The Time-Varying Risk Price of Currency Portfolios

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and risk prices. There are good reasons to suggest that currency risk factors may have time-varying betas and/or risk prices. The broad asset pricing literature mainly focuses on time-varying betas and much less on time-varying risk prices.[1] Factor betas are main concerns in portfolio risk management, and investors are likely to adjust betas to optimise their portfolio risk levels. However, Ferson and Harvey (1991), Evans (1994), and Adrian et al. (2015), amongst others, show that time-varying risk prices play an important role in the expected returns of stocks and bonds. Time-varying betas and risk prices as described by a conditional factor model are useful for investors, since investors change their positions in response to changes in economic states.[2] In this study, we extend the time-varying beta and risk price approach to currency markets, because currency markets are dependent upon changes in macroeconomic fundamentals.

The first contribution of this study is the investigation of the time variation of risk prices in currency portfolios. Time-varying risk prices are important in other asset classes, but have not been investigated in the literature on currency portfolios. We also investigate the importance of time varying betas. This study is related to the work of Christiansen et al. (2011) and Lustig et al. (2011). Christiansen et al. (2011) investigate time varying betas for carry trades, but not time varying risk prices. Lustig et al. (2011) use rolling regressions to estimate conditional carry models, and although their empirical results are promising, there is no interpretation of the time variation.[4] In addition, their conditional results do not fully account for transaction costs, while such costs obviously matter to managed funds as they are linked to the frequency of trading dictated by portfolio adjustments. This study also extends attempts to explain currency carry portfolio returns through the market factor. Several recent studies distinguish between up-side and down-side risk prices, but do not investigate the time variation therein

[1]Jagannathan and Wang (1996), Cochrane (1996), Ferson and Harvey (1999), Lettau and Ludvigson (2001), Lewellen and Nagel (2006) and Hollestein et al. (2020) propose conditional factor models in the stock market and allow time-varying betas to reflect changes in economic states.

[2]Ferson and Harvey (1991) and Ferson and Schadt (1996) emphasi e the importance of conditional models for managed investment funds when stock and bond returns are predictable.

[3]Bacchetta and Wincoop (20013) propose a scapegoat model and a time evolving link between economic fundamentals and currencies as investors react to new information. In a portfolio context, the notion that betas or risk prices remain constant despite events such as economic recessions and/or financial crisis is counter intuitive. Sarno and Valente (2009), Rossi (2013) and Byrne et al. (2018), among others, identify empirically an unstable relationship between exchange rates and macro fundamentals.

[4]Gagliardini et al. (2016) question the use of rolling windows in estimating conditional CAPM models.

(Atanasov and Nitschka, 2014; Dobrynskaya, 2014; Lettau et al., 2014; Daniel et al., 2017). The risk prices themselves do not change over time in their dummy variable approach, and the definition of downside states is determined by an arbitrary rule. In this paper, we use a more flexible model and allow for continuous change in risk prices. Importantly, we explore how risk prices vary over time based on economic states by using the econometrics methods of Adrian et al. (2015). These methods have been applied fruitfully in the identification of time-varying risk prices and factor betas in stock and bond markets. In contrast to rolling regressions, Adrian et al. (2015) propose a more general method that incorporates forecast variables with risk factors. The main advantage of this methodology relative to the traditional conditional factor model is that it allows for time variations in both risk prices and factor betas, which allows for a comparison of which time variation matters most in our asset pricing model.

The second contribution of our paper is the examination of the dollar factor in a cross-sectional context. This factor is linked to time series currency portfolio returns (Lustig et al., 2011), and does not bear a risk premium. However, recent important work by Verdelhan (2018) using dollar sorted currency portfolios indicates that the dollar factor has a risk premium. We investigate whether it commands a risk premium using more varieties of currency portfolios. Considering a larger number of portfolios should lead to more general and precise results. For instance, Lewellen et al. (2010) warns against the use of portfolios sorted by si e to investigate the risk price of the si e factor.

The third contribution of this paper is our focus on three types of High-minus-Low (HML) factors: carry, momentum, and value. The carry factor proposed by Lustig et al. (2011) has been widely used in the previous literature.[5] However, momentum and value strategies are also used by currency (Pojarliev and Levich, 2010) and multi-asset investors (Asness et al., 2013; Kroencke, et al., 2014; Barroso and Santa-Clara, 2015; Menkhoff et al., 2017). The literature has not focused on the momentum and the value factors, and the cross-sectional pricing property of these factors is still an open area for research. These factors are directly constructed as return spreads from currency portfolios, and hence economic interpretation is required.

[5]Menkhoff et al. (2012a) show that the carry factor is linked to global FX market volatility and Byrne et al. (2019) observe that it is associated with commodity price factors.

To preview our results, we find significant time variation in the risk price of the dollar factor but weak time variation in the three HML factors. Furthermore, our important finding is that the time-varying risk price and constant beta model has the smallest pricing errors, which is in contrast to the other portfolio results from the prior literature (Adrian et al. 2015). The dollar factor betas, rather than their time variation, are responsible for a significant explanatory power across all currency portfolios in the time series context. This is particularly the case in currency portfolios that are constructed relative to the U.S. dollar, which is the main difference in this context from those that focus on stock and bond portfolios.

The rest of the paper is organi ed as follows: Section 2 lays out the econometrics, Section 3 describes the data, Section 4 presents the empirical results, Section 5 presents robustness analyses, and Section 6 concludes.

2. Estimation Methodology

This section sets out our empirical methods. To account for the role of time-varying factor betas and/or risk prices for carry returns, we adopt Adrian et al.'s (2015) approach, which is sufficiently flexible to allow for the following two combinations: constant betas but time-varying risk prices, and time-varying betas and risk prices. Distinguishing these combinations is important, as our results will show below. The constant beta and time-varying risk price model is described in subsection 2.1. where the betas are constant and not obtained by a conditional approach. We introduce the time-varying beta and time-varying risk pirce model in subsection 2.2. where conditional betas are estimated.

2.1. *Constant Betas and Time-varying Risk Prices*

The expected excess return on currency portfolio i, $E[R_i]$, is represented by the product of risk prices, λ, and factor betas, β_i, using a standard factor pricing specification:

$$E[R_i] = \lambda' \beta_i. \tag{1}$$

We use the popular Fama and MacBeth (1973) two-step procedure to obtain factor betas and risk prices. Factor betas are obtained by time-series regressions, where the dependent variable is the excess return of portfolio i, $R_{i,t+1}$, which is a $T \times 1$ vector. This is regressed on a vector of risk factors, h_{t+1}, which is a $T \times p$ vector, where p is the number of risk factors:

$$R_{i,t+1} = \alpha_i + \beta_i' h_{t+1} + e_{i,t+1} \tag{2}$$

where $e_{i,t+1}$ is an error term. The risk prices, λ, are estimated by a cross-sectional regression, by substituting all n portfolios' estimated betas $\hat{\beta}_i$ into equation (1).

Basic expected return models assume that both factor betas and risk prices are constant. However, if expected returns change over time to reflect changes in underlying economic states, factor betas and/or risk prices need to vary over time. Adrian et al. (2015) propose a general approach to estimate time-varying betas and risk prices. First, we focus on time-varying risk prices and estimate a model with constant betas but time-varying risk prices. This model is:

$$R_{i,t+1} = \beta_i' \lambda_0 + \beta_i' \Lambda_1 F_t + \beta_i' u_{t+1} + e_{i,t+1} \tag{3}$$

where λ_0 and Λ_1 are risk price parameters, F_t is a vector of forecast factors, and u_{t+1} are the innovations to risk factors. We assume no-arbitrage, which implies $\alpha_i = \beta_i' \lambda_0$. The first two terms in the right hand side of equation (3) are the expected returns, the third term is the component that is conditionally correlated with the innovations, and the last term represents the pricing errors. There are two key differences between equations (2) and (3). First, the forecast factors, F_t, are introduced to reflect predictability of carry trades. Second, the innovations to the risk factors are employed instead of risk factors, h_{t+1}, since innovation components capture uncertainty in investment opportunities and, hence, are linked to risk prices (Campbell, 1996 and Petkova, 2006).

