Dollar and Carry Redux*

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Abstract

Contrary to existing literature, we establish that two factors, dollar and carry, suffice to explain a large cross-section of currency returns with R^2s exceeding 80%. Our paper highlights the importance of accounting for time-variation in conditional moments. Unconditional estimations that ignore this time-variation mistakenly reject the two-factor model. We propose a parsimonious framework to estimate conditional currency factor models and provide testable restrictions. Our findings imply that currency markets are well described by a model in which (i) each country-specific SDF loads on one country-specific—dollar—and one global—carry—shock, and (ii) risk loadings are time-varying. Other risk factors proposed in the literature are useful to describe the time variation in dollar and carry factor risk premia.

JEL-Classification: F31, G12, G15.

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Introduction

The seminal work of Lustig and Verdelhan (2007) shifted the focus from explaining country-specific currency returns to explaining portfolios of currencies sorted on interest rate differentials. Lustig et al. (2011) document that one factor, carry (CAR), which borrows in low and invests in high interest rate currencies, explains almost all of the cross-sectional variation in interest-rate sorted currency returns. Hence, equilibrium stochastic discount factors (SDFs) need to differ in their exposure to only one global shock. US-specific shocks, on the other hand, are identified via an idiosyncratic shock, dollar (DOL), which borrows in US dollars and lends in all other currencies. Their two-factor DOL-CAR model is shown to explain many salient features of international asset returns. These papers marked not only the beginning of a new era in international finance in the quest for understanding the factor structure of currency returns but also spurred a growing number of new currency risk factors.

The proliferation of new factors can be motivated by the fact that the two-factor DOL-CAR model performs poorly when applied to currency portfolios beyond the classic interest-rate differential sort, such as currency momentum, value, correlation risk, or dollar-beta sorted portfolios. The reasons for rejection of the two-factor model can be twofold. First, the default conclusion drawn in the literature is that two factors are not enough and additional country-specific or global shocks are needed. Alternatively, while the unconditional two-factor model may fail, a conditional version may help explain the momentum and value effects, among others. In that case, each country-specific SDF loads on only one global shock and one idiosyncratic shock but time-varying risk loadings, such that DOL and CAR suffice to span both the US-specific and global shocks. However, the time-varying risk loadings imply that the covariance between the conditional risk premia of the DOL and CAR and the conditional loadings of test assets on these factors is non-zero. According to Jagannathan and Wang (1996), this covariance term leads to a rejection of the unconditional DOL-CAR model (i.e., significant unconditional pricing errors), while the conditional DOL-CAR model holds.

In this paper, we propose a novel conditional factor model approach and we provide empirical evidence in favor of this alternative explanation: Each country-specific SDF loads on only one global shock and one idiosyncratic shock as in Lustig et al. (2011) but with time-varying risk loadings. We show that this parsimonious model can explain over 80% of the variation of a rich cross-section of various test assets.

In our empirical analysis, we first construct a cross-section of 27 currency portfolios as test assets and confirm the finding in the literature that the unconditional *DOL*-*CAR* factor model fails to explain the average returns of our test assets using several testable restrictions. Most importantly, the pricing errors of the test assets are jointly significantly different from zero. Moreover, the model's R^2 is essentially zero.

We then introduce a novel GMM estimation setting to assess conditional factor models. More specifically, our approach builds on the idea of Jagannathan and Wang (1996) to take unconditional expectations of the conditional model to obtain unconditional moment conditions. However, in contrast to Jagannathan and Wang (1996) (and much of the subsequent literature) our approach does not require us to specify a set of conditioning variables. Instead, our approach is closely related to the "direct" estimation of the conditional CAPM by Lewellen and Nagel (2006) which relies on estimating intercepts and risk loadings by short-window regressions. The time-series of the estimated coefficients can then be used to formally test the conditional *DOL*-*CAR*-model. We estimate the conditional *DOL*-*CAR* factor model, and find that contrary to the unconditional model, none of the testable restrictions can reject the model. Moreover, the model fit is astounding, reaching an R^2 of 89% to explain the average returns of our 27 FX portfolios.

Using our estimates, we then proceed to document the following findings. First, we follow in spirit Lewellen and Nagel (2006) and investigate the pricing implications of the covariation $\sigma_{\beta\gamma}$ between conditional factor loadings (β_t) and conditional factor risk premia (γ_t), as well as the average conditional loadings versus the unconditional loadings $\bar{\beta} - \beta$. We document a striking relation between unconditional pricing errors of assets and $\sigma_{\beta\gamma}$ and $\bar{\beta} - \beta$. While pricing errors roughly range from -3% to over 5.5% per year in the unconditional *DOL*-*CAR* model, these errors reduce to an insignificant amount (well between -1% and 1.5%) after accounting for $\sigma_{\beta\gamma}$ and $\bar{\beta} - \beta$. Therefore, the conditional version of the *DOL*-*CAR* factor model resolves many anomalies documented in the literature.

Furthermore, we document that $\sigma_{\beta\gamma}$ is of first order importance to explain the superior performance of the conditional *DOL*-*CAR* model over its unconditional counterpart. In contrast, $\bar{\beta} - \beta$ is of secondary importance. This emphasizes again the importance to account for the time variation in the conditional factor loadings and risk premia when assessing factor models. Unconditional estimations which ignore the time-variation in the conditional moments mistakenly reject the *DOL*-*CAR* two factor model.

Meanwhile beyond the importance of time-varying information, we emphasize the uniqueness of *DOL* and *CAR* in the significant improvement of cross-sectional pricing power. Despite under the conditional setting, other currency factors and their combinations perform inferior to the *DOL*-*CAR* two-factor model and are all rejected in the cross-sectional asset pricing test based on the GMM estimation results.

The success of the conditional *DOL*-*CAR* model is at odds with the idea that the underlying no-arbitrage model features multiple global shocks or multiple idiosyncratic shocks in each country. We therefore conclude that country-specific SDFs load on one global shock and one idiosyncratic shock, and risk loadings are time-varying.

Second, time variation in risk loadings implies predictability in factor returns. Accordingly, we estimate lower bounds for the predictive regression R^2 of 7.55% for the *DOL* and 4.44% for the *CAR*. Moreover, statistical or economic constraints to address estimation errors reduce these lower bounds by roughly half. Contrary to the equity literature, which has argued that time-variation in risk loadings need to be unreasonably large to explain asset pricing anomalies, we find that the required time-variation in risk loadings in the no-arbitrage model, and therefore, the time-variation in the factor risk premia in currency markets, does not appear to be implausible.

Third, recent work shows that currency momentum is a useful state variable to explain the conditional risk premia of *DOL* and *CAR*, see, e.g., Zhang (2022) and Sarno et al. (2022). However, our results thus far seem to indicate that these results are more general. More specifically, other popular pricing factors, beyond currency momentum such as value, correlation risk, and dollar-beta slope, must be useful state-variables to describe the time-variation in the *DOL* and *CAR* factor risk premia and the conditional factor loadings of the test assets. In other words, they describe the time-variation in the SDF's risk loadings on the global shock and the idiosyncratic shock. Moreover, these factors are not only important to describe the time-variation in conditional factor risk premia but also in the conditional factor loadings of the test assets.

Finally, our findings provide guidance for the international macro-finance literature in at least two ways. First, it suffices to focus on economic risks that are related to interest rate differentials. It is reassuring that this is the main focus in the literature. Second, our results also pose a new challenge, namely that quantitatively successful models must generate sufficient variation in the SDF's risk loadings. Most models in the literature generate constant risk loadings and constant risk premia. Accordingly, more research is desired in this dimension.

Our paper is related to several strands in the literature. The desire to assess conditional models is motivated by a large literature that provides evidence that factor loadings and factor risk premia are time-varying. For example, Lustig et al. (2014), Verdelhan (2018), Panayotov (2020), and Chiang and Mo (2022) show that it is important to condition factors on the average forward discount across currencies. Balduzzi and Chiang (2020) and Dahlquist and Penasse (2022) document that real exchange rates predict currency returns and imply a substantial time-variation in currency risk premia. Zhang (2022) traces currency momentum back to time-varying risk premia in the DOL and CAR factor. Ma and Zhang (2022) show that changes in residential-to-nonresidential investment have a significant effect on conditional currency risk premia. Hassan and Mano (2019) decompose currency returns into a cross-currency, a between-time-and-currency, and a cross-time component. Maurer et al. (2023) show that it is important to consider the time-variation in conditional return moments in the construction of mean-variance optimized currency portfolios. Maurer et al. (2022) and Chernov et al. (2023) show that a mean-variance optimized currency portfolio with optimal market timing based on the time-variation in return moments is able to explain the average returns of a large cross-section of test assets.

We follow this literature and show that there are significant differences between the unconditional DOL-CAR factor model, which ignores the time-variation in conditional factor loadings and factor risk premia, and its conditional counterpart. We document that the conditional DOL-CAR model fixes the shortcomings of its unconditional counterpart, and is able to price a rich cross-section of currency returns.

Our paper is also related to the empirical literature which analyzes various pricing factors in FX markets: carry factor (Lustig and Verdelhan, 2007; Lustig et al., 2011), global volatility factor (Menkhoff et al., 2012a; Christiansen et al., 2011), momentum factor (Burnside et al., 2011; Menkhoff et al., 2012b), global currency skewness factor (Rafferty, 2012), FX correlation risk factor (Cenedese et al., 2016; Mueller et al., 2017), dollar beta factor (Lustig et al., 2014; Verdelhan, 2018), downside beta risk factor (Dobrynskaya, 2014; Lettau et al., 2014; Galsband and Nitschka, 2014), FX liquidity risk factor (Mancini et al., 2013), economic size factor (Hassan, 2013), economic momentum (Dahlquist and Hasseltoft, 2020), surplus-consumption risk factor (Colacito et al., 2020), sovereign risk Corte et al. (2022), and FX trade volume Cespa et al. (2022).

In contrast to this literature, we are not looking for new factors that are able to price assets which feature significant pricing errors in the unconditional DOL-CAR factor model. Instead, we show that the DOL and CAR are sufficient and we do not need additional factors if we properly account for the time-variation in conditional return moments and assess a conditional version of the model. To that extend, additional factors in the literature do not give rise to new risks in a reduced form no-arbitrage model, but they provide important information about the time-variation in the factor risk premia and factor loadings of the test assets.

Finally, our paper is closely related to Sarno et al. (2022), who show that in an unconditional model at least three factors are important and that these factors are related but not exactly equal to DOL, CAR, and momentum (MOM). Moreover, these authors do not estimate significant risk premia for other factors. Our results show that the model can be further reduced to two factors, DOL and CAR, if we consider a conditional model.

Our paper is organized as follows. Section 1 describes the data, as well as the construction of our pricing factors and test assets. Section 2 describes the GMM estimations and testable restrictions of the unconditional and conditional models. Section 3 presents our empirical results. Finally, Section 4 concludes. Appendix A provides technical details about the GMM estimations of the conditional and unconditional models. Appendix B provides all tables and figures. The Online Appendix further provides robustness results using an alternative estimation approach for conditional factor loadings as well as GMM estimation results for different currency factors other than DOL and CAR.

1 Pricing Factors and Test Assets

We first define currency returns and describe the data. Then, we describe the construction of our pricing factors and test assets.

1.1 Currency Returns

We take the view of an investor with the USD as the base currency. We define 1-month currency excess return $r_{i,t+1}$ as an uncovered long position in the 1-month forward exchange rate contract of currency i against the USD. Note that positions in forward contracts are net-zero investments, and returns are excess returns. We denote by $X_{i,t}$ and $X_{i,t,t+1}$ the spot and 1-month forward exchange rates in USD per unit of currency i at the end of month t. We further write the forward discount of currency i as $fd_{i,t} = \ln\left(\frac{X_{i,t}}{X_{i,t,t+1}}\right)$, and the exchange rate growth of currency i against the USD as $\Delta x_{i,t+1} = \ln\left(\frac{X_{i,t+1}}{X_{i,t}}\right)$. The forward discount is observed at the end of month t, while the exchange rate growth is only realized at the end of month $t+1$. Accordingly we can write the currency return as

$$r_{i,t+1} = \ln\left(\frac{X_{i,t+1}}{X_{i,t,t+1}}\right) = fd_{i,t} + \Delta x_{i,t+1}.$$

We define by $\theta^s_{i,t}$ the weights of currency portfolio s in currency i at the end of month t. The portfolio excess return in the subsequent month is $R_{s,t+1} = \sum_i \theta^s_{i,t} r_{i,t+1}$. The portfolio weights $\theta^s_{i,t}$ do not necessarily have to add up to one. However, most trading strategies in the literature scale portfolio weights such that the notional value is constant through time, $\sum_i |\theta^s_{i,t}| = c$ for time-invariant constant $c > 0$.

We obtain daily spot and 1-month forward exchange rates against the USD from December 1983 to March 2021 from Barclays Bank International and Reuters via Datastream. We use quotes of the last day of the month to compute monthly currency returns $r_{i,t+1}$. Our main analysis uses a set of 29 currencies from 15 developed and 14 emerging countries. We follow the classification of Lustig et al. (2011) and use currencies of the following 15 developed countries: Australia, Belgium, Canada, Denmark, Euro Area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, United Kingdom. The Euro was introduced in January 1999 and we exclude all countries which have joined the Euro after that and only keep the Euro as a currency.

Finally, the set of 14 emerging countries and regions follows Maurer et al. (2022): Brazil, Czech Republic, Greece, Hungary, Iceland, Ireland, Mexico, Poland, Portugal, Singapore, South Africa, South Korea, Spain, Taiwan. The Online Appendix discusses additional data filters.

1.2 Pricing Factors

Our main focus and contribution are the analysis of the *DOL*-*CAR* two factor model. We describe the construction of the two factors in the following.

DOL (Lustig et al., 2011): The Dollar factor (*DOL*) is a traded portfolio that (borrows USD and) invests equally in all currencies.

CAR (Lustig et al., 2011): First, at the end of each month we sort currencies according to the current forward discount $fd_{i,t}$. For each quintile, we then construct an equally weighted portfolio, and denote these five portfolios by $Int1$-$Int5$. The CAR factor takes a long position in the high forward discount portfolio $Int5$ and a short position in the low forward discount portfolio $Int1$.

1.3 Test Assets

We use $N = 27$ test assets in our model estimations. First, we use the five forward discount sorted portfolios $Int1$ to $Int5$ as described in the discussion of the CAR factor (section 1.2). Second, we use the $CSCAR$ pricing factor as a test asset when we estimate and test the DOL-CAR model. We describe the remaining 21 assets in the following.

Mom1-Mom5 (Burnside et al., 2011; Menkhoff et al., 2012b): We sort currencies based on past 1-month currency returns into quintiles. The top quintile contains the winner currencies and the bottom quintile the losers. We construct equally weighted currency portfolios for each quintile, and denote these five portfolios by $Mom1$ to $Mom5$.[1]

Val1-Val5 (Asness et al., 2013; Menkhoff et al., 2017): Currency value strategies posit that in the long-run undervalued currencies with low real exchange rates appreciate against overvalued currencies with high real exchange rates. We sort currencies according to the 5-year change in purchasing power parity (PPP).[2] We construct equally weighted currency portfolios for each quintile, and denote these five portfolios by $Val1$ to $Val5$.

FXC1-FXC4 (Mueller et al., 2017): The FX correlation dispersion measure is defined as the difference between the average of the top and the bottom deciles of the realized conditional correlations between all exchange rates. We then sort currencies into four portfolios based on the loadings of the currency returns on the innovations in the FX correlation dispersion measure. The equally weighted portfolios corresponding to each quartile are denoted by $FXC1$ to $FX4$.

DB1-DB6 (Verdelhan, 2018): First, we regress monthly currency returns on the DOL and CAR factors using 60-month rolling windows. Then, we sort currencies based on the DOL factor loading into six quantiles, and construct equally weighted currency portfolios for each quantile. The six $DB1$ to $DB6$ portfolios take long (short) positions in the corresponding equally weighted quantile portfolios if the median forward discount rate of developed currencies is positive (negative).

DDOL (Lustig et al., 2014): $DDOL$ takes a long (short) position in the DOL when the median forward discount across developed currencies is positive (negative).

[1] Note that Menkhoff et al. (2012b) find that momentum constructed based on sorting 1-month past returns yields more profitable portfolios than 3-, 6-, 9- or 12-month formation periods. Therefore, the 1-month past return sorted portfolios pose a bigger challenge and set a higher bar for pricing models.

[2] Menkhoff et al. (2017) further construct modified value portfolios, which utilize macroeconomic information. We only implement the benchmark portfolios based on PPP.

CSCAR (Maurer et al., 2022): The $CSCAR$ adjusts the CAR to account for the time-variation in the covariances among exchange rates and the forward discounts or spreads $fd_{i,t}$. It is shown to price the cross-section of various FX test assets well. The portfolio weights are $\theta_t^{CSCAR} = \widetilde{\Omega}_t^{-1} fd_t$, where $\widetilde{\Omega}_t^{-1}$ is a robust version of the inverse of the conditional covariance matrix Ω_t of all exchange rate growths. First, at the end of month t, we use daily exchange rate growths over the past 6 months and apply an exponential weighting scheme with a decay factor of 0.95 to put more (less) emphasize on more recent (distant) data. Second, we use principal component analysis (PCA) and remove PCs that explain less than 1% of the common variation in exchange rate growths. We then use the remaining PCs to construct the robust inverse of the conditional covariance matrix $\widetilde{\Omega}_t^{-1}$. This procedure exploits the strong factor structure in FX markets and has been shown to efficiently mitigate estimation errors. In contrast to DOL and CAR, the notional value of $CSCAR$ is time-varying, which is an important feature to enhance its unconditional performance as a trading strategy and as a pricing factor (Maurer et al., 2023, 2022). The $CSCAR$ is equivalent to a mean-variance efficient portfolio or the inverse of the minimum variance stochastic discount factor (SDF) in FX markets (Hansen and Jagannathan, 1991), if we assume that the forward discount $fd_{i,t}$ is a proxy for the conditional expected excess return of $r_{i,t+1}$. This assumption is equivalent to the random walk hypothesis of Meese and Rogoff (1983), and has been exploited in recent literature, see, e.g., Baz et al. (2001); Della Corte et al. (2009); Ackermann et al. (2016); Daniel et al. (2017); Maurer et al. (2023, 2022).

2 Model Estimation using GMM

In this section, we describe our estimation approach of unconditional and conditional factor models using GMM and provide an overview of the testable restrictions of the models.

2.1 Estimation of the Unconditional Model

The estimation of the unconditional model is standard in the literature. We briefly review the approach and relegate technical details to Appendix A.

We estimate a linear factor pricing model

$$E\left[R_t\right] = \beta\gamma. \tag{1}$$

R_t is the $N \times 1$ vector of excess returns of N test assets at time t, $N \times K$ matrix β are the loadings of the N test assets on K pricing factors, $K \times 1$ vector γ are the risk premia of the K factors, and $E[.]$ is the unconditional expectation operator.

We use GMM to estimate model (1) (Hansen, 1982; Cochrane, 2005). The $K+(2+K)N$ moment conditions are,

$$g(b) = \begin{pmatrix} E\left[F_t - \bar{F}\right] \\ E\left[\begin{pmatrix} 1 \\ F_t \end{pmatrix} \otimes (R_t - \alpha - \beta F_t)\right] \\ E\left[R_t - \beta\gamma\right] \end{pmatrix} = \begin{pmatrix} 0_{\{K\times 1\}} \\ 0_{\{(1+K)N\times 1\}} \\ 0_{\{N\times 1\}} \end{pmatrix} \quad (2)$$

to estimate the $2K + (1 + K)N$ parameters $b = \left[\bar{F}', \alpha', vec(\beta)', \gamma'\right]'$. $\otimes$ is the Kronecker product. F_t is the $K \times 1$ vector of excess returns of the K traded pricing factors at time t, and $\bar{F}$ is the corresponding $K \times 1$ vector of expected excess returns. We implicitly assume that pricing factors F are traded portfolios. We refer to $R_t = \alpha + \beta F_t + \varepsilon_t$ as time-series pricing equations, while $E\left[R_t\right] = \beta\gamma + \alpha^*$ are cross-sectional pricing equations, where α^* are the residuals and also referred to as cross-sectional pricing errors. $N \times 1$ vector $\alpha = E\left[R_t - \beta F_t\right]$ are abnormal returns of the N test assets in the first set of N time-series equations. We also refer to α as time-series pricing errors. $vec(\beta)$ is an $NK \times 1$ vector of all elements in the factor loadings matrix β, i.e., stacking the columns on top of each other. $1_{\{N\times 1\}}$ is an $N \times 1$ vector of 1 and $0_{\{Z\times 1\}}$ is an $Z \times 1$ vector of 0. We take into account cross- and autocorrelations and heteroskedasticity following Newey and West (1987) when constructing the covariance matrix of the parameter estimates.

2.2 Estimation of Conditional Model

We now discuss our novel estimation method for the conditional factor model using GMM. In a nutshell, our approach builds on the idea of Jagannathan and Wang (1996) to take the unconditional expectation of the conditional model. In the following, we describe the important elements of our approach, while we relegate technical details to Appendix A.

We focus on a linear conditional factor pricing model

$$\mu_t = \beta_t \gamma_t. \quad (3)$$

$N \times 1$ vector $\mu_t = E_t\left[R_{t+1}\right]$ are the conditional expected excess returns of N test assets at time t, and R_{t+1} is the $N \times 1$ vector of realized excess returns at time $t+1$. $E_t[.]$ is the conditional expectation operator given the information at time t. $N \times K$ matrix β_t are the conditional factor loadings of the N test assets on K pricing factors, i.e., the β_t are the conditional analog to the unconditional β. $K \times 1$ vector γ_t are the conditional risk premia of the K factors, i.e., γ_t are the conditional analog to the unconditional γ. We assume that factors are traded, and therefore, $\gamma_t = E_t\left[F_{t+1}\right]$, where F_{t+1} is the $K \times 1$ vector of realized excess returns of the factors.

Following Jagannathan and Wang (1996) we write the conditional model (3) in the following unconditional form,

$$\mu = E\left[R_{t+1}\right] = \bar{\beta}\gamma + \sigma_{\beta\gamma} 1_{K\times 1}. \tag{4}$$

$\bar{\beta} = E\left[\beta_t\right]$, $\gamma = E\left[\gamma_t\right]$, and $\sigma_{\beta\gamma} = E\left[\left(\beta_t - \bar{\beta}\right) diag\left(\gamma_t - \gamma\right)\right]$ is the $N \times K$ matrix of covariances between the conditional factor loadings and the corresponding factor premia, i.e., element (i,k) is the covariance of asset i's conditional loading on factor k with the conditional risk premium of factor k, $Cov\left(\beta_{i,k,t}, \gamma_{k,t}\right)$. $diag\left(\gamma_t - \gamma\right)$ is the $K \times K$ diagonal matrix and the diagonal is given by the $K \times 1$ vector $\gamma_t - \gamma$.

2.2.1 Estimation of Conditional Factor Loadings β_t

To estimate equation (4), we first need to construct a time-series of conditional factor loadings β_t. In this section we provide an estimate method for the conditional factor loadings β_t. The aim of the approach is to use more "real-time" information about the factor loadings and test assets to construct β_t. However, we show that the estimates and the conclusions are essentially the same as the results based on 6-month simple rolling windows in the Appendix D.

