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Equity tail risk and currency risk premiums☆

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ABSTRACT

We find that an option-based equity tail risk factor is priced in the cross section of currency returns; more exposed currencies offer a low risk premium because they hedge against equity tail risk. A portfolio that buys currencies with high equity tail beta and shorts those with low beta extracts the global component in the tail factor. The estimated price of risk of this novel global factor is consistently negative in currency carry and momentum portfolios, and in portfolios of other asset classes, suggesting that excess returns of these strategies can be partially understood as compensations for global tail risk.

1. Introduction

Rare disaster models that emphasize the role of tail events have been shown to explain a variety of financial market anomalies, including exchange rate puzzles (see, for instance, Barro, 2006; Wachter, 2013; Farhi and Gabaix, 2015). The large returns of popular currency investment strategies, such as carry trade and momentum, are among the exchange rate puzzles most actively explored in the literature. While most existing empirical studies focus on the role of tail risk in individual currencies, in this paper, we explore a risk-based explanation of exchange rate puzzles using a novel global tail risk factor. We find that high-interest-rate and winner currencies tend to have higher excess returns than low-interest-rate and loser currencies because they have lower exposures to the global tail risk factor.

We build on the intuition that, if a currency appreciates with respect to the US dollar when equity tail risk increases, this currency is essentially a hedge against tail risk. This makes the currency more attractive to investors seeking to hedge tail risk and, therefore, reduces its expected returns. To motivate our empirical analysis, we use a stylized reduced-form model following Verdelhan (2018) to assess the pricing implications

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of global and country-specific risks in the cross section of currency returns. We show that if a country's equity tail risk contains a global component, currencies' heterogeneous exposures to this equity tail factor could help us isolate the global component of tail risk.

We construct an 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 each country's equity market. 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 by institutional investors and hence is a tradable factor. Our choice to use a tail factor using information from equity markets can be interpreted as the expected exchange rate movement perceived by a risk-averse investor whose wealth is invested in the stock market (see, for instance, Lettau et al., 2014; Kremens and Martin, 2019). The tail risk factor is countercyclical; it takes higher values around market downturns (when equity tail risk is high) and lower values during "calmer" times (when the equity tail risk is low). Given the availability of sufficiently liquid equity options for the United States for a longer sample than for any other country in our sample, we calculate the tail risk measure using S&P 500 options. Moreover, the global component in the return of the US stock market is broadly consistent with the "global financial cycle" view in Miranda-Agrippino and Rey (2020). Several recent studies show that, as a consequence of trade and financial linkages, movements in US equity markets have important implications for the pricing of international assets. For instance, Rapach et al. (2013) find evidence that US stock returns have a leading role in the predictability of international stock returns, while non-US stock returns have almost no additional predictability. Aït-Sahalia et al. (2015) show that most equity markets tend to reflect US equity jumps quickly, while statistical evidence for the reverse transmission is much less pronounced. Bollerslev et al. (2014) and Londono (2015) find that the US equity variance risk premium has predictive power for international stock returns.

We test the implications of the reduced-form model using exchange rate data for 37 currencies from emerging and developed markets, quoted in units of foreign currency per one US dollar, between January 1990 and April 2018. Our paper makes two main empirical contributions to the literature. First, we find that the US equity tail risk factor carries a negative price of risk in the cross section of currency returns calculated from the perspective of a US investor. Specifically, we build tail portfolios of currencies sorted by their time-varying exposures to the equity tail factor (i.e., tail betas). We find that the future returns of quintile currency portfolios sorted on equity tail betas exhibit a decreasing trend. 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 currencies (developed-market currencies) with a Sharpe ratio of 0.7 (0.6). We show that these return spreads cannot be explained by other factors in the currency market literature, including the dollar and carry factor in Verdelhan (2018), the foreign exchange (FX) volatility factor in Menkhoff et al. (2012a) and the global equity factor.

Why do some currencies have high tail betas while others have low tail betas? We find that currency tail betas are related to several country-level economic fundamentals. In particular, we find that countries with a lower basic export ratio, lower international currency exposure, and more centrality in the global trade network tend to have relatively high tail betas. These currencies are more likely to appreciate with respect to the US dollar when equity tail risk increases and, therefore, provide a hedge against equity tail risk.

Consistent with the implications of our model that the cross-sectional pricing of the equity tail risk factor holds irrespective of the reference currency, we find that the US equity tail risk is also priced in the cross section of UK pound- and Japanese yen-denominated currencies. The high-minus-low return spread is 3.82% and 4.69% for UK investors and Japanese investors, respectively, in the universe of all currencies, and 4.90% and 4.69% in the universe of developed markets' currencies, confirming that the US equity tail risk factor has a global component.

An important implication of our model is that a global tail risk factor cannot be easily estimated by aggregating tail risks of individual currencies because exchange rates are relative quantities. For example, aggregating tail risks of the currencies denominated in US dollars could cancel out the global tail component if the US equity tail risk exposure to the global tail component is similar to the aggregated exposure of the other countries' equity markets to the global tail component. Therefore, in our second contribution, we construct a novel global tail factor, Gtail, using the high-minus-low return spread of the Tail-beta currency portfolios. We use this factor along with the dollar and carry factors to conduct asset pricing tests. We find that the Gtail factor not only explains carry and momentum portfolios separately, but also jointly, and the results remain robust when the cross section is augmented by currency portfolios from other strategies. Across various currency portfolios, our evidence show that the Gtail factor always carries a significant negative risk premium.

We assess the robustness of our results for the ability of the global tail factor to price currency portfolios through two exercises. First, we show that our results hold both for the cross section of portfolios from a single currency strategy (e.g., carry or momentum) and for joint portfolios from different currency strategies, including currency value and variance risk premium portfolios. Second, we show that the global tail factor shows significant pricing power in the cross section of currency portfolio returns after controlling for multiple factors studied in the literature, such as the FX volatility factor in Menkhoff et al. (2012a), the global disaster risk factor in Gao et al. (2019), the dollar carry and global dollar risk factor in Verdelhan (2018), and innovations to the Chicago Board Options Exchange® (CBOE) Volatility Index (VIX).

We extend our results for the pricing ability of the global tail factor to other asset classes. We find that the global tail factor also has strong explanatory power for the cross section of a variety of global equity portfolios, sovereign bonds, and value and momentum portfolios in the fixed income and commodity markets.

This paper contributes to three branches of the literature. First, this paper contributes to the literature that tries to understand the excess return of currency carry trade and momentum investment strategies. Most studies focus on proposing a risk factor to explain a single currency strategy (for instance, US consumption risk in Lustig and Verdelhan, 2007; innovations to FX volatility in Menkhoff et al., 2012a; US equity downside risk in Lettau et al., 2014; global long-run consumption news in Colacito et al., 2018; and global political risk in Filippou et al., 2018). A notable exception is Della Corte et al. (2016b), who propose a global imbalance factor to explain a variety of currency portfolios. We contribute to this branch of the literature by proposing a novel global tail risk factor extracted from the high-minus-low Tail-beta currency portfolio. This global factor is able to explain a large portion of the cross-sectional variation in currency portfolios for multiple strategies.

This paper also contributes to the literature on crash risk in currency markets. Brunnermeier et al. (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 et al. (2011) and Jurek (2014) study the contribution of crash risk to carry trade using the returns on option-hedged carry trade. In a parametric model, Chernov et al. (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. Several papers highlight the importance of systematic disaster risk in currency markets. Using a structural approach, Farhi and Gabaix (2015) show that an exchange rate model with global disaster risk can reproduce the forward premium puzzle. Farhi et al. (2015) find empirical evidence that disaster risk accounts for a considerable amount of the carry trade return.

Our paper differs from these papers in two main aspects. First, we study the global component in country-level equity tail risk and show that our construction can better identify this global component. Second, we examine the extent to which the global tail risk factor explains the cross section of currency portfolio returns.

Finally, this paper contributes to the literature relating equity market risk to currency return dynamics. Glen and Jorion (1993) and Campbell et al. (2010) show that currencies can be used to hedge equity risks. Ranaldo and Söderlind (2010) provide empirical evidence that traditional *safe-haven* currencies appreciate when the US equity market declines. Kremens and Martin (2019) show that the quanto-implied covariance between equity returns and currency returns predicts future currency returns. Jiang et al. (2021) provide empirical evidence for the relation between the VIX and currency returns, and Londono and Zhou (2017) find that the US equity variance risk premium is a useful predictor of currency returns. Lettau et al. (2014) and Dobrynskaya (2014) find that the equity downside risk helps explain the cross-sectional variation of currency portfolio returns. While it seems that our global tail risk factors shares many similarities with the equity downside risk, they are fundamentally different in two aspects. First, unlike the equity downside risk, which is a nontradable equity factor, the global tail risk factor in our paper is the return of a tradable currency portfolio. Second, our construction of the global tail risk factor guarantees that it has a global nature. As a result of these differences, our global tail factor is weakly correlated with the equity downside risk factor. We contribute to this literature by employing a standard factor-pricing framework to explore the relation between equity risks and currency returns. Our finding provides complementing evidence for the interconnection between equity and currency markets.

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 US as the home country and investigate the pricing of US equity tail risk in the cross section of currency returns from the perspective of a US investor. Section 4 shows the main empirical results and robustness checks regarding the pricing of US equity 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 various test assets. We conclude in Section 6.

2. Domestic and global tail risks and the cross section of currency returns

In this section, we explore the implications of country-specific and global tail risks in the cross section of currency returns in the framework of a reduced-form model. In the first part of the section, we explain the model and its main implications. In the second part, we introduce an equity tail risk factor with the potential to contain a global tail component.