The innovation term u_{t+1} in equation (3) is obtained by a Vector Autoregression (VAR). We follow Adrian et al. (2015) and assume X_{t+1} is a $K \times 1$ vector of state variables at $t + 1$ and contains three types of variables. The first is $X_{1,t+1} \in \mathbb{R}^{K_1}$, which are risk factors only, used to price the cross-section of returns. The second is $X_{2,t+1} \in \mathbb{R}^{K_2}$, which are risk and forecast factors both used to price the cross-section of returns and to forecast the risk factors. Finally, $X_{\ ,t+1} \in \mathbb{R}^{K_3}$ are forecast factors only.

It is also possible to use the same variables as both the risk and the forecast variables. The number of factors is denoted by: $K_C = K_1 + K_2$, $K_F = K_2 + K$, and $K = K_1 + K_2 + K$, where the subscript C indicates cross-section and the subscript F denotes forecast factors. The VAR dynamics are written as:

$$X_{t+1} = \mu + \Phi X_t + v_{t+1}, \tag{4}$$

where μ and Φ are coefficient vectors, and v_{t+1} is the innovations vector with its first K_c columns written as u_{t+1}. Our aim is to obtain the time-varying risk prices $\lambda_0 + \Lambda_1 F_t$ in equation (3). To this end, we need to estimate both the factor betas, β_i, and the risk price parameters, λ_0 and Λ_1. Following Adrian et al. (2015), we employ a three-step approach. In the first step, the VAR system in equation (4) is estimated and $\hat{u}_{t+1}$ is extracted. In the second step, $\hat{u}_{t+1}$ is substituted into equation (3) and the estimated betas, $\hat{\beta}_i$, and the predictive slopes, $\hat{w}_0$ and $\hat{w}_1$, are obtained. The predictive slopes, w_0 and w_1, are:

$$w_0 = \beta_i \lambda_0, w_1 = \beta_i \Lambda_1. \tag{5}$$

Finally, the risk price parameters, $\hat{\lambda}_0$ and $\hat{\Lambda}_1$, are obtained by substituting $\hat{\beta}_i$, $\hat{w}_0$, and $\hat{w}_1$ into equation (5). Adrian et al. (2015) show that these estimated risk price parameters, $\hat{\lambda}_0$ and $\hat{\Lambda}_1$, converge to the limiting normal distribution, and they derive the variance which takes into account estimation uncertainty of the innovations term and factor betas.

The risk prices vary over time through their dependence on the forecast factors, F_t. We test whether a sample average of risk prices for given pricing factors, $\bar{\lambda}$, is significantly different from ero. This is obtained as:

$$\bar{\lambda} = \lambda_0 + \Lambda_1 E[F_t]. \tag{6}$$

$\bar{\lambda}$ converges to the limiting normal distribution, as shown by Adrian et al. (2015), and we use their closed form variance to conduct statistical inference.[6] This subsection described the constant beta and time-varying risk price model. In the next subsection, we allow for time-varying betas.

[6]Further detail is described in Adrian et al. (2015) Appendix D.

This change is based on a technical aspect to satisfy uniform convergence.[7] Using the estimation results in equations (8) and (9), the risk price parameters, Λ^{tv}, are obtained as:

$$vec(\hat{\Lambda}^{tv}) = \left(\sum_{t=0}^{T-1} (\hat{F}_t \hat{F}_t' \otimes \hat{B}_t \hat{B}_t' + \rho_T)^{-1} \sum_{t=0}^{T-1} (\hat{F}_t \otimes \hat{B}_t')(R_{t+1} - \hat{B}_t \hat{u}_{t+1}) \right) \tag{10}$$

where $vec(\cdot)$ is the vectori ation operator, $\otimes$ is the Kronecker product, $\hat{B}_t$ is the factor beta matrix that stacks $\beta_{i,t}$, $\hat{F}_t = (1, F_t')'$, and ρ_T is a positive sequence that satisfies $\rho_T \to 0$. u_{t+1} is obtained by the VAR with the weighted least squares coefficients in equation (8). Adrian et al. (2015) show that Λ^{tv} converges to the limiting normal distribution. When the factor betas are time-varying, the sample average of risk prices in equation (6) is changed to:

$$\bar{\lambda} = \lambda_0 + \Lambda_1 \cdot \lim_{T \to \infty} T^{-1} \sum_{t=1}^{T} E[F_t]. \tag{11}$$

$\bar{\lambda}$ also converges to the limiting normal distribution, as described in the constant beta model. Having set out our empirical method, we introduce the data next.

3. Data

This section describes our currency portfolios, risk factors, and forecast variables. We consider the widely used three currency portfolios: carry, momentum, and value. We construct five portfolios for each strategy and use a total of 15 currency portfolios as test assets. The risk factors are: dollar, carry, momentum, and value factors. These four factors are constructed from currency portfolios. We also use the stock market as a risk factor. We consider four basic forecast variables: short-term interest rate, term spread, industrial production growth, and the TED spread. These are related to business cycles and market conditions, and hence are associated with many types of assets. In this study we seek to incorporate macroeconomic conditions that are not currency market specific. This is related to the proposal of Cochrane (2011) who highlights the importance of fundamental state variables that affect many assets.

[7] Lemma D.1. (c) and (d) in Adrian et al. (2015) is derived from the result of Kristensen (2009).

3.1. *Currency portfolios*

We explain our data in this section and begin with currency portfolios. We obtain spot and one month forward exchange rates from Datastream, and employ the G10 currencies, which are the most liquid currencies.[8] Aloosh and Bekaert (2020) present empirical evidence that some pegged currencies impact estimation results, and hence, we focus upon the G10 currencies. The base currency is the U.S. dollar, and the dataset extends from November 1983 to May 2021. As data availability for some currencies does not extend back to November 1983, the total number of exchange rates varies over the sample period. A currency's excess return at time t is calculated as the difference between the forward rate at time $t-1$ and the spot rate at time t. It is written as:

$$r_{i,t} = \frac{F_{i,t-1} - S_{i,t}}{S_{i,t}} \tag{12}$$

where $F_{i,t-1}$ is the forward price of foreign currency i per unit of U.S. dollar agreed at $t-1$ but delivered at t; and $S_{i,t}$ is its spot price at t. Following Lustig et al. (2011), we take into account transaction costs using bid-ask prices. Data are pre-treated using the method of Darvas (2009) who uses the previous day's values when there is no difference between bid and ask prices, or when the spread of the forward rates is smaller than that of the spot rates.

The three types of currency portfolios we use, namely, carry, momentum, and value, are described below. We sort currencies based upon characteristics, and each strategy has five currency portfolios. If there is a strong factor structure then it would not be surprising that a factor can account for currency portfolios sorted by the characteristic corresponding to that factor, as pointed out by Lewellen et al. (2010).[9] We use G10 currency portfolios as test assets in our base analysis. Further, we explore whether a factor can price across assets and therefore we employ 10 stock portfolios sorted by si e in the robustness test.

[8] The G10 currencies are the Australian dollar (AUD), Canadian dollar (CAD), Danish krone (DKK), Swiss franc (CHF), British pound (GBP), Japanese yen (JPY), Norwegian krone (NOK), New Zealand dollar (NZD), Swedish krona (SEK), and euro (EUR). We replace the Deutsche mark with the euro prior to 1999.

[9] Lettau et al. (2014) test whether stock market factor prices multi-asset portfolios and Della Corte et al. (2016) include several types of currency portfolios as test assets.