The estimation procedure of this "real-time" approach is as follows. Since we consider only traded pricing factors we can estimate factor loadings from the covariance matrix of individual currency returns. Denote by $C_t \times N$ matrix Θ_t^R and $C_t \times K$ matrix Θ_t^F the currency portfolio holdings of the N test assets and K pricing factors, where C_t is the number of individual currencies at time t. The $N \times 1$ and $K \times 1$ vectors of excess returns at time $t+1$ of the N test assets and K factors are $R_{t+1} = \Theta_t^{R\prime} r_{t+1}$ and $F_{t+1} = \Theta_t^{F\prime} r_{t+1}$, where r_{t+1} is the $C_t \times 1$ column vector of currency returns as described in section 1.1.

We can write the conditional pricing model as,

$$R_{t+1} = \beta_t F_{t+1} + \varepsilon_{t+1},$$

where ε_{t+1} is an $N \times 1$ vector of residuals. Post multiplying by F'_{t+1} and taking conditional expectations,

$$\begin{aligned} E_t\left[R_{t+1}F'_{t+1}\right] &= E_t\left[\Theta_t^{R\prime} r_{t+1} r'_{t+1}\Theta_t^F\right] \\ &= E_t\left[(\beta_t F_{t+1}+\varepsilon_{t+1})F'_{t+1}\right] = E_t\left[\beta_t \Theta_t^{F\prime} r_{t+1} r'_{t+1}\Theta_t^F\right] + E_t\left[\varepsilon_{t+1}F'_{t+1}\right]. \end{aligned}$$

Noticing that $E_t\left[r_{t+1}r'_{t+1}\right] = \Omega_t$ is the $C_t \times C_t$ conditional covariance matrix of the individual currency returns, and residuals ε_{t+1} are not correlated with the factor returns F_{t+1}, we obtain

$$\beta_t = \Theta_t^{R\prime}\Omega_t\Theta_t^F\left(\Theta_t^{F\prime}\Omega_t\Theta_t^F\right)^{-1}. \tag{5}$$

This estimation of β_t is similar to the simple rolling window estimates. However, there is a crucial difference. Only the estimation of the conditional covariance matrix $\widetilde{\Omega}_t$ is obtained from rolling estimations. The portfolio weights Θ_t^F are real-time. That is, we estimate β_t directly in rolling window regressions of R_t on F_t, but both $\widetilde{\Omega}_t$ and Θ_t^F are (weighted) averages of historical data. In that sense, the approach using Θ_t^F produces β_t that are more real-time and rely less on historical data. An implicit key assumption of this approach is that the pricing factors are traded, and we have portfolio weights Θ_t^F.

In the subsequent GMM estimation of equation (4), we take our first stage estimates of β_t as data and neglect estimation errors. As long as the estimated β_t are unbiased and the estimation noise is not correlated with future factor returns, then this does not introduce any bias. However, our inference may be affected as the estimated errors will be too small, and we may reject the conditional model too often. This, however, does not affect our main results (in section 3.2) that the conditional *DOL*-*CAR* cannot be rejected by the data, and is able to explain a comprehensive cross-section of average FX returns.

Table 1 and 2 provide summary statistics of β_t for all 27 test assets and the *DOL* and *CAR* factors. The first column, labeled "uncon", further reports the unconditional factor loadings obtained from the unconditional model estimation. For some test assets the difference can be substantial between the unconditional loading β and the average conditional loading $\bar{\beta}$. For instance, for *CSCAR* the unconditional loadings for *DOL* are half the size of the average conditional loadings. These differences imply differences in model implied expected returns across the conditional and unconditional models. However, as we show later, the more important difference between the conditional and unconditional models comes from the covariation between conditional loadings and risk premia.

Some assets feature a large time-series variation in the conditional loadings. For instance, we observe large dispersion in the conditional loading of the $CSCAR$. This is intuitive for the following reason. While DOL and CAR have a constant notional value, the $CSCAR$ has market timing and adjusts its notional value in response to changes in the first two moments of currency returns. These moments are volatile, and thus, conditional loadings are volatile. Similarly, there is a lot of volatility in conditional factor loadings of the DB portfolios and the $DDOL$ on the DOL factor. This is not surprising as these test assets by construction switch between positive and negative exposures to the DOL when the sign of the average forward discount flips from one month to the next. The sizable volatility in conditional loadings (and covariation with conditional risk premia as we show later) is the first order explanation for the success of the conditional DOL-CAR factor model.

2.2.2 Estimation of $\sigma_{\beta\gamma}$

Equipped with a times-series of β_t, we can now estimate $\bar{\beta}$ in equation (4). In addition, we need to estimate the covariation of β_t with conditional risk premia γ_t. The problem is that we do not directly observe γ_t. A common approach in the literature is to impose a functional form on γ_t (and β_t) and use conditioning variables to construct a time-series. However, an obvious limitation is that the estimation of equation (4) critically hinges on the specific functional form and the set of conditioning variables.

To address this concern we use an approach which is model-free and does not require a specific set of conditioning variables. By definition of $\gamma_t = E_t\left[F_{t+1}\right]$ the law of iterative expectations yields $E\left[F_{t+1}\right] = E\left[E_t\left[F_{t+1}\right]\right] = E\left[\gamma_t\right] = \gamma$. Applying again the law of iterative expectations to the unconditional covariance of β_t with F_{t+1},

$$\begin{aligned}
Cov\left(\beta_t, F_{t+1}\right) &= E\left[\left(\beta_t - \bar{\beta}\right) diag\left(F_{t+1} - E\left[F_{t+1}\right]\right)\right] \\
&= E\left[E_t\left[\left(\beta_t - \bar{\beta}\right) diag\left(F_{t+1} - \gamma\right)\right]\right] \\
&= E\left[\left(\beta_t - \bar{\beta}\right) diag\left(\gamma_t - \gamma\right)\right] = \sigma_{\beta\gamma}. \qquad (6)
\end{aligned}$$

Notice that this approach is analogous to the methodology employed by Lewellen and Nagel (2006) and Kozak and Santosh (2020).

2.2.3 GMM: Conditional Model

We can now estimate equation (4) using GMM (Hansen, 1982; Cochrane, 2005). We use the following $K + 2NK + N$ moment conditions,

$$g(b) = \begin{pmatrix} E\left[F_{t+1} - \bar{F}\right] \\ E\left[vec\left(\beta_t - \bar{\beta}\right)\right] \\ E\left[vec\left(\left(\beta_t - \bar{\beta}\right) diag\left(F_{t+1} - \bar{F}\right) - \sigma_{\beta\gamma}\right)\right] \\ E\left[R_t - \bar{\beta}\gamma - \sigma_{\beta\gamma} 1_{K\times 1}\right] \end{pmatrix} = \begin{pmatrix} 0_{\{K\times 1\}} \\ 0_{\{NK\times 1\}} \\ 0_{\{NK\times 1\}} \\ 0_{\{N\times 1\}} \end{pmatrix} \tag{7}$$

to estimate the $K + 2NK + K$ parameters $b = \left[\bar{F}', vec(\bar{\beta})', vec(\sigma_{\beta\gamma})', \gamma'\right]'$. We need $N > K$ so that the model is overidentified. We take into account cross- and autocorrelations and heteroskedasticity following Newey and West (1987) when constructing the covariance matrix of the parameter estimates. This is our benchmark model while we also consider the GMM estimation setup which allows a free coefficient δ for the term $\sigma_{\beta\gamma}$, in which case $K + 2NK + 2K$ parameters $b = \left[\bar{F}', vec(\bar{\beta})', vec(\sigma_{\beta\gamma})', \gamma', \delta\right]'$ are estimated.

There are two main differences between the GMM estimations of the unconditional and conditional models. First, in contrast to the moment conditions (2) of the unconditional model, we do not have a time-series pricing equation in the moment conditions (7) of the conditional model. The time-series pricing equations are equivalent to equation (11), and we directly use β_t from equation (11) as an input in our GMM estimation in the conditional model.

The second main difference is the additional explanatory variable $\sigma_{\beta\gamma}$ in the cross-sectional pricing equation, $E\left[R_t\right] = \bar{\beta}\gamma + \sigma_{\beta\gamma} 1_{K\times 1} + \alpha^*$. Our empirical analysis shows that this term is the main driving force that the unconditional *DOL-CAR* model is rejected in the data (section 3.1), while the conditional *DOL-CAR* model is able to successfully explain average currency returns in a large cross-section of test assets (section 3.2).

2.3 Testable Restrictions

We use several tests to evaluate our factor pricing models. In the following, we denote by $\hat{b}$ the estimates of parameters b.

First, to validate pricing factor k, we check whether it is priced in the cross-section of asset returns. We use the t-test statistic $\frac{\hat{\gamma}_k}{\sqrt{Var(\hat{\gamma}_k)}}$ to check whether the estimated factor premium $\hat{\gamma}_k$ is statistically significantly different from 0. If $\hat{\gamma}_k$ is not significantly different from 0, then factor k is not important to explain the cross-section of average returns in FX markets.

Second, since all pricing factors are traded, the factor premium has to be equal to its expected excess return, $\gamma_k = \bar{F}_k$. We use the t-test statistic $\frac{\hat{\gamma}_k - \hat{\bar{F}}_k}{\sqrt{Var\left(\hat{\gamma}_k - \hat{\bar{F}}_k\right)}}$ with $Var\left(\hat{\gamma}_k - \hat{\bar{F}}_k\right) = Var\left(\hat{\gamma}_k\right) + Var\left(\hat{\bar{F}}_k\right) - 2Cov\left(\hat{\gamma}_k, \hat{\bar{F}}_k\right)$ to test whether $\hat{\gamma}_k - \hat{\bar{F}}_k$ is statistically significantly different from 0. If it is significantly different from 0, then we reject the model.

Third, in the conditional model we have the prediction $\delta_k = 1\ \forall k$. For the conditional model setup with free δ, we test whether $\hat{\delta}_k$ is statistically significantly different from 0 or 1 using the t-test statistic $\frac{\hat{\delta}_k}{\sqrt{Var(\hat{\delta}_k)}}$ or $\frac{\hat{\delta}_k - 1}{\sqrt{Var(\hat{\delta}_k)}}$. In theory, if there is a covariation between $\beta_{k,t}$ and $\gamma_{k,t}$, then this covariation appears in the cross-sectional pricing equation, and δ_k is equal to one. Only if there is no covariation between $\beta_{k,t}$ and $\gamma_{k,t}$, then δ_k can deviate from one, and it should be close to zero in empirical tests. Therefore, a $\hat{\delta}_k$ that significantly differs from zero, but does not significantly differ from one, suggests that the conditional model significantly differs from the unconditional version due to the covariation between the risk premium of factor k and the factor loadings of the test assets on factor k.

Fourth, we test whether the estimated abnormal returns $\hat{\alpha}^* = E[R_t] - \hat{\beta}\hat{\gamma}$ (in case of the unconditional model) or $\hat{\alpha}^* = E[R_t] - \hat{\bar{\beta}}\hat{\gamma} - \hat{\sigma}_{\beta\gamma}1_{K\times 1}$ (in case of the conditional model) in the N cross-sectional pricing equations are jointly statistically significantly different from 0. We use $\hat{\alpha}^{*'}Cov(\hat{\alpha}^*)^{-1}\hat{\alpha}^*$ as the test-statistic. It is χ^2 distributed with $N-K$ degrees of freedom for both the unconditional and conditional model with $\delta = 1$. A large test-statistic means a rejection of the model. For the conditional model which allows a free δ, $\hat{\alpha}^* = E[R_t] - \hat{\bar{\beta}}\hat{\gamma} - \hat{\sigma}_{\beta\gamma}\hat{\delta}$ and χ^2 is distributed with $N - 2K$ degrees of freedom.

Fifth, in case of the unconditional model, we test whether the estimated abnormal returns $\hat{\alpha} = E\left[R_t - \hat{\beta}F_t\right]$ in the N time-series pricing equations are jointly statistically significantly different from zero. Our test-statistic is $\frac{T-N-K}{NT}\hat{\alpha}'Cov(\hat{\alpha})^{-1}\hat{\alpha} \sim F_{N,T-N-K}$. A large test-statistic is a rejection of the unconditional model. We cannot use this test for the conditional model as we do not estimate time-series pricing equations with GMM. Instead, β_t is determined in equation (11) without any testable restrictions.

Finally, we report the R^2 of the N cross-sectional pricing equations. R^2 provides an indication of how well the model explains the average returns in the cross-section. It is, however, not a formal test to reject a model.

3 Empirical Results

Our main finding is that the unconditional DOL-CAR factor pricing model is rejected by the data, while the conditional DOL-CAR model is able to explain the average returns in our extensive cross-section of 27 test assets.

3.1 The Unconditional DOL-CAR Factor Pricing Model

We first test the unconditional DOL-CAR two factor pricing model. It is well-known in the literature that this model correctly prices the cross-section of forward discount sorted portfolios, but is rejected in a richer cross-section of FX market returns. Accordingly, this section merely confirms already known results, and serves as a benchmark for our main analysis in section 3.2.

Columns 1 and 4 in Table 3 provide the GMM estimation results of the unconditional DOL-CAR two factor pricing model. Column 1 reports results for our cross-section of five Int, five Mom, and five Val portfolios (15 test assets). This is a popular cross-section in the literature, and motivates previous research to add momentum and value factors to the pricing models. Column 4 utilizes our complete cross-section of 27 test assets discussed in section 1.3.

The risk premium $\hat{\gamma}_{DOL}$ is positive but small in magnitude and insignificant (1.70% resp. 2.21% per year). In contrast, $\hat{\gamma}_{CAR}$ is positive and significant (3.72% resp. 7.69% per year) in both sets of 15 and 27 test assets. Thus, only the CAR factor appears to matter to explain the cross-section of currency returns.

In the case of 27 test assets, we reject the unconditional model based on the finding that $\hat{\gamma}_{DOL} = 2.21\%$ is significantly larger than the average return of DOL (1.65%). Moreover, $\hat{\gamma}_{CAR} = 7.69\%$ is significantly larger than the average return of CAR (4.71%). In the case of 15 test assets, we find a marginally significant difference between $\hat{\gamma}_{CAR} = 3.72\%$ and the average return of CAR (4.71%).

More importantly, we find that the cross-sectional pricing errors α^* and the time-series pricing errors α are jointly significantly different from zero independent from specific set of test assets used. In case of the smaller cross-section the p-values are around 3%, while in the larger cross-section the rejection of the model comes with p-values below 0.1%. This provides clear evidence that the unconditional DOL-CAR model fails to explain the cross-section of average currency returns.

Finally, the R^2s are 35% and -2% for the cross-sections of 15 and 27 test assets. Recall that the R^2 is not bounded below by zero in our analysis as our cross-sectional regression does not include a constant. While the R^2 does not provide a formal test, it is still indicative. The low or even negative values suggest that the unconditional DOL-CAR model does not explain much of the cross-section of average currency returns.

We further illustrate the poor model fit in Figure 1. The vertical axis measures the expected returns in the unconditional DOL-CAR model. The horizontal axis reports the average returns between 1983 and 2021. The model implied and historical average returns are essentially orthogonal. We observe particularly large deviations from the 45 degree line in the case of $CSCAR$, most of the DB portfolios, $Mom1$, and $Val1$.

Column 1 and 2 in Table 4 provide additional insights on whether the unconditional DOL-CAR model explains the average returns of the test assets. We report the cross-sectional pricing errors α^* of each test asset. The pricing errors are statistically significant and large in magnitude for many assets. The model does a particularly poor job explaining the average returns of $Int5$, $Mom1$, $Val1$, $FXC2$, (almost) every DB portfolio, factor $DDOL$ and the $CSCAR$.

Consistent with earlier literature, we find strong evidence that the unconditional DOL-CAR two factor model strongly rejected in the data. This finding has motivated a large literature in search of new FX factors.

3.2 The Conditional DOL-CAR Factor Pricing Model

Given the failure of the unconditional DOL-CAR two factor model, we next test whether a conditional version of the model performs better. If not, then additional pricing factors are necessary as suggested in the literature. In contrast, if the conditional model fares well, then we do not need additional pricing factors. In that sense, the additional factors in the literature can be interpreted as useful variables to capture the variation in the conditional factor loadings and the conditional moments of the two factors DOL and CAR.

We show that the conditional DOL-CAR two factor model does a good job explaining the cross-section of currency returns, and the model cannot be rejected. This is the main contribution of our paper.

Columns 2, 3, 5 and 6 in Table 3 provide the GMM estimation results of the conditional DOL-CAR two factor pricing model. Column 2 and 3 report results for our cross-section of 15 test assets, while column 5 and 6 consider our full set of 27 test assets. $\delta = 1$ refers to our benchmark exercise when we set δ exactly to 1 which is theoretically true if the conditional DOL-CAR model holds. For robustness, we also estimate the case with a free δ, which enables us to test whether δ is significantly different from 1. Relative GMM estimation procedures can be found in Appendix A.1 and A.2.

The risk premium $\hat{\gamma}_{DOL}$ is again small (1.81% resp. 1.76% per year) and insignificant, while $\hat{\gamma}_{CAR}$ is positive (4.45% resp. 6.27% per year) and significant for both sets of 15 and 27 test assets. Accordingly, the CAR factor matters significantly for pricing. The model implied risk premia are consistent with (or not significantly different from) the average returns of DOL and CAR. Thus, we cannot reject the model based on our second test. Note that the estimation errors are slightly larger in the conditional model with free δ as we need to estimate more parameters (i.e., δ_k) compared to the unconditional model.

As predicted by the theory $\hat{\delta}_{DOL}$ and $\hat{\delta}_{CAR}$ do not significantly differ from one in either specification. $\hat{\delta}_{CAR}$ is always significantly different from zero, while we can only reject the hypothesis of $\hat{\delta}_{DOL} = 0$ in the larger cross-section of 27 test assets. This difference in significance appears to be a power issue in the smaller cross-section. The point estimate do not change much (and if anything they decrease as we increase the number of test assets) but the standard errors are decreasing a lot. The higher precision increases the significance. These results suggest that the conditional model significantly differs from the unconditional model due to the covariation between the factor risk premia and the factor loadings of the test assets.

We cannot reject the null hypothesis that the cross-sectional pricing errors α^* are jointly equal to zero in either set of 15 or 27 test assets. The p-values are 16% resp. 13%, therefore exceeding standard testing thresholds. Accordingly, there is no evidence of mispricing, and the conditional DOL-CAR appears to do an excellent job explaining the cross-section of currency returns.

Finally, the fit of the conditional model is remarkable. The R^2s are 74% and 89% for the cross-sections of 15 and 27 test assets. This is a substantial improvement over the 35% and -2% R^2 in the unconditional model. We further illustrate the astounding model fit in Figure 2 and 3. Notice that in stark contrast to the unconditional DOL-CAR model (Figure 1), the expected returns in the conditional DOL-CAR model line up almost perfectly with the historical average returns in both cases with either a restricted or a free δ. Not a single test asset displays a sizable deviation from the 45 degree line.

Column 3, 4, 5 and 6 in Table 4 provide additional insights how well the conditional DOL-CAR model explains the average returns of each test asset separately. The reduction in pricing errors is substantial across the board as we move from the unconditional to the conditional model. We find that the cross-sectional pricing errors α^* of 25 out of 27 test assets are insignificantly different from zero. In $\delta = 1$ case, only for $Val1$ and $CSCAR$ the pricing errors are significant at the 10% and 5% level respectively. They economically moderate with $\alpha^*_{Val1} = 1.82\%$ and $\alpha^*_{CSCAR} = 1.12\%$ per year. Even significant, comparing with the unconditional model, these two portfolios also experience a reduction in their magnitudes. Given a cross-section of 27 test assets we expect to observe roughly two rejections at the 10% level when the null hypothesis is true. In other words, the rejections are no reason for concern. In contrast, they confirm that the distribution of α^* is as expected under the null hypothesis.

In previous analysis, the conditional *DOL-CAR* model shows drops of unconditional pricing errors in the cross-section for almost all test portfolios regarding their significance and magnitudes. Beyond that evidence, we next turn to time-series pricing errors of these currency test assets. In Table 5, we report mean, standard deviation, significance and skewness of time-series pricing error α of each test asset after the conditional model fitting, which is called *Hedged*, and compare it to asset return of each test portfolio, which is referred as *Original*. For original test assets that have significant asset returns including $Int5$, $Mom4$, $Val4$, all DB portfolios, $DDOL$ and $CSCAR$, it is shown that their time-series pricing errors α have either become insignificant or received a reduction after fitting the conditional model with conditional betas and factor returns with the only exception being $Val1$. To alleviate the concern of single portfolio driving our result, we run a F-test to test whether these time-series pricing errors are jointly significantly different from zero. While this null hypothesis is strongly rejected for the original test assets at a 1% significance level with p-value equal to zero, we could only reject the hedged portfolios at a 10% level, which suggests an improvement of reduced time-series pricing errors for the conditional *DOL-CAR* model. Std of hedged DDOL is 0.00 but whether keep it or not in the F-test generates robust results.

To sum up, we find strong evidence in favor of the conditional *DOL-CAR* two factor pricing model. None of our tests rejects the conditional model, and the model does a very good job to explain a rich cross-section of average currency returns. This is an important contribution to the literature. Our results suggest that we do not require additional FX risk factors beyond the *DOL* and the *CAR*. However, it is important to account for the time variation in the conditional factor loadings and risk premia. Unconditional estimations which ignore the time-variation in the conditional moments mistakenly reject the *DOL-CAR* two factor model. This may lead to the misleading conclusion that there is a need for additional pricing factors orthogonal to DOL and CAR. In contrast, additional factors proposed in the literature appear to capture the variation in the conditional moments of the conditional two factor model.

Finally, we document that the stark difference between the unconditional and conditional models appears to be due to the significant covariation between the factor risk premia and the loadings of the test assets on the factors. In section 3.3, we provide additional evidence that the unconditional and conditional models mainly differ due to the covariation between factor premia and factor loadings.

3.3 Decomposition of Unconditional Pricing Errors α

In section 3.2, we document that $\hat{\delta}_{DOL}$ and $\hat{\delta}_{CAR}$ are significantly different from zero but not significantly different from one. This is suggestive that the main improvement of the conditional DOL-CAR model over its unconditional counterpart stems from the covariation between the conditional factor risk premia and the conditional factor loadings of the test assets. In this section, we further investigate the difference between the unconditional and conditional model.

We follow the derivation of Lewellen and Nagel (2006) and decompose the unconditional time-series pricing errors α_n of every asset $n \in \{1, \ldots, N\}$ in the unconditional DOL-CAR model,

$$\alpha_n \quad = \quad \sum_{k \in \mathcal{K}} \gamma_k \left(\bar{\beta}_{n,k} - \beta_{n,k} \right) + \sum_{k \in \mathcal{K}} \sigma_{\beta_{n,k} \gamma_k}, \tag{8}$$

for $\mathcal{K} = \{DOL, CAR\}$. γ_k is the unconditional risk premium of factor k in the unconditional pricing model. $\bar{\beta}_{n,k} = E\left[\beta_{n,kt}\right]$ is the average conditional factor loading of asset n on factor k in the conditional pricing model. $\beta_{n,k}$ is the unconditional factor loading of asset n on factor k in the unconditional pricing model. $\sigma_{\beta_{n,k}\gamma_k} = Cov\left(\gamma_{k,t}, \beta_{n,k,t}\right)$ is the covariation between the conditional factor loading of asset n on factor k and the conditional risk premium of factor k. $\gamma_{k,t}$ is the conditional risk premium of factor k in the conditional pricing model.

