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Pricing Implications of Covariances and Spreads in Currency Markets

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We introduce a covariance and spread (i.e., exchange rate forward discount) adjusted carry factor that prices the cross-section of FX market returns, where many other single- and multifactor models fail. Both the covariance matrix of exchange rate growths and forward discounts contain important information for pricing that is not captured by well-known factors. The time-varying conditional covariance matrix and forward discounts forecast future realized currency returns. (*JEL* F31, F37, G12, G15, G17)

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A large empirical literature extends the seminal carry (*CAR*) factor analysis of Lustig and Verdelhan (2007) and Lustig, Roussanov, and Verdelhan (2011) and uncovers various currency portfolios with average returns that cannot be explained by the *CAR* factor. Going beyond interest-rate-sorted portfolios, the test assets commonly studied in the literature are characteristic-sorted portfolios based on momentum, value, dollar beta, FX correlations, and volatility-managed and mean-variance-optimized currency portfolios. We investigate whether we need additional pricing factors,

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such as momentum, value, dollar beta, FX correlation dispersion, volatility, illiquidity, skewness, downside risk, or financial intermediary, or factors containing other information to price the aforementioned broad set of test assets. However, we find that simple adjustments to CAR are sufficient, and we do not need additional pricing factors.

Guided by a mean-variance optimization (or, equivalently, the construction of the minimum variance stochastic discount factor), we find that the covariance matrix of exchange rate growths and forward discounts have important information for pricing. We denote our factor as the covariance and spread (or forward discount) adjusted carry ($CSCAR$) factor. We show that $CSCAR$ as a single pricing factor explains the cross-section of average returns, and it subsumes the relevant information of other factors.

First, we find that $CSCAR$ is priced in the cross-section and has a large and significant risk premium. Second, the implied risk premium is not statistically significantly different from the average return of $CSCAR$, which is an important validation test for a traded factor.

Third, there is no evidence of mispricing, and the abnormal returns of all test assets are not jointly significantly different from zero, both in the cross-sectional and in time-series pricing equations. Fourth, the model fit (R^2) of the cross-sectional pricing equation is large. Fifth, and finally, both components of $CSCAR$, namely, the conditional exchange rate correlations and forward discounts, are time varying and forecast future realized currency returns.

Carry factors, which do not use all the information of the covariance matrix and forward discounts, do not price assets adequately. In particular, the following three variants do not explain the cross-section of average returns: (a) a spread-adjusted carry, which ignores the information of the covariance matrix, (b) a covariance-adjusted carry, which does not properly account for the size of forward discounts, or (c) a volatility-managed carry factor (in the spirit of Fleming, Kirby, and Ostdiek 2001; Moreira and Muir 2016), which ignores the information of the correlation matrix. Popular single- and multifactor models, which incorporate CAR, dollar carry, momentum, value, illiquidity, skewness, downside risk, and intermediary asset pricing factors, do not span the $CSCAR$ factor and are rejected in our tests. We conclude that accounting for both the covariance matrix (i.e., variances and correlations of exchange rate growths) and forward discounts is important for pricing, and well-known factors in the literature do not capture this pricing information.

We document that the conditional covariance matrix of exchange rate growths and forward discounts vary through time, and $CSCAR$ dynamically adjusts its risk exposure (measured by its notional value or leverage) in response to this variation. It is important to properly account for this time-series variation. We construct a variant of $CSCAR$, which keeps its risk exposure constant through time, and show that this variant is rejected in our tests.

Finally, if the conditional covariance matrix and forward discounts are important determinants of conditional expected returns and if they vary through time, then FX market returns should be predictable. We verify this hypothesis and show that the notional value, leverage and turnover of $CSCAR$ (which capture changes in the conditional covariance matrix of exchange rate growths and forward discounts) forecast FX market returns, volatility, and illiquidity 1 to 18 months ahead.

$CSCAR$ is the return of the portfolio with weights $\theta_t^{CSCAR} = \Omega_t^{-1} fd_t$, where the ith element $\theta_{i,t}^{CSCAR}$ is the portfolio weight placed on the position in currency i against the USD; Ω_t is the conditional covariance matrix of exchange rate growths; and fd_t a vector of forward discounts at time t (see the details in Section 1). If the forward discount $fd_{i,t}$ is a proxy for the conditional expected excess return of the position in currency i against the USD, then $CSCAR$ is the return of a mean-variance efficient currency portfolio or the inverse of the minimum-variance stochastic discount factor in FX markets. Although this interpretation of $CSCAR$ is appealing, our empirical tests and results do not rely on the assumption that forward discounts are proxies for conditional expected excess returns or the assumption that investors only care about the first two moments of the return distribution. We do not take a stance on the underlying model. We provide new evidence that the covariance matrix of exchange rate growths and forward discounts have important information for pricing assets in FX markets.