(2014) and Barroso and Santa-Clara (2015):

$$VA_{i,t} = \frac{S_{i,t-}\ CPI_{i,t-60}CPI_{US,t-}}{S_{i,t-60}CPI_{i,t-}\ CPI_{US,t-60}} \tag{14}$$

where $CPI_{i,t-}$ is the price level of consumer goods in country i at $t-3$, and $CPI_{US,t-}$ is the U.S. price level. We follow Kroencke et al. (2014) in adopting a three month lag to avoid overlaps between momentum and value strategies. Further, Barroso and Santa-Clara (2015) document that a lag value is appropriate since there is a time lag involved in the observation of price levels.

3.5. *Risk factors*

Next, we describe our risk factors. The first factor is the dollar factor (DOL) introduced by Lustig et al. (2011). This factor is associated with time series fluctuations of currency portfolios, but does not bear a risk premium since factor exposures do not vary across portfolios. However, Verdelhan (2018) proposes sorting currency portfolios by exposures to the dollar factor, and presents results that the dollar factor bears a risk premium. We focus upon time variation of the dollar factor since both Lustig et al. (2011) and Verdelhan (2018) employ constant risk price models and observe only an average risk premium. However, the risk premium might change over time to reflect economic states.

We also examine whether HML-type factors play an important role in the cross-sectional context. Lustig et al. (2011) propose the carry factor (HML_{carry}) calculated from High-minus-Low interest rate currency portfolios.[10] This factor is directly constructed from currency portfolios themselves, so it is not surprising that it has a high explanatory power for currency carry portfolios. Moreover, this factor is required for economic explanation and our model contains state variables that affect the risk price. Furthermore, we also test momentum (HML_{mom}) and value (HML_{value}) factors. These two strategies received attention since Asness et al. (2013) show that they operate across assets. Pojarliev and Levich (2010) observe that most currency investors employ one of three strategies (carry, momentum, or value). In contrast to their importance in other markets, however, the momentum and value factors have not been investigated in the cross-section of currency portfolios, and hence it is important to explore whether their risk prices vary over time and what forecast variables are associated with these risk prices. Figure 1

[10] To avoid confusion, we do not use the notation of HML_{FX}, which is more widely used in the literature.

4. Empirical Results

4.1. *Estimated Risk Price Parameters*

We begin the results section by examining possible relations between the forecast and risk factors. We link risk prices and forecast factors because the latter generate time variations of risk prices. Risk price parameters are key elements in the links, since time-varying risk prices are obtained by the product of the risk price parameters and the forecast factors ($\Lambda_1 F_t$). Note that the risk price parameters are constant while the risk prices vary with changes in the forecast factors. Table 1 reports estimates of the risk price parameters, λ_0 and Λ_1, in equation (5) based on the forecast factors, namely, the short-term interest rate, the term spread, the TED spread, and the U.S. industrial production growth. Average risk prices $\bar{\lambda}$ from equation (6), and the Wald test results of the null hypothesis that the row is all eros, are presented to examine our estimation accuracy. We report the results when the TED spread and the U.S. industrial production growth are used as forecast factors. Other results are presented in the online Appendix.

Panel A of Table 1 present results for constant beta models, and these reveal that the time-variation of the dollar factor is driven by the growth of industrial production. U.S. industrial production growth (ip) is a key driver of the time-variation of DOL. One standard deviation of ip is 0.4 and the parameter estimate is 0.25, and therefore one standard deviation increase in ip leads to 1.0% increase in the risk price on the dollar factor (0.4×0.25). The average risk price is not statistically significant, and this is consistent with many studies that adopt the dollar factor. The TED spread is negatively related to the dollar factor while the estimated parameter is marginally insignificant. Figure 2 illustrates how the risk price of DOL varies over time, and we observe that it rises after economic recessions. In particular, the GFC in 2008 and the COVID-19 pandemic in 2020 have significant impacts. The pandemic induces strong government restrictions on business activity that negatively affect industrial production and result in DOL risk price fluctuations. See, for example, Baker et al. (2020) and Gormsen and Koijen (2020).

The relationships between the three HML factors and the forecast variables are weak, which indicates that the risk prices on carry, momentum and value factors do not vary with the state of the economy.

Interestingly, HML_{carry} and HML_{value} command average positive risk prices, while the average risk price of HML_{carry} is smaller than the result reported by Lustig et al. (2011). This is related to a structural change in economies after the GFC and a decline in carry return profits. Ready et al. (2017) regard the GFC as a large productivity shock in the commodity importing countries, causing declines in the commodity price and the carry return. Bussiere et al. (2019) find that uncovered interest rate parity (UIRP) is satisfied after the crisis, which results in a weak carry trade performance. See also Figure 1 and Table A4.

Time-varying betas are introduced in Panel B in Table 1. We observe the strong link between DOL and ip, which is consistent with the constant beta model. The average risk price of the carry and value factors are insignificant, which is not consistent with the results of the constant beta model and the literature. Thus, adding time-varying betas may not lead to precise beta estimations.

In summary, we uncover that the risk price on the dollar factor is positively linked to U.S. economic growth, and the risk prices on the three HML factors do not change over time.

4.2. *Pricing Errors*

Having found that the forecast factors considered add time variation to the risk prices, we investigate which time variations matter more in terms of the currency pricing model. We assess the pricing errors of each portfolio using the Root Mean Squared Error (RMSE). Table 2 presents the average RMSE of each portfolio, and the last row presents the average of all portfolios. We consider six models: (a) time-varying beta and time-varying risk price, (b) constant beta and time-varying risk price, (c) time-varying beta and constant risk price, (d) constant beta and constant risk price (Fama and MacBeth), (e) rolling Fama and MacBeth, and (f) Ferson and Harvey (1991). The latter two conventional time-varying models, (e) and (f), estimate betas and risk prices using 36-month rolling regressions.

Table 2 presents the results of the dollar and the momentum factors.[1] We observe that the average RMSE of the constant beta and time-varying risk price is the smallest. On average, the constant beta and time varying risk RMSE is around 3% lower than that of time varying beta and risk models, which

[13]We also report the carry and the value factors in Table A10 and our main finding does not change.

in turn is more than 6% lower than that of time varying beta and constant risk premium models. Also, 12 out of 15 estimates that have constant beta and time varying risk prices produce the lowest RMSE, and on all occasions a time varying risk price is necessary to produce the lowest RMSE. This result is in contrast with the stock and bond market results reported by Adrian et al. (2015). To investigate further, we repeat the same analysis with either the dollar or momentum factors.

Panel A of Table 3 presents results of the dollar factor. RMSEs are close to those of the two factor model reported in Table 2, and the constant beta and time-varying risk price model generates the smallest average RMSE. In contrast, Panel B of Table 3 demonstrates that RMSEs of the momentum factor are larger than those of the two factor model. This indicates that the risk price on the spread between low and high momentum currency portfolios (HML_{mom}) does not vary over time, as reported by Table 1. Neither the time-varying beta and risk price model nor the constant beta and time-varying risk price model successfully reduces RMSE.

Next, we investigate beta estimates further for the reasons why the consideration of time-varying betas does not lead to smaller pricing errors in the two factor model. Table 4 presents empirical evidence that the betas on the dollar factor are statistically significant in all portfolios, while the betas on the HML_{mom} are statistically significant only in the four momentum portfolios and one of the value portfolios. In other words, HML_{mom} is not associated with carry and value sorted currency portfolios.[14] All currency portfolios have the same base currency and, consequently, the betas on the dollar factor are highly significant. This finding relates to the discussion of Aloosh and Bekaert (2020) that highlights the importance of the base currency. The relation between the base currency and currency portfolios is stable because of the way these portfolios are constructed, and hence the time-varying betas model does not lead to an improvement in the pricing errors. The betas on the momentum factor, however, are not statistically significant for many portfolios. The insignificant beta estimates might be improved by the time-varying beta model, including the rolling Fama and MacBeth. This discussion also features in Adrian et al. (2015), and Table 1 in their paper demonstrates that the constant betas on the market and the si e factors are not statistically significant.