To understand the improvement of the conditional over the unconditional DOL-CAR model, we run the following linear regression,

$$\alpha_n \quad = \quad c + \sum_{k} \gamma_k \left(\bar{\beta}_{n,k} - \beta_{n,k} \right) + \sum_{k} \sigma_{\beta_{n,k} \gamma_k} \delta_k + u_n \tag{9}$$

where c is the intercept, and u_n are residuals. Estimates of all other explanatory variables are discussed above.

Table 6 reports the estimated regression coefficients when we use the time-series pricing errors α of our 27 test assets estimated in the unconditional model (equation (2), Table 3). First, we find highly significant coefficients $\hat{\delta}_{DOL}$ and $\hat{\delta}_{CAR}$. This suggests that the covariances $\sigma_{\beta_{n,DOL}\gamma_{DOL}}$ and $\sigma_{\beta_{n,CAR}\gamma_{CAR}}$ are important to explain the cross-sectional variation in α. In turn, they are key to explain the superior performance of the conditional model. Second, for the case with free δ, $\hat{\gamma}_{DOL}$ is insignificant, while $\hat{\gamma}_{CAR}$ is significant in regression (9) and both of them are significantly priced in the benchmark $\delta = 1$ case. The R^2s are remarkable 93% and 91% respectively, suggesting that the conditional model is able to explain almost all the time-series pricing errors in the unconditional model.

To evaluate the relative importance of $\sigma_{\beta\gamma}$ and $\bar{\beta} - \beta$ we compute the partial R^2 in regression (9). The partial R^2 is defined as $1 - \frac{SSE_{full}}{SSE_{reduced}}$, where SSE_m are the sum of squared errors of model $m \in \{full, reduced\}$, model $m = full$ includes all variables, and $m = reduced$ excludes the variables of interest. If the partial R^2 is high, then the variables that are excluded in the reduced model specification are important and contribute much to the R^2 in the full model. When we exclude the regressors $\sigma_{\beta\gamma}$ in the reduced model, then the partial R^2 is $R^2_{\sigma_{\beta\gamma}} = 80\%$ and 74% respectively. This suggests that $\sigma_{\beta\gamma}$ are important to reduce the SSE and contribute a lot to the R^2 in the full model. Accordingly, they are important variables to capture the cross-section of unconditional time-series pricing errors α. In contrast, when we exclude the regressors $\bar{\beta} - \beta$ in the reduced model, then the partial R^2 is only $R^2_{\bar{\beta}-\beta} = 39\%$ for the free δ case and 68% for the benchmark model when $\delta = 1$.

To sum up, the partial R^2 analysis suggests that the regressors $\bar{\beta} - \beta$ do not substantially reduce the SSE or contribute to the model fit. As such they are less important to capture the cross-section of unconditional time-series pricing errors α. The partial R^2 analysis provides evidence that the covariation between the conditional factor loadings and factor risk premia $\sigma_{\beta\gamma}$ are the first order reason explaining the superior performance of the conditional over the unconditional model. On the other hand, the difference between the average conditional and the unconditional factor loadings $\bar{\beta} - \beta$ are of secondary importance.

Finally, we compare the average magnitude of the time-series pricing errors in the unconditional model, $E[|\alpha|] = 1.58\%$ per year, to the average magnitude of the intercept plus the residual in regression (9), $E[|c + u|] = 0.43\%$ and $E[|c + u|] = 0.51\%$ respectively. $c + u$ is an estimate of the time-series pricing errors in the conditional model as it is the unexplained part of α after accounting for the correction as we switch from the unconditional to the conditional model. The reductions in the average pricing error are 73% and 68%, which are substantial. Although this result focuses on the pricing errors α in the time-series pricing equation, it is comparable to and consistent with the difference in cross-sectional pricing errors α^* across the unconditional and conditional model in Table 3 and 4, and certainly Table 5.

Figure 4 and 5 plot α against $c+u$. The large dispersion along the vertical axis, ranging from almost -3% to 5.5%, illustrates that the time-series pricing errors α are substantial in the unconditional *DOL*-*CAR* model. In contrast, the dispersion along the horizontal axis is small, and is roughly within -1% and 1.5%. The small dispersion along the horizontal axis suggests that the pricing errors in the conditional *DOL*-*CAR* model are close to zero.

The figures further reveal that the unconditional model particularly struggles to correctly price the *CSCAR*, *Mom*1, *DDOL* and all of the *DB* portfolios. The magnitude of the time-series pricing errors $|\alpha|$ are well over 1.5% and up to 5.5% per year for these test assets. The reduction to less than 1.5% (i.e., $|c+u| < 1.5\%$, is remarkable, when we switch to the conditional model.

To conclude, we find a significant reduction in the magnitude of the time-series pricing errors α as we switch from the unconditional to the conditional *DOL*-*CAR* model. The reduction in the pricing errors is mostly due to the covariation between conditional factor risk premia and the conditional factor loadings of the test assets. The covariation is important for both the *DOL* and the *CAR* factors. The difference between average conditional and unconditional factor loadings is of second order importance to explain the unconditional pricing errors.

3.4 Comparison to Different Factor Pricing Model

In previous sections, we show the success of the *DOL*-*CAR* pricing model in a conditional setting in explaining the cross-section of currency returns comparing with the unconditional model. Now in this section, we investigate the uniqueness and importance of *DOL* and *CAR*. It is shown that despite considering the conditional information, other well-documented currency factors and their combinations perform worse than *DOL* and *CAR*. Moreover, these conditional models with pricing factors other than *DOL* and *CAR* are significantly rejected in the cross-sectional tests.

Different currency factors and combinations include *CSCAR*, *DOL* and *MOM*, *DOL* and *VAL*, *DOL* and *FXC*, *DOL* and *DB*, and *CAR* and *DB*, among which we would like to emphasize $CSCAR$, a strategy that has involved the market timing information. Maurer et al. (2022) show that the unconditional $CSCAR$ single factor model does a good job explaining the cross-section of currency returns. They also provide evidence that the $CSCAR$ model outperforms many popular multi-factor models in the literature. In addition, they emphasize the importance of $CSCAR$'s market timing, suggesting that the $CSCAR$ model works well conditionally and unconditionally.

We compare the conditional models of different currency factors to the conditional *DOL-CAR* model, and document a superior performance of the conditional *DOL-CAR* model. Table 7 reports the results for different conditional factor pricing models when we set δ to be one. In the first column, we show that the $CSCAR$ factor is compensated with a large risk premium of roughly 13%. However, this single factor conditional model is significantly rejected in explaining the rich cross section of currency returns. Note that we do not use the $CSCAR$ as a test asset when $CSCAR$ itself is the pricing factor, and thus, the cross-section reduces from 27 to 26 test assets in its case.

Results of test restrictions for conditional models with other risk factors are reported in column 2 to 6. When the first pricing factor is DOL, MOM is significantly priced and FXC is marginally priced while VAL and DB don't have a significant risk premium. In the last column, we show that CAR and DB are both priced and we can't reject the null hypothesis that their risk premia are equal to their factor means. However, all these currency factors and combinations, even under the conditional model framework, are significantly rejected in the cross section χ^2 tests. Meanwhile, comparing with the conditional *DOL-CAR* model, they generate lower R^2. Appendix E lists GMM estimation results for each of these factors respectively.

Overall this section illustrates the superior performance of the conditional *DOL-CAR* model stems not only from the time-varying information considered but also the uniqueness of the two factors: DOL and CAR, which cannot be replaced by other well-documented currency factors.

3.5 Predictability of Factor Returns

Lewellen and Nagel (2006) dismiss the conditional CAPM for equities based on the argument that the covariation between the conditional β and the market premium, and thus also the variation in the conditional premium would have to be unreasonably large to explain abnormal returns of momentum and value portfolios. Following this idea, we estimate a lower bound of the variation in $\gamma_{DOL,t}$ and $\gamma_{CAR,t}$, and show that these bounds are reasonably moderate.

Suppose the joint distribution of the conditional factor loadings and factor premium of factor k is described by

$$\begin{pmatrix} \beta_{k,t} \\ \gamma_{k,t} \end{pmatrix} = \begin{pmatrix} \mu^{\beta_k} \\ \mu^{\gamma_k} \end{pmatrix} + \begin{pmatrix} \sigma^{\beta_k} \\ \sigma^{\gamma_k} \end{pmatrix} z_t.$$

$\beta_{k,t}$ is the $N \times 1$ vector of conditional loadings of the N assets on factor k (i.e., column k of β_t). Scalar $\gamma_{k,t}$ is the conditional premium of factor k (i.e., element k of vector γ_t). z_t is an $(N+1) \times 1$ vector of independent random variables with $E_t[z_t] = 0$ and $Var_t[z_t] = 1$. $N \times 1$ vectors $\mu^{\beta_k}, \mu^{\gamma_k}$ are the expected realizations and the $N \times (N+1)$ matrix σ^{β_k} and $1 \times (N+1)$ vector σ^{γ_k} determine the covariances of β_t and γ_t.

A Cholesky decomposition of the covariance matrix of $\beta_{k,t}$ yields

$$\sigma^{\beta_k} \sigma^{\beta_k \prime} = L^{\beta_k} L^{\beta_k \prime},$$

where L^{β_k} is a $N \times N$ lower triangular matrix. We can re-write the joint distribution of conditional factor loadings and the premium in the observationally equivalent way

$$\begin{pmatrix} \beta_{k,t} \\ \gamma_{k,t} \end{pmatrix} = \begin{pmatrix} \mu^{\beta_k} \\ \mu^{\gamma_k} \end{pmatrix} + \begin{pmatrix} L^{\beta_k} & 0 \\ l^{\gamma_k}_{[1N]} & l^{\gamma_k}_{N+1} \end{pmatrix} \tilde{z}_t,$$

where l^{γ_k} is a $(N+1) \times 1$ vector, $l^{\gamma_k}_{[1N]}$ is the vector with the first N elements and $l^{\gamma_k}_{N+1}$ is the last element of l^{γ_k}, and $\tilde{z}_t$ is a rotation of z_t with $E_t[\tilde{z}_t] = 0$ and $Var_t[\tilde{z}_t] = 1$.

We can further write the $N \times 1$ vector of covariances between the N factor loadings and the premium as

$$\sigma_{\beta_k, \gamma_k} = \sigma^{\beta_k} \sigma^{\gamma_k \prime} = L^{\beta_k} l^{\gamma_k \prime}_{[1N]}.$$

Since the variance of $\gamma_{k,t}$ is given by $Var[\gamma_{k,t}] = \sigma^{\gamma_k} \sigma^{\gamma_k \prime} = l^{\gamma_k} l^{\gamma_k \prime}$, we can define the lower bound

$$\underline{Var}[\gamma_{k,t}] = l^{\gamma_k}_{[1N]} l^{\gamma_k \prime}_{[1N]} = \sigma'_{\beta_k, \gamma_k} (L^{\beta_k})^{-1 \prime} (L^{\beta_k})^{-1} \sigma_{\beta_k, \gamma_k} = \sigma'_{\beta_k, \gamma_k} \left(\sigma^{\beta_k} \sigma^{\beta_k \prime} \right)^{-1} \sigma_{\beta_k, \gamma_k}.$$

Moreover, the lower bound on the predictability of the factor returns is

$$\underline{R}_k^2 \ = \ \frac{\underline{Var}[\gamma_{k,t}]}{Var[F_{k,t}]}. \tag{10}$$

We have estimates of the $\sigma_{\beta_k,\gamma_k}$ from the GMM estimation. We further use a standard sample estimator for the covariance matrix of factor loadings $\sigma^{\beta_k}\sigma^{\beta_k}{}'$ and the variance of factor returns $Var[F_{k,t}]$. The first row of Table 8 reports the lower bound $\underline{R}_k^2$ for $k \in \{DOL, CAR\}$ when we use all 27 test assets. For DOL we find the lower bound $\underline{R}_{DOL}^2 = 7.55\%$, while it is $\underline{R}_{CAR}^2 = 4.44\%$ for CAR[3].

Our estimator of $\sigma_{\beta_k,\gamma_k}$ is unbiased. Nevertheless, estimation errors of $\sigma_{\beta_k,\gamma_k}$ cause an upward bias of the lower bound $\underline{R}_k^2$. Suppose for asset $n = 1$ the true $\sigma_{\beta_{n,k},\gamma_k} = 0$. Because of estimation errors we observe $\hat{\sigma}_{\beta_{n,k},\gamma_k} = \sigma_{\beta_{n,k},\gamma_k} + \varphi_n = \varphi_n \neq 0$, where the hat indicates the estimated value, and φ_n is noise. Since L^{β_k} is a lower triangular matrix (i.e., only the first element on the first row is non-zero) the first element of the true l^{γ_k} has to be zero to match the true $\sigma_{\beta_{n,k},\gamma_k} = 0$ for $n = 1$. However, because of the noise φ_n the first element of the estimated $\hat{l}^{\gamma_k}$ cannot be zero to match the estimated $\hat{\sigma}_{\beta_{n,k},\gamma_k} = \varphi_n \neq 0$. Accordingly, $\hat{l}^{\gamma_k}_{[1N]}\hat{l}^{\gamma_k}_{[1N]}{}' > l^{\gamma_k}_{[1N]}l^{\gamma_k}_{[1N]}{}'$, and the estimated lower bounds $\underline{Var}[\gamma_{k,t}]$ and $\underline{R}_k^2$ are higher than the true values. Similarly, estimation errors in $\sigma_{\beta_{n,k},\gamma_k}$ for $n > 1$ cause to an upward bias of the lower bounds. Moreover, a similar argument holds for true $\sigma_{\beta_{n,k},\gamma_k}$ different from but close to zero and sufficiently large estimation errors.

To address estimation errors and obtain robust lower bounds we impose statistical and economic constraints. As a statistical criterion we only use assets in the construction of the lower bounds if the estimated covariance $\sigma_{\beta_{n,k},\gamma_k} = Cov\left(\beta_{n,k,t}, F_{k,t+1}\right)$ is statistically significant. In other words, we set element n of $\sigma_{\beta_k,\gamma_k}$ equal to zero if the p-value of $\sigma_{\beta_{n,k},\gamma_k}$ is larger than 10%. We use Newey and West (1987) standard errors to account for auto-correlations and heteroskedasticity when we compute the p-value. The second row of table 8 shows that for the DOL factor ($k = DOL$) $\sigma_{\beta_{n,k},\gamma_k} = Cov\left(\beta_{n,k,t}, F_{k,t+1}\right)$ is statistically significant for 8 out of 27 assets. For the CAR factor ($k = CAR$) this number drops to 2. Using this statistical constraint, we find $\underline{R}_{DOL}^2 = 3.64\%$ and $\underline{R}_{CAR}^2 = 1.63\%$.

As an economic constraint we only use assets in the construction of the lower bounds if the pricing error α_n^* in the unconditional DOL-CAR model is statistically significant.

[3] We exclude test assets with conditional betas of extremely small (less than 10^{-8}) variance or covariance between DOL or CAR. For example, in the full sample case, covariance of conditional beta between test asset $DDOL$ and factor CAR is less than 10^{-8}, then $DDOL$ is excluded and that's why # Assets for CAR in the table is 26.

That is, we set element n of $\sigma_{\beta_k,\gamma_k}$ equal to zero if the cross-sectional pricing error α_n^* in the unconditional model has a p-value larger than 10%. The point estimate and standard error of α_n^* are obtained from the GMM estimation in Table 3. The idea is that if there is no pricing error in the unconditional model, then it is likely that the covariance $\sigma_{\beta_{n,k},\gamma_k}$ is close to zero.[4] The third row of Table 8 shows that for 9 out of 27 assets the unconditional pricing errors are significant (see also Table 4). Using this economic constraint we find $\underline{R}^2_{DOL} = 3.07\%$ and $\underline{R}^2_{CAR} = 2.13\%$.

In the second panel of Table 8, we further report results when we only use assets in the construction of the lower bounds if the magnitude of the unconditional pricing error is larger than a certain threshold value, $|\alpha_n^*| > c$. We investigate thresholds $c \in [0.25\%, 4\%]$. For 21 out of 27 assets the annualized unconditional pricing errors are larger than 0.25%, and the lower bounds are $\underline{R}^2_{DOL} = 6.06\%$ and $\underline{R}^2_{CAR} = 4.27\%$. At the other end, only 2 assets have an annualized unconditional pricing error larger than 4%, and the bounds decrease to $\underline{R}^2_{DOL} = 1.89\%$ and $\underline{R}^2_{CAR} = 0.10\%$.

In the third panel of Table 8, we repeat the analysis of the second panel but focus directly on the covariance $\sigma_{\beta_{n,k},\gamma_k}$ instead of α_n^*. This is more direct as α_n^* is a combination of both $\sigma_{\beta_{n,DOL},\gamma_{DOL}}$, $\sigma_{\beta_{n,CAR},\gamma_{CAR}}$, $\bar{\beta}_{n,DOL} - \beta_{n,DOL}$, and $\bar{\beta}_{n,CAR} - \beta_{n,CAR}$. We document that $|\sigma_{\beta_{n,DOL},\gamma_{DOL}}|$ is larger than 0.25% for 17 out of 27 assets, and larger than 4% for 3 assets. In comparison $|\sigma_{\beta_{n,CAR},\gamma_{CAR}}|$ is larger than 0.25% for 11 assets, and never even close to 4%. This is interesting as it suggests that $\sigma_{\beta_{n,DOL},\gamma_{DOL}}$ causes more mispricing for more assets in the unconditional model than $\sigma_{\beta_{n,CAR},\gamma_{CAR}}$. The six DB portfolios display the largest covariances $\sigma_{\beta_{n,DOL},\gamma_{DOL}}$. The lower bounds range from $\underline{R}^2_{DOL} = 5.16\%$ and $\underline{R}^2_{CAR} = 2.66\%$ (for the threshold value $c = 0.25\%$) to $\underline{R}^2_{DOL} = 1.89\%$ and $\underline{R}^2_{CAR} = 0.00\%$ (for the threshold value $c = 4\%$).

Overall, the lower bounds are relatively moderate and within a reasonable range. Lustig et al. (2014) are the first to document that DOL is well forecasted by the average forward discount. The profitability of the $DDOL$ strategy is based on this forecastability. There is also evidence of predictability of the CAR. For instance, Dupuy (2021) and Maurer et al. (2023) show that the magnitude of forward discounts has predictive power and can be used as signals to enhance the profitability of the CAR. To get a sense of the magnitude, Maurer et al. (2022) report R^2 of 5.12% and 2.22% for DOL and CAR. They only look at a small set of predictors and do not provide a comprehensive analysis. As such, we expect that the

[4] It is possible that $\sigma_{\beta_{n,k},\gamma_k}$ is sizable but offset by $\sigma_{\beta_{n,j},\gamma_j}$ for $j \neq k$ or $\gamma_i(\bar{\beta}_{n,i} - \beta_{n,i})$ for $i \in \{k, j\}$ and the resulting pricing error in the unconditional model is close to zero.

true forecastability is higher. These values from the literature are roughly in line with our lower bounds.

In summary, the evidence in favor of a conditional DOL-CAR model together with the rejection of its unconditional counterpart implies predictability in the factor returns. The estimated lower bounds are $\underline{R}^2_{DOL} = 7.55\%$ and $\underline{R}^2_{CAR} = 4.44\%$. Statistical or economic constraints to address estimation errors reduce the lower bounds by roughly half.

4 Conclusion

A conditional two-factor model explains over 80% of the variation of a rich cross-section of currency strategies. To this end, we build on Jagannathan and Wang (1996) and introduce a novel GMM estimation procedure to assess conditional factor models. We apply the approach to FX markets, and find strong evidence in favor of the conditional DOL-CAR two factor pricing model. None of our tests reject the conditional model, and the model does a remarkable job to explain a rich cross-section of average currency returns. Moreover, this superior performance of the conditional DOL-CAR model cannot be replaced by other currency risk factors or their combinations even when the conditional setup is applied. This is an important contribution to the literature. Our results suggests that we do not require additional FX risk factors beyond the DOL and the CAR. However, it is important to account for the time variation in the conditional factor loadings and risk premia. Unconditional estimations which ignore the time-variation in the conditional moments mistakenly reject the DOL-CAR two factor model. This may lead to the misleading conclusion that we need additional pricing factors. Our finding further suggests that additional factors introduced in the literature do not capture pricing information beyond the DOL and CAR, but they capture relevant information describing the variation in conditional moments of DOL and CAR and conditional factor loadings. Finally, our finding has implications for the predictability in factor returns. We estimate lower bounds for R^2 in predictive regressions for DOL and CAR, $\underline{R}^2_{DOL} = 7.55\%$ and $\underline{R}^2_{CAR} = 4.44\%$. Statistical or economic constraints to address estimation errors reduce the lower bounds by roughly half.

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Appendix

A Technical Details about GMM Estimation

A.1 Details about GMM Estimation of the Conditional Model

We solve

$$Ag_T(\hat{b}) = 0 \quad \text{with} \quad A = \begin{pmatrix} I_K & 0 & 0 & 0 \\ 0 & I_{NK} & 0 & 0 \\ 0 & 0 & I_{NK} & 0 \\ 0 & 0 & 0 & \hat{\beta}' \\ 0 & 0 & 0 & \hat{\sigma}'_{\beta\gamma} \end{pmatrix},$$

$$g_T(\hat{b}) = \frac{1}{T}\sum_{t=1}^{T} h_t(\hat{b}) \quad \text{and} \quad h_t(\hat{b}) \;=\; \begin{pmatrix} F_{t+1} - \bar{F} \\ vec\,(\beta_t - \beta) \\ vec\left((\beta_t - \beta)\,diag\left(F_{t+1} - \bar{F}\right) - \sigma_{\beta\gamma}\right) \\ R_t - \beta\gamma - \sigma_{\beta\gamma}\delta \end{pmatrix}.$$

$g_T(\hat{b})$ is the sample estimate of $g(b)$. I_x is an identity matrix with dimension $x \times x$. Note that matrix A has dimension $[K + 2NK + 2K] \times [K + 2NK + N]$.