We are not the first to construct mean-variance efficient currency portfolios. In that sense, our covariance and spread adjustments are not new. However, the related literature focuses on the profitability of trading strategies and documents that mean-variance optimized portfolios in FX markets generate large out-of-sample returns (Baz et al. 2001; Della Corte, Sarno, and Tsiakas 2009; Ackermann, Pohl, and Schmedders 2016; Daniel, Hodrick, and Lu 2014; Maurer, To, and Tran 2020). In contrast, our paper studies the ability to price the cross-section of average returns in FX markets. We identify the importance of an efficient combination of the first two moments of FX returns to construct a single-factor model that prices the cross-section of a large set of FX securities. Market timing as discussed by Maurer, To, and Tran (2020) is a crucial component for the model to succeed in unconditional tests. In addition, other papers have studied correlation risk or spread adjustments (Hassan and Mano 2019; Mueller, Stathopoulos, and Vedolin 2017; Verdelhan 2018). However, we show that both adjustments are needed, and they have to be incorporated in a specific manner for the factor pricing model to succeed.

Our findings have important implications for theoretical models and empirical research. Many theoretical models focus on forward discounts and do not analyze how variances and correlations influence exchange rate growths. Our findings suggest that the exchange rate growth variances and correlations contain important information for pricing and should be relevant in economic models. We also document a substantial time-series variation in the conditional covariance matrix of exchange rate growths and forward discounts, and accounting for this variation is a critical step in pricing assets. Future empirical research should investigate the underlying economic fundamentals that drive this time-series variation. We study the *CSCAR* factor in the model of Mueller, Stathopoulos, and Vedolin (2017) and show how it differs from their FX correlation risk factor.

Our paper is related to that of Bekaert and Panayotov (2020), who document that, among G-10 currencies, traditional carry trades (labeled as "bad carries"), which involve prototypical currencies with the highest and lowest interest rates (i.e., AUD, JPY, and CHF), offer substantially lower Sharpe ratios and high negative skewness compared to other currencies (labeled as "good carries") with less extreme interest rates. Their study questions the role of return skewness and crash risk in rationalizing the performance of traditional carry trades based on interest rate differentials. Our paper concurs with this finding in that our *CSCAR* factor has a positive skewness and high Sharpe ratio. *CSCAR* differs from good carry trades of Bekaert and Panayotov (2020) along three aspects; namely, *CSCAR* does not preclude prototypical currencies, its portfolio composition is time varying, and it features market timing (quantified by its time-varying notional value). That is, *CSCAR* integrates prototypical currencies back into the set of admissible currencies, while it efficiently trades off exchange rate covariances (i.e., risk) and forward spreads (i.e., expected rewards) to pin down the priced risks in FX markets.

Daniel, Hodrick, and Lu (2014) also examine different carry trade strategies: spread-weighted (or varying portfolio weights with interest rate differentials), risk-balanced (or controlling for the volatility of strategy returns), mean-variance efficient with fixed notional values, and dollar carry. They show that while spread-weighting, risk-balancing, and mean-variance optimization improve the performance of carry trades, the most remarkable improvement is with the dollar carry strategy. Our results not only reinforce these findings on the improvement of the carry trade performance but also demonstrate the enhancing effect of combining spread weighting, risk balancing, and mean-variance efficiency *without* rigidly fixing notional values. As a result, *CSCAR* significantly outperforms the dollar carry in both measures of profitability and risk pricing.

Hassan and Mano (2019) decompose currency returns into a cross-currency, a between-time-and-currency, and a cross-time component. They explain the differences between the forward premium puzzle and the dollar trade versus the carry trade. Our *CSCAR* factor builds on this and demonstrates that both the portfolio composition in a specific month and the market timing across months (i.e., the time variation in the notional value) are important to price FX market risks.

Mueller, Stathopoulos, and Vedolin (2017) introduce a model and a factor to study the pricing implications of FX correlation risk. Verdelhan (2018) further introduces a model of systematic dollar risk exposure, which also captures correlations. We show that the *CSCAR* factor has information beyond the FX correlation factor in the model of Mueller, Stathopoulos, and Vedolin (2017). Moreover, in the data *CSCAR* is able to explain a large cross-section of FX returns, while several tests reject the factor models of Mueller, Stathopoulos, and Vedolin (2017) and Verdelhan (2018).

Our paper is also related to the empirical literature that analyzes various pricing factors in FX markets: carry factor (Lustig and Verdelhan 2007; Lustig, Roussanov, and Verdelhan 2011), global volatility factor (Menkhoff et al. 2012; Christiansen, Ranaldo, and Söderlind 2011), momentum factor (Burnside, Eichenbaum, and Rebelo 2011; Menkhoff et al. 2012), global currency skewness factor (Rafferty, 2012), dollar factor (Lustig, Roussanov, and Verdelhan, 2014), downside beta risk factor (Dobrynskaya, 2014; Lettau, Maggiori, and Weber 2014; Galsband and Nitschka 2013), FX liquidity risk factor (Mancini, Ranaldo, and Wrampelmeyer 2013), economic size factor (Hassan, 2013), economic momentum (Dahlquist and Hasseltoft 2020), and surplus-consumption risk factor (Riddiough and Sarno 2020). We show that the covariance matrix and forward discounts contain important information about pricing not captured by the popular factors in the literature.