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:

$$-m_{k,t+1} = i_{k,t} + a_{k,t} + \gamma_k u_{k,t+1} + \delta_k u_{g,t+1} + \lambda_k \text{Tail}_{k,t+1}, \quad (1)$$

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 $\text{Tail}_{k,t+1}$ captures shocks related to the time-varying jump tails.[1] We use the capitalized notation “Tail” to refer to the particular tail risk factor to distinguish it from the general

[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.

concept "tail." The three shocks (or factors), $u_{k,t+1}$, $u_{g,t+1}$, and $\mathrm{Tail}_{k,t+1}$, are assumed to be independently distributed.

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

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

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

The exchange rate is expressed in units of foreign currency per one unit of the domestic currency; for instance, per each US dollar. 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 et al., 2001). That is,

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

where m denotes the log nominal SDF of the domestic country.

In the model, the excess currency returns for the domestic investor who invests in currency k is given by

$$\begin{aligned} rx_{k,t+1} &= -\Delta fx_{k,t+1} + i_{k,t} - i_t \\ &= a_t - a_{k,t} - \gamma_k u_{k,t+1} + \gamma u_{t+1} - \lambda_k \mathrm{Tail}_{k,t+1} \\ &\quad + \lambda \mathrm{Tail}_{t+1} + (\delta - \delta_k) u_{g,t+1}, \end{aligned} \tag{4}$$

$$\begin{aligned} &= a_t - a_{k,t} - \underbrace{(\gamma_k u_{k,t+1} + \lambda_k \mathrm{Tail}_{k,t+1}^{local})}_{\text{foreign country shocks}} + \underbrace{(\gamma u_{t+1} + \lambda \mathrm{Tail}_{t+1}^{local})}_{\text{home country shocks}} \\ &\quad + \underbrace{(\lambda\zeta - \lambda_k \zeta_k)\mathrm{Tail}_{t+1}^{global} + (\delta - \delta_k) u_{g,t+1}}_{\text{global shocks}}. \end{aligned} \tag{5}$$

Since Tail^{global} is not directly observable, we instead focus on the conditional beta of currency excess return to the domestic tail factor, which has a global component. Eq. (4) suggests that the conditional beta of the currency excess return associated with the tail risk factor of the home country, $\beta_{Tail,k,t}$, is

$$\begin{aligned} \beta_{Tail,k,t} &\equiv \frac{\mathrm{cov}_t(rx_{k,t+1}, \mathrm{Tail}_{t+1})}{\mathrm{Var}_t(\mathrm{Tail}_{t+1})} \\ &= \frac{\zeta(\lambda\zeta - \lambda_k\zeta_k)\mathrm{Var}_t(\mathrm{Tail}_{t+1}^{global}) + \lambda \mathrm{Var}_t(\mathrm{Tail}_{t+1}^{local})}{\mathrm{Var}_t(\mathrm{Tail}_{t+1})}. \end{aligned} \tag{6}$$

If the tail risk of the home country, Tail_t, is not exposed to the global tail component ($\zeta = 0$ in Eq. (2) for the home country), $\beta_{Tail,k,t}$ is equal to λ for all foreign currencies. Also, if the pricing kernel of the foreign country does not have a tail risk component ($\lambda_k = 0$) or the tail risk component of the foreign countries is not exposed to the global tail component ($\zeta_k = 0$), $\beta_{Tail,k,t}$ does not vary across countries. However, if $\zeta \neq 0$ and λ_k and ζ_k vary across countries, the conditional beta of foreign currency k varies across currencies for different $\lambda_k\zeta_k$.

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

$$\begin{aligned} \beta_{Tail,k,t}^{global} &\equiv \frac{\mathrm{Cov}_t(rx_{k,t+1}, \mathrm{Tail}_{t+1}^{global})}{\mathrm{Var}_t(\mathrm{Tail}_{t+1}^{global})} \\ &= \frac{(\lambda\zeta - \lambda_k\zeta_k)\mathrm{Var}_t(\mathrm{Tail}_{t+1}^{global})}{\mathrm{Var}_t(\mathrm{Tail}_{t+1}^{global})}. \end{aligned} \tag{7}$$

Comparing Eq. (7) with Eq. (6), we can see that sorting currencies by $\beta_{Tail,k,t}$ is equivalent to sorting them by $\beta_{Tail,k,t}^{global}$. Hence, when $\beta_{Tail,k,t}^{global}$ is not observable, $\beta_{Tail,k,t}$ can be used as a proxy for $\beta_{Tail,k,t}^{global}$, as long as $\zeta \neq 0$.

Inspired by Verdelhan (2018), Tail-beta 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 the global tail factor (Gtail),

$$\mathrm{Gtail}_{t+1} = \frac{1}{N_{H_\beta}} \sum_{k \in H_\beta} rx_k - \frac{1}{N_{L_\beta}} \sum_{k \in L_\beta} rx_k, \tag{8}$$

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 we assume that the currencies' Tail betas given by Eq. (7) do not depend on their exposures to the global or country-specific diffusion shocks. Therefore, in the limit when $N \to \infty$, the high-beta and low-beta currency baskets are likely to share the same average foreign country shocks, home country shocks, and global diffusion risks in Eq. (5). As a result, the long-short portfolio return is dominated by the global tail risk component. When $N \to \infty$, the global tail risk factor is thus:

$$\lim_{N \to \infty} \mathrm{Gtail}_{t+1} = (\bar{\beta}_t^{H_\beta} - \bar{\beta}_t^{L_\beta})\mathrm{Tail}_{t+1}^{global}. \tag{9}$$

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

An interesting implication of our framework is that the long-short portfolio in Eq. (9) can be constructed for currency excess returns expressed in any currency (that is, assuming any home country). For example, to calculate the global tail factor, we could consider currency-l denominated exchange rates, where l can be the USD, the JPY, or any other currency.

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 et al. (2019). Suppose we observe the tail risk from currency returns. This alternative global tail, denoted as $\overline{\mathrm{Gtail}}$, is calculated as the sum of tail risk across all currencies:

$$\begin{aligned} \overline{\mathrm{Gtail}} &\equiv n\lambda \mathrm{Tail}_{t+1} - \sum_{k=1}^{n} \lambda_k \mathrm{Tail}_{k,t+1} \\ &= \left(n\lambda\zeta - \sum_{k=1}^{n} \lambda_k \zeta_k\right)(\mathrm{Tail}_{t+1}^{global}) \\ &\quad + \left(n\lambda - \sum_{k=1}^{n} \lambda_k\right)(\mathrm{Tail}_{t+1}^{local}). \end{aligned} \tag{10}$$

Unlike our Gtail factor, which, by construction, has a positive exposure to Tail^{global} at all times, the exposure to Tail^{global} in $\overline{\text{Gtail}}$, $n\lambda\zeta - \sum_{k=1}^{n}\lambda_k\zeta_k$, 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 better proxy of Tail^{global} than $\overline{\text{Gtail}}$.

To sum up, our framework suggests that a long-short Tail-beta currency portfolio has a positive exposure to the global tail factor and can therefore be used as a proxy for the global tail factor. In the remainder of this paper, we take the perspective of a US investor and regard the US as the home country.

2.2. The equity 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 a factor that potentially satisfies these characteristics.

We consider an equity tail factor to approximate the tail component in the pricing kernel in Section 2.1. It has been widely documented that stock market tail (jump) risk is priced in the cross section of stock returns (see Cremers et al., 2015, Lu and Murray, 2019; Atilgan et al., 2020, among others). 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 consider 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 out-of-the-money (OTM) options.

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

$$LT_t^{\mathbb{Q}}(T,k) \equiv \frac{P_t(T,k)}{S_t} \approx \mathbb{E}_t^{\mathbb{Q}}[(k - e^{J_T\Delta N_T})^+], \tag{11}$$

where $P_t(T,k)$ is the price of an OTM put option with moneyness k defined as $k = \frac{K}{e^{i(t,T)}S_t}$ and maturity T, S_t is the current stock price, and $J_t\Delta N_t$ represents jumps in the log stock price process. J_t is the jump amplitude at time t, and ΔN_t equals 1 if a jump occurs and 0 otherwise. 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,

$$\Delta N_T = \begin{cases} 1 & \text{with probability } q_t \text{ from } t \text{ to } T, \\ 0 & \text{with probability } 1 - q_t \text{ from } t \text{ to } T. \end{cases} \tag{12}$$

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 $\nu e^{-\nu}$.

