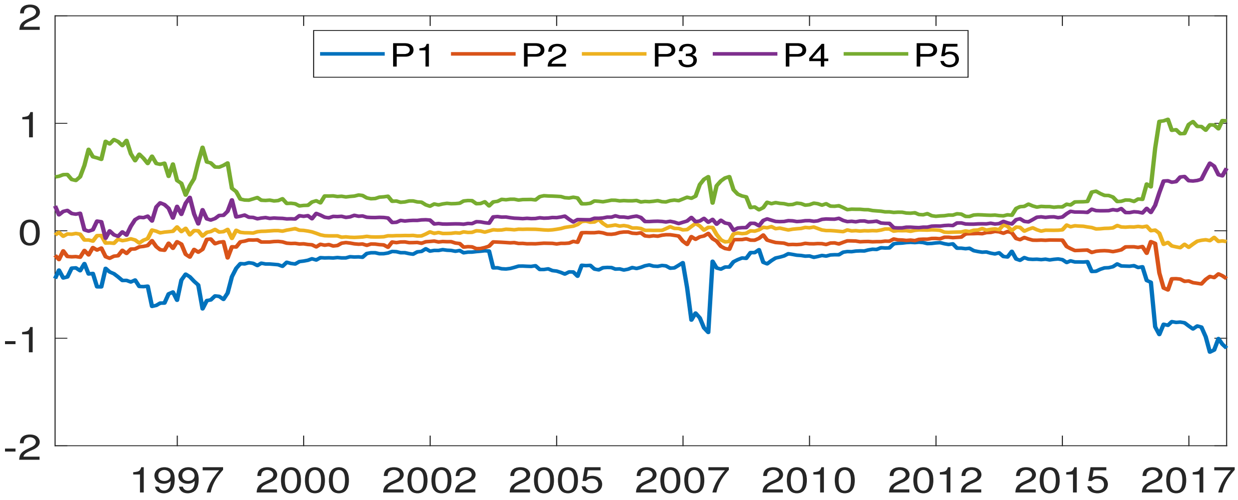
This figure shows time series of the U.S. equity tail risk factor and the S&P 500 index returns from February 1990 to April 2018 in Panels A and Panel B, respectively. The details of constructing the tail factor is provided in Section 3.1. The grey-shaded areas indicate NBER recession periods for the U.S..

Figure 2: Time Series Betas of the Five Tail-beta-sorted Portfolios

A. All Currencies

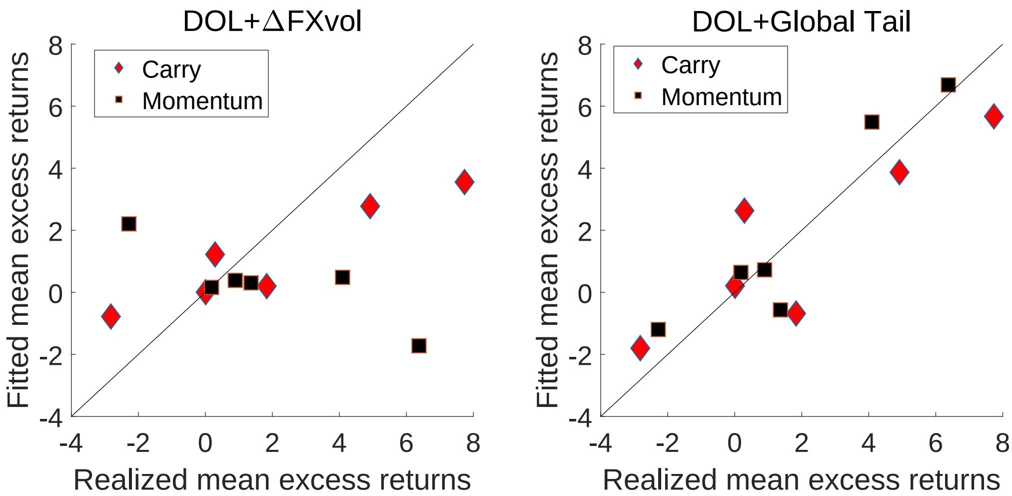


B. DM Currencies



This figure shows the time series of the tail betas for the five tail-beta-sorted currency portfolios in case of all currencies (a) and DM currencies (b). The tail betas are estimated using the following regression: $rx_{i,t} = \alpha_i + \beta_{Mkt,i}\text{MKT}_t + \beta_{Dol,i}\text{Dol}_t + \beta_{Tail,i}\text{Tail}_t + \varepsilon_{i,t}$, where $rx_{i,t}$ is the excess return of currency i over month t, Dol_t is the dollar factor, MKT_t is the diffusion component of market return, proxied by the Put-protected return of the S&P 500 index over the same period, and $Tail$ is the U.S. equity tail factor (see figure 1). The regressions are estimated using 60-month rolling windows in the pre-formation period. The sample period runs from February 1995 to April 2018.

Figure 3: Currency Portfolio Returns, Cross-sectional Model Performances



This figure shows scattered plots of realized annualized mean excess returns against the fitted excess returns, in percent, for the FX factor model (FX) on the left panel and our model (Global Tail) on the right panel. Test assets are the cross section of 6 carry portfolios in the upper row and the cross section of 6 momentum portfolios in the bottom row. For either portfolio style, we also include the return of the H-L portfolio. The sample period runs from February 1995 to April 2018.