1. Currency Returns and Data

We denote spot and 1-month forward exchange rates as USD per unit of currency i at time t by $X_{i,t}$ and $F_{i,t}$. Following the literature, we define the 1-month realized currency return between currency i and the USD (denominated in USD) by $CT_{i,t+1} = \ln\left(\frac{X_{i,t+1}}{F_{i,t}}\right)$. This is the return of an uncovered long position in the forward exchange rate contract of currency i against the USD. We can decompose this into the forward discount $fd_{i,t} = \ln\left(\frac{X_{i,t}}{F_{i,t}}\right)$ (known at time t) and the exchange rate growth $\Delta x_{i,t+1} = \ln\left(\frac{X_{i,t+1}}{X_{i,t}}\right)$ (realized at time $t+1$), $CT_{i,t+1} = fd_{i,t} + \Delta x_{i,t+1}$.[1]

We build currency portfolios for our test assets and traded factors as follows. Let $\theta_{i,t}$ be the portfolio weight at time t on the currency return $CT_{i,t+1}$; that is, $||\theta_{i,t}||$ indicates the dollar amount per USD of wealth invested in a long (if $\theta_{i,t} > 0$) or short (if $\theta_{i,t} < 0$) position in the uncovered forward

[1] Under the premise of the covered interest rate parity (CIP), that is, the forward discount is equal to the interest rate differential $fd_{i,t} = \ln\left(\frac{R_{i,t}}{R_{US,t}}\right)$ where $R_{US,t}$ and $R_{i,t}$ are 1-month risk-free interest rates in the USD and currency i, the currency return is equivalent to borrow $\frac{1}{R_{US,t}}$ USD and lend $\frac{1}{R_{US,t}X_{i,t}}$ units of currency i. We do not require the CIP to hold for the construction of our factors and test assets. We implement all currency returns using forward and spot exchange rates and do not need information about interest rates.

exchange rate contract in currency i against the USD. θ_t is an $N \times 1$ column vector containing $\theta_{i,t}$ for all currencies i, where N denotes the number of exchange rates against the USD in our sample. Because of fluctuating data availability, the number of currencies N changes through time. To simplify the notation, we drop the time subscript for N. Since currency returns are net-zero investments (i.e., excess returns), the portfolio weights do not need to sum to one. We define $\sum_i ||\theta_{i,t}||$ as portfolio θ_t's notional value or total dollar exposure per dollar of wealth. Furthermore, $\sum_i \theta_{i,t}$ is the leverage or net-dollar position in all risky currency returns per dollar of wealth. Large (small) notional value and leverage indicate that the strategy is aggressive (conservative) and has a large (small) risk exposure. The realized excess return (over the risk-free rate in USD) of the portfolio is $\sum_i \theta_{i,t} CT_{i,t+1}$.

We collect daily spot and 1-month forward exchange rates from Barclays Bank International and Reuters via Datastream. We use quotes of the last day of the month to compute monthly currency returns $CT_{i,t+1}$. Potential concerns of currencies of emerging countries are capital controls and major trading frictions. Menkhoff et al. (2012) and Della Corte, Ramadorai, and Sarno (2016) suggest excluding countries with a negative score on the capital account openness index of Chinn and Ito (2006). Following this literature, we use 29 exchange rates against the USD from January 1984 to February 2016. We follow Lustig, Roussanov, and Verdelhan (2011) and split our sample into 15 developed and 14 emerging countries. The 15 developed countries are Australia, Belgium, Canada, Denmark, euro area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom. The 14 emerging countries are Brazil, Czech Republic, Greece, Hungary, Iceland, Ireland, Mexico, Poland, Portugal, Singapore, South Africa, South Korea, Spain, and Taiwan. The euro was introduced in January 1999, and we exclude all countries that have joined the euro after that and only keep the euro as a currency. Except for the empirical results concerning the $CSCAR$ factor pricing analysis, results pertaining to the set of 29 exchange rates against the USD are relegated to the Internet Appendix.

Besides selecting currencies according to the capital account openness index of Chinn and Ito (2006), we apply the following filters to remove individual currency-month observations, which are likely to be subject to major trading frictions, market segmentation or feature a substantial default risk in the short-term sovereign bond market. All filters use information known ex ante without introducing bias. First, we exclude a currency in month t 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 and 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 between January 1984 and February 2016.

2. Pricing Factors

We first describe the well-known high minus low forward discount carry trade factor of Lustig, Roussanov, and Verdelhan (2011). Then, we introduce two simple adjustments to take into account the size of forward discounts and the covariation between exchange rates. We show that these adjustments are important to enhance the carry factor and enable it to fully capture the cross-section of average returns of a broad set of currency portfolios. We further introduce and test several additional factors that are contenders.