Similar to Bollerslev and Todorov (2011), we assume that a deep OTM put option can only become in the money if $\Delta N_T = 1$. In this case, the left tail measure $LT^{\mathbb{Q}}$ in Eq. (11) can be further expressed as

$$\begin{aligned} LT_t^{\mathbb{Q}}(T,k) &= \mathbb{E}_t^{\mathbb{Q}}\Big[\mathbb{E}_t^{\mathbb{Q}}[(k - e^{J_T\Delta N_T})^+ | \Delta N_T]\Big] \\ &= q_t(k - \mathbb{E}_t^{\mathbb{Q}}[e^{J_T}]). \end{aligned} \tag{13}$$

The intertemporal capital asset pricing model (ICAPM) of Merton et al. (1973) suggests that risk premiums are associated with the conditional covariances between asset returns and innovations in state variables that describe the time variation of the investment 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 $LT_t^{\mathbb{Q}}$ in Eq. (13) is a potential pricing factor,

$$\begin{aligned} \Delta LT_{t+1}^{\mathbb{Q}}(T,k) &\equiv LT_{t+1}^{\mathbb{Q}}(T,k) - LT_t^{\mathbb{Q}}(T,k) \\ &= q_{t+1}(k - \mathbb{E}_{t+1}^{\mathbb{Q}}[e^{J_T}]) - q_t(k - \mathbb{E}_t^{\mathbb{Q}}[e^{J_T}]) \\ &= k(q_{t+1} - q_t) - (q_t\mathbb{E}_t^{\mathbb{Q}}[e^{J_T}] - q_{t+1}\mathbb{E}_{t+1}^{\mathbb{Q}}[e^{J_T}]). \end{aligned} \tag{14}$$

$\Delta LT_{t+1}^{\mathbb{Q}}(T,k)$ captures two important aspects of the time-varying jump risk. The first term on the right hand side of Eq. (14) is the change in the risk-neutral jump probability.[3] This probability differs from the risk-neutral third moment contributed by jumps in Gao et al. (2019) and the systematic jumps in index returns in Bégin et al. (2020). The second term on the right hand side of Eq. (14) 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., $\mathbb{E}_{t+1}^{\mathbb{Q}}[e^{J_T}] = \mathbb{E}_t^{\mathbb{Q}}[e^{J_T}]$, then $\Delta LT_{t+1}^{\mathbb{Q}}(T,k)$ only captures changes in jump intensity. Otherwise, it also captures the change in investors' beliefs of the jump magnitude. This feature differentiates $\Delta LT_{t+1}^{\mathbb{Q}}(T,k)$ from the measure in Lu and Murray (2019), which only depends on the stochastic driver of jump intensity but not on the change in jump sizes.

Notice that $\Delta LT^{\mathbb{Q}}$ in Eq. (14) is not a traded factor. To relate $\Delta LT^{\mathbb{Q}}$ to returns, we can approximate $\Delta LT^{\mathbb{Q}}$ by the difference between the log returns of two tradable portfolios. Because the price of a short-maturity OTM put option is small compared with the index price, $LT_t^{\mathbb{Q}}(T,k)$ is approximately equal to $\log(1 + LT_t^{\mathbb{Q}}(T,k))$, which leads to

$$\begin{aligned} \Delta LT_{t+1}^{\mathbb{Q}}(T,k) &\approx \log(LT_{t+1}^{\mathbb{Q}}(T,k) + 1) - \log(LT_t^{\mathbb{Q}}(T,k) + 1) \\ &= \log\Big(\frac{P_{t+1} + S_{t+1}}{S_{t+1}}\Big) - \log\Big(\frac{P_t + S_t}{S_t}\Big) \\ &= \log\Big(\frac{P_{t+1} + S_{t+1}}{P_t + S_t}\Big) - \log\Big(\frac{S_{t+1}}{S_t}\Big) \\ &=: \text{Tail}_{t+1}. \end{aligned} \tag{15}$$

The expression in Eq. (15) is our measure of the tail risk factor in our reduced-form model (Eq. (2)). For simplicity, in the remainder of the paper, we denote this mea-

[2] In an extensive Monte Carlo simulation study designed to investigate the finite sample accuracy of the approximations of $LT^{\mathbb{Q}}$, Bollerslev and Todorov (2011) show that the error involved in approximating $LT^{\mathbb{Q}}$ through Eq. (11) is trivial for options and empirical settings designed to mimic those of the actual data.

[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 et al. (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.

sure as Tail_{t+1}. 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. 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.

Our 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 US equity market events (Lettau et al., 2014), downside global equity market events (Dobrynskaya, 2014), and high frequency currency jumps (Lee and Wang, 2018). Second, our Tail factor is the difference between the log returns of two portfolios. Prevailing tail measures are typically constructed as either realized jumps or option-implied jumps, which cannot be replicated by self-financing portfolios. Lastly, our measure also differs from currency volatility measures, such as the FX volatility factor in Menkhoff et al. (2012a) and the currency variance risk premium in Londono and Zhou (2017), because our Tail factor focuses on investors' perception about unfavorable stock market events.

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 US equity tail factor

To construct the 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 CBOE from 1990 to 2018. We rely on information from US equity and option markets for two main reasons. On the one hand, equity index options in the US 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 shorter samples, starting in 2000 and 2006, respectively. On the other hand, the US tail factor is more likely to have a global component that affects the pricing of global equities. In unreported results, we find that the US 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 US stock market return. The predictability of the US tail factor is significant for the following countries' stock returns: the US, France, Germany, Japan, the UK, Switzerland, Italy, and the Netherlands.

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.[4] 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 95% of the closing price of the S&P 500 index.[5] We only select options with expiration day on the third Friday of next month and options with nonzero trading volumes. We track the price change of the selected 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 keep only the last value of the tail factor each month. On each trading day excluding roll dates, daily Tail is calculated as in Eq. (15). 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:

$$\text{Tail}_{t+1} = \log\left(\frac{P_{t+1,settle} + S_{t+1}}{P_t + S_t}\right) - \log\left(\frac{S_{t+1}}{S_t}\right), \tag{16}$$

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

Table 1 shows a set of summary statistics for our tail factor. For comparison, we also show summary statistics for a set of US 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 (DOL) and carry (CAR) factors in Lustig et al. (2011), and the change in volatility of the foreign exchange market (ΔFXvol), which is calculated following Menkhoff et al. (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

[4] 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.

[5] 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
Summary statistics for US equity and currency factors.

Panel A: Summary statistics (in percentage)						
	Tail	MKT	ΔVIX	DOL	CAR	ΔFXvol
Mean	0.09	0.39	0.36	0.11	0.78	0.05
Std.	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	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 US equity- and currency-related factors. Summary statistics include the mean, standard deviations (Std.), skewness (Skew), kurtosis (Kurt), 5th percentile (Q5), 95th percentile (Q95), and autocorrelation (AC). The details for the construction of the tail factor (Tail) are 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 all currencies in our sample. CAR 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 log 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.

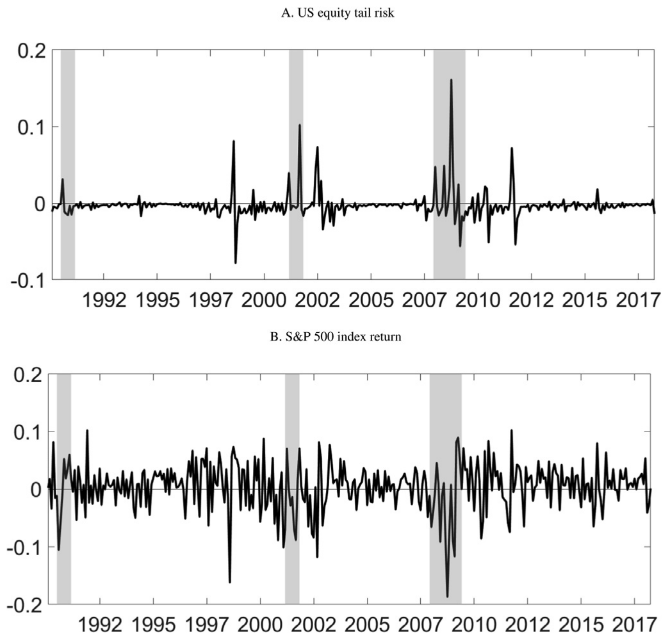

Fig. 1. Time series of the US equity tail risk factor and S&P 500 returns.
This figure shows time series of the US equity tail risk factor and the S&P 500 index return from February 1990 to April 2018 in Panel A and B, respectively. The details on the construction of the tail factor are provided in Section 3.1. The gray-shaded areas indicate NBER recession periods for the United States.

positively correlated with the VIX innovation (0.43). Correlations between the tail and dollar and carry factors are negative with coefficients 0.29 and 0.16, respectively. Finally, the correlation between the tail factor and the innovation in currency volatility is relatively small and positive (0.18).

Fig. 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 is countercyclical and tends to have extremely positive spikes around episodes of large negative jumps in the time series of S&P 500 returns.

3.2. Spot and forward exchange rates

We obtain spot and one-month forward exchange rates with respect to the US 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 one US 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: 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 UK.[6] 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. In our empirical exercises, 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, Switzerland, and the UK. This reduced sample allows us to assess the robustness of our results to issues like liquidity and tradability (see Menkhoff et al., 2012b).

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

$$rx_{k,t+1} = (i_{k,t} - i_t) + (fx_{k,t} - fx_{k,t+1}) \approx f_{k,t} - fx_{k,t+1}, \tag{17}$$

where f and fx denote the log of the forward and spot exchange rates, respectively. Here, we assume that the covered interest rate parity holds so that the forward rate is equal to the interest rate differential minus the spot exchange rate.

4. Evidence for the relation between equity tail risk and the cross section of currency returns

The model in Section 2 suggests that Tail betas, which are the coefficients of currency excess returns associated with the Tail factor, capture currencies' exposures to the global tail factor. As a consequence, sorting currencies on their Tail betas should generate variations in expected returns if the Tail factor contains a global component. In this section, we test this model implication by considering the Tail factor introduced in Section 2.2 and calculated in Section 3.1.

4.1. Currency portfolios sorted by US equity tail exposures

To assess whether the equity tail risk is priced in the cross section of currency returns, we sort currencies into five portfolios depending on their lagged equity tail exposures. To do so, we estimate the following regression for each currency's monthly excess return from the perspective of a US investor, rx_k in Eq. (17), on the equity tail factor, Tail, using a rolling window of 60 months,

$$rx_{i,t} = \alpha_i + \beta_{DOL,i}\mathrm{DOL}_t + \beta_{Mkt,i}\mathrm{MKT}_t + \beta_{Tail,i}\mathrm{Tail}_t + \varepsilon_{i,t}, \tag{18}$$

where we control for the dollar (DOL) factor and the US (S&P 500 index) stock market return (MKT), which serve as proxies for the global diffusion and US-specific shocks in our reduced-form model ($u_{g,t}$ and u_t, respectively, in Eq. (4)). The dollar factor (DOL), proposed by Lustig et al. (2011), is the equally-weighted cross-sectional average of foreign currency excess returns with respect to the US dollar. This factor corresponds to the return of a strategy that borrows money in the US and invests it in global money markets outside of the US. Lustig et al. (2011) find that the dollar factor is highly correlated with the first principal component of all-currency returns and accounts for a large fraction of the variation in currency excess returns.