Table 1: Summary Statistics

Panel A: Summary Statistics (in percent)

	Tail	MKT	ΔVIX	DOL	CARRY	ΔFXvol
Mean	-0.09	0.39	-0.36	0.11	0.78	-0.05
SD	1.79	4.11	18.32	1.99	2.54	9.96
Skew	5.03	-0.80	0.55	-0.61	-0.38	0.96
Kurt	45.59	4.88	4.46	4.60	4.34	7.67
Q5	-6.78	-18.66	-48.60	-7.85	-8.61	-34.39
Q95	-3.35	-11.69	-40.11	-6.25	-6.59	-24.08
AC	0.18	0.05	-0.19	0.13	0.21	-0.31

Panel B: Correlation Matrix

	Tail	MKT	ΔVIX	DOL	CARRY	ΔFXvol
Tail	1	-0.61	0.43	-0.29	-0.16	0.18
MKT		1	-0.64	0.33	0.21	-0.19
ΔVIX			1	-0.21	-0.22	0.22
DOL				1	0.34	-0.21
CARRY					1	-0.34
ΔFXvol						1

This table reports summary statistics (Panel A) and correlation matrix (Panel B) for a set of U.S. equity- and currency-related factors. Summary statistics include mean, standard errors (SD), skewness (Skew), Kurtosis (Kurt), 5th percentile (Q5), 95th percentile (Q95) and autocorrelation (AC). The details of constructing the tail factor (Tail) is provided in Section 3.1. MKT is the excess return of the S&P 500 index, which is calculated as $\text{MKT}_t = \log(\text{SPX}_t) - \log(\text{SPX}_{t-1}) - i_{t-1}$, where i_{t-1} is the continuous compounded risk free rate effective from $t-1$ to t. ΔVIX is the log change of the CBOE VIX index. DOL is the dollar risk factor in Lustig et al. (2011), which is calculated as the average excess return of a set of foreign currency portfolios. CARRY is the carry trade risk factor in Lustig et al. (2011), which is calculated as the high minus low return spread of the currency portfolios sorted by forward discount. ΔFXvol is the logarithm change of volatility in the foreign exchange market, constructed following Menkhoff et al. (2012a). All factors are at the monthly frequency. The sample runs from January 1990 to April 2018.

Table 2: Tail-beta-sorted Currency Portfolios (U.S. Investor)

Panel A: All Currencies							
Portfolio	1	2	3	4	5	Average	H-L
Mean	2.78	0.02	0.55	1.39	-1.95	0.56	-4.73***
	(1.63)	(0.01)	(0.44)	(0.95)	(-1.08)	(0.41)	(-3.39)
Std. Dev.	8.23	7.39	6.00	7.03	8.72	6.54	6.73
Skew	-0.16	-0.54	-1.00	-0.14	-0.43	-0.45	-0.03
Kurt	3.47	5.01	7.31	4.89	4.99	4.60	3.66
SR	0.34	0.00	0.09	0.20	-0.22	0.09	-0.70
AC	0.11	0.08	0.00	-0.02	0.08	0.07	0.12
Pre-FD	2.96	1.85	1.03	0.67	1.30	1.56	-1.66
Pre-β	-0.44	-0.14	-0.02	0.10	0.37	-0.03	0.81
FX return	-0.18	-1.83	-0.47	0.72	-3.25	-1.00	-3.07
RX(-1,0)	2.62	1.70	-0.34	1.59	-2.23	0.67	-4.85

Panel B: DM Currencies							
Portfolio	1	2	3	4	5	Average	H-L
Mean	2.02	0.77	-0.57	0.41	-2.54	0.02	-4.57***
	(1.20)	(0.43)	(-0.39)	(0.24)	(-1.37)	(0.01)	(-2.70)
Std. Dev.	8.15	8.56	7.16	8.29	8.94	7.02	8.16
Skew	-0.16	-0.26	-0.45	0.00	-0.15	-0.18	0.60
Kurt	3.29	5.85	6.34	3.25	5.65	4.10	5.90
SR	0.25	0.09	-0.08	0.05	-0.28	0.00	-0.56
AC	0.08	0.03	0.00	-0.04	0.08	0.05	-0.01
Pre-FD	0.89	0.12	-0.25	-0.46	-0.44	-0.03	-1.32
Pre-β	-0.35	-0.13	-0.01	0.13	0.36	0.00	0.72
FX return	1.13	0.65	-0.32	0.87	-2.11	0.05	-3.24
RX(-1,0)	2.29	0.03	0.72	0.10	-2.49	0.13	-4.78

This table reports excess returns of the tail-beta-sorted portfolios for all currencies (Panel A) and for the subsample of currencies from developed markets (Panel B) from the point of view of a U.S. investor. We first estimate $\beta_{Tail,i}$ for each currency i in the regression in Equation (16) using a rolling window of 60 months. Then, we sort currencies into five portfolios based on their estimated $\beta_{Tail,i}$. For each portfolio j (j = 1,..., 5, Average, and H-L), we report the mean excess return in the next month, the t-statistics (in parenthesis), standard deviation (Std. Dev), skewness, kurtosis, the Sharpe ratio (SR), the autocorrelation coefficient (AC), the mean return of the spot exchange rate (FX return), the pre-formation forward discount (Pre-FD), the pre-formation $\beta_{Tail,i}$ (Pre-β), and the excess return in the pre-formation period ($RX(-1,0)$). All moments are annualized and reported in percentage points. *, **, and *** represent 10%, 5%, and 1% significance levels. The sample period runs from February 1995 to April 2018.