[14] Table A12 reports the same pattern for the carry and value factors.

5. Robustness

5.1. Currency and stock market portfolios

As a further robustness exercise, we consider 10 stock market portfolios sorted by si e, as test assets. We use the data kindly provided by Kenneth French in his data library. Lewellen et al. (2010) propose to include portfolios sorted by other characteristics when test portfolios have a factor structure. Furthermore, investigating whether a risk factor is common across assets is an important finance question, see Cochrane (2011).

Table 5 presents the results using 15 currency and 10 stock portfolios. Panel A uses only the dollar factor, and Panel B considers both the dollar and the three HML factors. We employ the constant beta and the time-varying risk price model that generates the smallest pricing errors in Table 2. The results in Panel A indicate that the relationship between the time variation of the dollar factor and ip is still strong. Moreover, TED is negatively linked to the dollar factor, which is statistically significant at the 10% level. The average risk price is statistically significant at the 5% level, since the factor exposures between currency and stock portfolios are different, as reported by Table A11. This is associated with the discussion of Verdelhan (2018) who employs dollar sorted currency portfolios and finds the risk price on the dollar factor to be significant. The reason why he uses dollar sorted portfolios is to create beta spreads across portfolios. Our analysis extends his approach since Lewellen et al. (2010) point out that testing a risk factor with the corresponding sorting rule might more easily generate a statistically significant result. We set a higher hurdle than Verdelhan (2018), but the dollar factor bears a risk price.

5.2. Other risk factors

Table A2 presents the results of the dollar and the global imbalance factor model proposed by Della Corte et al. (2016). Again, we observe that the dollar factor is associated with forecast variables, while the global imbalance factor model is not. In particular, the global imbalance factor (HML_{imb}) is unrelated to our business cycle indicators: TED and ip. This is a similar finding to the other HML factors. We also adopt the international correlation risk factor (HML_{fxc}) of Mueller et al. (2017)

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The time-varying risk price of currency portfolios

The time-varying risk price of currency portfolios

Table 1

Risk Price Parameter Estimates on Forecast Factors

	Risk Factor	λ_0	Forecast Factors TED	ip	$\bar{\lambda}$	$Wald$
Panel A: Constant beta and time-varying risk price model						
(a)	DOL	0.26	-0.46	0.25**	0.08	9.29**
		(0.18)	(0.28)	(0.11)	(0.12)	
	HML_{carry}	0.32	-0.15	0.15	0.28*	5.40
		(0.22)	(0.36)	(0.14)	(0.15)	
(b)	DOL	0.26	-0.46	0.25**	0.08	9.30**
		(0.18)	(0.28)	(0.11)	(0.12)	
	HML_{mom}	0.02	0.17	-0.01	0.10	0.75
		(0.22)	(0.35)	(0.14)	(0.14)	
(c)	DOL	0.26	-0.46	0.25**	0.08	9.33**
		(0.18)	(0.28)	(0.11)	(0.12)	
	HML_{value}	0.27	0.17	-0.01	0.35*	5.95
		(0.23)	(0.39)	(0.15)	(0.15)	
Panel B: Time-varying beta and time-varying risk price model						
(d)	DOL	0.19	-0.39	0.25**	0.04	7.31*
		(0.17)	(0.27)	(0.12)	(0.11)	
	HML_{carry}	0.26	-0.26	0.12	0.16	2.47
		(0.22)	(0.35)	(0.16)	(0.14)	
(e)	DOL	0.20	-0.41	0.24**	0.04	7.28*
		(0.17)	(0.27)	(0.12)	(0.11)	
	HML_{mom}	0.08	0.22	-0.04	0.18	2.18
		(0.22)	(0.35)	(0.16)	(0.14)	
(f)	DOL	0.21	-0.47	0.25	0.02	0.81
		(0.55)	(0.89)	(0.40)	(0.35)	
	HML_{value}	0.33	-0.49	-0.18	0.07	0.00
		(5.06)	(8.11)	(3.62)	(3.19)	

Notes: This table presents risk price parameter estimates on forecast factors, TED spread (TED) and U.S. industrial production growth (ip). The risk price parameter estimates in Panel A using constant betas are from equation (5) and time-varying betas are from equation (10) in Panel B. Risk price parameters show relationships between risk and forecast factors, and risk prices are computed as risk price parameters times forecast factors. These methods are from Adrian et al. (2015). The average risk price $\bar{\lambda}$ is obtained by equation (6) in Panel A and equation (11) in Panel B. The risk factors are dollar (DOL), stock market (MKT), return spread between low and high interest rate currency portfolios (HML_{carry}), return spread between low and high momentum currency portfolios (HML_{mom}), and return spread between low and high value currency portfolios (HML_{value}). $Wald$ indicates the Wald test statistic of the null hypothesis that the associated row is all ero. Heteroskedasticity robust standard errors are reported in parentheses. The test assets are five carry, five momentum, and five value sorted currency portfolios. The sample period is November 1983 to May 2021. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 5

Risk Price Parameter Estimates on Forecast Factors: Currency and Stock Portfolios

	Risk Factor	λ_0	Forecast Factors TED	ip	$\bar{\lambda}$	$Wald$
Panel A: One factor model						
(a)	DOL	0.62***	-0.63*	0.22*	0.36**	15.14***
		(0.21)	(0.36)	(0.13)	(0.14)	
Panel B: Two factor model						
(b)	DOL	0.35*	-0.50*	0.24**	0.15	10.26**
		(0.18)	(0.29)	(0.11)	(0.13)	
	HML_{carry}	2.33***	-1.16	-0.13	1.76***	11.40***
		(0.78)	(1.25)	(0.42)	(0.57)	
(c)	DOL	0.60***	-0.62*	0.22*	0.34**	14.57***
		(0.23)	(0.36)	(0.13)	(0.14)	
	HML_{mom}	-1.47***	0.87	0.11	-1.05***	13.04***
		(0.51)	(0.93)	(0.31)	(0.32)	
(d)	DOL	0.39**	-0.53*	0.24**	0.17	10.86**
		(0.18)	(0.30)	(0.11)	(0.13)	
	HML_{value}	2.64***	-1.20	-0.19	2.05***	11.72***
		(0.99)	(1.65)	(0.54)	(0.62)	

Notes: This table presents risk price parameter estimates on forecast factors, TED spread (TED) and U.S. industrial production growth (ip). The test assets are five carry, five momentum, and five value sorted currency portfolios, and 10 si e sorted stock portfolios. The risk price parameter estimates using constant betas are from equation (5) in Panel B and time-varying betas are from equation (10) in Panel A. Risk price parameters show relationships between risk and forecast factors, and risk prices are computed as risk price parameters times forecast factors. These methods are from Adrian et al. (2015). The average risk price $\bar{\lambda}$ is obtained by equation (6) in Panel B and equation (11) in Panel A. The risk factors are dollar (DOL), return spread between low and high interest rate currency portfolios (HML_{carry}), return spread between low and high momentum currency portfolios (HML_{mom}), and return spread between low and high value currency portfolios (HML_{value}). $Wald$ indicates the Wald test statistic of the null hypothesis that the associated row is all ero. Heteroskedasticity robust standard errors are reported in parentheses. The sample period is November 1983 to May 2021. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