Fig. 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 Panel A and B, respectively. During almost the entire sample, the bottom quintile portfolio (P1) has negative betas, while the top quintile portfolio (P5) 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 US equity tail risk of the currencies in the different Tail-beta portfolios strengthens during market downturns.

Table 2 reports the descriptive statistics of the Tail-beta 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 equity 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 of 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

[6] The selection of the currency universe is largely consistent with the literature, e.g., Menkhoff et al. (2012b). Note that we do not include the ten countries that adopted the euro in 1999. These countries are: Austria, Belgium, Finland, France, Germany, Italy, Ireland, the Netherlands, Portugal, and Spain. Because our exchange rate sample starts in 1990, there are not many observations for these countries' currencies after 1990. In addition, these countries' currencies typically comoved greatly before they were officially replaced by the euro.

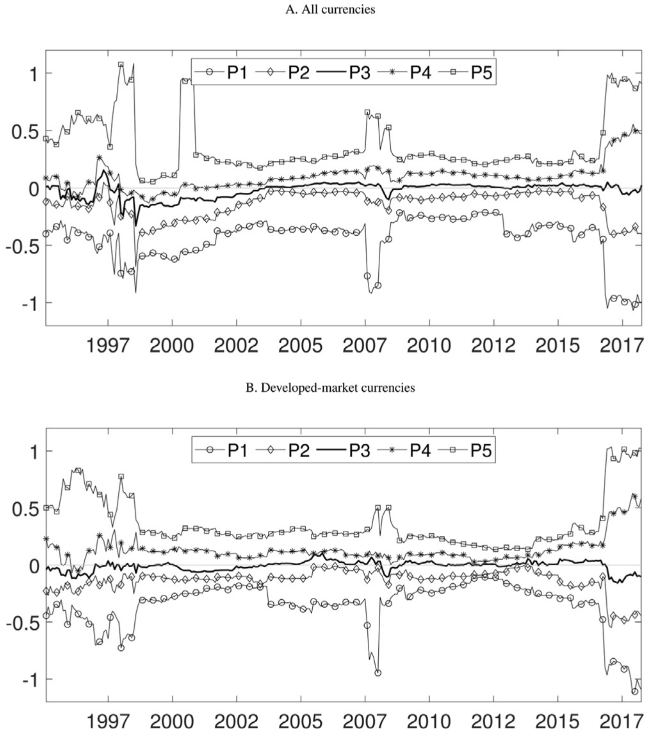

Fig. 2. Time series for the betas of the five Tail-beta portfolios.
This figure shows the time series of the Tail betas for the five Tail-beta currency portfolios for the sample with all currencies (Panel A) and for that with only the currencies of developed markets (DM, in Panel B). The Tail betas are estimated using the following regression: $rx_{i,t} = \alpha_i + \beta_{Mkt,i}\mathrm{MKT}_t + \beta_{DOL,i}\mathrm{DOL}_t + \beta_{Tail,i}\mathrm{Tail}_t + \varepsilon_{i,t}$, where $rx_{i,t}$ is the excess return of currency i over month t, DOL_t is the dollar factor, MKT_t is the S&P 500 index return, and Tail_t is the US equity tail factor. The regressions are estimated using a 60-month rolling window. The sample period runs from February 1995 to April 2018.

(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 comove with the US equity tail risk while some have hedging potential against this risk. The turnover rate (measured in terms of changes in the composition of the portfolio) of the H-L portfolio is 10%, which is lower than the turnover rates of the carry and momentum strategy in our sample (14% and 51%, respectively; see Section 5).

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 lower exposure to the US tail risk factor typically have higher interest rates than the US, implying that portfolios sorted on Tail betas share some similarities with the carry trade portfolios. Our results show 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 "winner" currencies tend to have lower Tail betas. Hence, our results indicate that Tail-beta portfolios bear both features of carry and momentum portfolios.

Panel B of Table 2 reports the descriptive statistics for the currencies from developed markets. For developed market 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 three robustness checks for our empirical results. First, because the equity tail factor is constructed from OTM put returns, it contains information about both volatility and jump risk. As shown in Andersen et al. (2015), short-maturity deep OTM put options load mostly on negative jumps and have hardly any exposure to the diffusive volatility. However, the equity 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:

$$rx_{i,t} = \alpha_i + \beta_{DOL,i}\mathrm{DOL}_t + \beta_{Mkt,i}\mathrm{MKT}_t + \beta_{\mathrm{VIX},i}\Delta\mathrm{VIX}_t + \beta_{Tail,i}\mathrm{Tail}_t + \varepsilon_{i,t}. \quad (19)$$

Table 2
Tail-beta currency portfolios (US 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***
Ste.	(1.71)	(1.53)	(1.24)	(1.46)	(1.81)	(1.36)	(1.39)
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
Turnover	0.09	0.20	0.25	0.23	0.12	0.01	0.10
Panel B: DM Currencies							
Mean	2.02	0.77	0.57	0.41	2.54	0.02	4.57***
Ste.	(1.69)	(1.78)	(1.49)	(1.72)	(1.85)	(1.46)	(1.69)
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
Turnover	0.10	0.23	0.26	0.22	0.10	0.00	0.10

This table reports excess returns of the Tail-beta portfolios for all currencies (Panel A) and for the subsample of currencies from developed markets (Panel B) from the point of view of a US investor. We first estimate $\beta_{Tail,i}$ for each currency i in regression (18) 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, standard errors (Ste.) in parenthesis, 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), the excess return in the pre-formation period (RX(-1,0)), and turnover rates. All moments are annualized and reported in percentage points. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively. The sample period runs from February 1995 to April 2018.

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 $\hat{\beta}_{Tail,i}$. Online Appendix Table A1 shows the summary statistics of these portfolios when we use the sample of all currencies. The high-minus-low (H-L) returns remain significantly negative with a 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, because equity Tail-beta portfolios have features of carry and momentum portfolios, we assess whether our results for the significant returns of the high-minus-low Tail-beta portfolio are robust to controlling for the carry factor (CAR) in Lustig et al. (2011). We run the following regression:

$$rx_{i,t} = \alpha_i + \beta_{DOL,i}\mathrm{DOL}_t + \beta_{Mkt,i}\mathrm{MKT}_t + \beta_{\mathrm{CAR},i}\mathrm{CAR}_t + \beta_{Tail,i}\mathrm{Tail}_t + \varepsilon_{i,t}. \tag{20}$$

As shown in Online Appendix Table A2, we obtain a significant annualized excess return of 3.20% for the high-minus-low Tail-beta portfolio and a Sharpe ratio of 0.47 when we control for the carry factor.

Third, one may argue that, to capture large-magnitude jump risk, we could construct the equity tail factor using put options with moneyness deeper than 95%. In Online Appendix Table A3, 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 except that, 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 A3 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 drivers of currencies' exposure to equity tail risk

Why do some currencies hedge against equity tail risk while some are more prone to tail risk? To further understand the heterogeneity in currencies' exposures to the equity tail risk factor, we explore the potential economic drivers of Tail betas. Since the Tail factor is countercyclical, we define currencies with low Tail beta as tail-prone currencies and those with high Tail beta as tail-resistant currencies.

We consider the following five hypotheses inspired by the literature. First, countries with tail-prone currencies may be larger in economic capacity than tail-resistant currencies, as they are better hedges against consumption

Table 3
Economic drivers of currencies' Tail betas.

	Full sample	DM currencies	EM currencies
Intercept	0.05	0.10*	0.43*
	(0.09)	(0.06)	(0.23)
GDP share	0.09	0.14	22.84
	(1.43)	(0.65)	(17.57)
Basic export ratio	0.22**	0.20***	0.11
	(0.10)	(0.06)	(0.44)
FXAGG	1.14*	0.47**	1.79
	(0.59)	(0.19)	(1.13)
Centrality	0.48**	0.16*	0.17***
	(0.20)	(0.09)	(0.06)
Inflation	0.01	0.01	0.04
	(0.02)	(0.01)	(0.05)
No. of countries	22	12	10
No. of obs.	3216	1939	1277
Adj. R^2	0.18	0.16	0.30
Time FE	Yes	Yes	Yes

This table reports regression results of currencies' Tail betas on several explanatory variables for the full sample, the developed-market (DM) sample, and the emerging-market (EM) sample. Tail betas are estimated from the regression in Eq. (18) 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 excess of foreign liabilities in total cross-border holdings. Centrality is the export-share-weighted average of bilateral trade intensities. 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.

risk. Following Hassan (2013), we use each country's Gross Domestic Product (GDP) share of the aggregate GDP for all countries in the sample to characterize the country's relative size (source: International Monetary Fund). 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 exposures. We use the measure of aggregate foreign currency exposure (FXAGG) in Bénétrix et al. (2015), which is defined as

$$\mathrm{FXAGG}_{i,t} = \omega^A_{i,t} s^A_{i,t} - \omega^L_{i,t} s^L_{i,t}, \tag{21}$$

where $\omega^A_{i,t}$ ($\omega^L_{i,t}$) is the share of foreign assets (liabilities) denominated in foreign currencies, $s^A_{i,t}$ ($s^L_{i,t}$) 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 US 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 be more tail-prone. 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 ten from emerging markets, from 1999 to 2012.[7] The results for the full sample of currencies show that currencies in countries with a lower basic export ratio, that is, those that specialize in producing final goods instead of basic goods are more resistant to US tail risk. Currencies in countries with higher international currency exposure (FXAGG) are significantly more prone to US tail risk. Trade network centrality is also a significant driver of heterogeneity in currencies' exposures to US 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 US 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 market.