Table 3: Explanatory Regressions for U.S. Tail Betas

	Full Sample	DM Currencies	EM Currencies
Intercept	0.051	0.095*	-0.428*
	(0.59)	(1.67)	(-1.83)
GDP Share	-0.086	0.137	-22.837
	(-0.06)	(0.21)	(-1.30)
Basic Export Ratio	-0.218**	-0.198***	0.110
	(-2.14)	(-3.40)	(0.25)
FXAGG	-1.141*	-0.465**	-1.783
	(-1.95)	(-2.46)	(-1.58)
Centrality	0.480**	0.159*	0.166***
	(2.42)	(1.79)	(2.70)
Inflation	-0.007	-0.011	0.038
	(-0.38)	(-0.76)	(0.81)
No. of Countries	22	12	10
No. of Obs.	3216	1939	1277
Adj. R^2	0.182	0.155	0.297
Time FE	Yes	Yes	Yes

This table reports regression results of U.S. tail beta on several explanatory variables for the full sample, the developed market (DM) sample and the emerging market (EM) sample. U.S. tail betas are estimated from regression (eq: reg) in Section 4.1. GDP share is the share of world GDP for each country, where world GDP is the total GDP of all available countries in the sample for that year. Basic export ratio is calculated as (Net exports of Basic Goods Net exports of Complex Goods)/Total Trade, where total trade is the sum of the country's imports and exports for all goods. FXAGG is a measure of aggregate foreign-currency exposure, defined as weighted shares of foreign assets in access of foreign liabilities in total cross-border holdings. Centrality is the export-share weighted average of countries bilateral trade intensitiespairwise total trade divided by pairwise total GDP. Inflation is the percentage change in CPI. All specifications include time fixed effects. Standard errors in parentheses are clustered by country using Cameron et al. (2011). *, **, and *** represent 10%, 5%, and 1% significance levels.

Table 4: Time Series Regressions of the Tail-beta-sorted Currency Portfolios

Panel A: All Currencies						
	P1	P2	P3	P4	P5	H-L
α	1.87**	-0.80	-0.06	0.62	-2.95***	-4.82***
	(2.10)	(-1.02)	(-0.08)	(0.80)	(-3.58)	(-3.47)
Dol-β	1.07	0.96	0.71	0.92	1.17	0.10
	(24.02)	(22.52)	(19.26)	(18.40)	(23.87)	(1.27)
ΔFXvol-β	24.44	2.11	-15.56	25.79	6.31	-18.13
	(2.23)	(0.23)	(-1.59)	(2.28)	(0.53)	(-0.93)
R^2 (%)	73.03	74.82	66.25	72.27	79.96	1.89

Panel B: DM Currencies						
	P1	P2	P3	P4	P5	H-L
α	2.02**	0.76	-0.58	0.41	-2.55**	-4.57***
	(2.06)	(0.90)	(-0.74)	(0.48)	(-2.57)	(-2.70)
Dol-β	0.95	1.07	0.87	1.04	1.08	0.12
	(18.54)	(21.75)	(17.32)	(24.57)	(18.91)	(1.24)
ΔFXvol-β	4.43	-12.38	-3.34	16.09	-0.92	-5.35
	(0.37)	(-0.96)	(-0.31)	(1.29)	(-0.06)	(-0.22)
R^2 (%)	66.91	77.52	72.30	75.34	71.66	1.24

This table reports the time series regressions of the tail-beta-sorted currency portfolios for all currencies in Panel A and for the developed markets in Panel B. The independent variables are the dollar risk factor (DOL) and the FX volatility (ΔFXvol). DOL is the average excess return of foreign currencies against USD and ΔFXvol is innovation in aggregated FX volatility. We report regression coefficients along with their t-statistics (in parentheses) and R^2's (in percent). *, **, and *** represent 10%, 5%, and 1% significance levels. The sample runs from February 1995 to April 2018.

Table 5: Summary Statistics of Currency Carry and Momentum Portfolios

Portfolio	1	2	3	4	5	H-L
Panel A: Carry Portfolio – All Currencies						
Excess Return	-2.11	0.35	1.70	1.85	4.46	6.57
Std. Dev	6.50	6.26	6.66	9.15	9.98	8.66
Skew	-0.02	0.30	-0.63	-1.31	-0.82	-0.64
Kurt	3.67	5.84	5.44	10.67	6.49	4.92
SR	-0.32	0.06	0.25	0.20	0.45	0.76
Panel B: Momentum Portfolio – All Currencies						
Excess Return	-2.76	0.59	2.18	2.22	4.85	7.62
Std. Dev	9.84	6.86	7.16	7.49	7.82	9.39
Skew	-0.88	-1.02	-0.32	-0.51	0.09	0.56
Kurt	9.37	8.11	5.20	6.65	5.90	8.57
SR	-0.28	0.09	0.30	0.30	0.62	0.81

This table reports the excess returns of the carry and momentum portfolios in Panel A and B, respectively, for all currencies in our sample. For each portfolio j ($j = 1, 2, 3, 4, 5$, H-L), we report the mean excess return, standard deviation (Std. Dev), skewness, kurtosis, and Sharpe ratio (SR). All moments are annualized and reported in percentage points. The carry portfolios are constructed by sorting currencies into five groups at time t based on their forward discount at $t-1$. The momentum portfolios are constructed by sorting currencies into five groups at time t based on their excess returns at $t-1$. The sample period runs January 1990 to April 2018.