2.1 Covariance- and spread-adjusted carries

CAR: Lustig, Roussanov, and Verdelhan (2011) introduce an equally weighted Carry (CAR) factor. On the last day of every month t, we sort currencies according to the current forward discount $fd_{i,t}$, and for each quintile $k \in \{1, \ldots, 5\}$ we construct an equally weighted portfolio fdP_k of currency returns $CT_{i,t+1}$ for all currencies i in quintile k. The CAR factor takes a long position in the high forward discount portfolio fdP_5 and a short position in the low forward discount portfolio fdP_1. CAR is well-known to explain the cross-section of average returns of forward-discount-sorted portfolios. However, it does not capture the cross-sectional variation of average returns of other currency portfolios. To address this shortcoming, we enhance the carry factor by taking into account the size and time variation in the forward discounts and the covariation of exchange rates. That is, we construct a Covariance- and Spread-adjusted Carry ($CSCAR$) factor.

SCAR: We define the Spread-adjusted Carry ($SCAR$) factor as the realized portfolio excess return $\sum_i \theta_{i,t}^{SCAR} CT_{i,t+1}$ with

$$\theta_t^{SCAR} = fd_t,$$

where fd_t is a column vector containing the forward discounts $fd_{i,t}$ for all N exchange rates i. The spread adjustment has implications on the portfolio composition at time t and on the time variation in the notional value $\sum_i ||\theta_{i,t}^{SCAR}||$. CAR ranks currencies according to the forward discount and equally weights top- and bottom-ranked currencies, whereas $SCAR$ has more fine-tuned weights and a currency with a large (small) forward discount receives a proportionally large (small) weight. Moreover, forward discounts change through time and if the sum of absolute forward discounts $\sum_i ||fd_{i,t}||$ is large (small), then the notional value of $SCAR$ is large (small). Thus, $SCAR$ is dynamic and times the market based on the absolute size of the forward discounts. In contrast, CAR has a constant notional value through time, that is, no market timing.

CSCAR: $CSCAR$ adjusts $SCAR$ using information (available at time t) about the covariation between exchange rate growths. We normalize the portfolio weights of $SCAR$ by the conditional covariance matrix,

$$\theta_t^{CSCAR} = \tilde{\Omega}_t^{-1} \theta_t^{SCAR} = \tilde{\Omega}_t^{-1} fd_t,$$

where $\tilde{\Omega}_t^{-1}$ is a robust version of the inverse of the conditional covariance matrix Ω_t of all exchange rate growths. Similar to $SCAR$, $CSCAR$ is dynamic, and its notional value varies through time. However, $\sum_i ||\theta_{i,t}^{CSCAR}||$ not only depends on the absolute size of the forward discounts but also takes into account changes in covariances. Thus, it is a covariance managed portfolio. In particular, $CSCAR$ invests more aggressively in FX markets when forward discounts are large (in absolute size) and the (co)variation in exchange rate growths is low.

$CSCAR$ 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 $CT_{i,t+1}$. Such an assumption can be motivated by the fact that exchange rate changes $\Delta x_{i,t+1}$ are difficult to predict (Meese and Rogoff 1983). Baz et al. (2001), Della Corte, Sarno, and Tsiakas (2009), Ackermann, Pohl, and Schmedders (2016), Daniel, Hodrick, and Lu (2014), and Maurer, To, and Tran (2020) analyze the performance of mean-variance efficient trading strategies similar to $CSCAR$, but none of these papers investigates the performance of a mean-variance efficient strategy as a pricing factor. Under this interpretation, the notional value of $CSCAR$ is large and the factor invests aggressively when the conditional Sharpe ratio and the conditional variance of the minimum variance SDF are large (i.e., forward discounts are large and covariances small), and the factor invests conservatively when the conditional Sharpe ratio and the conditional variance of the minimum variance SDF are small. We revisit this market timing property of $CSCAR$ in Section 3.7 and show that $CSCAR$ is able to forecast FX market returns, volatility and illiquidity.

We use an exponentially weighted moving average (EWMA) of squared, demeaned daily exchange rate growths over the past 6 months to estimate the monthly conditional covariance matrix Ω_t. Element (i, j) of Ω_t is $Cov_t(CT_{i,t+1}, CT_{j,t+1}) = Cov_t(\Delta x_{i,t+1}, \Delta x_{j,t+1}) = \frac{T_t}{6} \frac{\sum_{\tau=1}^{T_t} \delta^{T_t-\tau}(\Delta x_{d,i,\tau} - \bar{\Delta x}_{d,i,\tau})(\Delta x_{d,j,\tau} - \bar{\Delta x}_{d,j,\tau})}{\sum_{\tau=1}^{T_t} \delta^{T_t-\tau}}$, where $\Delta x_{d,i,\tau}$ is the daily exchange rate growth of currency i against the USD on day τ in the 6-month period preceding the last day of month t, $\bar{\Delta x}_{d,i,\tau} = \frac{1}{T_t}$