The closed form solution of $\hat{b}$ is

$$\begin{aligned} \hat{\bar{F}} &= E\left[F_{t+1}\right] \\ vec\left(\hat{\beta}\right) &= E\left[vec\left(\beta_t\right)\right] \\ vec\left(\hat{\sigma}_{\beta\gamma}\right) &= E\left[vec\left(\left(\beta_t - \hat{\beta}\right) diag\left(F_{t+1} - \hat{\bar{F}}\right)\right]\right. \\ \begin{pmatrix} \hat{\gamma} \\ \hat{\delta} \end{pmatrix} &= \left[\begin{pmatrix} \hat{\beta}' \\ \hat{\sigma}'_{\beta\gamma} \end{pmatrix} \begin{pmatrix} \hat{\beta} & \hat{\sigma}_{\beta\gamma} \end{pmatrix}\right]^{-1} \begin{pmatrix} \hat{\beta}' \\ \hat{\sigma}'_{\beta\gamma} \end{pmatrix} E\left[R_t\right], \end{aligned}$$

with $E[x]$ being estimated using the sample average $\frac{1}{T}\sum_{t=1}^{T} x_t$. Note that we choose A to fully separate the estimation of $\bar{F}$, $vec\,(\beta)$, $vec\,(\sigma_{\beta\gamma})$, and $\begin{pmatrix}\gamma' & \delta'\end{pmatrix}$. Therefore, the point estimates of $\begin{pmatrix}\hat{\gamma}' & \hat{\delta}'\end{pmatrix}'$ are identical to the estimates in the second-stage cross-sectional regressions of

Fama and MacBeth (1973). The covariance matrix of $\hat{b}$ and $g_T(\hat{b})$ are estimated as follows,

$$\begin{aligned} Cov\left(\hat{b}\right) &= \frac{1}{T}[AD(\hat{b})]^{-1}AS(\hat{b})\left([AD(\hat{b})]^{-1}A\right)' \\ Cov\left(g_T(\hat{b})\right) &= \frac{1}{T}\left(I_{(K+2NK+N} - D(\hat{b})[AD(\hat{b})]^{-1}A\right)S(\hat{b})\left(I_{(K+2NK+N} - D(\hat{b})[AD(\hat{b})]^{-1}A\right)', \end{aligned}$$

with the $[K+2NK+N] \times [K+2NK+2K]$ matrix of partial derivatives

$$\begin{aligned} D(\hat{b}) &= \frac{\partial g_T(\hat{b})}{\partial \hat{b}'} \\ &= \begin{pmatrix} -I_K & 0 & 0 & 0 & 0 \\ 0 & -I_{NK} & 0 & 0 & 0 \\ -diag\left(vec\left(\tilde{\beta}_t\right)\right)\left(I_K \otimes 1_{\{N\times 1\}}\right) & -diag\left(\tilde{F}_{t+1}\right)\otimes I_N & -I_{NK} & 0 & 0 \\ 0 & -\hat{\gamma}'\otimes I_N & -\hat{\delta}'\otimes I_N & -\hat{\beta} & -\hat{\sigma}_{\beta\gamma} \end{pmatrix}, \end{aligned}$$

with $\tilde{\beta}_t = \beta_t - \hat{\beta}$, $\tilde{F}_{t+1} = F_{t+1} - \hat{\bar{F}}$ and following Newey and West (1987) the $[K+2NK+N] \times [K+2NK+N]$ matrix $S(\hat{b})$, which is a consistent estimate of the covariance matrix $E\left[g(b)g(b)'\right]$,

$$S(\hat{b}) = \frac{1}{T}\sum_{t=1}^{T} h_t(\hat{b})h_t(\hat{b})' + \sum_{l=1}^{L}\left(1 - \frac{l}{1+L}\right)\frac{1}{T-l}\sum_{t=1+l}^{T}\left(h_t(\hat{b})h_{t-l}(\hat{b})' + h_{t-l}(\hat{b})h_t(\hat{b})'\right),$$

with $L = T^{1/4}$. Note that the estimate $S(\hat{b})$ takes into account cross- and auto-correlations and heteroskedasticity.

In our tests we use the following elements of $Cov(\hat{b})$. $Var(\hat{\gamma}_k)$ is the diagonal element of $Cov(\hat{b})$ on row and column $K+2NK+k$. $Var(\hat{\bar{F}}_k)$ is the diagonal element of $Cov(\hat{b})$ on row and column k. $Cov\left(\hat{\gamma}_k, \hat{\bar{F}}_k\right)$ is the element of $Cov(\hat{b})$ on row k and column $K+2NK+k$. $Var(\hat{\delta}_k)$ is the diagonal element of $Cov(\hat{b})$ on row and column $K+2NK+K+k$. $Cov\left(\hat{\alpha}\right)$ is the $N \times N$ lower, right sub-matrix of $Cov\left(g_T(\hat{b})\right)$.

A.2 Details about GMM Estimation of the Conditional Model: $\delta = 1$

We solve

$$Ag_T(\hat{b}) = 0 \quad \text{with} \quad A = \begin{pmatrix} I_K & 0 & 0 & 0 \\ 0 & I_{NK} & 0 & 0 \\ 0 & 0 & I_{NK} & 0 \\ 0 & 0 & 0 & \hat{\beta}' \end{pmatrix},$$

$$g_T(\hat{b}) = \frac{1}{T}\sum_{t=1}^{T} h_t(\hat{b}) \quad \text{and} \quad h_t(\hat{b}) \;=\; \begin{pmatrix} F_{t+1} - \bar{F} \\ vec\,(\beta_t - \beta) \\ vec\left((\beta_t - \beta)\,diag\left(F_{t+1} - \bar{F}\right) - \sigma_{\beta\gamma}\right) \\ R_t - \beta\gamma - \sigma_{\beta\gamma} I_{K,1} \end{pmatrix}.$$

$g_T(\hat{b})$ is the sample estimate of $g(b)$. I_x is an identity matrix with dimension $x \times x$. Note that matrix A has dimension $[K + 2NK + K] \times [K + 2NK + N]$.

The closed form solution of $\hat{b}$ is

$$\begin{aligned} \hat{\bar{F}} &= E\left[F_{t+1}\right] \\ vec\left(\hat{\beta}\right) &= E\left[vec\left(\beta_t\right)\right] \\ vec\left(\hat{\sigma}_{\beta\gamma}\right) &= E\left[vec\left(\left(\beta_t - \hat{\beta}\right) diag\left(F_{t+1} - \hat{\bar{F}}\right)\right]\right. \\ \hat{\gamma} &= \left(\hat{\beta}'\hat{\beta}\right)^{-1} \hat{\beta}' E\left(R_t - \hat{\sigma}_{\beta\gamma}\right) \end{aligned}$$

with $E[x]$ being estimated using the sample average $\frac{1}{T}\sum_{t=1}^{T} x_t$. Note that we choose A to fully separate the estimation of $\bar{F}$, $vec\,(\beta)$, $vec\,(\sigma_{\beta\gamma})$, and γ'. Therefore, the point estimates of $\hat{\gamma}'$ are identical to the estimates in the second-stage cross-sectional regressions of Fama and MacBeth (1973). The covariance matrix of $\hat{b}$ and $g_T(\hat{b})$ are estimated as follows,

$$\begin{aligned} Cov\left(\hat{b}\right) &= \frac{1}{T}[AD(\hat{b})]^{-1} AS(\hat{b})\left([AD(\hat{b})]^{-1}A\right)' \\ Cov\left(g_T(\hat{b})\right) &= \frac{1}{T}\left(I_{K+2NK+N} - D(\hat{b})[AD(\hat{b})]^{-1}A\right) S(\hat{b}) \left(I_{K+2NK+N} - D(\hat{b})[AD(\hat{b})]^{-1}A\right)', \end{aligned}$$

with the $[K+2NK+N] \times [K+2NK+K]$ matrix of partial derivatives

$$
\begin{aligned}
D(\hat{b}) &= \frac{\partial g_T(\hat{b})}{\partial \hat{b}'} \\
&= \begin{pmatrix}
-I_K & 0 & 0 & 0 \\
0 & -I_{NK} & 0 & 0 \\
-diag\left(vec\left(\tilde{\beta}_t\right)\right)\left(I_K \otimes 1_{\{N\times 1\}}\right) & -diag\left(\tilde{F}_{t+1}\right) \otimes I_N & -I_{NK} & 0 \\
0 & -\hat{\gamma}' \otimes I_N & -I_{1,K} \otimes I_N & -\hat{\beta}
\end{pmatrix},
\end{aligned}
$$

with $\tilde{\beta}_t = \beta_t - \hat{\beta}$, $\tilde{F}_{t+1} = F_{t+1} - \hat{\bar{F}}$ and following Newey and West (1987) the $[K+2NK+N] \times [K+2NK+N]$ matrix $S(\hat{b})$, which is a consistent estimate of the covariance matrix $E\left[g(b)g(b)'\right]$,

$$
S(\hat{b}) = \frac{1}{T}\sum_{t=1}^{T} h_t(\hat{b})h_t(\hat{b})' + \sum_{l=1}^{L}\left(1 - \frac{l}{1+L}\right)\frac{1}{T-l}\sum_{t=1+l}^{T}\left(h_t(\hat{b})h_{t-l}(\hat{b})' + h_{t-l}(\hat{b})h_t(\hat{b})'\right),
$$

with $L = T^{1/4}$. Note that the estimate $S(\hat{b})$ takes into account cross- and auto-correlations and heteroskedasticity.

In our tests we use the following elements of $Cov(\hat{b})$. $Var(\hat{\gamma}_k)$ is the diagonal element of $Cov(\hat{b})$ on row and column $K+2NK+k$. $Var(\hat{\bar{F}}_k)$ is the diagonal element of $Cov(\hat{b})$ on row and column k. $Cov\left(\hat{\gamma}_k, \hat{\bar{F}}_k\right)$ is the element of $Cov(\hat{b})$ on row k and column $K+2NK+k$. $Cov\left(\hat{\alpha}\right)$ is the $N \times N$ lower, right sub-matrix of $Cov\left(g_T(\hat{b})\right)$.

A.3 Details about GMM Estimation of the Unconditional Model

We solve

$$A_1 g_T(\hat{b}) = 0 \quad \text{with} \quad A_1 = \begin{pmatrix} I_K & 0 & 0 \\ 0 & I_{(1+K)N} & 0 \\ 0 & 0 & \hat{\beta}' \end{pmatrix},$$

where I_x is an identity matrix with dimension $x \times x$ and

$$g_T(\hat{b}) = \frac{1}{T}\sum_{t=1}^{T} h_t(\hat{b}) \quad \text{with} \quad h_t(\hat{b}) = \begin{pmatrix} F_t - \hat{\bar{F}} \\ \begin{pmatrix} 1 \\ F_t \end{pmatrix} \otimes \left(R_t - \hat{\alpha} - \hat{\beta} F_t\right) \\ R_t - \hat{\beta}\hat{\gamma} \end{pmatrix},$$

is the sample estimate of $g(b)$.

The closed form solution of $\hat{b}$ is

$$\begin{aligned} \hat{\bar{F}} &= E[F_t] \\ \begin{pmatrix} \hat{\alpha}' \\ \hat{\beta} \end{pmatrix} &= E\left[\begin{pmatrix} 1 \\ F_t \end{pmatrix}\begin{pmatrix} 1 & F_t' \end{pmatrix}\right]^{-1} E\left[\begin{pmatrix} 1 \\ F_t \end{pmatrix} R_t'\right] \\ \hat{\gamma} &= \left[\hat{\beta}'\hat{\beta}\right]^{-1}\hat{\beta}' E\left[R_t\right] \end{aligned}$$

with $E[x]$ being estimated using the sample average $\frac{1}{T}\sum_{t=1}^{T} x_t$. Note that we choose A_1 to fully separate the estimate of $\bar{F}$, $\begin{pmatrix} \alpha \\ \beta \end{pmatrix}$, and γ. Therefore, the point estimate of $\hat{b}$ is identical to the estimate in 2-stage time-series and cross-sectional regressions (Fama and MacBeth, 1973). The covariance matrix of $\hat{b}$ and $g_T(\hat{b})$ are estimated as follows,

$$\begin{aligned} Cov(\hat{b}) &= \frac{1}{T}[A_1 D(\hat{b})]^{-1} A_1 S(\hat{b})([A_1 D(\hat{b})]^{-1} A_1)' \\ Cov(g_T(\hat{b})) &= \frac{1}{T}(I_{(2+K)N} - D(\hat{b})[A_1 D(\hat{b})]^{-1} A_1) S(\hat{b})(I_{(2+K)N} - D(\hat{b})[A_1 D(\hat{b})]^{-1} A_1)', \end{aligned}$$

with the $[K + (2 + K)N] \times [K + (1 + K)N + K]$ matrix of partial derivatives

$$D(\hat{b}) = \frac{\partial g_T(\hat{b})}{\partial \hat{b}'} = \begin{pmatrix} -I_K & 0 & 0 & 0 \\ 0 & -I_N & -E[F_t'] \otimes I_N & 0 \\ 0 & -E[f_t] \otimes I_N & -E[F_t \otimes F_t'] \otimes I_N & 0 \\ 0 & 0 & -\hat{\gamma}' \otimes I_N & -\hat{\beta} \end{pmatrix},$$

and following Newey and West (1987) the $[K + (2 + K)N] \times [K + (2 + K)N]$ matrix $S(\hat{b})$, which is a consistent estimate of the covariance matrix $E[g(b)g(b)']$,

$$S(\hat{b}) = \frac{1}{T}\sum_{t=1}^{T} h_t(\hat{b})h_t(\hat{b})' + \sum_{l=1}^{L}\left(1 - \frac{l}{1+L}\right)\frac{1}{T-l}\sum_{t=1+l}^{T}\left(h_t(\hat{b})h_{t-l}(\hat{b})' + h_{t-l}(\hat{b})h_t(\hat{b})'\right),$$

with $L = T^{1/4}$. Note that the estimate $S(\hat{b})$ takes into account cross- and auto-correlations and heteroskedasticity.

In our tests we use the following elements of $Cov\left(\hat{b}\right)$. $Cov(\hat{\alpha})$ is given by the $N \times N$ sub-matrix between rows $K + 1$ and $K + N$ and columns $K + 1$ and $K + N$ of $Cov(\hat{b})$. $Var(\hat{\gamma}_k)$ is the element on row $K + (1 + K)N + k$ and column $K + (1 + K)N + k$ of $Cov(\hat{b})$. $Var(\hat{\bar{F}}_k)$ is equal the element on row k and column k of $Cov(\hat{b})$. $Cov(\hat{\bar{F}}_k, \hat{\gamma}_k)$ is equal to the element on row k and column $K + (1 + K)N + k$ of $Cov(\hat{b})$. $Cov(\hat{\alpha}^*)$ is the $N \times N$ lower, right sub-matrix of $Cov(g_T(\hat{b}))$.

B Tables and Figures

Table 1: **Summary Statistics of Conditional Betas of** DOL

	uncon	*mean*	*med*	*std*	*skew*	*kurt*	*min*	*max*	5%	95%
$Int1$	0.96	0.96	0.96	0.12	-0.08	3.02	0.57	1.29	0.95	0.97
$Int2$	0.98	1.03	1.01	0.26	-0.03	3.17	0.10	1.70	1.01	1.06
$Int3$	1.04	1.03	1.02	0.23	-0.02	2.62	0.38	1.69	1.01	1.05
$Int4$	1.12	1.03	1.03	0.20	0.01	2.44	0.51	1.59	1.02	1.05
$Int5$	0.96	0.96	0.96	0.12	-0.08	3.00	0.57	1.29	0.95	0.97
$Mom1$	0.95	0.93	0.95	0.32	-0.35	2.84	-0.03	1.77	0.90	0.96
$Mom2$	1.03	0.99	1.03	0.29	-0.25	2.67	0.16	1.69	0.97	1.02
$Mom3$	1.07	1.06	1.06	0.22	-0.07	3.28	0.31	1.66	1.03	1.08
$Mom4$	1.07	1.04	1.06	0.25	-0.45	3.59	0.08	1.66	1.02	1.07
$Mom5$	0.92	0.98	1.02	0.28	-0.28	2.53	0.22	1.64	0.96	1.01
$Val1$	-0.14	-0.03	0.00	0.48	-0.09	2.25	-1.23	1.12	-0.07	0.01
$Val2$	0.08	0.19	0.16	0.49	0.19	2.88	-1.06	1.38	0.14	0.23
$Val3$	0.88	0.92	0.95	0.32	-0.24	2.26	-0.06	1.72	0.89	0.95
$Val4$	1.00	1.02	1.02	0.26	0.04	3.59	0.28	1.93	1.00	1.05
$Val5$	1.03	1.05	1.04	0.22	0.04	2.98	0.40	1.66	1.03	1.07
$FXC1$	1.04	1.04	1.07	0.24	-0.33	3.10	0.18	1.65	1.02	1.06
$FXC2$	1.01	0.99	1.01	0.21	-0.13	3.02	0.43	1.66	0.97	1.01
$FXC3$	0.91	0.87	0.90	0.31	-0.60	3.21	0.01	1.56	0.85	0.90
$FXC4$	1.02	0.95	0.96	0.19	-0.08	2.94	0.42	1.56	0.93	0.97
$DB1$	0.14	0.05	0.10	0.42	-0.19	1.94	-1.03	1.02	0.01	0.09
$DB2$	0.31	0.13	0.47	0.70	-0.38	1.65	-1.40	1.30	0.07	0.20
$DB3$	0.42	0.18	0.74	0.95	-0.41	1.34	-1.67	1.65	0.09	0.27
$DB4$	0.47	0.26	1.03	1.10	-0.43	1.25	-1.45	1.56	0.15	0.36
$DB5$	0.49	0.28	1.12	1.21	-0.42	1.23	-1.51	1.54	0.17	0.39
$DB6$	0.53	0.31	1.20	1.33	-0.42	1.23	-1.60	1.72	0.18	0.43
$DDOL$	0.40	0.21	1.00	0.98	-0.43	1.18	-1.00	1.00	0.12	0.30
$CSCAR$	0.10	0.22	0.11	0.60	1.65	10.64	-1.51	4.35	0.16	0.28

Notes: This table shows summary statistics of conditional betas of test assets with regard to the Dollar factor. *uncon* refers to corresponding unconditional beta of each test asset with regard to the Dollar factor. *mean*, *med* ,*std*, *skew*, *kurt*, *min*, *max*, 5% and 95% report the mean, median, standard deviation, skewness, kurtosis, minimum, maximum value and the [5%, 95%] confidence interval of conditional betas. The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table 2: **Summary Statistics of Conditional Betas of CAR**

	uncon	*mean*	*med*	*std*	*skew*	*kurt*	*min*	*max*	5%	95%
$Int1$	-0.48	-0.50	-0.51	0.14	-0.05	2.29	-0.83	-0.22	-0.51	-0.49
$Int2$	-0.18	-0.17	-0.17	0.13	0.27	3.09	-0.48	0.25	-0.18	-0.16
$Int3$	-0.09	-0.07	-0.08	0.13	0.08	2.95	-0.49	0.28	-0.09	-0.06
$Int4$	0.07	0.03	0.03	0.14	-0.06	3.08	-0.38	0.44	0.01	0.04
$Int5$	0.52	0.50	0.50	0.14	-0.06	2.29	0.17	0.78	0.49	0.51
$Mom1$	0.14	0.01	0.00	0.35	0.43	3.16	-0.82	1.21	-0.02	0.05
$Mom2$	-0.02	-0.07	-0.08	0.24	0.59	4.66	-0.64	1.17	-0.09	-0.05
$Mom3$	-0.08	-0.06	-0.07	0.21	0.28	3.19	-0.64	0.71	-0.08	-0.04
$Mom4$	-0.08	-0.02	-0.02	0.22	0.12	2.75	-0.62	0.67	-0.04	-0.00
$Mom5$	0.00	0.09	0.10	0.25	0.03	2.53	-0.54	0.78	0.07	0.12
$Val1$	-0.09	-0.01	-0.04	0.44	0.39	2.75	-1.03	1.48	-0.05	0.03
$Val2$	-0.12	-0.16	-0.25	0.47	0.52	2.76	-1.44	1.05	-0.21	-0.12
$Val3$	-0.05	0.04	0.01	0.25	0.35	3.08	-0.59	0.78	0.02	0.07
$Val4$	0.06	0.02	0.01	0.29	0.35	4.70	-1.26	1.46	-0.00	0.05
$Val5$	0.00	0.01	0.00	0.25	0.03	3.00	-0.67	0.79	-0.02	0.03
$FXC1$	0.00	0.01	-0.04	0.27	1.06	5.92	-0.68	1.43	-0.02	0.04
$FXC2$	0.07	-0.02	-0.01	0.19	-0.05	2.81	-0.46	0.54	-0.04	-0.00
$FXC3$	0.09	0.10	0.13	0.30	-0.36	2.81	-0.71	1.01	0.07	0.13
$FXC4$	-0.10	-0.04	-0.05	0.20	0.29	3.46	-0.55	0.79	-0.06	-0.02
$DB1$	0.01	0.03	0.03	0.35	0.13	3.31	-0.86	1.19	0.00	0.07
$DB2$	-0.05	-0.04	-0.05	0.31	0.45	3.92	-0.84	1.43	-0.06	-0.01
$DB3$	0.08	-0.01	0.02	0.24	-0.30	3.01	-0.66	0.83	-0.03	0.02
$DB4$	-0.01	-0.00	0.01	0.26	-0.08	3.28	-0.72	0.87	-0.03	0.02
$DB5$	-0.00	0.03	0.07	0.30	0.02	3.10	-1.03	1.04	-0.00	0.05
$DB6$	0.01	-0.02	-0.01	0.23	0.01	2.38	-0.60	0.58	-0.04	0.00
$DDOL$	0.01	0.00	0.00	0.00	0.58	35.59	-0.00	0.00	-0.00	0.00
$CSCAR$	0.72	0.92	0.75	0.77	2.55	15.43	-0.38	7.10	0.85	0.99

Notes: This table shows summary statistics of conditional betas of test assets with regard to the Carry factor. *uncon* refers to corresponding unconditional beta of each test asset with regard to the Carry factor. *mean*, *med* ,*std*, *skew*, *kurt*, *min*, *max*, 5% and 95% report the mean, median, standard deviation, skewness, kurtosis, minimum, maximum value and the [5%, 95%] confidence interval of conditional betas. The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table 3: **GMM Tests of *DOL*-*CAR* Model**

	15 assets			27 assets		
	Uncond	$\delta = 1$	Free δ	Uncond	$\delta = 1$	Free δ
$\hat{\gamma}_{DOL}$	1.70	1.81	1.78	2.21	1.76	1.73
(t-stat)	(1.12)	(1.20)	(1.18)	(1.44)	(1.15)	(1.14)
$\hat{\gamma}_{CAR}$	3.72**	4.45***	4.14**	7.69***	6.27***	4.58**
(t-stat)	(2.47)	(3.14)	(2.83)	(4.46)	(3.87)	(2.75)
$\hat{\delta}_{DOL}$			1.40			0.97
(t-stat)			(1.51)			(5.10)***
$\left(t\text{-stat};\hat{\delta} - 1\right)$			(0.43)			(-0.13)
$\hat{\delta}_{CAR}$			1.92			2.04
(t-stat)			(1.99)*			(3.10)***
$\left(t\text{-stat};\hat{\delta} - 1\right)$			(0.95)			(1.58)
$\hat{\gamma}_{DOL} - \bar{F}_{DOL}$	0.04	0.12	0.10	0.56**	0.07	0.04
(t-stat)	(0.62)	(0.15)	(0.12)	(2.57)	(0.09)	(0.06)
$\hat{\gamma}_{CAR} - \bar{F}_{CAR}$	-0.99*	-0.25	-0.56	2.98***	1.56	-0.12
(t-stat)	(-2.04)	(-0.30)	(-0.64)	(3.10)	(1.48)	(-0.12)
χ^2-test of $\hat{\alpha}^* = 0$	23.79**	17.98	11.02	53.39***	33.09	26.17
(p-value)	(0.0331)	(0.1583)	(0.4420)	(0.0008)	(0.1288)	(0.2931)
F-test of $\hat{\alpha} = 0$	1.64*			2.02***		
(p-value)	(0.0615)			(0.0021)		
R^2	0.35	0.74	0.78	-0.02	0.89	0.93