Table 6: Cross-section Asset Pricing Results of Carry and Momentum Portfolios

	Panel A: Carry					Panel B: Momentum				
	CAPM	DR-CAPM	DOL	FX	Global Tail	CAPM	DR-CAPM	DOL	FX	Global Tail
MKT	0.96	0.43				-0.18	0.43			
	(1.68)	(—)				(-0.33)	(—)			
DR		-1.51					-1.23***			
		(-1.59)					(-2.84)			
DOL			0.14	0.07	0.08			0.02	0.08	0.05
			(1.20)	(0.62)	(0.67)			(0.19)	(0.65)	(0.43)
ΔFXvol				-0.06***					0.10**	
				(-3.77)					(2.19)	
Global Tail					-2.90**					-2.17**
					(-2.36)					(-2.32)
χ^2	22.40	11.15	28.56	8.93	6.27	12.74	9.01	12.50	4.49	1.65
p-value (%)	0.02	1.09	0.00	3.02	9.91	1.26	2.92	1.40	21.29	64.86
RMSE	0.28	0.24	0.31	0.09	0.14	0.27	0.18	0.27	0.14	0.08
R^2 (%)	8.52	30.85	-12.90	89.27	76.80	-38.17	37.03	-39.70	63.72	87.39

This table reports the results of the asset pricing tests on the cross-section of currency carry (Panel A) and momentum (Panel B). MKT is the return of the S&P 500 index; DR is the downside risk factor, defined as MKT when it is one standard deviation below its mean; DOL is the dollar risk factor; CARRY is the high-minus-low currency carry return factor; and the Global Tail factor is the long-short portfolio of the U.S. tail beta sorted portfolio returns. Returns are expressed in monthly percentage. We run the Fama-MacBeth regressions and report the estimated risk prices, errors-in-variables corrected t-statistics (in parentheses), root-mean-squared pricing error (RMSE), and cross-sectional R^2's. We also report the χ^2 test statistics and p-values on the null hypothesis that the pricing errors are jointly zero. *, **, and *** represent 10%, 5%, and 1% significance levels. The sample period runs from February 1995 to April 2018.

Table 7: Asset Pricing Tests for Carry and Momentum Portfolios

	CAPM	DR-CAPM	DOL	FX	Global Tail
MKT	0.39	0.43			
	(0.71)	(—)			
DR		-1.30***			
		(-3.15)			
DOL			0.08	0.06	0.07
			(0.70)	(0.50)	(0.60)
ΔFXvol				-0.03**	
				(-2.07)	
Global Tail					-2.47***
					(-3.56)
χ^2	41.38	30.66	43.55	30.11	8.99
p-value (%)	0.00	0.03	0.00	0.04	43.83
RMSE	0.30	0.21	0.30	0.27	0.12
R^2 (%)	-27.60	32.83	-27.62	-9.94	78.49

This table reports the results of the asset pricing tests on the joint cross-section of currency carry and momentum portfolios, and on the joint cross-section of currency carry and momentum portfolios. MKT is the return of the S&P 500 index, DR is the downside risk factor, which is defined as MKT times an indicator function that takes the value of 1 when MKT<0; DOL is the dollar risk factor; CARRY is the high-minus-low currency carry trade factor; and the Global Tail factor is the long-short portfolio of the US tail beta sorted portfolio returns. We run the Fama-MacBeth regressions and report the estimated risk prices, errors-in-variables corrected t-statistics (in parentheses), root mean squared pricing error (RMSE), and cross-sectional R^2's. We also report the GRS test statistics and p-values on the null hypothesis that the pricing errors are jointly zero. *, **, and *** represent 10%, 5%, and 1% significance levels. The sample period runs from February 1995 to April 2018.

Table 8: Asset Pricing Tests for Carry and Momentum Portfolios with Control Factors

	CARRY	ΔFXvol	ΔGRIX	Dollar Carry	Global Dol	ΔVIX
DOL	0.06	0.06	0.10	0.07	0.06	0.06
	(0.51)	(0.54)	(0.69)	(0.60)	(0.55)	(0.54)
Global Tail	-2.21***	-2.38***	-2.52***	-2.05***	-2.32***	-2.48***
	(-2.78)	(-3.19)	(-3.39)	(-3.11)	(-2.92)	(-3.57)
Control	0.59***	-0.02	0.03	0.01**	-0.24	-0.06
	(4.18)	(-0.72)	(0.09)	(2.04)	(-0.52)	(-0.74)
χ^2	6.49	8.36	7.91	7.38	8.83	7.86
pval	59.27	39.88	44.22	49.62	35.69	44.77
RMSE	0.11	0.12	0.14	0.10	0.12	0.11
R^2 (%)	83.06	80.48	75.09	84.75	80.45	80.92