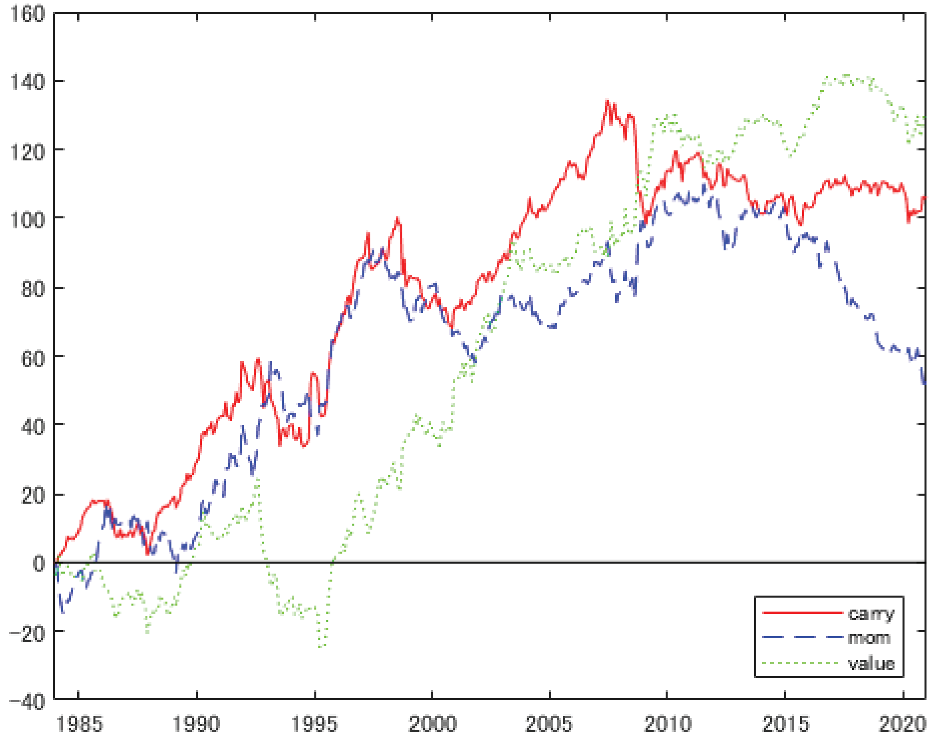

Fig re 1.

Cumulative returns of HML portfolios

Notes: This figure displays cumulative returns of HML portfolios. We consider the return spread between low and high interest rate currency portfolios (HML_{carry}), the return spread between low and high momentum currency portfolios (HML_{mom}), and the return spread between low and high value currency portfolios (HML_{value}). The sample period is November 1983 to May 2021.

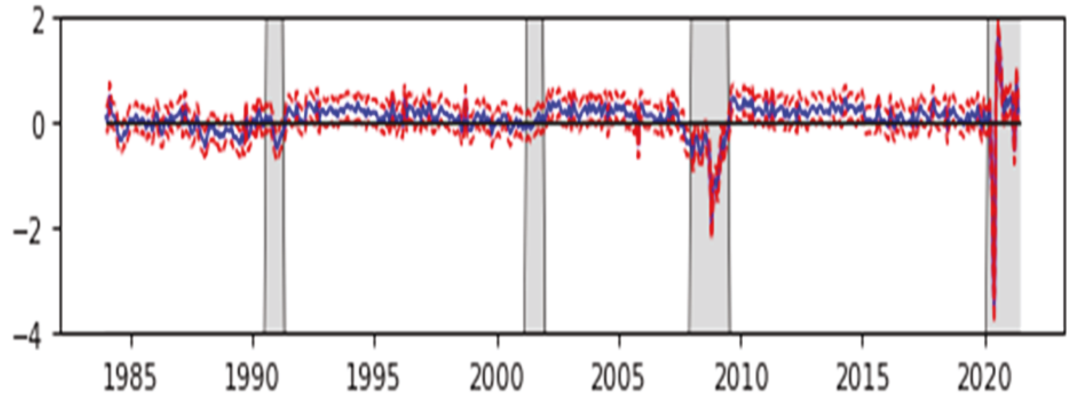

Fig re 2.

Time-varying risk price (λ) of DOL

Notes: This figure displays time series risk price of the dollar factor (DOL) with their 95% confidence intervals. The risk price is obtained as the risk price parameter (λ_0) plus the risk price parameters (Λ_1) multiplied by the time forecast factors (F_t), $\lambda = \lambda_0 + \Lambda_1 F_t$. The forecast factors are TED spread (TED) and U.S. industrial production growth (ip). Constant betas are obtained by equation (5). The shaded regions are NBER recessions.

The time-varying risk price of currency portfolios

The time-varying risk price of currency portfolios

by parametric least squares. Following Ang and Kristensen (2012), we choose the polynomial order of degree as 6. For each i, we compute $\breve{W}_i$ and $\breve{M}_i$ as:

$$\breve{W}_i = \frac{\kappa_2}{T}\breve{\Omega}_x^{-1} \otimes \breve{\Sigma}_v, \quad \breve{M}_i = \frac{1}{T}\sum_{t=1}^{T} ||\breve{\Phi}_{i,t}^{(2)}||^2 \tag{A-13}$$

where $\kappa_2 = 0.2821$ for the Gaussian kernel, $||\cdot||$ is the Euclidean norm, and $\breve{\Phi}_{i,t}^{(2)} = 2\breve{a}_{2,i} + 6\breve{a}\ _{,i}t + \cdots + p(p-1)\breve{a}_{p,i}t^{p-2}$. The first-pass bandwidth $\breve{b}_i$ is obtained using these estimates:

$$\breve{b}_i = \left[\frac{\breve{W}_i}{\breve{M}_i}\right]^{1/5} \times T^{-1/5} \tag{A-14}$$

Next, we estimate $\hat{\mu}_{i,t}$, $\hat{\Phi}_{i,t}$, $\hat{\Omega}_{x,t}$, and $\hat{\Sigma}_{v,t}$ using the first-pass bandwidth, $\breve{b}_i$. Then, $\hat{W}_i$ and $\hat{M}_i$ are computed as:

$$\hat{W}_i = \frac{\kappa_2}{T}\hat{\Omega}_{x,t}^{-1} \otimes \hat{\Sigma}_{v,t}, \quad \hat{M}_i = \frac{1}{T}\sum_{t=1}^{T} ||\hat{\Phi}_{i,t}^{(2)}||^2. \tag{A-15}$$

Applying the same step of the first-pass, the second-pass bandwidth $\hat{b}_i$ is obtained as:

$$\hat{b}_i = \left[\frac{\hat{W}_i}{\hat{M}_i}\right]^{1/5} \times T^{-1/5}. \tag{A-16}$$

C. Other Factors

C1. Global Imbalance Factor

The robustness section employs the global imbalance (HML_{IMB}) factor proposed by Della Corte et al. (2016). This factor is based upon the theory that net debtor countries are riskier than net creditor countries, and hence these countries' currencies provide risk premia. In particular, the net debtor countries which are funded by foreign currencies are riskier than those are founded by their own currencies. This factor is associated with the theoretical model of Gabaix and Maggiori (2015) who propose capital flows in imperfect financial markets affect exchange rates.

The global imbalance factor is constructed by the two steps (Della Corte et al. 2016). First, currencies are assigned into two baskets based upon the net foreign asset to GDP ratio (nfa). The data of foreign assets and liabilities, and gross domestic product (GDP) are shared by Lane and Milesi-Feretti (2004, 2007). Second, currencies are assigned into three baskets within each nfa basket based upon the share of foreign liabilities in domestic currency (ldc). Data of the proportion of external liabilities denominated in foreign currency are constructed by Lane and Shambaugh (2010), and Benetrix et al. (2015), which is downloaded from the author's website. Portfolio 1 includes high nfa and high ldc countries, which are robust against negative financial shocks, while Portfolio 5 does low nfa and low ldc countries, which are risky and provide risk premia. Therefore, the global imbalance factor is calculated as the return spread between portfolios 5 and 1.