Notes: GMM estimation of unconditional and conditional *DOL*-*CAR* two factor pricing models. *DOL* invests equally in all foreign currencies against the USD. *CAR* is the equally weighted currency Carry trade. Cross-sectional pricing equation of unconditional model: $E\left[R_{n,t}\right] = \sum_k \beta_{n,k}\gamma_k + \alpha_n^*$, with the corresponding time-series equation $R_{n,t} = \alpha_n + \sum_k \beta_{n,k} F_{k,t} + \epsilon_{n,t}$. Cross-sectional pricing equation of conditional model: $E\left[R_{n,t}\right] = \sum_k \bar{\beta}_{n,k}\gamma_k + \sum_k \sigma_{\beta_{n,k}\gamma_k}\delta_k + \alpha_n^*$. $k \in \{DOL, CAR\}$, $R_{n,t}$ and $F_{k,t}$ are excess returns of test assets and pricing factors, α_n^* and $\epsilon_{n,t}$ are residuals, $\sigma_{\beta_{n,k}\gamma_k}$ are the covariances between $\gamma_{k,t}$ (or $F_{k,t+1}$) and $\beta_{n,k,t}$, $\bar{\beta}_{n,k} = E\left[\beta_{n,k,t}\right]$ and $\beta_{n,k,t}$ are estimated from daily currency return data. Details about the estimation are in Appendix A.1, A.2 and **??**. The first (last) three columns report results for 15 (27) test assets. R^2 is the model fit of the cross-sectional pricing equation. χ^2-test is the joint test statistic of cross-sectional pricing errors (or residuals) $\alpha_n^* = 0$ for all test assets $n \in \{1, \ldots, N\}$. F-test is the joint test statistic of time-series pricing errors (or intercept) $\alpha_n = 0$ for all test assets $n \in \{1, \ldots, N\}$ in the time-series equation of the unconditional model. (t-stat) indicates the significance of the difference between the coefficient and zero, (t-stat; $\delta = 1$) indicates the significance of the difference between the coefficient and one, and (p-value) indicates the significance of the χ^2 or F-test statistic. Significance at the 1%, 5% or 10% level are indicated by ***,** or *. Errors are estimated taking into account auto- and cross-sectional correlations and heteroskedasticity according to Newey and West (1987). The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table 4: **Cross-Sectional Pricing Errors α^* in DOL-CAR Model**

	Uncond		$\delta = 1$		Free δ	
	α^*	(t-stat)	α^*	(t-stat)	α^*	(t-stat)
$Int1$	0.73	(1.09)	0.79	(1.28)	-0.11	(-0.21)
$Int2$	-0.73	(-1.16)	-0.19	(-0.36)	-0.23	(-0.42)
$Int3$	0.39	(0.69)	0.41	(0.84)	0.32	(0.63)
$Int4$	-0.74	(-1.15)	0.21	(0.35)	0.46	(0.75)
$Int5$	-2.25***	(-3.31)	-0.84	(-1.69)	-0.05	(-0.10)
$Mom1$	-3.59***	(-3.29)	-1.08	(-1.27)	-0.81	(-0.85)
$Mom2$	-1.38	(-1.59)	-0.10	(-0.18)	-0.03	(-0.05)
$Mom3$	0.50	(0.63)	0.88	(1.66)	1.13*	(1.92)
$Mom4$	1.01	(1.66)	0.79	(1.51)	0.63	(0.96)
$Mom5$	0.07	(0.08)	-0.76	(-1.31)	-0.93	(-1.29)
$Val1$	2.66*	(1.92)	1.82*	(1.94)	1.36	(1.29)
$Val2$	0.24	(0.16)	0.51	(0.49)	0.83	(0.66)
$Val3$	-0.17	(-0.22)	-0.50	(-0.73)	-0.60	(-0.78)
$Val4$	0.14	(0.20)	0.46	(0.72)	-0.02	(-0.03)
$Val5$	0.08	(0.10)	0.63	(1.02)	0.26	(0.38)
$FXC1$	-1.01	(-1.52)	-0.21	(-0.40)	0.39	(0.69)
$FXC2$	-1.71**	(-2.38)	-0.25	(-0.48)	0.16	(0.28)
$FXC3$	-0.59	(-0.57)	-0.34	(-0.49)	-0.53	(-0.64)
$FXC4$	-0.16	(-0.29)	-0.32	(-0.70)	-0.52	(-0.99)
$DB1$	1.52	(1.32)	0.37	(0.47)	0.53	(0.56)
$DB2$	2.87**	(2.23)	0.07	(0.08)	-0.16	(-0.17)
$DB3$	1.40	(0.97)	-0.62	(-0.59)	-0.20	(-0.25)
$DB4$	2.86	(1.66)	-0.65	(-0.65)	-0.29	(-0.40)
$DB5$	5.33***	(3.00)	0.90	(0.86)	0.81	(1.28)
$DB6$	4.14**	(2.49)	-0.45	(-0.42)	-0.48	(-0.77)
$DDOL$	3.24**	(2.54)	-0.11	(-0.16)	-0.01	(-0.06)
$CSCAR$	3.41***	(4.31)	1.12**	(2.31)	0.29	(0.56)

Notes: The table reports the cross-sectional pricing errors (or residuals) α_n^* for each test asset $n \in \{1, \ldots, N\}$ in the estimated cross-sectional pricing equations of the unconditional and conditional DOL-CAR two factor pricing models in Table 3. The GMM estimation is based on the 27 test assets listed in this table. (t-stat) indicates the significance of the difference between α^* and zero. Significance at the 1%, 5% or 10% level are indicated by ***,** or *. Errors are estimated taking into account auto- and cross-sectional correlations and heteroskedasticity according to Newey and West (1987). The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table 5: **Time-Series Pricing Errors α in DOL-CAR Model**

	Original				Hedged			
	mean	*std*	(t-stat)	*skew*	*mean*	*std*	(t-stat)	*skew*
$Int1$	-0.78	0.84	(-0.57)	0.17	0.04	0.19	(0.13)	0.24
$Int2$	0.06	0.87	(0.04)	-0.26	-0.44	0.29	(-0.92)	-0.45
$Int3$	2.03	0.91	(1.35)	-0.15	0.31	0.27	(0.66)	0.30
$Int4$	2.31	1.01	(1.34)	-0.67	0.33	0.33	(0.62)	-0.62
$Int5$	3.92**	1.00	(2.27)	-0.73	0.05	0.19	(0.14)	0.24
$Mom1$	-0.35	0.97	(-0.22)	-0.58	-1.01	0.39	(-1.35)	-0.47
$Mom2$	0.77	0.94	(0.47)	-0.64	-0.17	0.31	(-0.33)	-0.82
$Mom3$	2.29	0.95	(1.40)	-0.30	0.84	0.29	(1.70)	0.03
$Mom4$	2.82*	0.94	(1.74)	-0.24	0.82*	0.29	(1.74)	-0.05
$Mom5$	2.17	0.86	(1.52)	-0.05	-0.56	0.30	(-1.10)	0.05
$Val1$	1.68	0.67	(1.44)	0.43	1.82**	0.48	(2.24)	0.58
$Val2$	-0.50	0.71	(-0.41)	-0.03	0.25	0.49	(0.28)	-0.01
$Val3$	1.40	0.84	(1.02)	0.31	-0.34	0.35	(-0.58)	0.24
$Val4$	2.87*	0.95	(1.84)	-0.27	0.54	0.34	(0.97)	-0.14
$Val5$	2.41	0.93	(1.52)	-0.36	0.68	0.33	(1.25)	0.24
$FXC1$	1.34	0.94	(0.84)	-0.61	-0.18	0.32	(-0.34)	-1.03
$FXC2$	1.06	0.91	(0.64)	-0.59	-0.23	0.26	(-0.52)	-0.85
$FXC3$	2.11	0.90	(1.32)	-0.62	-0.16	0.34	(-0.26)	0.26
$FXC4$	1.38	0.89	(0.92)	-0.24	-0.34	0.27	(-0.74)	-0.40
$DB1$	1.88*	0.63	(1.82)	0.28	0.48	0.44	(0.66)	0.22
$DB2$	3.24**	0.77	(2.64)	-0.15	0.13	0.40	(0.20)	-0.11
$DB3$	2.95*	0.93	(1.93)	-0.68	-0.55	0.43	(-0.77)	-0.74
$DB4$	3.81**	1.03	(2.30)	-0.24	-0.54	0.40	(-0.85)	0.42
$DB5$	6.46***	1.06	(3.81)	-0.10	1.04*	0.34	(1.90)	0.49
$DB6$	5.46***	1.10	(3.06)	-0.35	-0.32	0.31	(-0.63)	0.48
$DDOL$	4.26***	0.82	(3.20)	-0.31	-0.00***	0.00	(-2.89)	-2.44
$CSCAR$	9.20***	1.01	(5.54)	0.11	2.68**	0.64	(2.63)	-0.40
$DDOL$	*Yes*	*No*			*Yes*	*No*		
F-test of $\hat{\alpha} = 0$	2.52***	2.55***			1.46*	1.52*		
(p-value)	(0.0001)	(0.0001)			(0.0676)	(0.0517)		

Notes: The table reports mean, standard deviation, (t-stat) and skewness of time-series pricing errors α_n for each test asset $n \in \{1, \ldots, N\}$ after the conditional model fitting which is calculated as the sum of multiplications of conditional betas and Dollar and Carry factor returns, which are reported in the Hedged panel. Statistics of the test assets without conditional model fitting are reported in the Original panel. F-test statistics are reported to test whether time-series pricing errors α_n are jointly significantly different from zero for two experiments with and without $DDOL$. (t-stat) indicates the significance of the difference between the coefficient and zero. Significance at the 1%, 5% or 10% level are indicated by ***,** or *. Errors are estimated taking into account auto- and cross-sectional correlations and heteroskedasticity according to Newey and West (1987). The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table 6: **Decomposition of Unconditional Time-Series α**

	Free δ		$\delta = 1$	
	Coeff	(t-stat)	Coeff	(t-stat)
$\hat{c}$	0.12	(0.93)	0.19	(1.53)
$\hat{\gamma}_{DOL}$	4.82	(1.62)	2.91***	(3.00)
$\hat{\gamma}_{CAR}$	6.24**	(2.27)	11.16***	(4.43)
$\hat{\delta}_{DOL}$	1.13***	(7.37)		
$\hat{\delta}_{CAR}$	1.74***	(7.36)		
R^2	0.93		0.91	
$R^2_{\sigma_{\beta\gamma}}$	0.80		0.74	
$R^2_{\bar{\beta}-\beta}$	0.39		0.68	
$E[\lvert\alpha\rvert]$	1.58		1.58	
$E[\lvert\hat{c}+u\rvert]$	0.43		0.51	

Notes: Estimation of the cross-sectional regression,

$$\alpha_n \quad = \quad c + \sum_k \gamma_k \left(\bar{\beta}_{n,k} - \beta_{n,k}\right) + \sum_k \sigma_{\beta_{n,k}\gamma_k}\delta_k + u_n.$$

$k, h \in \{DOL, CAR\}$, α_n are the pricing errors (or intercept) in the time-series equation of the unconditional model estimated using GMM in Table 3, c is the intercept, u_n are residuals, $\sigma_{\beta_{k,h}\gamma_k}$ are the covariances between $\beta_{n,h,t}$ and $\gamma_{k,t}$ (or $F_{k,t+1}$), and $\beta_{n,k,t}$ are estimated from daily currency return data. The results are for 27 test assets. R^2 is the model fit of the cross-sectional pricing equation. $R^2_{\sigma_{\beta\gamma}}$ is the partial R^2 that quantifies the importance of $\sigma_{\beta\gamma}$. $R^2_{\bar{\beta}-\beta}$ is the partial R^2 that quantifies the importance of $\bar{\beta}-\beta$. $E\left[\lvert\alpha\rvert\right]$ is the cross-sectional average of absolute values of α_n. $E\left[\lvert c+u\rvert\right]$ is the cross-sectional average of absolute values of $\hat{c}+u_n$. (t-stat) indicates the significance of the difference between the coefficient and zero. Significance at the 1%, 5% or 10% level are indicated by ***,** or *. Errors u_n are are assumed i.i.d. The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table 7: **GMM Tests of Different Factor Model**

	CSCAR	DOL+MOM	DOL+VAL	DOL+FXC	DOL+DB	CAR+DB
			$\delta = 1$			
$\hat{\gamma}_{Factor1}$	13.14***	1.84	1.83	1.72	1.95	6.17**
(t-stat)	(3.03)	(1.21)	(1.20)	(1.13)	(1.30)	(2.47)
$\hat{\gamma}_{Factor2}$		12.30***	1.45	-2.44*	2.19	5.69**
(t-stat)		(3.15)	(1.22)	(-1.82)	(1.34)	(2.49)
$\hat{\gamma}_{Factor1} - \bar{F}_{Factor1}$	4.06	0.15	0.14	0.03	0.27	1.47
(t-stat)	(1.12)	(0.18)	(0.18)	(0.04)	(0.34)	(0.77)
$\hat{\gamma}_{Factor2} - \bar{F}_{Factor2}$		11.00***	-0.24	-1.94**	-1.40	2.11
(t-stat)		(3.06)	(-0.33)	(-2.39)	(-1.54)	(1.16)
χ^2-test of $\hat{\alpha}^* = 0$	42.75**	38.49**	38.74**	44.84***	41.85**	36.56*
(p-value)	(0.0149)	(0.0414)	(0.0391)	(0.0087)	(0.0187)	(0.0636)
R^2	0.08	0.59	0.51	0.39	0.52	0.85

Notes: GMM estimation of conditional currency factor pricing models with $\delta = 1$ for the sample with 27 test assets. Factors include $CSCAR$, CAR along with DB and combinations of DOL and either MOM, VAL, FXC or DB. Details about the estimation are in Appendix A.2. R^2 is the model fit of the cross-sectional pricing equation. χ^2-test is the joint test statistic of cross-sectional pricing errors (or residuals) $\alpha_n^* = 0$ for all test assets $n \in \{1, \ldots, N\}$. (t-stat) indicates the significance of the difference between the coefficient and zero while (p-value) indicates the significance of the χ^2 statistic. Significance at the 1%, 5% or 10% level are indicated by ***,** or *. Errors are estimated taking into account auto- and cross-sectional correlations and heteroskedasticity according to Newey and West (1987). The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table 8: **Lower Bound on Factor Predictability ($\underline{R}^2$)**

	DOL		*CAR*	
	# Assets	$\underline{R}^2(\%)$	# Assets	$\underline{R}^2(\%)$
Full Sample	27	7.55	26	4.44
p-val($\sigma_{\beta_{n,k},\gamma_k}$) < 0.1	8	3.64	2	1.63
p-val(α_n^*) < 0.1	9	3.07	8	2.13
$\lvert\alpha_n^*\rvert > 0.25\%$	21	6.06	20	4.27
$\lvert\alpha_n^*\rvert > 0.5\%$	20	5.89	19	4.13
$\lvert\alpha_n^*\rvert > 0.75\%$	15	4.38	14	3.10
$\lvert\alpha_n^*\rvert > 1.0\%$	15	4.38	14	3.10
$\lvert\alpha_n^*\rvert > 2.0\%$	9	3.09	8	1.89
$\lvert\alpha_n^*\rvert > 3.0\%$	5	2.92	4	1.30
$\lvert\alpha_n^*\rvert > 4\%$	2	1.89	2	0.10
$\lvert\sigma_{\beta_{n,k},\gamma_k}\rvert > 0.25\%$	17	5.16	11	2.66
$\lvert\sigma_{\beta_{n,k},\gamma_k}\rvert > 0.5\%$	8	3.64	4	1.75
$\lvert\sigma_{\beta_{n,k},\gamma_k}\rvert > 0.75\%$	8	3.64	1	1.20
$\lvert\sigma_{\beta_{n,k},\gamma_k}\rvert > 1\%$	7	3.23	1	1.20
$\lvert\sigma_{\beta_{n,k},\gamma_k}\rvert > 2\%$	6	2.42	1	1.20
$\lvert\sigma_{\beta_{n,k},\gamma_k}\rvert > 3\%$	5	2.42	0	0.00
$\lvert\sigma_{\beta_{n,k},\gamma_k}\rvert > 4\%$	3	1.89	0	0.00

Notes: Estimation of lower bound $\underline{R}_k^2$ (in percentage points) for factors $k \in \{DOL, CAR\}$ according to equation (10). The first row reports the values using information of all 27 test assets. The second row sets sets element n of $\sigma_{\beta_k,\gamma_k}$ equal to zero if the estimated covariance $Cov\left(\beta_{n,k,t}, F_{k,t+1}\right)$ is insignificant at the 10% level (two-sided test). The third row sets element n of $\sigma_{\beta_k,\gamma_k}$ equal to zero if the cross-sectional pricing error α_n^* in the unconditional model is insignificant at the 10% level (two-sided test). For the two-sided t-test errors are estimated taking into account auto-correlations and heteroskedasticity according to Newey and West (1987). The second (third) panel sets sets element n of $\sigma_{\beta_k,\gamma_k}$ equal to zero if the absolute value of the annualized α_n^* ($\sigma_{\beta_{n,k},\gamma_k}$) is smaller than the threshold value $c = \{0.25\%, 0.5\%, 0.75\%, 1\%, 2\%, 3\%, 4\%\}$. The column "# Assets reports the number of elements of $\sigma_{\beta_k,\gamma_k}$ that are not set to zero. The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Unconditional DOL-CAR Model Fit

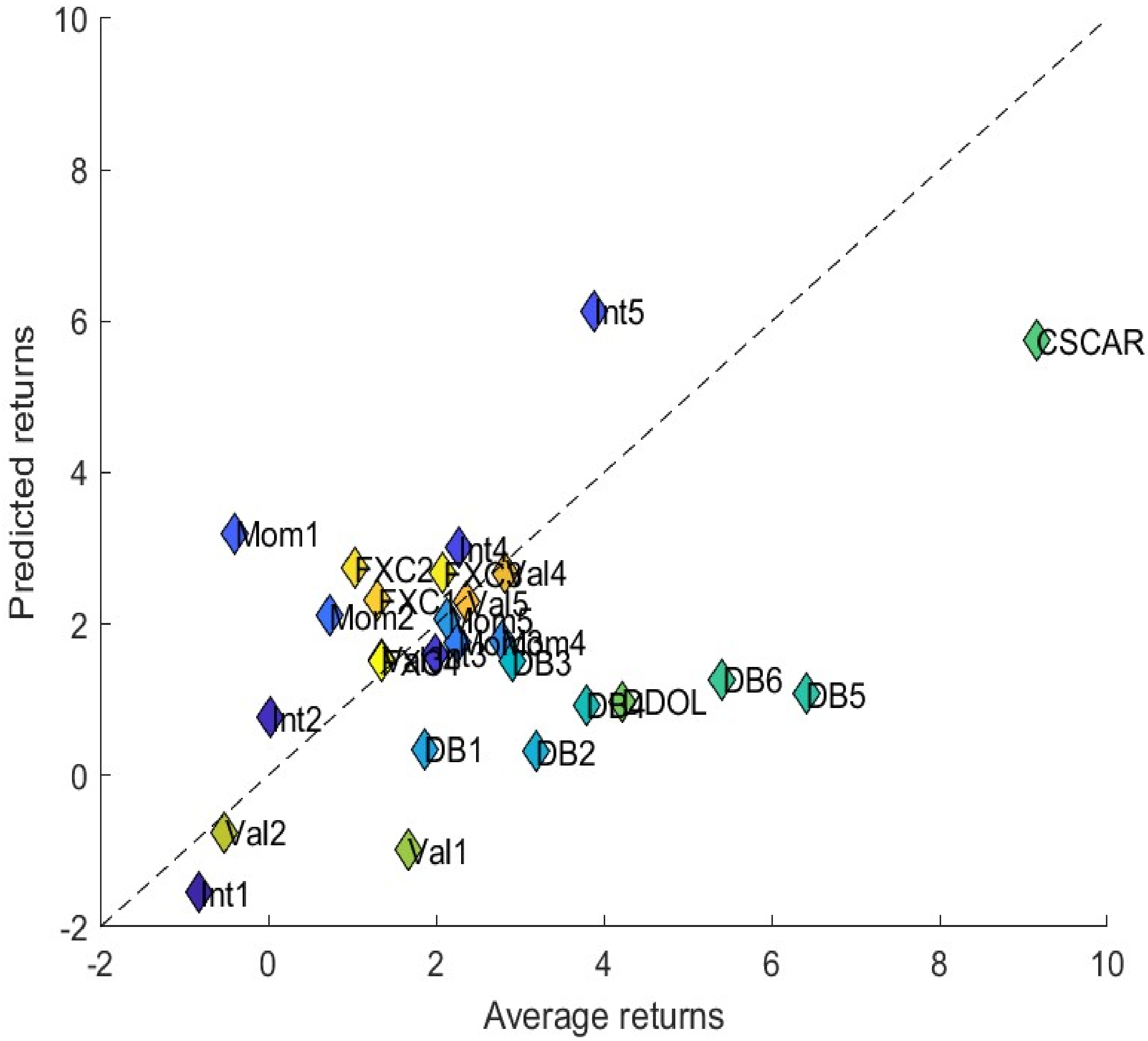

Figure 1: Scatter plot of average vs model implied returns. The model implied returns are based on the GMM estimates (Table 3) of the unconditional DOL-CAR model using 27 test assets constructed from our set of 29 developed and emerging currencies from December 1983 to March 2021.

Conditional DOL-CAR Model Fit: Free δ

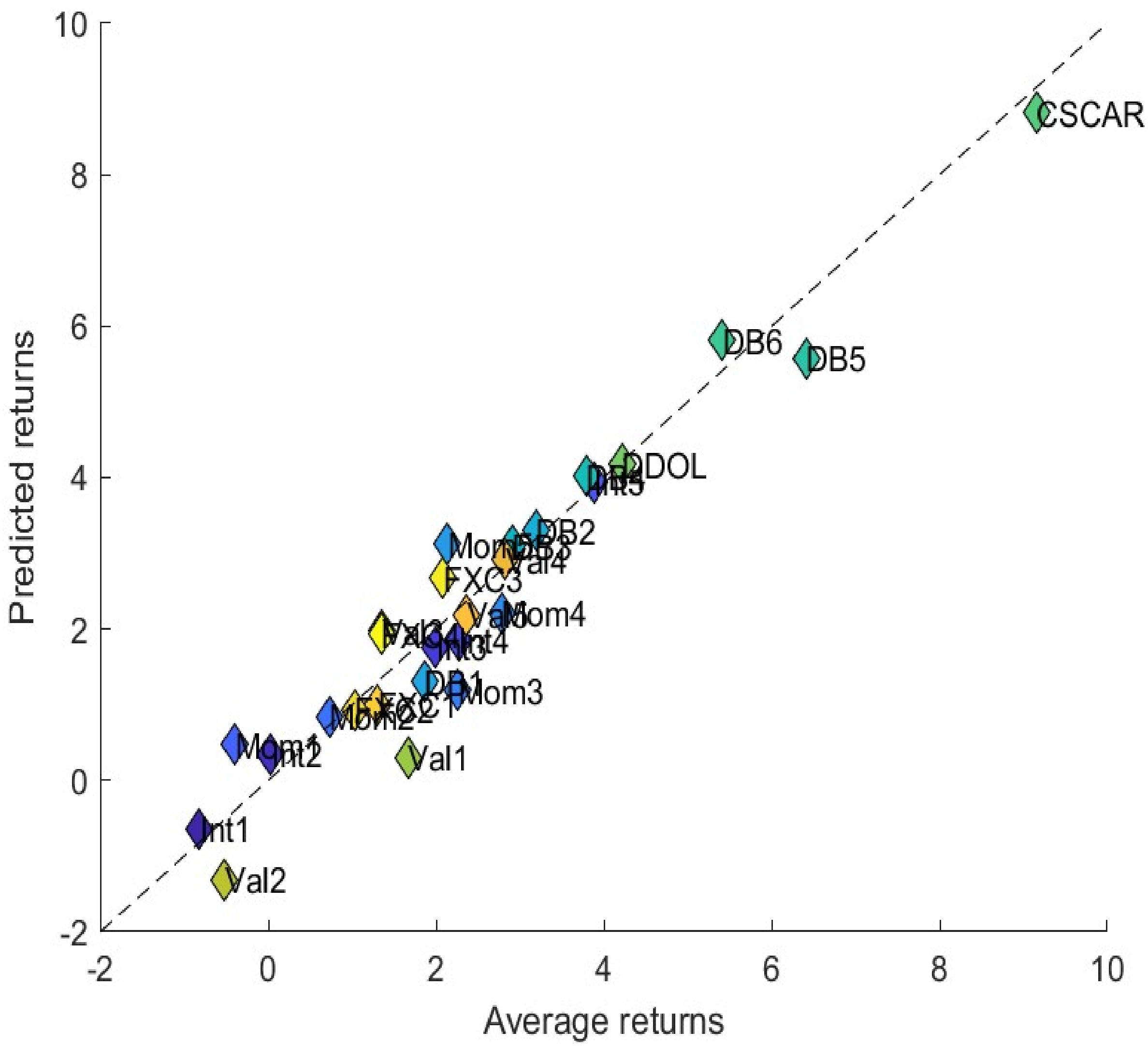

Figure 2: Scatter plot of average vs model implied returns. The model implied returns are based on the GMM estimates (Table 3) of the conditional DOL-CAR model with free δ using 27 test assets constructed from our set of 29 developed and emerging currencies from December 1983 to March 2021.