This table reports the results for the asset pricing tests on the cross-section of currency carry and momentum portfolios after including other control factors in addition to the global U.S. tail factor (Global Tail). The control factors include the CARRY factor, change in foreign exchange volatility (ΔFXvol) in Menkhoff et al. (2012a), the index of global ex-ante tail risk concerns (ΔGRIX) in Gao et al. (2018), the dollar carry in Lustig et al. (2014), and the global Dollar in Verdelhan (2018). We obtain the GRIX data from the website of Zhaogang Song: https://sites.google.com/a/cornell.edu/zgs/. The Global Dollar factor data is obtained from the website of Adrien Verdelhan. The test assets are 36 currency portfolios—12 carry portfolios , 12 momentum portfolios, and 12 tail-beta-sorted portfolios. Returns are expressed in monthly percentage. We run the Fama-MacBeth regression and report the estimated risk prices, errors-in-variables corrected t-statistics (in parentheses), root-mean-squared pricing error (RMSE), and cross-sectional R^2's. We also report the χ^2 test statistics and p-values on the null hypothesis that the pricing errors are jointly zero. *, **, and *** represent 10%, 5%, and 1% significance levels. The sample period runs from February 1995 to April 2018, except for ΔGRIX, when the sample runs from January 1996 to June 2012.

Table A1: Tail-beta sorted Currency Portfolios (U.S. investor, controlling for VIX)

Portfolio	1	2	3	4	5	Average	H-L
Mean	2.68	0.95	-0.01	0.65	-1.56	0.54	-4.23***
	(1.55)	(0.65)	(-0.01)	(0.45)	(-0.86)	(0.40)	(-3.08)
Std. Dev.	8.33	6.98	6.06	7.06	8.77	6.51	6.62
Skew	-0.19	-0.37	-0.49	-0.30	-0.47	-0.44	-0.12
Kurt	3.36	4.28	8.63	6.03	5.14	4.65	4.35
SR	0.32	0.14	0.00	0.09	-0.18	0.08	-0.64
AC	0.11	0.06	0.03	0.00	0.07	0.07	0.15
Pre-FD	2.83	1.42	1.06	0.87	1.49	1.53	-1.34
Pre-β	-0.50	-0.16	-0.02	0.12	0.41	-0.03	0.90
FX return	-0.15	-0.48	-1.07	-0.21	-3.04	-0.99	-2.90
RX(-1,0)	2.81	1.06	-0.18	0.98	-1.56	0.62	-4.37

This table reports excess returns of the tail-beta-sorted portfolios for all currencies, controlling for VIX. We first estimate $\beta_{Tail,i}$ for each currency i with ΔVIX as a control variable in the following regression: $rx_{i,t} = \alpha_i + \beta_{Mkt,i}\text{MKT}_t + \beta_{Tail,i}Tail_t + \beta_{VIX,i}\Delta\text{VIX}_t + \varepsilon_{i,t}$. with a rolling window of 60 months. Then, we sort currencies into five portfolios based on their estimated $\beta_{Tail,i}$. For each portfolio j ($j = 1, ..., 5$, Average, H-L), we report the mean excess return in the next month, t-statistics (reported in parentheses), standard deviations (Std. Dev), skewness, kurtosis, Sharpe ratio (SR), autocorrelation coefficient (AC), pre-formation forward discount (Pre-FD), pre-formation $\beta_{Tail,i}$ (Pre-β), and mean return of the spot exchange rate (FX return). *, **, and *** represent 10%, 5%, and 1% significance levels. All moments are annualized and reported in percentage points. The sample period runs from February 1995 to April 2018.

Table A2: Tail-beta sorted Currency Portfolios (Tail constructed with put options of 90% moneyness)

Portfolio	1	2	3	4	5	Average	H-L
Mean	2.15	1.80	0.69	0.79	-1.90	0.70	-4.05***
	(1.22)	(1.08)	(0.68)	(0.55)	(-1.04)	(0.52)	(-2.88)
Std. Dev.	8.47	7.98	4.94	6.90	8.82	6.50	6.78
Skew	-0.22	-0.47	-0.14	-0.46	-0.73	-0.46	-0.24
Kurt	3.09	4.38	3.55	6.75	7.13	4.89	3.68
SR	0.25	0.22	0.14	0.11	-0.22	0.11	-0.60
AC	0.05	0.06	0.02	0.12	0.06	0.07	0.10
Pre-FD	2.73	1.56	0.76	0.77	1.93	1.55	-0.81
Pre-β	-0.72	-0.22	-0.05	0.13	0.67	-0.04	1.38
FX return	-0.58	0.24	-0.07	0.02	-3.83	-0.84	-3.24
RX(-1,0)	1.60	2.26	0.26	0.62	-1.79	0.59	-3.39

This table reports excess returns of the tail-beta-sorted portfolios for all currencies, where Tail is constructed with put options of 90% moneyness instead of 95%. We first estimate $\beta_{Tail,i}$ for each currency i in the following regression: $rx_{i,t} = \alpha_i + \beta_{Mkt,i}\text{MKT}_t + \beta_{Tail,i}Tail_t + \varepsilon_{i,t}$. with a rolling window of 60 months. Then, we sort currencies into five portfolios based on their estimated $\beta_{Tail,i}$. For each portfolio j ($j = 1, ..., 5$, Average, H-L), we report the mean excess return in the next month, t-statistics (reported in parentheses), standard deviations (Std. Dev), skewness, kurtosis, Sharpe ratio (SR), autocorrelation coefficient (AC), pre-formation $\beta_{Tail,i}$ (Pre-β), and mean return of the spot exchange rate (FX return). *, **, and *** represent 10%, 5%, and 1% significance levels. All moments are annualized and reported in percentage points. The sample period runs from February 1995 to April 2018.