C2. International Correlation Risk Factor

We also adopt the international correlation risk factor (HML_{fxc}) proposed by Mueller et al. (2017). We calculate it as follows. First, a conditional correlation between FX spot rate returns is obtained and the rolling window si e is three months (66 days). Second, we sort all G10 FX pairs (base currency is the U.S. dollar) into deciles based on conditional correlations and take the difference between the average correlation in the top decile and that in the bottom decile. This is called as the cross-sectional dispersion in conditional FX correlation (FXC). Third, we pick up FXC at each end of month and take the innovation part of FXC (ΔFXC). Fourth, we construct three currency portfolios based upon factor betas on ΔFXC. The factor betas are estimated by regressing currency excess returns on ΔFXC, and the rolling window si e is 36 months. It means that the portfolios are rebalanced each month. Finally, HML_{fxc} is constructed by taking the return difference between portfolios 1 and 3.

C3. Average Forward Discount

We use the Average Forward Discount (AFD), which is calculated as the average forward discount on foreign currency against the U.S. dollar (Lustig et al., 2014).

Table A1

Risk Price Parameter Estimates on Forecast Factors: Market Factor

Risk Factor	λ_0	Forecast Factors TED	ip	$\bar{\lambda}$	$Wald$
Panel A: Constant beta and time-varying risk price model					
MKT	1.38***	-0.84	0.04	0.99***	21.45
	(0.36)	(0.57)	(0.22)	(0.25)	
Panel B: Time-varying beta and time-varying risk price model					
MKT	-0.65	0.48	0.92	-0.29	0.47
	(2.04)	(3.22)	(1.42)	(1.28)	

Notes: This table presents risk price parameter estimates on forecast factors, TED spread (TED) and U.S. industrial production growth (ip). The risk price parameter estimates using constant betas are from equation (5) in Panel A and time-varying betas are from equation (10) in Panel B. Risk price parameters show relationships between risk and forecast factors, and risk prices are computed as risk price parameters times forecast factors. These methods are from Adrian et al. (2015). The average risk price $\bar{\lambda}$ is obtained by equation (6) in Panel A and equation (11) in Panel B. The risk factor is stock market (MKT). $Wald$ indicates the Wald test statistic of the null hypothesis that the associated row is all ero. Heteroskedasticity robust standard errors are reported in parentheses. The test assets are five carry, five momentum, and five value sorted currency portfolios. The sample period is November 1983 to May 2021. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A2

Risk Price Parameter Estimates on Forecast Factors

	Risk Factor	λ_0	Forecast Factors TED	ip	$\bar{\lambda}$	$Wald$
Panel A: Constant beta and time-varying risk price model						
(a)	DOL	0.38	-0.59*	0.61***	0.18	15.19***
		(0.23)	(0.33)	(0.22)	(0.16)	
	HML_{imb}	0.91**	-0.78	0.45	0.59**	9.99**
		(0.38)	(0.49)	(0.35)	(0.25)	
Panel B: Time-varying beta and time-varying risk price model						
(b)	DOL	0.34	-0.54*	0.60***	0.17	15.50***
		(0.22)	(0.30)	(0.21)	(0.13)	
	HML_{imb}	0.66**	-0.71	0.26	0.34*	6.48*
		(0.33)	(0.45)	(0.31)	(0.20)	
Panel C: Constant beta and time-varying risk price model						
(c)	DOL	0.36	-0.74**	0.39*	0.09	9.44**
		(0.24)	(0.37)	(0.23)	(0.20)	
	HML_{fxc}	-1.55*	3.54**	-2.60	-0.38	6.33
		(0.92)	(1.78)	(1.60)	(0.85)	
Panel D: Time-varying beta and time-varying risk price model						
(d)	DOL	0.32	-0.71**	0.37*	0.06	10.52***
		(0.21)	(0.34)	(0.21)	(0.14)	
	HML_{fxc}	-0.30	0.85	-0.46	0.01	4.25
		(0.41)	(0.64)	(0.40)	(0.26)	

Notes: This table presents risk price parameter estimates on forecast factors, TED spread (TED) and U.S. industrial production growth (ip). The risk price parameter estimates using constant betas are from equation (5) in Panels A and C, and time-varying betas are from equation (10) in Panels B and D. Risk price parameters show relationships between risk and forecast factors, and risk prices are computed as risk price parameters times forecast factors. These methods are from Adrian et al. (2015). The average risk price $\bar{\lambda}$ is obtained by equation (6) in Panel A and equation (11) in Panel B. The risk factors are dollar (DOL), global imbalance (HML_{imb}) as in Della Corte et al. (2016) and international correlation risk (HML_{fxc}) as in Mueller et al. (2017). $Wald$ indicates the Wald test statistic of the null hypothesis that the associated row is all ero. Heteroskedasticity robust standard errors are reported in parentheses. The test assets are five carry, five momentum, and five value sorted currency portfolios. The sample period is November 1983 to December 2013 for HML_{imb}, and April 1993 to December 2013 for HML_{fxc}. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A3
Risk Price Parameter Estimates: Other Forecast Variables

	(1)		(2)		(3)		(4)	
	DOL	HML_{carry}	DOL	HML_{carry}	DOL	HML_{mom}	DOL	HML_{mom}
λ_0	0.05	0.44***	-0.20	1.11**	0.05	0.25*	-0.19	0.22
	(0.15)	(0.16)	(0.46)	(0.50)	(0.15)	(0.13)	(0.46)	(0.42)
AFD	1.94**	-0.66			1.91**	0.61		
	(0.85)	(0.89)			(0.85)	(0.76)		
$EPUI$			0.00	-0.01			0.00	0.00
			(0.00)	(0.00)			(0.00)	(0.00)
$\bar{\lambda}$	0.18	0.40***	0.23*	0.39**	0.18	0.29**	0.24*	0.30**
	(0.15)	(0.14)	(0.14)	(0.16)	(0.15)	(0.12)	(0.14)	(0.12)
$Wald$	6.97**	8.16**	3.88	9.29**	6.96**	6.21**	3.87	5.77*

	(5)		(6)	
	DOL	HML_{value}	DOL	HML_{value}
λ_0	0.05	0.50***	-0.20	0.37
	(0.15)	(0.16)	(0.47)	(0.50)
AFD	1.99**	-1.01		
	(0.87)	(0.91)		
$EPUI$			0.00	0.00
			(0.00)	(0.00)
$\bar{\lambda}$	0.18	0.43***	0.24*	0.44***
	(0.16)	(0.15)	(0.14)	(0.14)
$Wald$	6.97**	10.30**	3.75	8.86**

Notes: This table presents risk price parameter estimates on forecast factors including Average Forward Discount (AFD) as in Lustig et al. (2014), and Economic Policy Uncertainty Index (EPUI) as in Baker et al. (2016). The risk price parameter estimates using constant betas are from equation (5). Risk price parameters show relationships between risk and forecast factors, and risk prices are computed as risk price parameters times forecast factors. These methods are from Adrian et al. (2015). The average risk price $\bar{\lambda}$ is obtained by equation (6). The risk factors are the U.S. dollar (DOL), return spread between low and high interest rate currency portfolios (HML_{carry}), return spread between low and high momentum currency portfolios (HML_{mom}), and return spread between low and high value currency portfolios (HML_{value}). $Wald$ indicates the Wald test statistic of the null hypothesis that the associated row is all ero. Heteroskedasticity robust standard errors are reported in parentheses. The test assets of five carry, five momentum, and five value sorted currency portfolios. The sample period is November 1983 to December 2013. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A4
Descriptive Statistics

	Mean	Std.dev	Skew	Kurt	Max	Min	SR
C1	-0.12	10.96	0.06	3.36	9.80	-8.48	-0.01
C2	-0.98	9.21	-0.01	3.42	7.52	-10.60	-0.11
C3	0.44	8.61	-0.21	3.62	7.51	-11.20	0.05
C4	2.20	9.34	-0.06	4.90	9.77	-12.68	0.24
C5	2.82	9.95	-0.38	4.20	8.35	-12.51	0.28
M1	-0.23	9.90	-0.37	4.18	8.70	-12.66	-0.02
M2	2.08	10.18	-0.34	4.42	8.20	-12.29	0.20
M3	0.96	9.51	-0.13	3.94	9.45	-11.48	0.10
M4	0.65	9.34	0.01	3.16	8.38	-7.76	0.07
M5	1.28	9.30	-0.12	4.00	8.97	-10.91	0.14
V1	-0.40	9.85	-0.27	4.13	9.81	-11.28	-0.04
V2	-0.28	10.06	0.01	4.05	11.77	-10.05	-0.03
V3	1.36	9.63	-0.28	4.16	10.47	-13.29	0.14
V4	0.84	10.16	-0.17	4.34	8.53	-12.89	0.08
V5	3.22	9.51	-0.01	3.82	10.67	-8.00	0.34

Notes: This table reports annuali ed mean, annuali ed standard deviations, skewness, kurtosis, maximum, minimum, and the Sharpe ratio of excess returns of currency portfolios. Ci is a currency carry portfolio, Mi is a currency momentum portfolio, and Vi is a currency value portfolio. The sample period is November 1983 to May 2021.