$\sum_{h=1}^{T_t} \Delta x_{d,i,h}$ is the sample average of the daily exchange rate growth $\Delta x_{d,i,\tau}$ over the past 6 months, T_t is the number of trading days within the past 6 months, and EWMA weight $\delta = 0.95$. The EWMA weight of 0.95 implies a half-life of an exchange rate growth observation of 14 trading days. Our results are robust to various choices of the window length and the EWMA weight.[2]

To obtain a robust version of the inverse of the covariance matrix, we first diagonalize $\Omega_t = W_t \Lambda_t W_t'$, where W_t is the $N \times N$ rotation matrix (whose N columns are the $N \times 1$ eigenvectors) and Λ_t the $N \times N$ diagonal matrix with the eigenvalues $\lambda_{i,t}$ for $i \in \{1, \ldots, N\}$ on its diagonal. We then remove eigenvalue $\lambda_{k,t}$ (i.e., row and column k of Λ_t) and its corresponding eigenvector (i.e., column k of W_t) if $\frac{\lambda_{k,t}}{\sum_{h=1}^{N} \lambda_{h,t}} < 1\%$. We denote the new matrices after removing K small eigenvalues and corresponding eigenvectors by the $(N - K) \times (N - K)$ diagonal matrix $\tilde{\Lambda}_t$ and the $N \times (N - K)$ rotation matrix $\tilde{W}_t$, and define $\tilde{\Omega}_t^{-1} = \tilde{W}_t \tilde{\Lambda}_t^{-1} \tilde{W}_t'$. This procedure reduces estimation errors in the covariance matrix and provides us with a robust version of the inverse of the covariance matrix. Our approach is equivalent to a principal component analysis and building a factor model with the $N - K$ largest principal components (where each component explains 1% or more of the common variation in exchange rate growths). Removing principal components that explain only a small fraction of the exchange rate variation helps us to avoid in-sample overfitting and near-arbitrage opportunities, that is, factors with an unreasonably large in-sample Sharpe ratio (Ross 1976; Kozak, Nagel, and Santosh 2018).

2.2 Other pricing factors

DOL, DDOL: The dollar (*DOL*) is a traded factor that invests equally in all currencies (Lustig, Roussanov, and Verdelhan 2011), that is, $\theta_{i,t}^{DOL} = \frac{1}{N}$. The Dollar Carry (*DDOL*) takes a long (short) position in the *DOL* when the median forward discount across all exchange rates is positive (negative) (Lustig, Roussanov, and Verdelhan 2014), $\theta_t^{DDOL} = sign(median(\{fd_{j,t}\}_{j=1}^{N}))\theta_t^{DOL}$.

MOM: Momentum (*MOM*) portfolios in FX markets are analyzed by Burnside, Eichenbaum, and Rebelo (2011) and Menkhoff et al. (2012). On the last day of every month t we compute for each currency i the average monthly currency return over the past 12 months. We then sort currencies according to the past performance into quintiles (the top quintile contains the

2 We have tested window lengths between 3 and 12 months and EWMA weights between 0.9 and 1, and our findings remain essentially unchanged.

winner currencies and the bottom quintile the loser currencies) and build equally weighted currency portfolios for each quintile. We denote these five portfolios by $MomP_i$, $\forall i \in \{1, \ldots, 5\}$. MOM takes a long position in the winner currency portfolio $MomP_5$ and a short position in the loser currency portfolio $MomP_1$. In our sample at time t, we use only currencies for which we can observe all returns over the past 12 months.

VAL: The value (VAL) strategy assumes that in the long run undervalued currencies with low real exchange rates appreciate against overvalued currencies with high real exchange rates (Bilson , 1984). On the last day of every month t we sort currencies according to their real exchange rates against the USD into quintiles, where the top quintile contains overvalued and the bottom quintile undervalued currencies. The real exchange rate of currency i against USD is equal to the purchasing power parity (PPP) at time t (quoted as currency i per USD of a representative consumption bundle) multiplied by nominal exchange rate $X_{i,t}$. Our value portfolios do not use macroeconomic information to remove the effect of the expected real interest rate differential and the long-run expected real exchange rate from the real exchange rate as in Menkhoff et al. (2017). We construct equally weighted currency portfolios for each quintile, denoted by $ValP_i$, $\forall i \in \{1, \ldots, 5\}$. VAL takes a long position in the portfolio of undervalued currencies, $ValP_1$, and a short position in the portfolio of overvalued currencies, $ValP_5$. Finally, our construction of the value portfolios differs from that of Asness, Moskowitz, and Pedersen (2013) or Menkhoff et al. (2017), who use 5-year changes in PPP as a signal. We find that our overall conclusions are unaffected whether we use the current or 5-year changes in PPP.[3] However, our approach to construct value portfolios has the advantage that we have more data as we do not need 5 years of past data. The 5-year time lag means that our overall sample not only is 5 years shorter but also is problematic when new currencies enter the sample.