Table A3: Tail-beta-sorted Currency Portfolios (U.K. investor)

Panel A: All Currencies

Portfolio	1	2	3	4	5	Average	H-L
Mean	2.45	1.00	0.24	0.34	-2.17	0.37	-4.62***
	(1.37)	(0.57)	(0.16)	(0.21)	(-1.19)	(0.25)	(-3.09)
Std. Dev.	8.63	8.49	7.38	7.86	8.82	7.27	7.21
Skew	0.49	0.63	0.43	0.47	0.67	0.84	-0.02
Kurt	5.46	9.56	5.00	8.29	6.93	7.72	4.17
SR	0.28	0.12	0.03	0.04	-0.25	0.05	-0.64
AC	-0.07	-0.12	-0.03	-0.11	-0.07	-0.11	0.07
Pre-FD	2.42	0.99	0.56	0.15	0.26	0.88	-2.15
Pre-β	-0.61	-0.31	-0.16	-0.01	0.27	-0.16	0.87
FX return	0.03	0.01	-0.31	0.19	-2.43	-0.50	-2.46
RX(-1,0)	2.21	2.08	-0.07	0.46	-3.23	0.29	-5.43

Panel B: DM Currencies

Portfolio	1	2	3	4	5	Average	H-L
Mean	1.99	2.08	-3.34	0.72	-2.73	-0.26	-4.72***
	(1.12)	(1.23)	(-1.88)	(0.42)	(-1.50)	(-0.17)	(-2.81)
Std. Dev.	8.57	8.15	8.55	8.30	8.80	7.12	8.09
Skew	0.44	0.80	0.62	0.55	0.74	1.11	0.15
Kurt	4.77	5.70	7.10	9.45	6.53	9.29	3.04
SR	0.23	0.26	-0.39	0.09	-0.31	-0.04	-0.58
AC	-0.08	-0.12	-0.08	-0.08	-0.05	-0.10	0.03
Pre-FD	0.35	-0.55	-0.93	-0.92	-1.66	-0.74	-2.02
Pre-β	-0.54	-0.32	-0.18	-0.08	0.15	-0.19	0.69
FX return	1.64	2.63	-2.41	1.65	-1.07	0.49	-2.71
RX(-1,0)	1.70	1.69	-1.10	0.53	-3.39	-0.11	-5.09

This table reports excess returns of the tail-beta-sorted portfolios for all currencies (Panel A) and for the subsample of currencies from developed markets (Panel B) from the point of view of a UK investor (that is, when the U.K. pound is the reference currency). We first estimate $\beta_{Tail,i}$ for each currency i in the regression in equation (16) using a rolling window of 60 months. Then, we sort currencies into five portfolios based on their estimated $\beta_{Tail,i}$. For each portfolio j (j = 1, ..., 5, Average, and H-L), we report the mean excess return in the next month, the t-statistics (in parenthesis), standard deviation (Std. Dev), skewness, kurtosis, the Sharpe ratio (SR), the autocorrelation coefficient (AC), the mean return of the spot exchange rate (FX return), the pre-formation forward discount (Pre-FD), the post-formation forward discount (Post-FD), the pre-formation $\beta_{Tail,i}$ (Pre-β), and the excess return in the pre-formation period ($RX(-1,0)$). *, **, and *** represent 10%, 5%, and 1% significance levels. All moments are annualized and reported in percentage points. The sample period runs from February 1995 to April 2018.

Table A4: Tail-beta-sorted Currency Portfolios (Japanese investor)

Panel A: All Currencies							
Portfolio	1	2	3	4	5	Average	H-L
Mean	5.93	3.82	3.24	3.38	1.23	3.52	-4.69***
	(2.51)	(1.62)	(1.42)	(1.50)	(0.53)	(1.62)	(-3.07)
Std. Dev.	11.36	11.35	11.00	10.83	11.26	10.46	7.37
Skew	-0.64	-0.98	-0.85	-0.77	-0.92	-0.92	-0.04
Kurt	3.97	6.35	6.47	5.33	6.35	5.82	4.01
SR	0.52	0.34	0.30	0.31	0.11	0.34	-0.64
AC	0.00	-0.01	0.04	-0.02	0.12	0.03	0.07
Pre-FD	5.75	4.38	3.97	3.40	3.52	4.21	-2.23
Pre-β	-0.45	-0.15	-0.01	0.13	0.41	-0.02	0.86
FX return	0.18	-0.56	-0.73	-0.02	-2.29	-0.68	-2.46
RX(-1,0)	5.50	4.97	3.25	3.34	0.19	3.45	-5.30