4.3. Can FX factors explain the tail-beta portfolios?

Next, we explore how the Tail-beta portfolios are related to well-established common factors in currency mar-

[7] The developed market sample includes Australia, Canada, Denmark, Hong Kong, Japan, Korea, New Zealand, Norway, United Kingdom, Sweden, Switzerland, Singapore. The emerging market sample includes Czech Republic, Hungary, India, Indonesia, Malaysia, Mexico, Philippines, Poland, South Africa, Thailand.

Table 4
Time series regressions of Tail-beta 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***
	(0.89)	(0.78)	(0.74)	(0.77)	(0.82)	(1.39)
Dol-β	1.07	0.96	0.71	0.92	1.17	0.10
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.08)
ΔFXvol-β	24.44	2.11	15.56	25.79	6.31	18.13
	(10.95)	(9.22)	(9.82)	(11.34)	(11.86)	(19.51)
R^2 (%)	73.03	74.82	66.25	72.27	79.96	1.89
Panel B: DM currencies						
α	2.02**	0.76	0.58	0.41	2.55**	4.57***
	(1.01)	(0.97)	(0.85)	(1.05)	(1.10)	(1.69)
Dol-β	1.00	1.09	0.90	1.02	1.10	0.11
	(0.05)	(0.07)	(0.06)	(0.05)	(0.07)	(0.11)
ΔFXvol-β	25.95	9.89	15.75	35.12	21.87	4.08
	(11.94)	(14.95)	(11.38)	(14.55)	(16.59)	(24.57)
R^2 (%)	66.91	77.52	72.30	75.34	71.66	0.84

This table reports the time series regressions of the Tail-beta currency portfolios for all currencies in Panel A and for the currencies of developed markets in Panel B. The independent variables are the dollar risk factor (DOL), which is the average excess return of foreign currencies against the US dollar, and the innovation in aggregated FX volatility (ΔFXvol). We report regression coefficients along with their Newey-West standard errors (in parentheses) and R^2's (in percentage). *, **, and *** represent 10%, 5%, and 1% significance levels. The sample runs from February 1995 to April 2018.

kets. To do so, we regress the returns of each portfolio on the dollar and FX volatility factors. The FX volatility factor proposed by Menkhoff et al. (2012a) is the equally-weighted cross-sectional average of the realized volatility of foreign currency excess returns with respect to the US 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 the jth Tail-beta portfolio, $R_{j,t}$, on the dollar factor and the innovation of the FX volatility factor, ΔFXvol, as follows:

$$R_{j,t} = \alpha_j + \beta_{1,j}\mathrm{DOL}_t + \beta_{2,j}\Delta\mathrm{FXvol}_t + \epsilon_{j,t}. \tag{22}$$

The regression results are reported in Table 4. Regardless of whether we construct portfolios from the currencies of all countries or from those of developed markets (Panel A and B, respectively), the coefficients on ΔFXvol or DOL do not exhibit a recognizable pattern. For both samples of currencies, $\hat{\alpha}_j$'s display a decreasing trend 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 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 1.89% R^2 for the sample with all currencies and a 0.84% R^2 for the sample with only developed markets. Therefore, our results demonstrate that the dollar and the FX volatility factors cannot explain the cross section of Tail-beta portfolios.

Besides the dollar and FX volatility factors, we also run time series regressions of the Tail-beta portfolios on a series of potentially related factors as robustness checks. Specifically, we consider (i) the dollar and carry factors to make sure that the high-minus-low portfolio is not subsumed by the carry factor, (ii) the dollar factor and the change in global equity volatility, and (iii) the dollar factor and the change in the VIX index. The global equity volatility is calculated as the realized volatility of the MSCI World index using daily returns. These results are reported in Online Appendix Table A4, A5, and A6. Results show that the coefficients of carry (CAR), change in global equity volatility (ΔGlobal-RV), and change in the VIX index (ΔVIX) are not statistically significant. Furthermore, the estimated α for the return of the high-minus-low portfolio remains statistically significant after controlling for these additional factors. This evidence suggests that the return of the Tail-beta portfolios is not fully spanned by the carry factor. While it is very difficult to disentangle time-varying volatility risk from tail risk, we show that the high-minus-low Tail-beta portfolio return is not related to volatility changes.

4.4. Alternative reference currencies

The intuition from the model in Section 2 suggests that the return of the currency portfolio sorted on Tail betas uncovers the global tail component regardless of which country is assumed to be the home country, that is, irrespective of the reference currency. To confirm this implication, we estimate Tail betas in the cross section of pound-denominated or yen-denominated currency returns and sort the currencies into five quintiles. Online Appendix Table A7 and Table A8 show the corresponding statistics for the pound and yen, respectively. The results from the viewpoint of a US investor remain robust if we consider other reference currencies. That is, the return of the H-L portfolio is negative and significant for both UK and Japanese investors, and these results hold when we consider the full sample or the sample of only the developed markets currencies.

Table A9 reports the correlation matrix of Tail-beta 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 and the developed-market sample, the pairwise correlation of the global tail factor for 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 reference currency. In the remainder of the paper, we consider the global tail factor constructed from the cross-section of currency returns with the US dollar as the home currency.

5. The price of global tail risk in the cross section of currency returns

As suggested by the reduced-form model in Section 2, the return of a long-short portfolio that buys currencies with high Tail beta and shorts those with low Tail beta extracts the global component embedded in the equity tail risk factor. 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 et al. (2011) and other studies in the recent currency literature.[8] 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 difference between the forward FX rate and the 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 US and portfolio 5 contains the top quintile of currencies with the highest interest rate differentials. The high-minus-low return of the carry portfolio is referred to as the carry factor in the literature, which 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 et al. (2012b) find that currencies with higher returns in the past month have, on average, higher returns in the next month. 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).

Table 5 shows the summary statistics of the carry and momentum portfolios, in Panel A and B, respectively, for all the currencies in our sample. 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 6.4% annually, with a Sharpe ratio of 0.79. Average returns display an increasing trend 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 et al. (2012b) and Filippou and Taylor (2017), the momentum strategy in the all-currencies universe also generates considerable excess returns of 7.0% per year.

5.2. Explaining currency returns using the global tail factor

As suggested in the literature, such as in Verdelhan (2018), carry returns are mainly exposed to global shocks rather than to country-specific shocks. 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 equity tail risk factor might help us understand the risk-return profile of currency carry trade and momentum strategies.

We test the pricing power of the global tail factor for the cross section of various currency portfolios, including those of carry and momentum. If there are no arbitrage opportunities, the excess return of portfolio i, $R_{i,t+1}$, satisfies the following Euler equation:

$$E_t[M_{t+1}R_{i,t+1}] = 0, \tag{23}$$

where the pricing kernel, M_{t+1}, is linear in the pricing factors f_{t+1}:

$$M_{t+1} = 1 - b'(f_{t+1} - \mu). \tag{24}$$

Here, b is the vector of factor loadings and μ is the mean of the factors. This specification implies a beta pricing model, in which the expected excess return of portfolio i is equal to the factor price of risk λ times the quantity of risk β_i; $E[R_i] = \lambda'\beta_i$, where λ is related to the SDF loadings b through $\lambda = \Sigma_f b$, with Σ_f the covariance matrix of the factors.

The recent literature has considered the average excess return of the dollar and carry factors as common factors in the foreign exchange market (Lustig et al., 2011). In this paper, we consider a three-factor model with the dollar factor, the carry factor, and the global tail factor. To investigate the pricing performance of the global tail factor, we use the Fama–MacBeth regression and the generalized method of moments (GMM) estimation.

We first employ the two-stage Fama–MacBeth regression (Fama and MacBeth, 1973) to estimate portfolio betas and factor risk prices. In the first stage, we run the time series regression of the excess returns of each currency port-

[8] See, for instance, Bakshi and Panayotov (2013); Daniel et al. (2017); and Bekaert and Panayotov (2020).

Table 5
Summary statistics of currency carry and momentum portfolios.