Conditional *DOL*-*CAR* Model Fit: $\delta = 1$

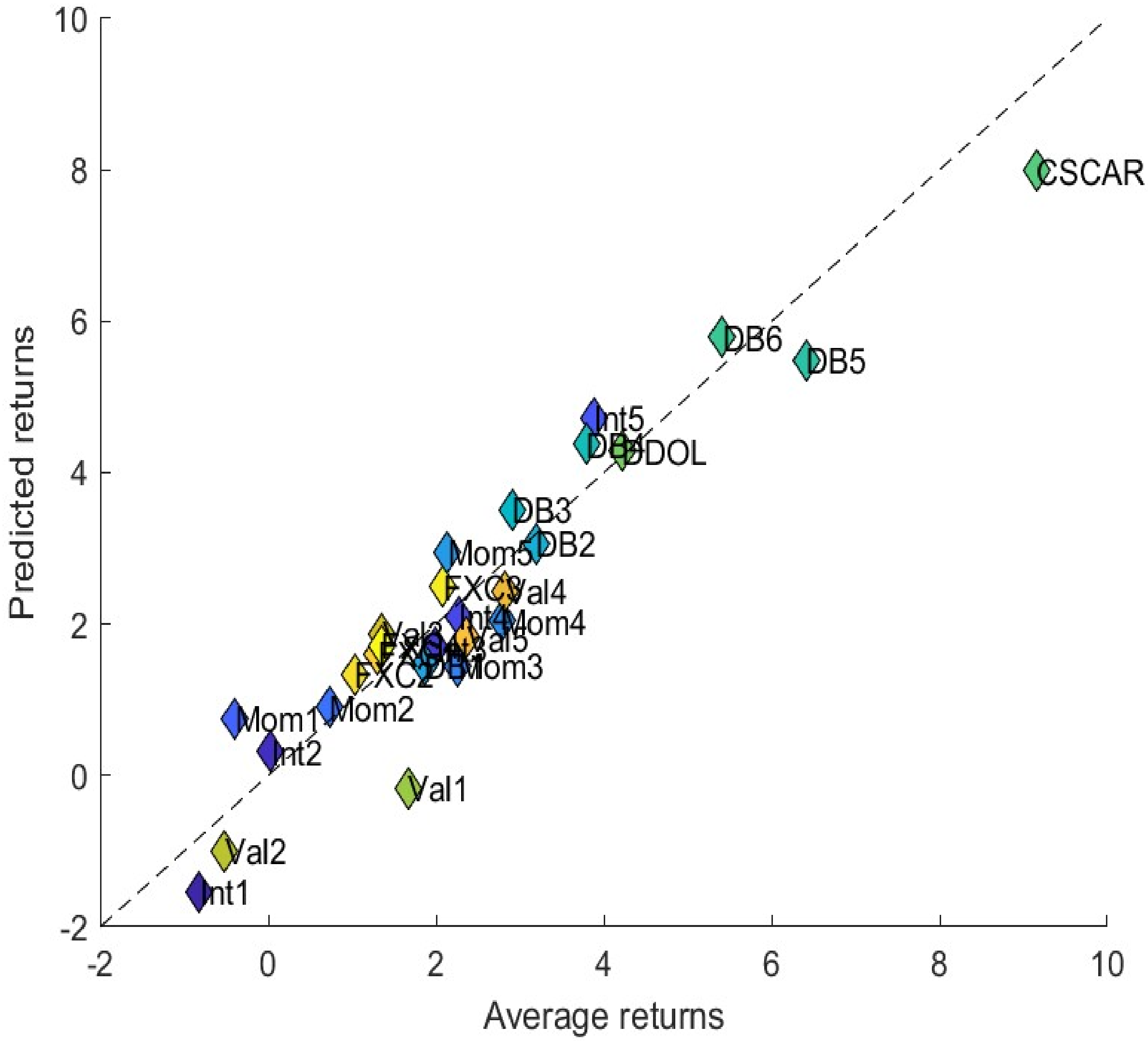

Figure 3: Scatter plot of average vs model implied returns. The model implied returns are based on the GMM estimates (Table 3) of the unconditional *DOL*-*CAR* model with $\delta = 1$ using 27 test assets constructed from our set of 29 developed and emerging currencies from December 1983 to March 2021.

Unconditional vs Conditional Model: Reduction in Pricing Error: Free δ

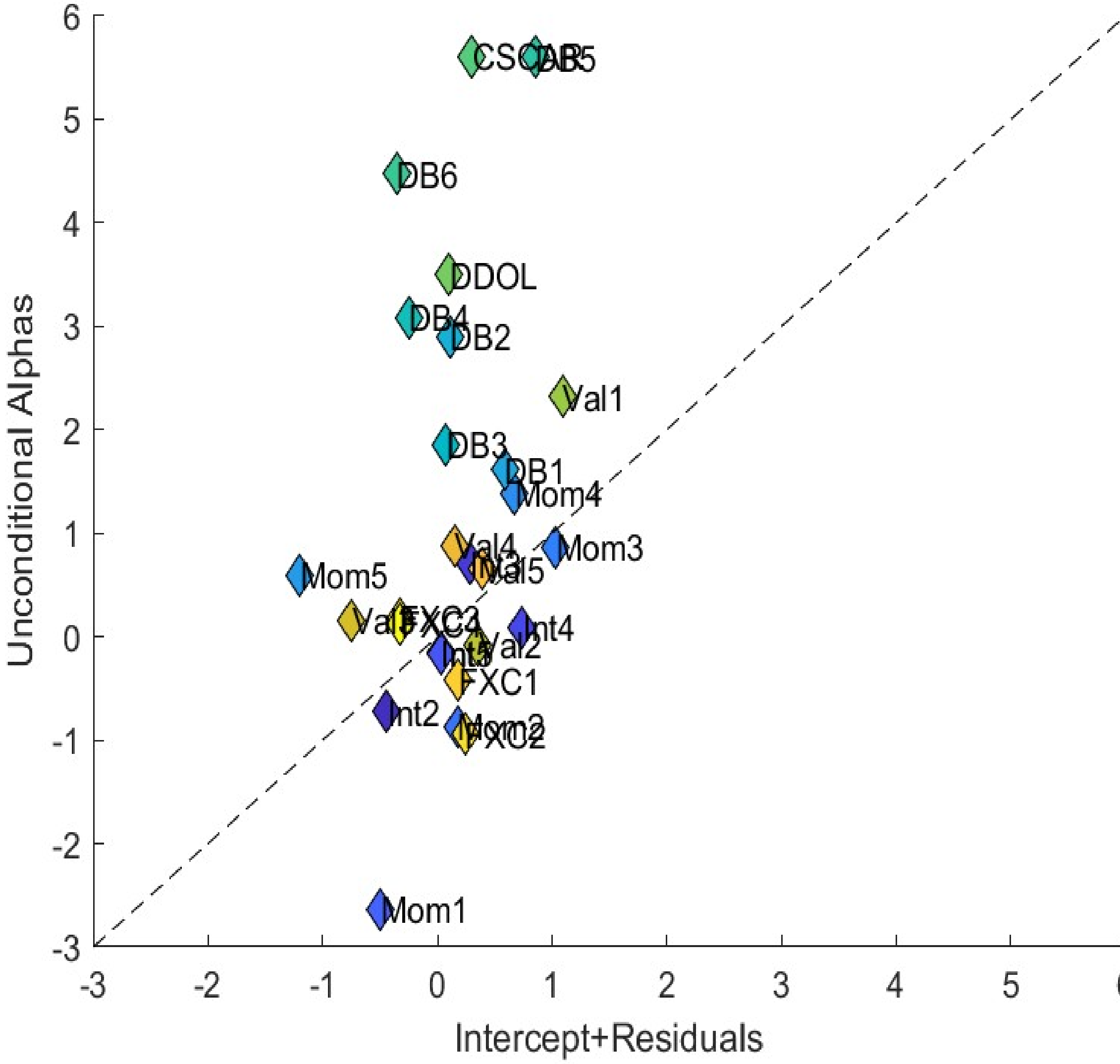

Figure 4: Scatter plot of α_i against $c + u_i$. α_i are the pricing errors (or intercept) in the time-series equation of the unconditional model estimated using GMM in Table 3. c is the intercept and u_i are residuals in the regression in Table 6. Conditional model has a free δ. The data are 27 test assets constructed from our set of 29 developed and emerging currencies from December 1983 to March 2021.

Unconditional vs Conditional Model: Reduction in Pricing Error, $\delta = 1$

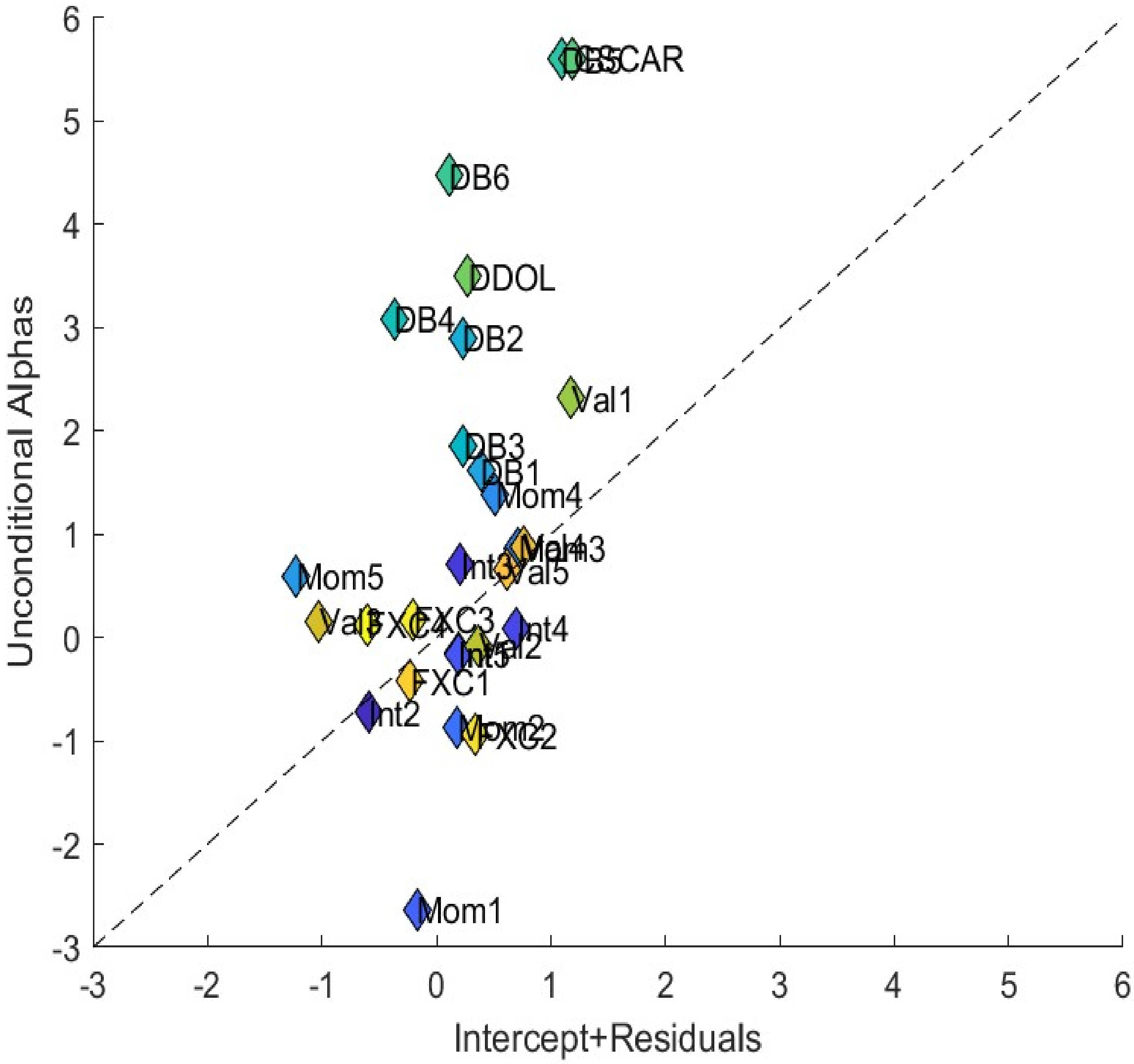

Figure 5: Scatter plot of α_i against $c + u_i$. α_i are the pricing errors (or intercept) in the time-series equation of the unconditional model estimated using GMM in Table 3. c is the intercept and u_i are residuals in the regression in Table 6. δ of the conditional model is set to one. The data are 27 test assets constructed from our set of 29 developed and emerging currencies from December 1983 to March 2021.

Online Appendix

In section Online Appendix we provide robustness results. In Section D we provide an alternative method to estimate the conditional factor loadings β_t. The approach uses an estimate of the conditional covariance matrix of individual currency returns and current portfolio weights of factors and test assets to construct "real-time" factor loadings. We find that the estimated β_t and the conclusions are essentially the same as the results reported in the main text. Section E lists detailed GMM estimation results for different currency factor models.

C Data Filters

We further follow Maurer et al. (2022) and apply the following filters to remove individual currency-month observations. The idea is to remove observations that are likely subject to major trading frictions, market segmentation or feature a substantial default risk in the short term sovereign bond market. We assume that currency carry trade investors are unlikely to invest in a currency under such conditions, and therefore, these currency-month observations are not important for the test assets and pricing factors that we intend to study. Our filters use only information known at the end of month t. Thus, the filters do not introduce any bias. First, we exclude a currency-month observation if the absolute value of the annualized forward discount $12 \times |fd_{i,t}|$ is larger than 20%. Forward discounts of more than 20% are rare. We believe that such large values likely indicate the presence of severe trading frictions, sizable sovereign default risk or an extraordinary large currency devaluation. Second, we remove a currency in month t if the relative bid-ask spread of either the forward or spot exchange rate (i.e., the monthly trading cost) is larger than 1%. These filters remove only 0.4% (1.7%) of currency-month observations in our sample of 15 (29) countries.

D Alternative Estimation of Conditional Factor Loadings

In this section we provide an alternative estimate method for the conditional factor loadings β_t, which is the widely used rolling-window estimation. To keep the analysis as simple and as model-free as possible, we run standard OLS regressions using daily data of 6-month rolling windows. That is, at time t (which is the last trading day of the month), we estimate β_t using the following regression,

$$R_{t-\tau} = a_t + \beta_t F_{t-\tau} + \varepsilon_{t-\tau}, \tag{11}$$

where a_t is the constant term of the regression, ε_{t+1} is the residual, $\tau \in \{1, \ldots, T\}$ and T is the number of daily observations within the 6-month window prior to t. In the main text, we show that a more sophisticated approach, which provides better "real-time" estimates based on current portfolio weights of the test assets and factors, yields very similar estimates of β_t and the subsequent conclusions are quantitatively the same.

Tables D1 to D6 and Figure D1 show the results using the simple rolling window approach to estimate β_t and for our set of 29 developed and emerging currencies.

Table D1: **Summary Statistics of Conditional Betas of** *DOL*

	uncon	*mean*	*med*	*std*	*skew*	*kurt*	*min*	*max*	5%	95%
$Int1$	0.96	0.96	0.97	0.11	-1.60	15.43	0.00	1.22	0.95	0.97
$Int2$	0.98	1.03	1.04	0.22	-0.41	3.91	0.00	1.55	1.01	1.05
$Int3$	1.04	1.02	1.02	0.18	-0.26	4.37	0.00	1.48	1.00	1.04
$Int4$	1.12	1.04	1.03	0.16	-0.48	6.27	0.00	1.44	1.02	1.05
$Int5$	0.96	0.96	0.97	0.11	-1.58	15.17	0.00	1.22	0.95	0.97
$Mom1$	0.95	0.96	0.96	0.22	-0.37	3.64	0.00	1.57	0.94	0.98
$Mom2$	1.03	1.00	0.99	0.15	-0.46	7.42	0.00	1.59	0.98	1.01
$Mom3$	1.07	1.04	1.04	0.12	-0.91	13.94	0.00	1.47	1.03	1.05
$Mom4$	1.07	1.04	1.05	0.14	-1.11	9.52	0.00	1.43	1.02	1.05
$Mom5$	0.92	0.97	0.97	0.16	-0.67	5.27	0.00	1.38	0.95	0.98
$Val1$	-0.14	0.91	0.97	0.29	-0.27	2.28	0.00	1.56	0.89	0.94
$Val2$	0.08	1.00	1.01	0.20	0.21	5.08	0.00	1.72	0.98	1.01
$Val3$	0.88	1.06	1.06	0.17	-0.50	6.06	0.00	1.49	1.04	1.07
$Val4$	1.00	1.04	1.08	0.18	-1.22	6.07	0.00	1.36	1.03	1.06
$Val5$	1.03	0.99	1.01	0.21	-0.34	3.88	0.00	1.73	0.97	1.01
$FXC1$	1.04	0.86	0.90	0.31	-0.79	3.34	-0.03	1.48	0.83	0.89
$FXC2$	1.01	0.94	0.94	0.16	-0.45	5.20	0.00	1.35	0.93	0.96
$FXC3$	0.91	1.09	1.08	0.16	-0.39	6.58	0.00	1.51	1.08	1.11
$FXC4$	1.02	1.06	1.09	0.20	-0.95	4.48	0.00	1.39	1.04	1.08
$DB1$	0.14	0.05	0.09	0.36	-0.26	2.11	-0.87	0.81	0.02	0.09
$DB2$	0.31	0.15	0.37	0.58	-0.48	1.86	-1.19	1.22	0.09	0.20
$DB3$	0.42	0.21	0.66	0.84	-0.48	1.61	-1.40	1.40	0.13	0.29
$DB4$	0.47	0.29	0.78	0.96	-0.47	1.50	-1.43	1.36	0.20	0.38
$DB5$	0.49	0.30	0.83	1.06	-0.47	1.49	-1.49	1.45	0.21	0.40
$DB6$	0.53	0.34	0.85	1.18	-0.44	1.48	-1.56	1.70	0.23	0.45
$DDOL$	0.40	0.23	0.64	0.86	-0.47	1.44	-1.00	1.00	0.15	0.31
$CSCAR$	0.10	0.21	0.16	0.47	0.54	4.04	-1.06	2.19	0.17	0.25

Notes: This table shows summary statistics of conditional betas of test assets with regard to the Dollar factor. Conditional betas are widely used rolling-window estimations. *uncon* refers to corresponding unconditional beta of each test asset with regard to the Dollar factor. *mean*, *med* ,*std*, *skew*, *kurt*, *min*, *max*, 5% and 95% report the mean, median, standard deviation, skewness, kurtosis, minimum, maximum value and the [5%, 95%] confidence interval of conditional betas. The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table D2: **Summary Statistics of Conditional Betas of** CAR

	uncon	*mean*	*med*	*std*	*skew*	*kurt*	*min*	*max*	5%	95%
$Int1$	-0.48	-0.50	-0.51	0.13	0.09	2.44	-0.78	0.00	-0.52	-0.49
$Int2$	-0.18	-0.15	-0.16	0.11	0.27	3.02	-0.48	0.16	-0.16	-0.14
$Int3$	-0.09	-0.08	-0.09	0.11	0.06	2.45	-0.34	0.18	-0.09	-0.07
$Int4$	0.07	0.02	0.03	0.12	-0.28	3.25	-0.31	0.35	0.01	0.04
$Int5$	0.52	0.50	0.49	0.13	-0.10	2.43	0.00	0.75	0.48	0.51
$Mom1$	0.14	0.04	0.05	0.25	-0.23	4.42	-0.82	0.89	0.02	0.06
$Mom2$	-0.02	-0.07	-0.07	0.15	-0.03	3.34	-0.69	0.39	-0.08	-0.05
$Mom3$	-0.08	-0.06	-0.08	0.14	0.47	3.26	-0.42	0.44	-0.08	-0.05
$Mom4$	-0.08	-0.04	-0.03	0.14	0.07	2.44	-0.42	0.29	-0.05	-0.03
$Mom5$	0.00	0.09	0.08	0.17	-0.06	2.88	-0.41	0.52	0.07	0.10
$Val1$	-0.09	0.04	0.02	0.23	0.36	3.46	-0.66	0.73	0.02	0.06
$Val2$	-0.12	0.00	-0.00	0.20	0.16	2.36	-0.45	0.64	-0.02	0.02
$Val3$	-0.05	-0.01	-0.03	0.20	0.57	3.80	-0.51	0.81	-0.03	0.01
$Val4$	0.06	0.01	-0.01	0.17	0.58	3.24	-0.35	0.55	-0.01	0.02
$Val5$	0.00	0.00	0.00	0.17	-0.01	2.58	-0.39	0.51	-0.01	0.02
$FXC1$	0.00	0.08	0.10	0.25	-0.38	2.75	-0.64	0.60	0.06	0.10
$FXC2$	0.07	-0.04	-0.05	0.15	0.33	2.89	-0.38	0.52	-0.06	-0.03
$FXC3$	0.09	-0.06	-0.06	0.16	0.35	2.99	-0.38	0.45	-0.07	-0.04
$FXC4$	-0.10	-0.06	-0.11	0.21	0.50	3.11	-0.50	0.57	-0.08	-0.04
$DB1$	0.01	0.03	0.03	0.30	0.14	3.76	-0.79	1.12	0.00	0.06
$DB2$	-0.05	-0.03	-0.05	0.27	0.68	4.83	-0.69	1.15	-0.06	-0.01
$DB3$	0.08	0.05	0.04	0.24	0.58	6.09	-0.74	1.09	0.03	0.07
$DB4$	-0.01	0.02	0.01	0.21	0.13	3.17	-0.54	0.78	-0.00	0.04
$DB5$	-0.00	0.05	0.08	0.24	-0.09	2.87	-0.61	0.80	0.02	0.07
$DB6$	0.01	-0.00	-0.01	0.23	0.43	3.65	-0.48	0.97	-0.03	0.02
$DDOL$	0.01	0.02	0.00	0.09	3.16	19.03	-0.20	0.76	0.01	0.02
$CSCAR$	0.72	0.95	0.82	0.63	1.53	7.13	0.00	4.55	0.89	1.01