Panel B: DM Currencies							
Portfolio	1	2	3	4	5	Average	H-L
Mean	5.08	5.33	0.11	3.79	0.38	2.94	-4.69***
	(2.09)	(2.20)	(0.04)	(1.63)	(0.18)	(1.35)	(-2.81)
Std. Dev.	11.72	11.65	12.34	11.22	10.04	10.48	8.05
Skew	-0.71	-0.89	-1.02	-0.60	-1.23	-0.99	0.14
Kurt	4.20	6.40	6.34	4.99	9.74	6.22	2.94
SR	0.43	0.46	0.01	0.34	0.04	0.28	-0.58
AC	0.01	-0.04	0.03	0.01	0.13	0.03	0.02
Pre-FD	3.68	2.78	2.40	2.38	1.69	2.59	-1.99
Pre-β	-0.39	-0.16	-0.03	0.08	0.31	-0.04	0.69
FX return	1.40	2.54	-2.28	1.41	-1.31	0.35	-2.71
RX(-1,0)	4.76	4.79	2.17	3.87	-0.33	3.05	-5.09

This table reports excess returns of the tail-beta-sorted portfolios for all currencies (Panel A) and for the subsample of currencies from developed markets (Panel B) from the point of view of a Japanese investor (that is, when the Japanese yen is the reference currency). We first estimate $\beta_{Tail,i}$ for each currency i in the regression in equation (16) using a rolling window of 60 months. Then, we sort currencies into five portfolios based on their estimated $\beta_{Tail,i}$. For each portfolio j (j = 1, ..., 5, Average, and H-L), we report the mean excess return in the next month, the t-statistics (in parenthesis), standard deviation (Std. Dev), skewness, kurtosis, the Sharpe ratio (SR), the autocorrelation coefficient (AC), the mean return of the spot exchange rate (FX return), the pre-formation forward discount (Pre-FD), the post-formation forward discount (Post-FD), the pre-formation $\beta_{Tail,i}$ (Pre-β), and the excess return in the pre-formation period ($RX(-1,0)$). *, **, and *** represent 10%, 5%, and 1% significance levels. All moments are annualized and reported in percentage points. The sample period runs from February 1995 to April 2018.

Table A5: Correlation Matrix of Global Tail from Different Base Currencies

Panel A: All Currencies				Panel B: DM Currencies			
	U.S.	U.K.	Japan		U.S.	U.K.	Japan
U.S.	1.00	0.86	0.87	U.S.	1.00	0.88	0.89
U.K.	0.86	1.00	0.98	U.K.	0.88	1.00	0.98
Japan	0.87	0.98	1.00	Japan	0.89	0.98	1.00

This table reports the correlation matrix of the Global Tail risk factor constructed from different base currencies for all currencies (Panel A) and DM currencies (Panel B). The Global Tail factor is the excess returns of the tail-beta-sorted portfolios for all currencies or the developed market currencies from the point of view of a U.S., U.K., or Japanese investor (that is, when the USD, GBP, or JPY is the reference currency). The sample period of each Global Tail factor runs from February 1995 to April 2018.

Table A6: Cross-section Asset Pricing Results of Carry and Momentum Portfolios (including DM Portfolios as Test Assets)

	Panel A: Carry					Panel B: Momentum				
	CAPM	DR-CAPM	DOL	FX	Global Tail	CAPM	DR-CAPM	DOL	FX	Global Tail
MKT	0.78	0.43				-0.08	0.43			
	(1.43)	(—)				(-0.14)	(—)			
DR		-0.81					-0.63***			
		(-1.54)					(-2.90)			
DOL			0.10	0.10	0.07			0.02	-0.01	0.06
			(0.86)	(0.83)	(0.56)			(0.15)	(-0.10)	(0.51)
ΔFXvol				-0.07***					0.05*	
				(-3.84)					(1.93)	
Global Tail					-1.95***					-2.01**
					(-2.85)					(-2.15)
χ^2	29.23	24.45	34.20	14.94	14.22	20.07	18.38	19.99	14.66	3.68
p-value (%)	0.11	0.36	0.02	9.25	11.48	2.86	3.10	2.93	10.08	93.09
RMSE	0.24	0.23	0.27	0.08	0.14	0.20	0.17	0.20	0.15	0.07
R^2 (%)	13.74	23.02	-9.17	90.19	70.56	-22.99	14.29	-22.93	31.91	83.67

This table reports the results of the asset pricing tests on the cross-section of currency carry (Panel A) and momentum (Panel B). In Panel A, test assets are the 6 carry portfolios from all currencies and 6 carry portfolios from developed market currencies. In Panel B, test assets are the 6 momentum portfolios from all currencies and 6 momentum portfolios from developed market currencies. MKT is the return of the S&P 500 index; DR is the downside risk factor, defined as MKT when it is one standard deviation below its mean; DOL is the dollar risk factor; CARRY is the high-minus-low currency carry return factor; and the Global Tail factor is the long-short portfolio of the U.S. tail beta sorted portfolio returns. Returns are expressed in monthly percentage. We run the Fama-MacBeth regressions and report the estimated risk prices, errors-in-variables corrected t-statistics (in parentheses), root-mean-squared pricing error (RMSE), and cross-sectional R^2's. We also report the χ^2 test statistics and p-values on the null hypothesis that the pricing errors are jointly zero. *, **, and *** represent 10%, 5%, and 1% significance levels. The sample period runs from February 1995 to April 2018.