Portfolio	1	2	3	4	5	H-L
Panel A: Carry portfolio – All currencies						
Mean	1.66	0.26	1.65	1.18	4.74***	6.40***
Ste.	(1.21)	(1.13)	(1.49)	(1.52)	(1.80)	(1.52)
Skew	0.04	0.02	0.62	1.26	0.65	0.44
Kurt	4.34	3.97	5.97	8.98	6.06	4.89
SR	0.26	0.04	0.21	0.15	0.49	0.79
Panel B: Momentum portfolio – All currencies						
Mean	2.63	0.57	2.05	2.47	4.41**	7.05***
Ste.	(1.21)	(1.13)	(1.49)	(1.52)	(1.80)	(1.52)
Skew	0.04	0.02	0.62	1.26	0.65	0.44
Kurt	4.34	3.97	5.97	8.98	6.06	4.89
SR	0.26	0.04	0.21	0.15	0.49	0.79

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 errors (Ste.) in parenthesis, skewness (Skew), kurtosis (Kurt), 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 $t-1$. *, **, and *** represent 10%, 5%, and 1% significance levels. The sample period runs January 1990 to April 2018.

folio on the factors,

$$R_{i,t} = \alpha_i + \beta_{DOL,i}\mathrm{DOL}_t + \beta_{CAR,i}\mathrm{CAR}_t + \beta_{Gtail,i}\mathrm{Gtail}_t + \varepsilon_{i,t}. \tag{25}$$

Having obtained estimates of the coefficients on the dollar, carry, and global tail factors, $\hat{\beta}_{DOL,i}$, $\hat{\beta}_{CAR,i}$, and $\hat{\beta}_{Gtail,i}$, respectively, we run the following cross-sectional regression in the second stage:

$$\bar{R}_i = \hat{\beta}_{DOL,i}\lambda_{DOL} + \hat{\beta}_{CAR,i}\lambda_{CAR} + \hat{\beta}_{Gtail,i}\lambda_{Gtail} + \eta_i, \tag{26}$$

where the dependent variable $\bar{R}_i$ is the time series average of the excess return of portfolio i; the first stage estimators, $\hat{\beta}_{DOL,p_i}$, $\hat{\beta}_{CAR,p_i}$ and $\hat{\beta}_{Gtail,i}$ are used as explanatory variables; λ_{DOL}, λ_{CAR}, and λ_{Gtail} are the risk prices of the dollar, carry, and global tail factors, respectively; and η_i is the pricing error of portfolio i. Note that we do not include a constant in the second stage of the Fama–MacBeth regressions. That is, we do not allow a common mispricing in the cross section of returns. We calculate the cross-sectional R^2 as:

$$R^2 = 1 - \frac{\frac{1}{N}\sum_{i=1}^{N}\hat{\eta}_i^2}{\mathrm{var}(\bar{R}_i)}. \tag{27}$$

After estimating the parameters from the second-stage regression, we calculate the model-predicted mean excess return as

$$\hat{\bar{R}}_i = \hat{\beta}_{DOL,i}\hat{\lambda}_{DOL} + \hat{\beta}_{CAR,i}\hat{\lambda}_{CAR} + \hat{\beta}_{Gtail,i}\hat{\lambda}_{Gtail},$$

and calculate the root mean squared error (RMSE) as $\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\bar{R}_{i,t} - \hat{\bar{R}}_{i,t})^2}$.

We consider five groups of test assets: carry portfolios, momentum portfolios, the joint cross section of carry and momentum portfolios, the joint cross section of momentum and value portfolios, and the joint cross section of the momentum, value, and variance risk premium (VRP) portfolios. Following Menkhoff et al. (2016), we construct currency value portfolios by sorting currencies on real exchange rates. Following Della Corte et al. (2016a), we construct VRP portfolios by sorting currencies on currency option-implied variance risk premium. We also consider individual currencies of developed markets as test assets to avoid data-snooping biases (Lo and MacKinlay, 1990).

Since the global tail factor is the return of a long-short portfolio, its price of risk should be equal to its expected return, which implies that λ_{Gtail} cannot be a free parameter in the estimation. Following the suggestion of Lewellen et al. (2010), we include the global tail factor as one of the test assets in each regression; effectively, we impose the constraint that the estimated price of risk of Gtail should equal its sample average.

Table 6 reports the results for the second-stage Fama-MacBeth regressions. We report the estimated price of risk of Gtail, DOL, and CAR, the cross-sectional R^2, the χ^2 statistics, and the corresponding p-value for the null hypothesis that all pricing errors are jointly zero. Standard errors reported in brackets are based on a Newey–West approach with optimal lag selection (NW) or the Shanken (1992) correction (Sh).

Across the different test assets, the estimated price of Gtail is significantly negative, ranging from 0.61% to 0.37% per month, close to the average monthly return of Gtail, which is 0.39% for our full sample according to the summary statistics in Table 2.[9] Moreover, the p-values of the χ^2 tests are above 10%, suggesting that the hypothesis that pricing errors are jointly zeros cannot be rejected for any group of test assets.

[9] The average annual return of the Gtail factor is −4.73%, which yields an average monthly return of −4.73%/12 = −0.39%. To formally test the hypothesis that the price of risk for Gtail is equal to its sample average, we employ the Wald test where the null hypothesis is $H_0 : \lambda_{\mathrm{Gatil}} = -0.39$. In unreported results, we show that the null hypothesis that the estimated price of risk for Gtail is equal to its sample average (−0.39% per month) cannot be rejected at any standard significance level. Following Lewellen et al. (2010), we also run a restricted asset pricing regression by setting λ_{Gatil} to its monthly average, −0.39. We report the restricted regression results in Online Appendix Table A10. In this case, the price of Gtail does not have standard errors. The results are qualitatively similar to those for the unrestricted regressions in Table 6 in that the p-values of χ^2 tests are sufficiently large and R^2's are only slightly smaller.

Table 6
Cross-section asset pricing results: Gtail + DOL + CAR.

	Carry	Momentum	Carry + momentum	Momentum + value	Momentum + value + VRP	DM currencies
Gtail	0.39	0.46	0.60	0.58	0.61	0.37
(NW)	(0.12)	(0.13)	(0.14)	(0.14)	(0.14)	(0.13)
(Sh)	(0.12)	(0.12)	(0.13)	(0.13)	(0.14)	(0.12)
DOL	0.07	0.07	0.05	0.01	0.00	0.09
(NW)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)
(Sh)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)
CAR	0.63	1.24	0.52	0.20	0.07	0.48
(NW)	(0.15)	(0.45)	(0.15)	(0.24)	(0.24)	(0.28)
(Sh)	(0.14)	(0.63)	(0.14)	(0.26)	(0.25)	(0.28)
χ^2	7.37	5.12	15.31	10.73	16.37	7.80
p-value	0.12	0.28	0.12	0.38	0.43	0.80
RMSE	0.07	0.12	0.18	0.14	0.14	0.06
R^2 (%)	95.93	83.04	61.20	60.85	51.65	82.54

This table reports the results for the asset pricing tests on the cross section of currency portfolios using Fama–MacBeth regressions. The test assets include carry portfolios (2nd column); momentum portfolios (3rd column); carry and momentum portfolios (4th column); momentum and value portfolios (5th column); momentum, value, and VRP portfolios (6th column); and individual developed market currencies (7th column). The linear factor model includes three factors: DOL, CAR, and Gtail. DOL is the dollar risk factor; CAR is the currency carry factor; and the Gtail is the global tail factor, constructed as the long-short portfolio of the Tail-beta portfolio returns. Returns are expressed in monthly percentage points. We report the estimated risk prices, standard errors (in parentheses), root-mean-squared pricing error (RMSE), and cross-sectional R^2's. The reported standard errors are based on the Shanken (1992) adjustments (Sh) or the Newey-West approach with optimal lag selection (NW). We also report the χ^2 test statistics and p-values on the null hypothesis that the pricing errors are jointly zero. The sample period runs from February 1995 to April 2018.

The three-factor model generates reasonable R^2's ranging from 51.65% to 95.93%. The high cross-sectional fit for the carry portfolios is not surprising because of the presence of the carry factor. The R^2 for the momentum portfolios is as high as 83%. Notice that the carry factor is estimated with significant positive price of risk only when carry portfolios are included in the asset assets. When carry portfolios are excluded in the test assets, such as for the momentum, momentum and value, or momentum, value, and VRP portfolios, the carry factor does not appear to be correctly priced.

While the literature offers several explanations for the FX carry portfolios, relatively fewer studies attempt to explain FX momentum portfolios, let alone the joint cross section of carry and momentum portfolios. We observe satisfactory cross-sectional R^2 of 61% in the joint portfolios of carry and momentum. Moreover, the three-factor model explains 83% of the momentum portfolios and over 51% in the joint cross section of momentum and value, as well as the momentum, value, and VRP portfolios. Our evidence suggest that the Gtail factor not only explains carry and momentum portfolios separately, but also jointly, and the results remain robust when the cross section is augmented by currency portfolios from other strategies. 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.

Table 6 suggests that the carry factor is not especially useful in pricing non-carry related portfolios. Thus, in Table 7, we repeat the asset pricing tests removing the carry factor. We observe that the price of risk for the Gtail factor remains negative and significant in all test assets. As expected, however, after removing the carry factor, R^2's become smaller for most of the test assets, especially those with carry portfolios. The decrease in R^2's is only marginal for momentum and value portfolios as well as for the momentum, value, and VRP portfolios. We conclude that the carry factor has little added value in explaining non-carry portfolios.

Besides the Fama–MacBeth regressions, we also estimate the SDF of Eq. (24) using GMM estimation following Hansen (1982). To implement GMM, we use the pricing errors as a set of moments and an identity weighting matrix. Table 8 reports the results of the asset pricing tests on the cross section of currency portfolios using GMM. We report GMM estimates of the factor loading b and the market price of risk λ. The reported standard errors (in parenthesis) are based on the Newey-West approach with optimal lag selection. We also report the HJ distance in Hansen and Jagannathan (1997) and the corresponding p-value to test the null hypothesis that the HJ is equal to zero. Consistent with the Fama–MacBeth regression results, we find that both b_{Gtail} and λ_{Gtail} are significantly negative in each group of test assets. This implies that Gtail is not only a priced factor, but it also helps to explain the currency returns in the presence of the dollar and carry factors. The HJ distances are not significant in all cases, suggesting that the null hypothesis that HJ = 0 cannot be rejected for the three-factor model. Overall, the results in Tables 6 and 8 suggest that Gtail contains information that is additional to that of the dollar and carry factors. The independent information in Gtail matters for pricing the currency portfolios.

To alleviate the concern that there are too few portfolios in the asset pricing tests (see Lewellen et al., 2010), we also consider 12 portfolios for each strategy—six portfolios constructed from all currencies including the long-short portfolio and six portfolios constructed from developed-market currencies. Online Appendix Table A11 reports the Fama–MacBeth regression results including developed market currency portfolios as test assets. In line with the

Table 7
Cross-section asset pricing results: Gtail + DOL.