Notes: This table shows summary statistics of conditional betas of test assets with regard to the Carry factor. Conditional betas are widely used rolling-window estimations. *uncon* refers to corresponding unconditional beta of each test asset with regard to the Carry factor. *mean*, *med* ,*std*, *skew*, *kurt*, *min*, *max*, 5% and 95% report the mean, median, standard deviation, skewness, kurtosis, minimum, maximum value and the [5%, 95%] confidence interval of conditional betas. The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table D3: **GMM Tests of *DOL*-*CAR* Model**

	15 assets			27 assets		
	Uncond	$\delta=1$	Free δ	Uncond	$\delta=1$	Free δ
$\hat{\gamma}_{DOL}$	1.70	1.66	1.71	2.21	1.77	1.72
(t-stat)	(1.12)	(1.28)	(1.30)	(1.44)	(1.32)	(1.25)
$\hat{\gamma}_{CAR}$	3.72**	4.37***	4.25***	7.69***	6.83***	7.37***
(t-stat)	(2.47)	(3.26)	(3.18)	(4.46)	(4.39)	(4.27)
$\hat{\delta}_{DOL}$			1.98			1.45
(t-stat)			(1.59)			(2.62)**
$\left(t\text{-stat};\hat{\delta}-1\right)$			(0.79)			(0.82)
$\hat{\delta}_{CAR}$			-0.87			-0.69
(t-stat)			(-0.48)			(-0.54)
$\left(t\text{-stat};\hat{\delta}-1\right)$			(-1.04)			(-1.32)
$\hat{\gamma}_{DOL}-\bar{F}_{DOL}$	0.04	-0.03	0.02	0.56**	0.08	0.03
(t-stat)	(0.62)	(-0.04)	(0.02)	(2.57)	(0.11)	(0.04)
$\hat{\gamma}_{CAR}-\bar{F}_{CAR}$	-0.99*	-0.34	-0.46	2.98***	2.13*	2.67**
(t-stat)	(-2.04)	(-0.40)	(-0.55)	(3.10)	(2.02)	(2.15)
χ^2-test of $\hat{\alpha}^*=0$	23.79**	13.67	9.13	53.39***	32.08	31.52
(p-value)	(0.0331)	(0.3971)	(0.6098)	(0.0008)	(0.1556)	(0.1105)
F-test of $\hat{\alpha}=0$	1.64*			2.02***		
(p-value)	(0.0615)			(0.0021)		
R^2	0.35	0.38	0.73	-0.02	0.69	0.81

Notes: GMM estimation of unconditional and conditional *DOL*-*CAR* two factor pricing models. *DOL* invests equally in all foreign currencies against the USD. *CAR* is the equally weighted currency Carry trade. Cross-sectional pricing equation of unconditional model: $E\left[R_{n,t}\right]=\sum_k \beta_{n,k}\gamma_k+\alpha_n^*$, with the corresponding time-series equation $R_{n,t}=\alpha_n+\sum_k \beta_{n,k}F_{k,t}+\epsilon_{n,t}$. Cross-sectional pricing equation of conditional model: $E\left[R_{n,t}\right]=\sum_k \bar{\beta}_{n,k}\gamma_k+\sum_k \sigma_{\beta_{n,k}\gamma_k}\delta_k+\alpha_n^*$. $k\in\{DOL, CAR\}$, $R_{n,t}$ and $F_{k,t}$ are excess returns of test assets and pricing factors, α_n^* and $\epsilon_{n,t}$ are residuals, $\sigma_{\beta_{n,k}\gamma_k}$ are the covariances between $\gamma_{k,t}$ (or $F_{k,t+1}$) and $\beta_{n,k,t}$, $\bar{\beta}_{n,k}=E\left[\beta_{n,k,t}\right]$ and $\beta_{n,k,t}$ are widely used rolling-window estimations. Details about the estimation are in Appendix A.1, A.2 and D. The first (last) three columns report results for 15 (27) test assets. R^2 is the model fit of the cross-sectional pricing equation. χ^2-test is the joint test statistic of cross-sectional pricing errors (or residuals) $\alpha_n^*=0$ for all test assets $n\in\{1,\ldots,N\}$. F-test is the joint test statistic of time-series pricing errors (or intercept) $\alpha_n=0$ for all test assets $n\in\{1,\ldots,N\}$ in the time-series equation of the unconditional model. (t-stat) indicates the significance of the difference between the coefficient and zero, (t-stat; $\delta=1$) indicates the significance of the difference between the coefficient and one, and (p-value) indicates the significance of the χ^2 or F-test statistic. Significance at the 1%, 5% or 10% level are indicated by ***,** or *. Errors are estimated taking into account auto- and cross-sectional correlations and heteroskedasticity according to Newey and West (1987). The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table D4: **Cross-Sectional Pricing Errors α^* in DOL-CAR Model**

	Uncond		$\delta = 1$		Free δ	
	α^*	(t-stat)	α^*	(t-stat)	α^*	(t-stat)
$Int1$	0.73	(1.09)	0.99	(1.63)	1.40*	(1.93)
$Int2$	-0.73	(-1.16)	-0.39	(-0.64)	0.00	(0.00)
$Int3$	0.39	(0.69)	0.69	(1.20)	0.64	(1.09)
$Int4$	-0.74	(-1.15)	0.28	(0.41)	-0.22	(-0.32)
$Int5$	-2.25***	(-3.31)	-1.21**	(-2.09)	-1.33*	(-1.94)
$Mom1$	-3.59***	(-3.29)	-2.55**	(-2.34)	-1.63	(-1.65)
$Mom2$	-1.38	(-1.59)	-0.23	(-0.28)	0.15	(0.20)
$Mom3$	0.50	(0.63)	1.00	(1.38)	1.07	(1.45)
$Mom4$	1.01	(1.66)	1.20*	(1.76)	1.04	(1.55)
$Mom5$	0.07	(0.08)	-0.32	(-0.38)	-0.95	(-1.26)
$Val1$	2.66*	(1.92)	-0.72	(-0.41)	0.61	(0.49)
$Val2$	0.24	(0.16)	-2.21	(-1.15)	-1.52	(-0.86)
$Val3$	-0.17	(-0.22)	-0.29	(-0.38)	0.28	(0.37)
$Val4$	0.14	(0.20)	1.29	(1.58)	0.47	(0.54)
$Val5$	0.08	(0.10)	0.95	(1.35)	-0.00	(-0.00)
$FXC1$	-1.01	(-1.52)	-0.80	(-0.83)	-0.00	(-0.00)
$FXC2$	-1.71**	(-2.38)	-0.73	(-1.00)	-0.80	(-1.00)
$FXC3$	-0.59	(-0.57)	0.45	(0.43)	0.28	(0.28)
$FXC4$	-0.16	(-0.29)	0.07	(0.09)	-0.13	(-0.19)
$DB1$	1.52	(1.32)	0.41	(0.44)	0.18	(0.17)
$DB2$	2.87**	(2.23)	1.71	(1.41)	0.46	(0.42)
$DB3$	1.40	(0.97)	-0.47	(-0.35)	-1.56*	(-1.75)
$DB4$	2.86	(1.66)	0.26	(0.18)	-0.48	(-0.66)
$DB5$	5.33***	(3.00)	2.59*	(1.76)	1.40*	(1.74)
$DB6$	4.14**	(2.49)	1.26	(0.82)	-0.07	(-0.11)
$DDOL$	3.24**	(2.54)	1.04	(0.96)	-0.01	(-0.04)
$CSCAR$	3.41***	(4.31)	1.40**	(2.54)	1.76**	(2.65)

Notes: The table reports the cross-sectional pricing errors (or residuals) α_n^* for each test asset $n \in \{1, \ldots, N\}$ in the estimated cross-sectional pricing equations of the unconditional and conditional DOL-CAR two factor pricing models in Table 3. Conditional betas are widely used rolling-window estimations. The GMM estimation is based on the 27 test assets listed in this table. (t-stat) indicates the significance of the difference between α^* and zero. Significance at the 1%, 5% or 10% level are indicated by ***,** or *. Errors are estimated taking into account auto- and cross-sectional correlations and heteroskedasticity according to Newey and West (1987). The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table D5: **Time-Series Pricing Errors α in DOL-CAR Model**

	Original				Hedged			
	mean	*std*	(t-stat)	*skew*	*mean*	*std*	(t-stat)	*skew*
$Int1$	-0.78	0.84	(-0.57)	0.17	-0.04	0.21	(-0.11)	0.06
$Int2$	0.06	0.87	(0.04)	-0.26	-0.68	0.34	(-1.22)	-0.76
$Int3$	2.03	0.91	(1.35)	-0.15	0.53	0.30	(1.03)	0.32
$Int4$	2.31	1.01	(1.34)	-0.67	0.43	0.36	(0.73)	-0.55
$Int5$	3.92**	1.00	(2.27)	-0.73	-0.04	0.21	(-0.12)	0.08
$Mom1$	-0.35	0.97	(-0.22)	-0.58	-2.40**	0.58	(-2.30)	-0.35
$Mom2$	0.77	0.94	(0.47)	-0.64	-0.33	0.42	(-0.47)	-0.95
$Mom3$	2.29	0.95	(1.40)	-0.30	0.92	0.37	(1.50)	-0.24
$Mom4$	2.82*	0.94	(1.74)	-0.24	1.19*	0.37	(2.04)	-0.17
$Mom5$	2.17	0.86	(1.52)	-0.05	-0.07	0.43	(-0.09)	0.53
$Val1$	1.68	0.67	(1.44)	0.43	-0.54	1.05	(-0.30)	0.40
$Val2$	-0.50	0.71	(-0.41)	-0.03	-2.14	1.08	(-1.14)	0.67
$Val3$	1.40	0.84	(1.02)	0.31	-0.18	0.50	(-0.22)	0.64
$Val4$	2.87*	0.95	(1.84)	-0.27	1.36*	0.48	(1.74)	-0.01
$Val5$	2.41	0.93	(1.52)	-0.36	1.00	0.42	(1.45)	0.52
$FXC1$	1.34	0.94	(0.84)	-0.61	-0.60	0.53	(-0.67)	-0.62
$FXC2$	1.06	0.91	(0.64)	-0.59	-0.77	0.37	(-1.27)	-0.38
$FXC3$	2.11	0.90	(1.32)	-0.62	0.39	0.57	(0.38)	0.05
$FXC4$	1.38	0.89	(0.92)	-0.24	0.00	0.42	(0.00)	-0.03
$DB1$	1.88*	0.63	(1.82)	0.28	0.53	0.57	(0.57)	0.66
$DB2$	3.24**	0.77	(2.64)	-0.15	1.75	0.66	(1.64)	0.78
$DB3$	2.95*	0.93	(1.93)	-0.68	-0.28	0.71	(-0.25)	-0.17
$DB4$	3.81**	1.03	(2.30)	-0.24	0.41	0.80	(0.32)	2.32
$DB5$	6.46***	1.06	(3.81)	-0.10	2.80**	0.82	(2.13)	3.70
$DB6$	5.46***	1.10	(3.06)	-0.35	1.41	0.81	(1.06)	1.82
$DDOL$	4.26***	0.82	(3.20)	-0.31	1.19	0.59	(1.25)	2.95
$CSCAR$	9.20***	1.01	(5.54)	0.11	3.54***	0.78	(2.93)	0.47
$DDOL$	*Yes*	*No*			*Yes*	*No*		
F-test of $\hat{\alpha} = 0$	2.52***	2.55***			1.28	1.30		

(p-value)	(0.0001)	(0.0001)			(0.1580)	(0.1480)

Notes: The table reports mean, standard deviation, (t-stat) and skewness of time-series pricing errors α_n for each test asset $n \in \{1, \dots, N\}$ after the conditional model fitting which is calculated as the sum of multiplications of conditional betas and Dollar and Carry factor returns, which are reported in the Hedged panel. Statistics of the test assets without conditional model fitting are reported in the Original panel. Conditional betas are widely used rolling-window estimations. F-test statistics are reported to test whether time-series pricing errors α_n are jointly significantly different from zero for two experiments with and without $DDOL$. (t-stat) indicates the significance of the difference between the coefficient and zero. Significance at the 1%, 5% or 10% level are indicated by ***,** or *. Errors are estimated taking into account auto- and cross-sectional correlations and heteroskedasticity according to Newey and West (1987). The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table D6: **Decomposition of Unconditional Time-Series α**

	Free δ		$\delta = 1$	
	Coeff	(t-stat)	Coeff	(t-stat)
$\hat{c}$	0.13	(0.70)	0.32	(1.55)
$\hat{\gamma}_{DOL}$	0.31	(0.28)	-0.80	(-1.04)
$\hat{\gamma}_{CAR}$	13.92***	(3.01)	12.90***	(3.02)
$\hat{\delta}_{DOL}$	1.34***	(7.65)		
$\hat{\delta}_{CAR}$	-0.47	(-0.56)		
R^2	0.80		0.75	
$R^2_{\sigma_{\beta\gamma}}$	0.69		0.61	
$R^2_{\bar{\beta}-\beta}$	0.55		0.46	
$E[\lvert\alpha\rvert]$	1.58		1.58	
$E[\lvert\hat{c}+u\rvert]$	0.68		0.83	

Notes: Estimation of the cross-sectional regression,

$$\alpha_n \quad = \quad c + \sum_k \gamma_k \left(\bar{\beta}_{n,k} - \beta_{n,k}\right) + \sum_k \sigma_{\beta_{n,k}\gamma_k}\delta_k + u_n.$$

$k, h \in \{DOL, CAR\}$, α_n are the pricing errors (or intercept) in the time-series equation of the unconditional model estimated using GMM in Table 3, c is the intercept, u_n are residuals, $\sigma_{\beta_{k,h}\gamma_k}$ are the covariances between $\beta_{n,h,t}$ and $\gamma_{k,t}$ (or $F_{k,t+1}$), and $\beta_{n,k,t}$ are widely used rolling-window estimations. The results are for 27 test assets. R^2 is the model fit of the cross-sectional pricing equation. $R^2_{\sigma_{\beta\gamma}}$ is the partial R^2 that quantifies the importance of $\sigma_{\beta\gamma}$. $R^2_{\bar{\beta}-\beta}$ is the partial R^2 that quantifies the importance of $\bar{\beta}-\beta$. $E\left[\lvert\alpha\rvert\right]$ is the cross-sectional average of absolute values of α_n. $E\left[\lvert c+u\rvert\right]$ is the cross-sectional average of absolute values of $\hat{c}+u_n$. (t-stat) indicates the significance of the difference between the coefficient and zero. Significance at the 1%, 5% or 10% level are indicated by ***,** or *. Errors u_n are are assumed i.i.d. The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Conditional *DOL-CAR* Model Fit: $\delta = 1$

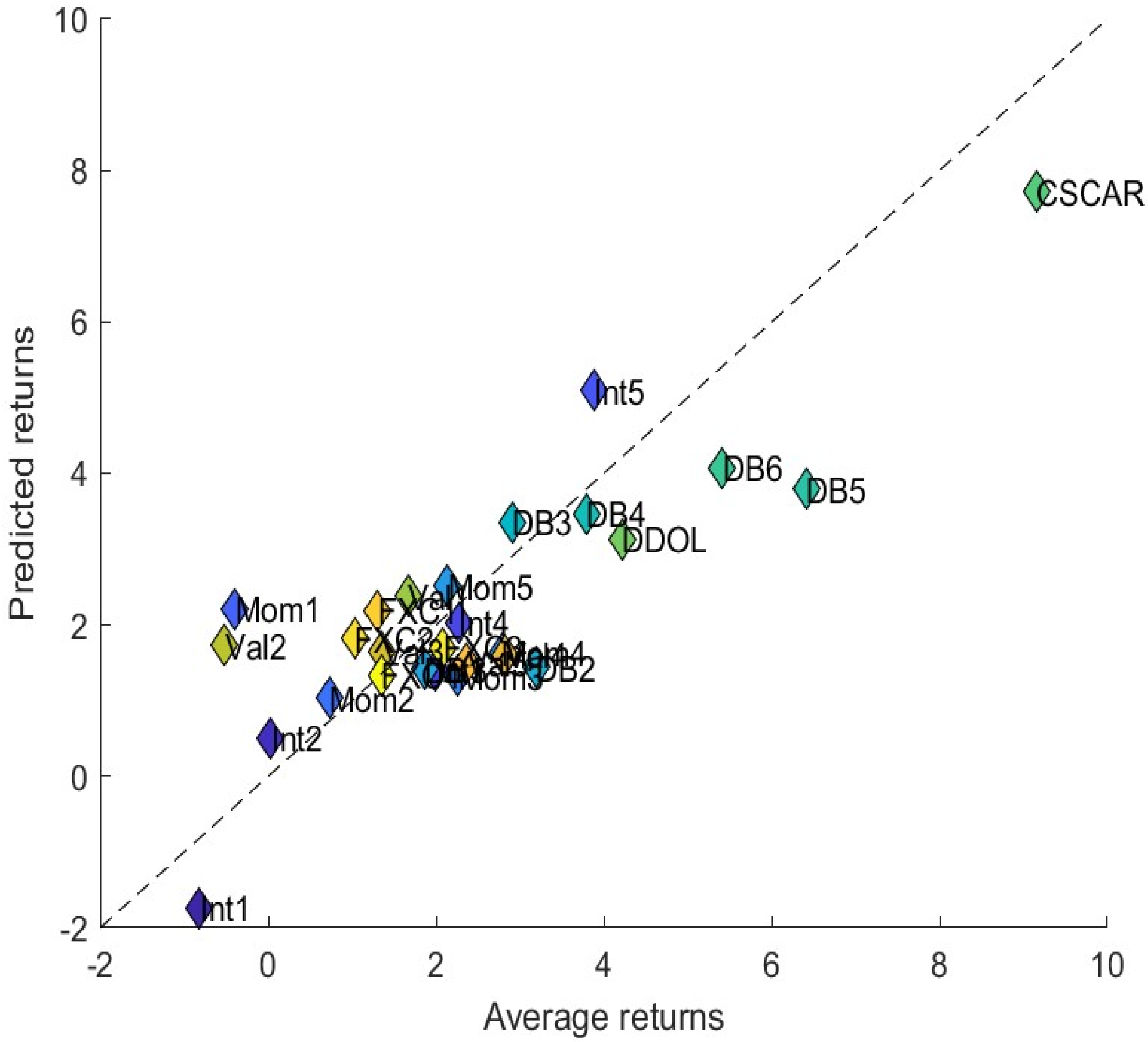

Figure D1: Scatter plot of average vs model implied returns. Conditional betas are widely used rolling-window estimations. The model implied returns are based on the GMM estimates (Table 3) of the unconditional *DOL-CAR* model with $\delta = 1$ using 27 test assets constructed from our set of 29 developed and emerging currencies from December 1983 to March 2021.

E GMM Estimations For Different Factors

Table E1: **GMM Tests of $CSCAR$ Model**

	15 assets			26 assets		
	Uncond	$\delta = 1$	Free δ	Uncond	$\delta = 1$	Free δ
$\hat{\gamma}_{CSCAR}$	9.74	10.97**	10.77	13.06	13.14***	9.63
(t-stat)	(1.24)	(2.65)	(1.57)	(1.56)	(3.03)	(1.44)
$\hat{\delta}_{CSCAR}$			0.96			0.35
(t-stat)			(1.21)			(0.42)
$\left(t\text{-stat};\hat{\delta} - 1\right)$			(-0.05)			(-0.79)
$\hat{\gamma}_{CSCAR} - \bar{F}_{CSCAR}$	0.70	1.88	1.69	4.02	4.06	0.55
(t-stat)	(0.09)	(0.53)	(0.27)	(0.51)	(1.12)	(0.09)
χ^2-test of $\hat{\alpha}^* = 0$	23.28*	19.86	19.83*	39.77**	42.75**	42.13**
(p-value)	(0.0559)	(0.1345)	(0.0994)	(0.0308)	(0.0149)	(0.0125)
F-test of $\hat{\alpha} = 0$	1.50*			1.52*		
(p-value)	(0.0999)			(0.0500)		
R^2	0.34	0.43	0.43	0.01	0.08	0.10

Notes: GMM estimation of unconditional and conditional $CSCAR$ single factor pricing models. $CSCAR$ is the mean-variance optimized currency trading strategy of Maurer et al. (2022). Cross-sectional pricing equation of unconditional model: $E\left[R_{n,t}\right] = \sum_k \beta_{n,k}\gamma_k + \alpha_n^*$, with the corresponding time-series equation $R_{n,t} = \alpha_n + \sum_k \beta_{n,k} F_{k,t} + \epsilon_{n,t}$. Cross-sectional pricing equation of conditional model: $E\left[R_{n,t}\right] = \sum_k \bar{\beta}_{n,k}\gamma_k + \sum_k \sigma_{\beta_{n,k}\gamma_k}\delta_k + \alpha_n^*$. $k = CSCAR$, $R_{n,t}$ and $F_{k,t}$ are excess returns of test assets and pricing factors, α_n^* and $\epsilon_{n,t}$ are residuals, $\sigma_{\beta_{n,k}\gamma_k}$ are the covariances between $\gamma_{k,t}$ (or $F_{k,t+1}$) and $\beta_{n,k,t}$, $\bar{\beta}_{n,k} = E\left[\beta_{n,k,t}\right]$ and $\beta_{n,k,t}$ are estimated from daily currency return data. Details about the estimation are in Appendix A. The first (last) two columns report results for 15 (26) test assets. R^2 is the model fit of the cross-sectional pricing equation. χ^2-test is the joint test statistic of cross-sectional pricing errors (or residuals) $\alpha_n^* = 0$ for all test assets $n \in \{1, \ldots, N\}$. F-test is the joint test statistic of time-series pricing errors (or intercept) $\alpha_n = 0$ for all test assets $n \in \{1, \ldots, N\}$ in the time-series equation of the unconditional model. (t-stat) indicates the significance of the difference between the coefficient and zero, (t-stat; $\delta = 1$) indicates the significance of the difference between the coefficient and one, and (p-value) indicates the significance of the χ^2 or F-test statistic. Significance at the 1%, 5% or 10% level are indicated by ***,** or *. Errors are estimated taking into account auto- and cross-sectional correlations and heteroskedasticity according to Newey and West (1987). The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table E2: **Cross-Sectional Pricing Errors α^* in CSCAR Model**