NSCAR, SCAR$_{CV}$: The Normalized-Spread-adjusted Carry ($NSCAR$) factor is a normalized version of $SCAR$ that keeps the notional value constant, and thus, it has no market timing (Daniel, Hodrick, and Lu, 2014), $\theta_t^{NSCAR} = \frac{\theta_t^{SCAR}}{\sum_j ||\theta_{j,t}^{SCAR}||} = \frac{fd_t}{\sum_j ||fd_{j,t}||}$. Although $NSCAR$ has a constant notional value, its conditional variance is still time varying because FX market volatility is changing through time. $SCAR_{CV}$ adjusts $SCAR$ to keep the conditional volatility constant equal to σ through time, $\theta_t^{SCAR_{CV}} = \sigma \frac{\theta_t^{SCAR}}{\sqrt{(\theta_t^{SCAR})' \tilde{\Omega}_t \theta_t^{SCAR}}} = \sigma \frac{fd_t}{\sqrt{fd_t' \tilde{\Omega}_t fd_t}}$ and where $\tilde{\Omega}_t = \tilde{W}_t \tilde{\Lambda}_t \tilde{W}_t'$.

[3] The robustness results are available on request.

CAR$_{VM}$, NSCAR$_{VM}$, VSCAR: We construct volatility-managed versions of CAR and $NSCAR$ according to Fleming, Kirby, and Ostdiek (2001) and Moreira and Muir (2016). We compute the conditional variance of CAR and $NSCAR$ denoted by σ_t^{CAR} and σ_t^{NSCAR} using daily returns of these factors over the past month and define the volatility-managed factors as $\theta_t^{CAR_{VM}} = \frac{\theta_t^{CAR}}{(\sigma_t^{CAR})^2}$ and $\theta_t^{NSCAR_{VM}} = \frac{\theta_t^{NSCAR}}{(\sigma_t^{NSCAR})^2}$. The Variance- and Spread-adjusted Carry ($VSCAR$) factor is a more sophisticated version of a volatility-managed carry factor and adjusts $SCAR$ by normalizing the portfolio weight $\theta_{i,t}^{SCAR}$ by the variance of exchange rate i, $\theta_t^{VSCAR} = D_t^{-1}\theta_t^{SCAR} = D_t^{-1} fd_t$, where D_t^{-1} is a diagonal matrix equal to the diagonal of $\tilde{\Omega}_t^{-1}$. In other words, $VSCAR$ is similar to $CSCAR$ but ignores (sets to zero) all correlations between exchange rate growths. The advantage of $VSCAR$ is that fewer parameters have to be estimated; this advantage reduces estimation errors. The disadvantage is the loss of important information about correlations.

CECAR: The Covariance-adjusted Equally weighted Carry ($CECAR$) factor follows the $CSCAR$ factor to make a covariance adjustment, but it does not fully account for the size of the forward discounts, $\theta_t^{CECAR} = \tilde{\Omega}_t^{-1} sign(fd_t)$.

CSCAR$_{CR}$, CSCAR$_{CV}$, CSCAR$_{\text{full}}$: $CSCAR_{CR}$ normalizes $CSCAR$ at every point in time so that its notional value is constant through time: $\theta^{CSCAR_{CR}} = \frac{\theta_t^{CSCAR}}{\sum_j ||\theta_{j,t}^{CSCAR}||}$. Ackermann, Pohl, and Schmedders (2016) and Daniel, Hodrick, and Lu (2014) show that this portfolio earns a large Sharpe ratio but they do not consider the properties of $CSCAR_{CR}$ as a pricing factor. $CSCAR_{CV}$ adjusts $CSCAR$ to keep the conditional volatility constant equal to σ through time: $\theta_t^{CSCAR_{CV}} = \sigma \frac{\theta_t^{CSCAR}}{\sqrt{(\theta_t^{CSCAR})'\tilde{\Omega}_t \theta_t^{CSCAR}}} = \sigma \frac{\tilde{\Omega}_t^{-1} fd_t}{\sqrt{fd_t' \tilde{\Omega}_t^{-1} fd_t}}$ where $\tilde{\Omega}_t = \tilde{W}_t \tilde{\Lambda}_t \tilde{W}_t'$. $CSCAR_{\text{full}}$ follows $CSCAR$ to adjust CAR, while taking into account the covariance matrix and forward discounts. In contrast to $CSCAR$, $CSCAR_{\text{full}}$ uses the covariance matrix Ω_t and inverts it instead of the robust version of the inverse covariance matrix $\tilde{\Omega}_t^{-1}$. Therefore, $\theta_t^{CSCAR_{\text{full}}} = \Omega_t^{-1} fd_t$.