	Carry	Momentum	Carry + momentum	Momentum + value	Momentum + value + VRP	DM currencies
Gtail	0.47	0.56	0.63	0.59	0.62	0.41
(NW)	(0.12)	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)
(Sh)	(0.12)	(0.13)	(0.13)	(0.14)	(0.14)	(0.12)
DOL	0.13	0.04	0.09	0.03	0.02	0.02
(NW)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
(Sh)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
χ^2	25.28	7.46	32.62	11.12	16.31	9.32
p-value	0.00	0.19	0.00	0.43	0.50	0.75
RMSE	0.26	0.19	0.24	0.15	0.15	0.10
R^2 (%)	36.89	56.08	33.47	57.35	50.11	55.96

This table reports the results for the asset pricing tests on the cross section of currency portfolios using Fama–MacBeth regressions. The test assets include carry portfolios (2nd column); momentum portfolios (3rd column); carry and momentum portfolios (4th column); momentum and value portfolios (5th column); momentum, value, and VRP portfolios (6th column); and individual developed market currencies (7th column). The linear factor model includes two factors: DOL and Gtail. DOL is the dollar risk factor and the Gtail is the global tail factor, constructed as the long-short portfolio of the Tail-beta portfolio returns. Returns are expressed in monthly percentage points. We report the estimated risk prices, standard errors (in parentheses), RMSE, and cross-sectional R^2's. The reported standard errors are based on the Shanken (1992) adjustments (Sh) or the Newey-West approach with optimal lag selection (NW). We also report the χ^2 test statistics and p-values on the null hypothesis that the pricing errors are jointly zero. The sample period runs from February 1995 to April 2018.

Table 8
Cross-section asset pricing results: GMM estimates.

	Carry	Momentum	Carry + momentum	Momentum + value	Momentum + value + VRP	DM currencies
b_{Gtail}	0.10	0.16	0.15	0.16	0.13	0.10
	(0.03)	(0.06)	(0.03)	(0.03)	(0.03)	(0.03)
λ_{Gtail}	0.39	0.45	0.56	0.57	0.49	0.37
	(0.13)	(0.20)	(0.12)	(0.12)	(0.11)	(0.13)
b_{DOL}	0.01	0.15	0.01	0.04	0.05	0.00
	(0.04)	(0.08)	(0.04)	(0.04)	0.04	0.04
λ_{DOL}	0.08	0.05	0.10	0.03	0.12	0.09
	(0.15)	(0.16)	(0.14)	(0.13)	0.14	0.15
b_{CAR}	0.11	0.32	0.09	0.04	0.00	0.08
	(0.03)	(0.16)	(0.03)	(0.04)	0.06	0.05
λ_{CAR}	0.61	1.48	0.53	0.10	0.13	0.48
	(0.16)	(0.77)	(0.15)	(0.20)	0.24	0.27
HJ distance	0.17	0.25	0.27	0.24	0.29	0.18
p-value	0.62	0.79	0.60	0.54	0.49	0.39

This table reports the results of the asset pricing tests on the cross section of currency portfolios using GMM. The test assets and pricing factors are the same as in Table 6. We report GMM estimates of the factor loadings b and the market price of risk λ. The reported standard errors (in parenthesis) are based on the Newey-West approach with optimal lag selection. We also report HJ and p-values for the null hypothesis that the HJ is equal to zero, where HJ denotes the Hansen and Jagannathan (1997) distance. The sample period runs from February 1995 to April 2018.

results in Table 6, the estimated risk premiums for Gtail are negative and statistically significant.

Fig. 3 plots the model-predicted returns against the sample average returns for the four groups of test assets: 1) carry, 2) momentum, 3) carry and momentum, and 4) momentum, value, and VRP portfolios. The portfolios are constructed using the full sample of currencies. The figure shows that the relation between model-predicted returns and sample average returns lies around the 45-degree line, suggesting that the three-factor model performs reasonably well in terms of cross-sectional fit.

To assess the added value of the Gtail factor, in Fig. 4, we plot the cross-sectional fit for the model without the Gtail factor. We consider the same four groups of test assets and plot their realized mean excess returns versus the prediction by the model with only the dollar and carry factors. We observe that, while the carry portfolios are accurately priced in this model, as shown in the upper left panel of Fig. 4, neither the momentum, value, or VRP portfolios lie close to the 45-degree line. For instance, the momentum, value, and VRP portfolios lie horizontally as shown in the bottom right panel. This evidence suggests that a model with only the dollar and carry factors predicts similar levels of mean excess returns for the momentum, value, or VRP portfolios, even though these portfolios have very different realized mean excess returns. In contrast, the consistency of the negative prices of risk of the global tail factor in carry and momentum portfolios helps to explain the joint cross section of portfolios for multiple strategies.

The asset pricing results presented in this section shed new light on currency anomalies, in particular, carry and momentum strategies. Existing literature relates carry returns to individual currency's crash risk. However, the empirical evidence in the literature is mixed. Burnside et al. (2011) find that most of the carry returns

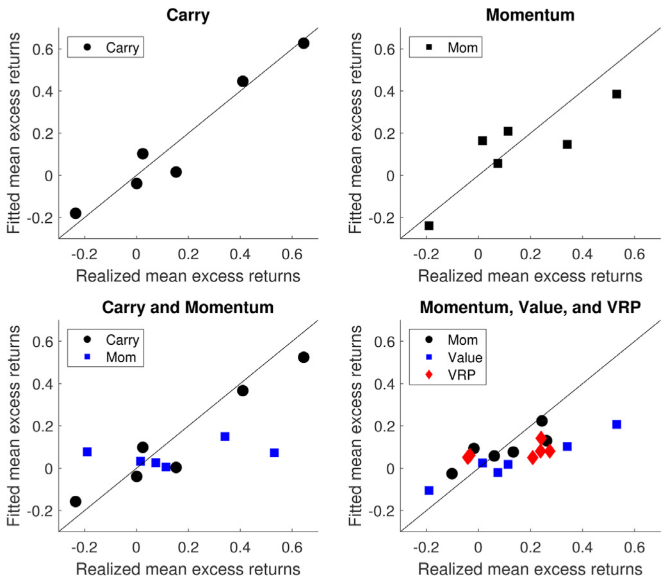

Fig. 3. Currency portfolio returns, cross-section model performance.
This figure shows scatter plots of realized annualized mean excess returns against the fitted excess returns, in percentages. Fitted excess returns are generated by a factor model with the dollar, carry, and Gtail factors. Test assets are the six carry portfolios in the upper left panel; six momentum portfolios in the upper right; 12 carry and momentum portfolios in the bottom left; and 18 momentum, value, and VRP portfolios in the bottom right. The sample period runs from February 1995 to April 2018.

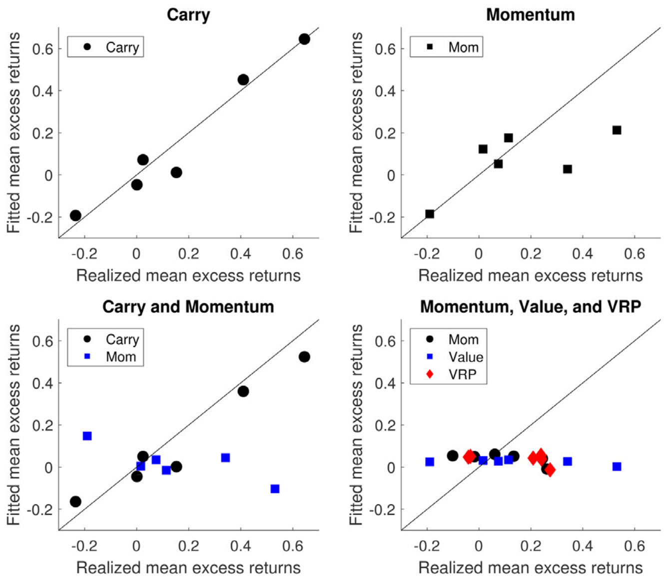

Fig. 4. Currency portfolio returns, cross-section model performance (without the Gtail factor).
This figure shows scatter plots of realized annualized mean excess returns against the fitted excess returns, in percents. Fitted excess returns are generated by a factor model with the dollar and carry (i.e., without Gtail) factors. Test assets are the six carry portfolios in the upper left panel; six momentum portfolios in the upper right; 12 carry and momentum portfolios in the bottom left; and 18 momentum, value, and VRP portfolios in the bottom right. The sample period runs from February 1995 to April 2018.

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. We argue that exposure to the *global* tail risk is a potential explanation for currency anomalies. For instance, currencies with higher interest rate or higher past returns provide investors with higher returns because they have a larger exposure to the global tail risk.

5.3. Controlling for other asset pricing factors

To assess the additional explanatory power of the global tail factor for currency returns, we consider a series of control risk factors. First, we control for the innovation in FX volatility (ΔFXvol) in Menkhoff et al. (2012a), which has been shown to exhibit explanatory power for currency carry portfolios. Second, we consider other tail risk

Table 9
Asset pricing tests for currency portfolios with control factors.