	Uncond		$\delta = 1$		Free δ	
	α^*	(t-stat)	α^*	(t-stat)	α^*	(t-stat)
$Int1$	-0.41	(-0.18)	-0.45	(-0.24)	-0.35	(-0.19)
$Int2$	-0.51	(-0.27)	-0.58	(-0.37)	-0.53	(-0.34)
$Int3$	0.56	(0.49)	0.78	(0.78)	0.64	(0.60)
$Int4$	-0.54	(-0.72)	-0.48	(-0.66)	-0.51	(-0.70)
$Int5$	-1.52	(-0.90)	-2.15	(-1.26)	-2.32	(-1.35)
$Mom1$	-3.24***	(-2.84)	-2.58***	(-2.82)	-2.78***	(-2.83)
$Mom2$	-1.62	(-1.62)	-1.02	(-0.94)	-0.97	(-0.89)
$Mom3$	0.32	(0.27)	0.57	(0.53)	0.50	(0.45)
$Mom4$	1.09	(0.94)	0.72	(0.86)	0.67	(0.75)
$Mom5$	-0.21	(-0.21)	-0.87	(-1.01)	-0.51	(-0.56)
$Val1$	2.82	(1.35)	2.92*	(1.81)	3.00*	(1.81)
$Val2$	0.22	(0.11)	0.95	(0.57)	0.31	(0.23)
$Val3$	-1.08	(-1.06)	-0.84	(-0.87)	-0.59	(-0.66)
$Val4$	-0.02	(-0.02)	-0.46	(-0.57)	0.14	(0.18)
$Val5$	0.30	(0.27)	-0.02	(-0.02)	0.17	(0.21)
$FXC1$	-0.79	(-0.85)	-0.45	(-0.58)	-0.84	(-0.87)
$FXC2$	-1.45	(-1.55)	-1.03	(-1.18)	-1.24	(-1.26)
$FXC3$	-0.51	(-0.45)	-0.80	(-0.80)	-0.46	(-0.65)
$FXC4$	-0.54	(-0.52)	-0.76	(-0.81)	-0.58	(-0.66)
$DB1$	1.36	(0.69)	1.25	(0.86)	1.21	(0.81)
$DB2$	2.91*	(1.71)	2.36*	(1.78)	2.39*	(1.75)
$DB3$	0.80	(0.55)	1.81	(1.36)	1.34	(1.27)
$DB4$	1.48	(1.01)	1.55	(1.22)	1.34	(1.17)
$DB5$	3.97**	(2.73)	3.42**	(2.72)	3.56**	(2.57)
$DB6$	2.99**	(2.16)	2.41*	(2.02)	2.32*	(1.97)
$DDOL$	2.83*	(1.97)	3.01**	(2.56)	2.93**	(2.56)

Notes: The table reports the cross-sectional pricing errors (or residuals) α_n^* for each test asset $n \in \{1, \ldots, N\}$ in the estimated cross-sectional pricing equations of the unconditional and conditional $CSCAR$ single factor pricing models in Table E1. The GMM estimation is based on the 26 test assets listed in this table. (t-stat) indicates the significance of the difference between α^* and zero. Significance at the 1%, 5% or 10% level are indicated by ***,** or *. Errors are estimated taking into account auto- and cross-sectional correlations and heteroskedasticity according to Newey and West (1987). The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table E3: **GMM Tests of *DOL*-*MOM* Model**

	15 assets			27 assets		
	Uncond	$\delta=1$	Free δ	Uncond	$\delta=1$	Free δ
$\hat{\gamma}_{DOL}$	1.73	1.83	1.84	2.18	1.84	1.74
(t-stat)	(1.14)	(1.20)	(1.20)	(1.44)	(1.21)	(1.15)
$\hat{\gamma}_{CAR}$	6.59**	4.48	-2.05	17.91***	12.30***	4.11
(t-stat)	(2.17)	(1.26)	(-0.35)	(3.34)	(3.15)	(0.77)
$\hat{\delta}_{DOL}$			1.99			0.98
(t-stat)			(1.76)			(5.09)***
$\left(t\text{-stat};\hat{\delta}-1\right)$			(0.87)			(-0.10)
$\hat{\delta}_{CAR}$			3.34			3.91
(t-stat)			(2.32)**			(3.20)***
$\left(t\text{-stat};\hat{\delta}-1\right)$			(1.62)			(2.38)**
$\hat{\gamma}_{DOL}-\bar{F}_{DOL}$	0.08	0.14	0.15	0.53***	0.15	0.05
(t-stat)	(1.13)	(0.18)	(0.20)	(2.80)	(0.18)	(0.07)
$\hat{\gamma}_{CAR}-\bar{F}_{CAR}$	5.28**	3.18	-3.35	16.59***	11.00***	2.82
(t-stat)	(2.29)	(1.08)	(-0.58)	(3.30)	(3.06)	(0.58)
χ^2-test of $\hat{\alpha}^*=0$	26.99**	21.87*	4.27	66.73***	38.49**	9.39
(p-value)	(0.0125)	(0.0574)	(0.9615)	(0.0000)	(0.0414)	(0.9945)
F-test of $\hat{\alpha}=0$	2.10***			2.21***		
(p-value)	(0.0093)			(0.0005)		
R^2	0.25	0.57	0.80	-0.16	0.59	0.87

Notes: GMM estimation of unconditional and conditional *DOL*-*MOM* two factor pricing models. *DOL* invests equally in all foreign currencies against the USD. *MOM* is the currency momentum trade of past 1-month. Cross-sectional pricing equation of unconditional model: $E\left[R_{n,t}\right]=\sum_k \beta_{n,k}\gamma_k+\alpha_n^*$, with the corresponding time-series equation $R_{n,t}=\alpha_n+\sum_k \beta_{n,k}F_{k,t}+\epsilon_{n,t}$. Cross-sectional pricing equation of conditional model: $E\left[R_{n,t}\right]=\sum_k \bar{\beta}_{n,k}\gamma_k+\sum_k \sigma_{\beta_{n,k}\gamma_k}\delta_k+\alpha_n^*$. $k\in\{DOL, MOM\}$, $R_{n,t}$ and $F_{k,t}$ are excess returns of test assets and pricing factors, α_n^* and $\epsilon_{n,t}$ are residuals, $\sigma_{\beta_{n,k}\gamma_k}$ are the covariances between $\gamma_{k,t}$ (or $F_{k,t+1}$) and $\beta_{n,k,t}$, $\bar{\beta}_{n,k}=E\left[\beta_{n,k,t}\right]$ and $\beta_{n,k,t}$ are estimated from daily currency return data. Details about the estimation are in Appendix A. The first (last) two columns report results for 15 (27) test assets. R^2 is the model fit of the cross-sectional pricing equation. χ^2-test is the joint test statistic of cross-sectional pricing errors (or residuals) $\alpha_n^*=0$ for all test assets $n\in\{1,\ldots,N\}$. F-test is the joint test statistic of time-series pricing errors (or intercept) $\alpha_n=0$ for all test assets $n\in\{1,\ldots,N\}$ in the time-series equation of the unconditional model. (t-stat) indicates the significance of the difference between the coefficient and zero, (t-stat; $\delta=1$) indicates the significance of the difference between the coefficient and one, and (p-value) indicates the significance of the χ^2 or F-test statistic. Significance at the 1%, 5% or 10% level are indicated by ***,** or *. Errors are estimated taking into account auto- and cross-sectional correlations and heteroskedasticity according to Newey and West (1987). The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table E4: **GMM Tests of *DOL*-*VAL* Model**

	15 assets			27 assets		
	Uncond	$\delta = 1$	Free δ	Uncond	$\delta = 1$	Free δ
$\hat{\gamma}_{DOL}$	1.65	1.77	1.80	2.27	1.83	1.67
(t-stat)	(1.09)	(1.16)	(1.18)	(1.49)	(1.20)	(1.11)
$\hat{\gamma}_{CAR}$	0.98	1.51	1.63	-1.36	1.45	1.82
(t-stat)	(0.82)	(1.27)	(1.38)	(-0.98)	(1.22)	(1.56)
$\hat{\delta}_{DOL}$			1.60			0.99
(t-stat)			(2.21)**			(5.02)***
$\left(t\text{-stat};\hat{\delta} - 1\right)$			(0.83)			(-0.03)
$\hat{\delta}_{CAR}$			1.82			3.61
(t-stat)			(2.47)**			(2.95)***
$\left(t\text{-stat};\hat{\delta} - 1\right)$			(1.11)			(2.14)**
$\hat{\gamma}_{DOL} - \bar{F}_{DOL}$	-0.00	0.08	0.12	0.62***	0.14	-0.02
(t-stat)	(-0.04)	(0.11)	(0.15)	(3.19)	(0.18)	(-0.02)
$\hat{\gamma}_{CAR} - \bar{F}_{CAR}$	-0.69**	-0.18	-0.06	-3.03***	-0.24	0.14
(t-stat)	(-2.74)	(-0.26)	(-0.08)	(-3.20)	(-0.33)	(0.16)
χ^2-test of $\hat{\alpha}^* = 0$	30.03***	18.55	12.26	60.37***	38.74**	22.14
(p-value)	(0.0047)	(0.1377)	(0.3442)	(0.0001)	(0.0391)	(0.5117)
F-test of $\hat{\alpha} = 0$	1.94**			2.12***		
(p-value)	(0.0183)			(0.0011)		
R^2	0.17	0.62	0.69	-0.50	0.51	0.71

Notes: GMM estimation of unconditional and conditional *DOL*-*VAL* two factor pricing models. *DOL* invests equally in all foreign currencies against the USD. *VAL* is currency value trade. Cross-sectional pricing equation of unconditional model: $E[R_{n,t}] = \sum_k \beta_{n,k}\gamma_k + \alpha_n^*$, with the corresponding time-series equation $R_{n,t} = \alpha_n + \sum_k \beta_{n,k}F_{k,t} + \epsilon_{n,t}$. Cross-sectional pricing equation of conditional model: $E[R_{n,t}] = \sum_k \bar{\beta}_{n,k}\gamma_k + \sum_k \sigma_{\beta_{n,k}\gamma_k}\delta_k + \alpha_n^*$. $k \in \{DOL, VAL\}$, $R_{n,t}$ and $F_{k,t}$ are excess returns of test assets and pricing factors, α_n^* and $\epsilon_{n,t}$ are residuals, $\sigma_{\beta_{n,k}\gamma_k}$ are the covariances between $\gamma_{k,t}$ (or $F_{k,t+1}$) and $\beta_{n,k,t}$, $\bar{\beta}_{n,k} = E[\beta_{n,k,t}]$ and $\beta_{n,k,t}$ are estimated from daily currency return data. Details about the estimation are in Appendix A. The first (last) two columns report results for 15 (27) test assets. R^2 is the model fit of the cross-sectional pricing equation. χ^2-test is the joint test statistic of cross-sectional pricing errors (or residuals) $\alpha_n^* = 0$ for all test assets $n \in \{1, \ldots, N\}$. F-test is the joint test statistic of time-series pricing errors (or intercept) $\alpha_n = 0$ for all test assets $n \in \{1, \ldots, N\}$ in the time-series equation of the unconditional model. (t-stat) indicates the significance of the difference between the coefficient and zero, (t-stat; $\delta = 1$) indicates the significance of the difference between the coefficient and one, and (p-value) indicates the significance of the χ^2 or F-test statistic. Significance at the 1%, 5% or 10% level are indicated by ***,** or *. Errors are estimated taking into account auto- and cross-sectional correlations and heteroskedasticity according to Newey and West (1987). The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table E5: **GMM Tests of *DOL*-*FXC* Model**

	15 assets			27 assets		
	Uncond	$\delta = 1$	Free δ	Uncond	$\delta = 1$	Free δ
$\hat{\gamma}_{DOL}$	1.67	1.75	1.68	2.26	1.72	1.66
(t-stat)	(1.11)	(1.15)	(1.11)	(1.48)	(1.13)	(1.09)
$\hat{\gamma}_{CAR}$	-0.91	-1.10	-0.94	-0.79	-2.44*	-1.69
(t-stat)	(-0.74)	(-0.90)	(-0.78)	(-0.60)	(-1.82)	(-1.37)
$\hat{\delta}_{DOL}$			0.48			0.91
(t-stat)			(0.34)			(4.74)***
$\left(t\text{-stat};\hat{\delta}-1\right)$			(-0.36)			(-0.48)
$\hat{\delta}_{CAR}$			2.86			4.01
(t-stat)			(2.98)**			(3.65)***
$\left(t\text{-stat};\hat{\delta}-1\right)$			(1.94)*			(2.74)**
$\hat{\gamma}_{DOL} - \bar{F}_{DOL}$	0.02	0.06	-0.00	0.61***	0.03	-0.03
(t-stat)	(0.24)	(0.08)	(-0.01)	(2.86)	(0.04)	(-0.04)
$\hat{\gamma}_{CAR} - \bar{F}_{CAR}$	-0.39	-0.60	-0.44	-0.27	-1.94**	-1.19
(t-stat)	(-1.70)	(-0.84)	(-0.60)	(-0.68)	(-2.39)	(-1.29)
χ^2-test of $\hat{\alpha}^* = 0$	29.83***	26.80**	10.74	63.05***	44.84***	15.65
(p-value)	(0.0050)	(0.0132)	(0.4649)	(0.0000)	(0.0087)	(0.8698)
F-test of $\hat{\alpha} = 0$	1.93**			2.21***		
(p-value)	(0.0193)			(0.0006)		
R^2	0.14	0.49	0.64	-0.50	0.39	0.67

Notes: GMM estimation of unconditional and conditional *DOL*-*FXC* two factor pricing models. *DOL* invests equally in all foreign currencies against the USD. *FXC* is high-minus-low currency trade sorted on loadings on the innovations in the FX correlation dispersion measure. Cross-sectional pricing equation of unconditional model: $E\left[R_{n,t}\right] = \sum_k \beta_{n,k}\gamma_k + \alpha_n^*$, with the corresponding time-series equation $R_{n,t} = \alpha_n + \sum_k \beta_{n,k}F_{k,t} + \epsilon_{n,t}$. Cross-sectional pricing equation of conditional model: $E\left[R_{n,t}\right] = \sum_k \bar{\beta}_{n,k}\gamma_k + \sum_k \sigma_{\beta_{n,k}\gamma_k}\delta_k + \alpha_n^*$. $k \in \{DOL, FXC\}$, $R_{n,t}$ and $F_{k,t}$ are excess returns of test assets and pricing factors, α_n^* and $\epsilon_{n,t}$ are residuals, $\sigma_{\beta_{n,k}\gamma_k}$ are the covariances between $\gamma_{k,t}$ (or $F_{k,t+1}$) and $\beta_{n,k,t}$, $\bar{\beta}_{n,k} = E\left[\beta_{n,k,t}\right]$ and $\beta_{n,k,t}$ are estimated from daily currency return data. Details about the estimation are in Appendix A. The first (last) two columns report results for 15 (27) test assets. R^2 is the model fit of the cross-sectional pricing equation. χ^2-test is the joint test statistic of cross-sectional pricing errors (or residuals) $\alpha_n^* = 0$ for all test assets $n \in \{1,\ldots,N\}$. F-test is the joint test statistic of time-series pricing errors (or intercept) $\alpha_n = 0$ for all test assets $n \in \{1,\ldots,N\}$ in the time-series equation of the unconditional model. (t-stat) indicates the significance of the difference between the coefficient and zero, (t-stat; $\delta = 1$) indicates the significance of the difference between the coefficient and one, and (p-value) indicates the significance of the χ^2 or F-test statistic. Significance at the 1%, 5% or 10% level are indicated by ***,** or *. Errors are estimated taking into account auto- and cross-sectional correlations and heteroskedasticity according to Newey and West (1987). The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table E6: **GMM Tests of *DOL*-*DB* Model**

	15 assets			27 assets		
	Uncond	$\delta = 1$	Free δ	Uncond	$\delta = 1$	Free δ
$\hat{\gamma}_{DOL}$	1.69	1.80	1.81	1.79	1.95	1.87
(t-stat)	(1.12)	(1.19)	(1.19)	(1.17)	(1.30)	(1.21)
$\hat{\gamma}_{CAR}$	6.74	5.11	-0.71	6.79***	2.19	2.86
(t-stat)	(1.28)	(0.81)	(-0.08)	(3.00)	(1.34)	(1.64)
$\hat{\delta}_{DOL}$			1.71			1.06
(t-stat)			(1.86)*			(5.46)***
$\left(t\text{-stat};\hat{\delta}-1\right)$			(0.77)			(0.30)
$\hat{\delta}_{CAR}$			1.90			2.71
(t-stat)			(2.67)**			(2.63)**
$\left(t\text{-stat};\hat{\delta}-1\right)$			(1.27)			(1.66)
$\hat{\gamma}_{DOL} - \bar{F}_{DOL}$	0.04	0.11	0.12	0.13*	0.27	0.18
(t-stat)	(0.55)	(0.14)	(0.16)	(1.72)	(0.34)	(0.23)
$\hat{\gamma}_{CAR} - \bar{F}_{CAR}$	3.19	1.53	-4.30	3.24*	-1.40	-0.73
(t-stat)	(0.61)	(0.25)	(-0.46)	(2.04)	(-1.54)	(-0.65)
χ^2-test of $\hat{\alpha}^* = 0$	26.98**	22.72**	14.75	63.14***	41.85**	23.16
(p-value)	(0.0125)	(0.0452)	(0.1944)	(0.0000)	(0.0187)	(0.4513)
F-test of $\hat{\alpha} = 0$	1.87**			2.18***		
(p-value)	(0.0240)			(0.0007)		
R^2	0.15	0.67	0.78	0.09	0.52	0.65

Notes: GMM estimation of unconditional and conditional *DOL*-*DB* two factor pricing models. *DOL* invests equally in all foreign currencies against the USD. *DB* is the high-minus-low dollar beta sorted currency trade. Cross-sectional pricing equation of unconditional model: $E\left[R_{n,t}\right] = \sum_k \beta_{n,k}\gamma_k + \alpha_n^*$, with the corresponding time-series equation $R_{n,t} = \alpha_n + \sum_k \beta_{n,k}F_{k,t} + \epsilon_{n,t}$. Cross-sectional pricing equation of conditional model: $E\left[R_{n,t}\right] = \sum_k \bar{\beta}_{n,k}\gamma_k + \sum_k \sigma_{\beta_{n,k}\gamma_k}\delta_k + \alpha_n^*$. $k \in \{DOL, DB\}$, $R_{n,t}$ and $F_{k,t}$ are excess returns of test assets and pricing factors, α_n^* and $\epsilon_{n,t}$ are residuals, $\sigma_{\beta_{n,k}\gamma_k}$ are the covariances between $\gamma_{k,t}$ (or $F_{k,t+1}$) and $\beta_{n,k,t}$, $\bar{\beta}_{n,k} = E\left[\beta_{n,k,t}\right]$ and $\beta_{n,k,t}$ are estimated from daily currency return data. Details about the estimation are in Appendix A. The first (last) two columns report results for 15 (27) test assets. R^2 is the model fit of the cross-sectional pricing equation. χ^2-test is the joint test statistic of cross-sectional pricing errors (or residuals) $\alpha_n^* = 0$ for all test assets $n \in \{1, \ldots, N\}$. F-test is the joint test statistic of time-series pricing errors (or intercept) $\alpha_n = 0$ for all test assets $n \in \{1, \ldots, N\}$ in the time-series equation of the unconditional model. (t-stat) indicates the significance of the difference between the coefficient and zero, (t-stat; $\delta = 1$) indicates the significance of the difference between the coefficient and one, and (p-value) indicates the significance of the χ^2 or F-test statistic. Significance at the 1%, 5% or 10% level are indicated by ***,** or *. Errors are estimated taking into account auto- and cross-sectional correlations and heteroskedasticity according to Newey and West (1987). The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.

Table E7: **GMM Tests of CAR-DB Model**

	15 assets			27 assets		
	Uncond	$\delta = 1$	Free δ	Uncond	$\delta = 1$	Free δ
$\hat{\gamma}_{DOL}$	3.60**	4.17**	4.25**	5.45**	6.17**	4.88*
(t-stat)	(2.35)	(2.79)	(2.82)	(2.09)	(2.47)	(1.90)
$\hat{\gamma}_{CAR}$	3.71	6.91	7.71	5.04*	5.69**	5.95**
(t-stat)	(0.68)	(0.87)	(1.00)	(1.95)	(2.49)	(2.57)
$\hat{\delta}_{DOL}$			0.60			1.70
(t-stat)			(1.08)			(2.58)**
$\left(t\text{-stat};\hat{\delta}-1\right)$			(-0.73)			(1.06)
$\hat{\delta}_{CAR}$			1.14			0.75
(t-stat)			(2.46)**			(1.28)
$\left(t\text{-stat};\hat{\delta}-1\right)$			(0.30)			(-0.44)
$\hat{\gamma}_{DOL} - \bar{F}_{DOL}$	-1.10*	-0.53	-0.45	0.74	1.47	0.18
(t-stat)	(-1.94)	(-0.62)	(-0.53)	(0.37)	(0.77)	(0.09)
$\hat{\gamma}_{CAR} - \bar{F}_{CAR}$	0.16	3.33	4.13	1.49	2.11	2.37
(t-stat)	(0.03)	(0.43)	(0.55)	(0.74)	(1.16)	(1.38)
χ^2-test of $\hat{\alpha}^* = 0$	20.34*	11.63	9.86	55.64***	36.56*	33.32*
(p-value)	(0.0871)	(0.5585)	(0.5431)	(0.0004)	(0.0636)	(0.0757)
F-test of $\hat{\alpha} = 0$	1.42			1.95***		
(p-value)	(0.1342)			(0.0035)		
R^2	0.39	0.85	0.86	0.42	0.85	0.87

Notes: GMM estimation of unconditional and conditional CAR-DB two factor pricing models. CAR is the equally weighted currency Carry trade. DB is the high-minus-low dollar beta sorted currency trade. Cross-sectional pricing equation of unconditional model: $E[R_{n,t}] = \sum_k \beta_{n,k}\gamma_k + \alpha_n^*$, with the corresponding time-series equation $R_{n,t} = \alpha_n + \sum_k \beta_{n,k}F_{k,t} + \epsilon_{n,t}$. Cross-sectional pricing equation of conditional model: $E[R_{n,t}] = \sum_k \bar{\beta}_{n,k}\gamma_k + \sum_k \sigma_{\beta_{n,k}\gamma_k}\delta_k + \alpha_n^*$. $k \in \{CAR, DB\}$, $R_{n,t}$ and $F_{k,t}$ are excess returns of test assets and pricing factors, α_n^* and $\epsilon_{n,t}$ are residuals, $\sigma_{\beta_{n,k}\gamma_k}$ are the covariances between $\gamma_{k,t}$ (or $F_{k,t+1}$) and $\beta_{n,k,t}$, $\bar{\beta}_{n,k} = E[\beta_{n,k,t}]$ and $\beta_{n,k,t}$ are estimated from daily currency return data. Details about the estimation are in Appendix A. The first (last) two columns report results for 15 (27) test assets. R^2 is the model fit of the cross-sectional pricing equation. χ^2-test is the joint test statistic of cross-sectional pricing errors (or residuals) $\alpha_n^* = 0$ for all test assets $n \in \{1, \ldots, N\}$. F-test is the joint test statistic of time-series pricing errors (or intercept) $\alpha_n = 0$ for all test assets $n \in \{1, \ldots, N\}$ in the time-series equation of the unconditional model. (t-stat) indicates the significance of the difference between the coefficient and zero, (t-stat; $\delta = 1$) indicates the significance of the difference between the coefficient and one, and (p-value) indicates the significance of the χ^2 or F-test statistic. Significance at the 1%, 5% or 10% level are indicated by ***,** or *. Errors are estimated taking into account auto- and cross-sectional correlations and heteroskedasticity according to Newey and West (1987). The data are our set of 29 developed and emerging currencies from December 1983 to March 2021.