Table A5 (from the previous page)

Panel C: HML_{mom}				
	(9)	(10)	(11)	(12)
λ_0	-0.17	0.55	-0.83	0.23
	(0.50)	(0.51)	(0.41)	(0.24)
int	0.02			
	(0.11)			
$term$		-0.33		
		(0.24)		
TED			1.52**	
			(0.71)	
ip				-1.24***
				(0.43)
$\bar{\lambda}$	-0.09	-0.09	-0.04	-0.08
	(0.27)	(0.32)	(0.27)	(0.23)
$Wald$	0.13	1.60	17.89***	27.87***
Panel D: HML_{value}				
	(13)	(14)	(15)	(16)
λ_0	0.50*	0.73**	0.68**	0.52***
	(0.28)	(0.32)	(0.27)	(0.20)
int	0.00			
	(0.02)			
$term$		-0.10		
		(0.14)		
TED			-0.33	
			(0.45)	
ip				0.31
				(0.42)
$\bar{\lambda}$	0.50***	0.54***	0.51***	0.57***
	(0.15)	(0.16)	(0.15)	(0.18)
$Wald$	3.09	5.54*	7.28**	9.09**

Notes: This table presents risk price parameter estimates on forecast factors, short-term interest rate (int), term spread ($term$), TED spread (TED) and U.S. industrial production growth (ip). The risk price parameter estimates using constant betas are from equation (5). Risk price parameters show relationships between risk and forecast factors, and risk prices are computed as risk price parameters times forecast factors. These methods are from Adrian et al. (2015). The average risk price $\bar{\lambda}$ is obtained by equation (6). The risk factors are stock market (MKT), return spread between low and high interest rate currency portfolios (HML_{carry}), return spread between low and high momentum currency portfolios (HML_{mom}), and return spread between low and high value currency portfolios (HML_{value}). $Wald$ indicates the Wald test statistic of the null hypothesis that the associated row is all ero. Heteroskedasticity robust standard errors are reported in parentheses. The test assets are five carry, five momentum, and five value sorted currency portfolios. The sample period is November 1983 to December 2013. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A6 (from the previous page)

Panel C: HML_{value}

	(1)		(2)		(3)		(4)	
	DOL	HML_{value}	DOL	HML_{value}	DOL	HML_{value}	DOL	HML_{value}
λ_0	0.31	0.39	-0.22	0.86***	0.59***	0.43*	0.05	0.48***
	(1.23)	(0.26)	(0.28)	(0.29)	(0.22)	(0.23)	(0.14)	(0.15)
int	-0.03	0.01						
	(0.05)	(0.05)						
$term$			0.20*	-0.22*				
			(0.12)	(0.13)				
TED					-0.78**	0.00		
					(0.33)	(0.36)		
ip							0.70***	-0.25
							(0.22)	(0.26)
$\bar{\lambda}$	0.18	0.43***	0.18	0.44***	0.18	0.43***	0.18	0.44***
	(0.17)	(0.14)	(0.17)	(0.16)	(0.16)	(0.14)	(0.14)	(0.14)
$Wald$	2.06	9.20**	4.42	12.21***	7.47**	9.15**	12.04***	9.98**

Notes: This table presents risk price parameter estimates on forecast factors, short-term interest rate(int), term spread($term$), TED spread (TED) and U.S. industrial production growth (ip). The risk price parameter estimates using constant betas are from equation (5). Risk price parameters show relationships between risk and forecast factors, and risk prices are computed as risk price parameters times forecast factors. These methods are from Adrian et al. (2015). The average risk price $\bar{\lambda}$ is obtained by equation (6). The risk factors are the U.S. dollar (DOL), return spread between low and high interest rate currency portfolios (HML_{carry}), return spread between low and high momentum currency portfolios (HML_{mom}), and return spread between low and high value currency portfolios (HML_{value}). $Wald$ indicates the Wald test statistic of the null hypothesis is that the associated row is all ero. Heteroskedasticity robust standard errors are reported in parentheses. The test assets of five carry, five momentum, and five value sorted currency portfolios. The sample period is November 1983 to December 2013. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A7 (from the previous page)

Panel C: HML_{mom}				
	(9)	(10)	(11)	(12)
λ_0	0.81	-0.80	-0.34	0.24
	(0.58)	(0.67)	(0.51)	(0.34)
int	-0.17			
	(0.12)			
$term$		0.29		
		(0.30)		
TED			0.29	
			(0.72)	
ip				-1.64***
				(0.55)
$\bar{\lambda}$	0.13	-0.23	-0.19	-0.06
	(0.31)	(0.33)	(0.32)	(0.33)
$Wald$	2.12	1.45	0.48	8.90**
Panel D: HML_{value}				
	(13)	(14)	(15)	(16)
λ_0	0.45	-0.67	-0.53	-0.03
	(0.52)	(0.69)	(0.54)	(0.32)
int	-0.10			
	(0.11)			
$term$		0.30		
		(0.31)		
TED			0.36	
			(0.77)	
ip				-0.61
				(0.49)
$\bar{\lambda}$	0.06	-0.09	-0.34	-0.15
	(0.29)	(0.35)	(0.34)	(0.31)
$Wald$	0.82	1.01	1.17	1.77

Notes: This table presents risk price parameter estimates on forecast factors, short-term interest rate(int), term spread($term$), TED spread (TED) and U.S. industrial production growth (ip). The risk price parameter estimates using time-varying betas are from equation (10). Risk price parameters show relationships between risk and forecast factors, and risk prices are computed as risk price parameters times forecast factors. These methods are from Adrian et al. (2015). The average risk price $\bar{\lambda}$ is obtained by equation (11). The risk factors are stock market (MKT), return spread between low and high interest rate currency portfolios (HML_{carry}), return spread between low and high momentum currency portfolios (HML_{mom}), and return spread between low and high value currency portfolios (HML_{value}). $Wald$ indicates the Wald test statistic of the null hypothesis that the associated row is all ero. Heteroskedasticity robust standard errors are reported in parentheses. The test assets of five carry, five momentum, and five value sorted currency portfolios. The sample period is November 1983 to December 2013. The asterisk *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A8 (from the previous page)

Panel C: HML_{value}	(1)		(2)		(3)		(4)	
	DOL	HML_{value}	DOL	HML_{value}	DOL	HML_{value}	DOL	HML_{value}
λ_0	0.36	0.39	-0.22	0.33	0.63***	0.15	0.06	0.48***
	(0.23)	(0.27)	(0.28)	(0.30)	(0.21)	(0.24)	(0.14)	(0.15)
int	-0.06	-0.02						
	(0.05)	(0.06)						
$term$			0.23*	-0.02				
			(0.12)	(0.13)				
TED					-0.78**	0.28		
					(0.31)	(0.36)		
ip							0.43***	-0.62***
							(0.15)	(0.23)
$\bar{\lambda}$	0.14	0.31**	0.22*	0.30	0.23*	0.29*	0.20	0.32**
	(0.13)	(0.15)	(0.13)	(0.15)	(0.13)	(0.15)	(0.13)	(0.14)
$Wald$	2.62	4.49	6.52**	3.94	7.47**	4.40	14.53***	11.59***