VOL: Menkhoff et al. (2012) introduce a factor that captures unexpected changes in global FX market volatility. Global FX market volatility at the end of month t is computed as follows:

$$\tilde{VOL}_t = \frac{1}{T_t \times N} \sum_{\tau=1}^{T_t} \sum_{i=1}^{N} ||\Delta x_{d,i,\tau}||,$$

where $\Delta x_{d,i,\tau}$ is the daily exchange rate growth of currency i against the USD on day τ in month t, T_t is the number of trading days τ in month t. The measure uses absolute instead of squared exchange rate growths so that outliers are less accentuated. The VOL index is the time series of residuals after estimating an AR(1) process for $\tilde{VOL}_t$ and thus captures unexpected changes in volatility, $\tilde{VOL}_t = \rho_v \tilde{VOL}_{t-1} + VOL_t$. Note that VOL is not a traded factor. Menkhoff et al. (2012) show that a traded portfolio that mimics VOL is almost identical to CAR.

HMLDB: Verdelhan (2018) develops a long-short strategy based on DOL factor loadings. Following Verdelhan (2018), we regress currency returns on the DOL and CAR factors. We then sort currencies into six quantiles $k \in \{1, \ldots, 6\}$ according to the dollar beta (i.e., the DOL factor loading). If the median forward discount rate of all developed currencies is positive (negative), then portfolio DB_k takes a long (short) position in the equally weighted portfolio of currency returns $CT_{i,t+1}$ for all currencies i in quantile k. The $HMLDB$ portfolio takes a long position in the high dollar beta portfolio DB_5 and a short position in the low dollar beta portfolio DB_1.

HMLC: Mueller, Stathopoulos, and Vedolin (2017) define the FX correlation dispersion measure (FXC) as the difference between the average of the top and the bottom deciles of the realized conditional correlations between all exchange rates. Following their procedure, we then sort currencies into four portfolios based on the beta of their returns with respect to innovations in FXC, denoted by ΔFXC. The equally weighted portfolios corresponding to each quartile are denoted by $FXCB_i$, $\forall i \in \{1, \ldots, 4\}$. The $HMLC$ portfolio takes a long position in the high ΔFXC beta portfolio ($FXCB_4$), and a short position in the low ΔFXC beta portfolio ($FXCB_1$).

ILL: We follow Karnaukh, Ranaldo, and Soederlind (2015) to construct a monthly systematic FX market illiquidity measure $\tilde{ILL}$ as the average of standardized daily relative bid-ask spreads and standardized 2-day Corwin and Schultz (2012) estimates within a month and across all currencies. Our data are not identical to Karnaukh, Ranaldo, and Soederlind (2015); that is, there is a difference in the set of currencies and the daily recording time of the bid-ask spreads, and our data cover the sample 1984–2016, while theirs cover 1991–2016.[4] The correlation between our measure and theirs is 57% for the monthly data from 1991 to 2016. Similar to the construction of the volatility factor VOL, we fit an AR(1) model to $\tilde{ILL}$ and use the residuals ILL as a proxy for unexpected changes in illiquidity, $\tilde{ILL}_t = \rho_{ILL} \tilde{ILL}_{t-1} + ILL_t$. Note that ILL is not a traded factor.

4 Karnaukh, Ranaldo, and Soederlind (2015) show that relative bid-ask spreads can be sensitive to the recording time.

SKEW: Rafferty (2012) introduces a FX market skewness (*SKEW*) factor, which is the average skewness of exchange rates with positive minus the average skewness of exchange rates with negative forward discounts, $SKEW_t = \frac{1}{N}\sum_i sign(fd_{i,t-1}) \frac{\frac{1}{T_t}\sum_{\tau}^{T_t}(\Delta x_{d,i,\tau} - \bar{\Delta x}_{d,i,\tau})^3}{\left(\frac{1}{T_t}\sum_{\tau}^{T_t}(\Delta x_{d,i,\tau} - \bar{\Delta x}_{d,i,\tau})^2\right)^{\frac{3}{2}}}$, where $\Delta x_{d,i,\tau}$ is the daily exchange rate growth of currency i against the USD on day τ in month t, $\bar{\Delta x}_{d,i,\tau} = \frac{1}{T_t}\sum_{h=1}^{T_t} \Delta x_{d,i,h}$ is the sample average of the daily exchange rate growth $\Delta x_{d,i,\tau}$ in month t, and T_t is the number of trading days in month t. Note that *SKEW* is not a traded factor.

MKT, INT: Finally, we use two stock market factors: the value weighted U.S. stock market index (*MKT*) and the traded intermediary capital risk factor (*INT*) of He, Kelly, and Manela (2017).

For a simple comparison of all 22 pricing factors employed in the paper, see the Internet Appendix, which contains the pairwise correlations for all factors. We analyze and discuss the factor characteristics in pricing the FX markets in the remaining parts of the paper.