Table A7: Asset Pricing Tests for Carry and Momentum Portfolios (including DM Portfolios as Test Assets)

	CAPM	DR-CAPM	DOL	FX	Global Tail
MKT	0.37	0.43			
	(0.68)	(—)			
DR		-0.67***			
		(-3.04)			
DOL			0.06	0.07	0.06
			(0.51)	(0.57)	(0.53)
ΔFXvol				-0.03**	
				(-2.28)	
Global Tail					-1.98***
					(-3.93)
χ^2	46.73	43.36	49.04	37.88	17.29
p-value (%)	0.16	0.28	0.08	1.33	69.32
RMSE	0.23	0.20	0.24	0.21	0.11
R^2 (%)	-11.65	20.18	-16.08	6.64	75.00

This table reports the results of the asset pricing tests on the joint cross-section of currency carry and momentum portfolios. Test assets are 24 portfolios—6 carry portfolios from all currencies, 6 carry portfolios from developed market currencies, 6 momentum portfolios from all currencies, and 6 momentum portfolios from developed market currencies. MKT is the return of the S&P 500 index, DR is the downside risk factor, which is defined as MKT times an indicator function that takes the value of 1 when MKT<0; DOL is the dollar risk factor; CARRY is the high-minus-low currency carry trade factor; and the Global Tail factor is the long-short portfolio of the U.S. tail beta sorted portfolio returns. We run the Fama-MacBeth regressions and report the estimated risk prices, errors-in-variables corrected t-statistics (in parentheses), root mean squared pricing error (RMSE), and cross-sectional R^2's. We also report the GRS test statistics and p-values on the null hypothesis that the pricing errors are jointly zero. *, **, and *** represent 10%, 5%, and 1% significance levels. The sample period runs from February 1995 to April 2018.

Table A8: Cross-section Asset Pricing Results of Carry, Momentum and Tail-beta Sorted Portfolios (including DM Portfolios as Test Assets)

	CAPM	DR-CAPM	DOL	FX	Global Tail
MKT	0.30	0.43			
	(0.54)	(—)			
DR		-0.64***			
		(-4.70)			
DOL			0.04	0.06	0.05
			(0.37)	(0.52)	(0.42)
ΔFXvol				-0.03**	
				(-2.30)	
Global Tail					-0.53***
					(-4.00)
χ^2	66.88	60.76	68.23	57.48	57.47
p-value (%)	0.06	0.23	0.04	0.52	0.52
RMSE	0.22	0.17	0.22	0.20	0.17
R^2 (%)	-0.11	37.88	-3.61	13.51	40.00

This table reports the results of the asset pricing tests on the joint cross-section of the carry, momentum, and tail-beta-sorted portfolios. Test assets are 36 portfolios—6 carry portfolios from all currencies, 6 carry portfolios from developed market currencies, 6 momentum portfolios from all currencies, 6 momentum portfolios from developed market currencies, 6 tail-beta-sorted portfolios from all currencies, and 6 tail-beta-sorted portfolios from developed market currencies. MKT is the return of the S&P 500 index; DR is the downside risk factor, defined as MKT when it is one standard deviation below its mean; DOL is the dollar risk factor; CARRY is the high-minus-low currency carry return factor; and the Global Tail factor is the long-short portfolio of the U.S. tail beta sorted portfolio returns. Returns are expressed in monthly percentage. We run the Fama-MacBeth regressions and report the estimated risk prices, errors-in-variables corrected t-statistics (in parentheses), root-mean-squared pricing error (RMSE), and cross-sectional R^2's. We also report the χ^2 test statistics and p-values on the null hypothesis that the pricing errors are jointly zero. *, **, and *** represent 10%, 5%, and 1% significance levels. The sample period runs from February 1995 to April 2018.

Table A9: Asset Pricing Tests with Restricted Price of Global Tail Risk (including DM Portfolios as Test Assets)

	Carry	Momentum	Carry & Momentum	Carry & Momentum & Tail
DOL	0.04	-0.02	0.03	0.03
	(0.37)	(-0.20)	(0.23)	(0.29)
ΔFXvol	-4.54***	4.44	-2.51*	-2.37*
	(-3.13)	(1.63)	(-1.86)	(-1.79)
Global Tail	-0.39	-0.39	-0.39	-0.39
RMSE	0.09	0.13	0.17	0.15
R^2 (%)	85.86	55.62	37.56	55.61

This table reports the results for the asset pricing tests on the cross-section of carry, momentum, and tail-beta-sorted portfolios, with the restriction that the price of the global tail to be equal to its sample average. Test assets are 36 carry, momentum, and tail-beta-sorted portfolios, including those formed using only the developed market sample. DOL is the dollar risk factor; CARRY is the high-minus-low currency carry return factor; and the Global Tail factor is the long-short portfolio of the U.S. tail beta sorted portfolio returns. The test assets are 36 currency portfolios—12 carry portfolios , 12 momentum portfolios, and 12 tail-beta-sorted portfolios. Returns are expressed in monthly percentage. We run the Fama-MacBeth regressions and report the estimated risk prices, errors-in-variables corrected t-statistics (in parentheses), root-mean-squared pricing error (RMSE), and cross-sectional R^2's.*, **, and *** represent 10%, 5%, and 1% significance levels. The sample period runs from February 1995 to April 2018.