Notes: This table presents risk price parameter estimates on forecast factors, short-term interest rate(int), term spread($term$), TED spread (TED) and U.S. industrial production growth (ip). The risk price parameter estimates using time-varying betas are from equation (10). Risk price parameters show relationships between risk and forecast factors, and risk prices are computed as risk price parameters times forecast factors. These methods are from Adrian et al. (2015). The average risk price $\bar{\lambda}$ is obtained by equation (11). The risk factors are the U.S. dollar (DOL), return spread between low and high interest rate currency portfolios (HML_{carry}), return spread between low and high momentum currency portfolios (HML_{mom}), and return spread between low and high value currency portfolios (HML_{value}). $Wald$ indicates the Wald test statistic of the null hypothesis that the associated row is all ero. Heteroskedasticity robust standard errors are reported in parentheses. The test assets are five carry, five momentum, and five value sorted currency portfolios. The sample period is November 1983 to December 2013. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A11

Constant betas on DOL for currency and stock porfolios

	(a)Currency porftolios	s.e.	(b)Currency and stock portfolios	s.e.
C1	1.06***	(0.05)	1.06***	(0.05)
C2	0.95***	(0.04)	0.95***	(0.04)
C3	0.94***	(0.03)	0.94***	(0.03)
C4	0.97***	(0.03)	0.97***	(0.03)
C5	1.09***	(0.03)	1.09***	(0.03)
M1	0.93***	(0.05)	0.93***	(0.05)
M2	1.06***	(0.05)	1.06***	(0.05)
M3	1.04***	(0.03)	1.04***	(0.03)
M4	1.01***	(0.03)	1.01***	(0.03)
M5	0.92***	(0.04)	0.92***	(0.04)
V1	0.89***	(0.05)	0.89***	(0.05)
V2	1.04***	(0.04)	1.04***	(0.04)
V3	1.06***	(0.03)	1.06***	(0.03)
V4	1.09***	(0.04)	1.09***	(0.04)
V5	0.97***	(0.04)	0.97***	(0.04)
ST1			0.39***	(0.14)
ST2			0.44***	(0.15)
ST3			0.48***	(0.14)
ST4			0.46***	(0.14)
ST5			0.49***	(0.14)
ST6			0.49***	(0.13)
ST7			0.50***	(0.13)
ST8			0.46***	(0.12)
ST9			0.44***	(0.12)
ST10			0.38***	(0.10)

Notes: This table provides plots of betas on the dollar factor (DOL).The forecast factors are TED spread (TED) and U.S. industrial production growth (ip). Test assets of column (a) are five carry, five momentum, and five value sorted currency portfolios. Ci is a currency carry portfolio, Mi is a currency momentum portfolio, and Vi is a currency value portfolio. Test assets of column (b) are 15 currency porftolios and 10 stock portfolios sorted by firm si e. STi represents a stock portfolio. Heteroskedasticity robust standard errors are reported in parentheses. The sample period is November 1983 to May 2021. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

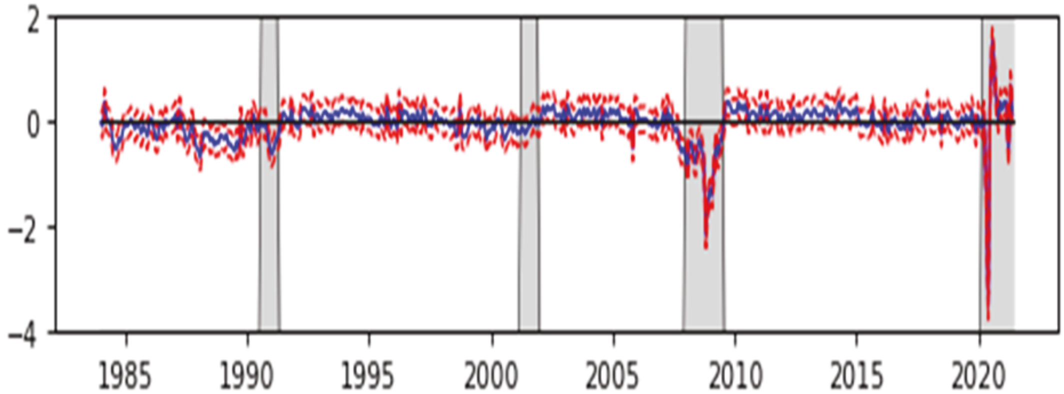

Fig re A1.

Time-varying risk price (λ) of DOL:Time-varying betas

Notes: This figure displays time series risk price of the U.S. dollar factor (DOL) with their 95% confidence intervals. The risk price is obtained as the risk price parameter (λ_0) plus the risk price parameters (Λ_1) multiplied by the time forecast factors (F_t), $\lambda = \lambda_0 + \Lambda_1 F_t$. The forecast factors are TED spread (TED) and U.S. industrial production growth (ip). Time-varying betas are obtained by equation (10). The shaded regions are NBER recessions.

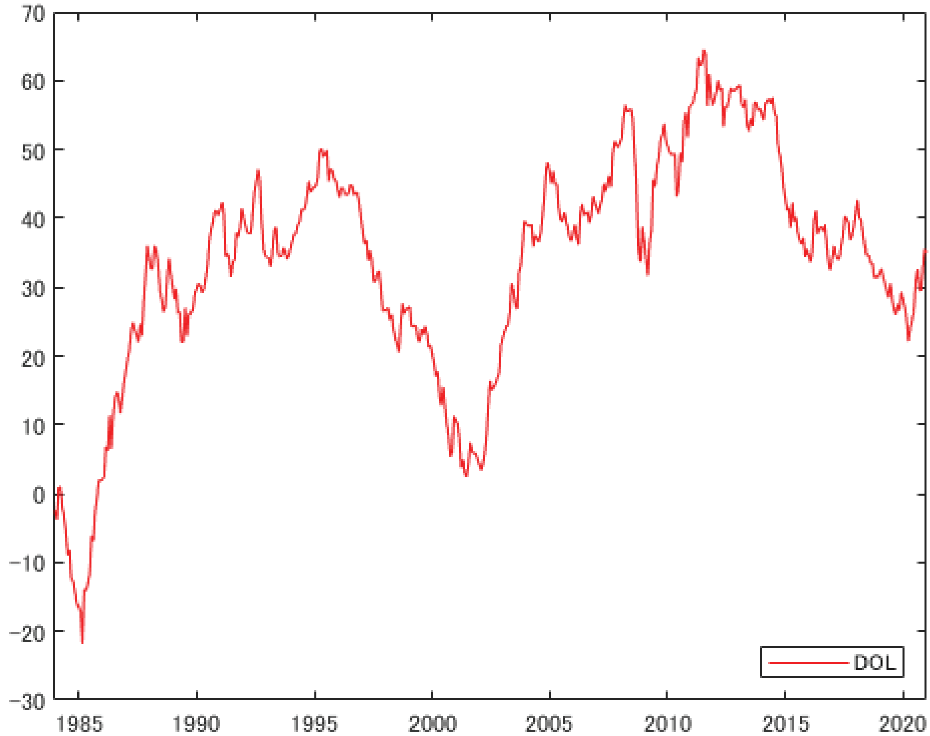

Fig re A2.

Cumulative return of *DOL*

Notes: This figure displays the cumulative return of the dollar factor (*DOL*) based on average excess return for an U.S. investor who invests in foreign currencies. A decline indicates the strong U.S. dollar. The sample period is November 1983 to May 2021.