	ΔFXvol	ΔGRIX	ΔEQRIX	ΔFXRIX	ΔBDRIX	Downside risk	Dollar carry	Global DOL	ΔVIX
Gtail	0.49	0.71	0.61	0.61	0.59	0.47	0.51	0.54	0.47
(NW)	(0.13)	(0.17)	(0.16)	(0.16)	(0.16)	(0.13)	(0.13)	(0.14)	(0.13)
(Sh)	(0.13)	(0.17)	(0.15)	(0.16)	(0.15)	(0.12)	(0.13)	(0.13)	(0.12)
Control	0.09	0.20	0.18	0.92	0.05	2.08	0.02	0.69	0.18
(NW)	(0.03)	(0.12)	(0.07)	(0.32)	(0.02)	(0.68)	(0.00)	(0.41)	(0.06)
(Sh)	(0.05)	(0.14)	(0.09)	(0.43)	(0.03)	(0.95)	(0.01)	(0.46)	(0.10)
DOL	0.06	0.11	0.10	0.12	0.14	0.08	0.06	0.05	0.08
(NW)	(0.12)	(0.16)	(0.15)	(0.16)	(0.15)	(0.12)	(0.12)	(0.12)	(0.12)
(Sh)	(0.12)	(0.15)	(0.14)	(0.15)	(0.14)	(0.12)	(0.12)	(0.12)	(0.12)
CAR	0.57	0.52	0.57	0.55	0.56	0.54	0.57	0.55	0.53
(NW)	(0.15)	(0.19)	(0.18)	(0.19)	(0.18)	(0.15)	(0.15)	(0.15)	(0.15)
(Sh)	(0.14)	(0.18)	(0.17)	(0.18)	(0.17)	(0.14)	(0.14)	(0.14)	(0.15)
χ^2	8.59	14.94	14.86	10.27	11.68	12.59	11.85	17.09	9.74
p-value	0.86	0.38	0.39	0.74	0.63	0.56	0.62	0.25	0.78
RMSE	0.12	0.15	0.12	0.12	0.11	0.12	0.13	0.15	0.12
R^2 (%)	77.48	73.46	81.72	84.71	85.58	79.90	75.87	68.62	78.34

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 Gtail, DOL (dollar), and CAR (carry) factors. The control factors include the change in foreign exchange volatility (ΔFXvol) in Menkhoff et al. (2012a), the change in global/equity/FX/bond tail risk concerns (ΔGRIX/ΔEQRIX/ΔFXRIX/ΔBDRIX) in Gao et al. (2019), the downside risk factor in Lettau et al. (2014), the dollar carry in Lustig et al. (2014), the global dollar in Verdelhan (2018), and the change in VIX (ΔVIX). We obtain the GRIX, EQRIX, FXRIX, and BDRIX 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 13 currency portfolios—six carry portfolios, six momentum portfolios, and Gtail. Returns are expressed in monthly percentage points. We run the Fama-MacBeth regression and report the estimated risk prices, standard errors (in parentheses), root-mean-squared pricing error (RMSE), and cross-sectional R^2's. The reported standard errors are based on the Shanken (1992) adjustments (Sh) or the Newey-West approach with optimal lag selection (NW). We also report the χ^2 test statistics and p-values on the null hypothesis that the pricing errors are jointly zero. The sample period runs from February 1995 to April 2018, except for ΔGRIX, ΔEQRIX, ΔFXRIX, and ΔBDRIX for which the sample runs from January 1996 to June 2012.

factors: the innovations in the indices of global, equity, FX, and bond tail risk concerns (ΔGRIX, ΔEQRIX, ΔFXRIX, and ΔBDRIX, respectively) in Gao et al. (2019). These tail risk factors are the option-implied tail risk concerns constructed across different asset classes, which might contain similar economic information as our Gtail factor. Third, since the global tail factor originates from equity tail risk, we consider two equity factors as additional controls, namely, the downside risk factor in Lettau et al. (2014) and the change in VIX (ΔVIX). Fourth, we consider the dollar carry in Lustig et al. (2014) to control for US-specific business cycle variations. Lastly, we control for the global dollar in Verdelhan (2018), which also has a global nature and may have substitutionary or complementary information to our Gtail factor. In all regressions, we control for the dollar and carry factor.

We run Fama–MacBeth regressions 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 9. The estimates of the price of risk of the Gtail factor are consistently negative and statistically significant irrespective of the control variable.[10]

[10] It is worth noting that the downside risk factor in Lettau et al. (2014) has a negative price of risk, which stands in contrast to the theoretical prediction, as downside risk is, by construction, pro-cyclical. In unreported result, we find a negative price of downside risk without controlling for the Gtail factor in the sample of 1995 to 2018. When we use the same sample 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 risk.

5.4. Asset pricing tests on other asset classes

In this section, we explore the pricing power of the global tail factor for other asset classes. In particular, we consider six sovereign bond portfolios and the related long-short portfolio from Borri and Verdelhan (2015). The bond portfolios are double sorted on the countries' probabilities of default and bond betas, and the data is available from February 1995 to April 2011. We also consider 18 value and momentum portfolios from Asness et al. (2013), including six fixed income and six commodity portfolios sorted on value and momentum (FI, Commodity Value/Mom). The data is available from February 1995 to June 2010. In addition, we use equity portfolios available from Kenneth French's website for 25 global size/momentum sorted portfolios (Global Equity Size/Mom), 25 global size/book-to-market sorted portfolios (Global Equity Size/BM), and 32 global size/investment/profitability sorted portfolios (Global Equity Size/Inv/Prof), using data spanning from February 1995 to April 2018.

Table 10 reports the GMM estimation results on these test assets. For all asset classes, we include the dollar factor to control for aggregate global risk. Similar to the asset pricing tests for the currency portfolios in Section 5.2, we add the global tail as a test asset in each group of test assets. In the column "Sovereign bonds" in Table 10, we also control for the Bond factor and the Bond H-L factor, which are the average return of all the sovereign bond portfolios and the average return of the high-minus-low portfolio sorted by sovereign risk, respectively. We find that the global tail factor is significantly priced after controlling for the dollar, Bond, and Bond H-L factors. In the col-

Table 10
Asset pricing tests on other asset classes.

	Sovereign bonds	FI,commodity value/mom	Global equity size/mom	Global equity size/BM	Global equity size/inv/prof
Gtail	0.51	0.46	0.41	0.41	0.42
	(0.18)	(0.10)	(0.24)	(0.17)	(0.16)
Dollar	0.95	0.19	2.09	0.34	0.24
	(0.36)	(0.24)	(0.88)	(0.41)	(0.25)
Bond	0.68				
	(0.33)				
Bond H-L	1.02				
	(0.47)				
Value		0.00			
		(0.08)			
Mom		0.33			
		(0.12)			
Gmkt			0.75	0.73	0.75
			(0.63)	(0.56)	(0.42)
Gsize			0.24	0.03	0.02
			(0.23)	(0.18)	(0.18)
Gvalue			0.28	0.22	0.33
			(0.64)	(0.18)	(0.28)
Gprof			0.18	0.56	0.43
			(0.43)	(0.32)	(0.14)
Ginv			0.63	0.27	0.22
			(0.47)	(0.33)	(0.15)
HJ distance	0.14	0.38	0.67	0.50	0.48
p-value	0.50	0.57	0.52	0.52	0.51
R^2 (%)	0.97	0.17	0.90	0.84	0.87

This table reports GMM estimation results for the cross-section of sovereign bonds, multi-assets value-momentum portfolios, and Fama-French global equity portfolios. "Sovereign bonds" refers to the sovereign bonds portfolios, including six portfolios double sorted on the countries' probabilities of default and bonds beta and one high-minus-low portfolio. "FI, commodity value/mom" refers to the 12 value and momentum portfolios, including six fixed income and six commodity portfolios sorted on value and momentum. "Global equity size/BM" refers to the 25 Fama-French global equity portfolios sorted on size and book-to-market. "Global equity size/inv/prof" refers to the 32 Fama-French global equity portfolios sorted on size, investment, and profitability. We consider the following asset pricing factors: Gtail is the long-short currency portfolio return sorted by their Tail betas; DOL is the dollar risk factor; Bond is the average return across all sovereign portfolios; Bond H-L is the high-minus-low return sorted on the countries' probabilities of default; Value (Mom) is average return of the "value (momentum) everywhere" portfolios; Gmkt, Gsize, Gvalue, Gprof, and Ginv refer to the Fama-French global market, size, value, profitability, and investment factors, respectively. We report the estimated risk prices and standard errors (in parentheses), and cross-sectional R^2's using GMM. We also report HJ and its p-value for the null hypothesis that the HJ is equal to zero, where HJ denotes the Hansen and Jagannathan (1997) distance.

umn "FI, commodity value/mom," in addition to the dollar factor, we also control for the aggregated value and momentum factors constructed by Asness et al. (2013), which are the equal-volatility-weighted average of value and momentum strategies across all markets and asset classes, respectively. In the last three columns of Table 10, "Global equity size/mom," "Global equity size/BM," and "Global equity size/inv/prof," we control for the dollar and the Fama-French five global equity factors: market (Gmkt), Size (Gsize), Value (Gvalue), Profitability (Gprof), and Investment (Ginv) factors. We find the price of the Gtail factor to be consistently significant and negative in all these portfolios.

Overall, the results in Table 10 suggest that the pricing performance of the Gtail factor is not limited to the currency portfolios in Section 5.2. This global factor is also priced in the cross section of other global assets, such as sovereign bonds, fixed income securities, commodities, and global equities.

6. Conclusion

This paper studies the pricing implications of 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 tail risk in equity markets and their pricing implications for currencies.

We find that the US equity tail risk factor bears a negative price of risk: Currencies with a higher exposure to equity tail risk have significantly lower returns than currencies with a lower exposure to this factor. In a reduced-form model in which each country's stochastic discount factor is exposed to country-specific and global risks, we show that a country'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 tail risk factor. We refer to this return spread as the global tail risk factor. We provide empirical evidence that our novel global tail risk factor can simultaneously explain a large portion of the cross section of currency portfolios of multiple strategies and is also a priced factor in the cross section of other asset classes.

Our results suggest that the US equity tail risk factor contains a global component and that currency risk premiums are related to currencies' exposures to this global component. Different exposures to the global tail factor might serve as a potential risk-based explanation for several anomalies in financial markets.

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