2.3 Importance of market timing

Some of the factors have proportional portfolio weight vectors at any point in time t, that is, for factors H and L, $\frac{\theta^H_{i,t}}{\sum_j ||\theta^H_{j,t}||} = \frac{\theta^L_{i,t}}{\sum_j ||\theta^L_{j,t}||}$ for all currencies i and points in time t. The difference between H and L is the time series of the notional values or in other words the market timing, that is, generally, $\frac{\sum_j ||\theta^H_{j,t}||}{\sum_j ||\theta^L_{j,t}||} \neq \frac{\sum_j ||\theta^H_{j,\tau}||}{\sum_j ||\theta^L_{j,\tau}||}$ for $t \neq \tau$. In particular, CAR and $CAR_{V\ M}$ have proportional portfolio weights at any time t, but CAR has a constant notional value, while $CAR_{V\ M}$ decreases (increases) its notional value if volatility increases (decreases). Similarly, $SCAR$, $SCAR_{CV,}$ $NSCAR$, and $NSCAR_{VM}$ have proportional portfolio weights at any time t, but the notional value of $NSCAR$ is constant through time, while $SCAR$, $SCAR_{CV,}$ and $NSCAR_{VM}$ time the market based on the absolute size of the current forward discounts and current volatility. Finally, $CSCAR$, $CSCAR_{CR}$, and $CSCAR_{CV}$ have proportional portfolio weights at any time t, but $CSCAR_{CR}$ has a constant notional value, while $CSCAR$ and $CSCAR_{CV}$ dynamically adjust their notional value depending on the absolute size of the forward discounts and the covariance matrix of exchange rate growths.

Conditional at time t the excess return distributions of factors with proportional portfolio weights are proportional; that is, they are identical up to the multiplication by the ratio of the notional values of the factors. However, the unconditional return distributions of these factors are different if the time series of the notional values are distinct. For instance, the unconditional correlation is 0.64 for returns of $CSCAR$ and $CSCAR_{CR}$, 0.79 for $CSCAR$ and $CSCAR_{CV,}$ and 0.93 for $CSCAR_{CR}$ and $CSCAR_{CV.}$ Accordingly, when we estimate and test a pricing model using general methods of moments, a factor that times the market may fit the data better or worse than a normalized factor with a constant notional value. It is eventually an empirical question which time series of the notional value generates a factor that is able to price assets. In the following, we document that $CSCAR$ explains the cross-section of FX market returns, while $CSCAR_{CR}$ and $CSCAR_{CV}$ are rejected in our tests.

3. Pricing Factor Model Tests

We test the ability of $CSCAR$ and the competing pricing factors (both single- and multifactor models) described in Section 2 to price a broad cross-section of test assets. We use the following $N = 36$ test assets: 5 forward-discount-sorted portfolios ($fdP_i\ \forall i \in \{1, \dots, 5\}$), 5 momentum-sorted portfolios ($MomP_i\ \forall i \in \{1, \dots, 5\}$), 5 value-sorted portfolios ($ValP_i\ \forall i \in \{1, \dots, 5\}$), 6 dollar beta portfolios ($DB_i\ \forall i \in \{1, \dots, 6\}$), 4 FX correlation dispersion portfolios ($FXCB_i\ \forall i \in \{1, \dots, 4\}$), and all traded pricing factors in Section 2, that is, $DDOL$, CAR_{VM}, $SCAR$, $NSCAR$, $NSCAR_{VM}$, $SCAR_{CV,}$ $VSCAR$, $CECAR$, $CSCAR$, $CSCAR_{CR}$, and $CSCAR_{CV.}$[5] We separately implement all our tests using data of the subset of 15 developed currencies and the full set of 29 developed and emerging currencies.[6] Except for the empirical results concerning $CSCAR$ factor pricing analysis, results pertaining to the set of 29 currencies have been relegated to the Internet Appendix. The results are robust across the two sets of currencies.

We demonstrate that the covariance and spread adjustments of the carry trade are important to price the cross-section of FX market returns. In particular, we show that the single-factor $CSCAR$ model cannot be rejected, while other single- and multifactor models are rejected in our tests.

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5 We exclude DOL, CAR, MOM, VAL, $HMLDB$, and $HMLC$ portfolios because they are spanned by the 25 fdP_i, $MomP_i$, $ValP_i$, DB_i, and $FXCB_i$ portfolios.

6 To obtain a balanced panel of factors and test assets starting in January 1984, we need additional data before January 1984 to construct signals for the $MomP_i$, DB_i, and $FXCB_i$ portfolios. Datastream has exchange rate data quoted against the GBP before 1984. However, these data are less complete and considered less reliable compared to the data in our main sample. We use only these earlier data to generate signals to sort currencies for $MomP_i$, DB_i, and $FXCB_i$ in the beginning of our main sample. Our results are robust if we do not use the earlier data, but the time series of our panel of factors and test assets becomes 5 years shorter, and the power of the tests decreases.

3.1 Estimation: Sequentially efficient GMM

We focus on linear factor pricing models $E[R_t] = \beta\gamma$, where R_t is the $N \times 1$ vector of excess returns at time t of N test assets, $N \times K$ matrix β are the loadings of the N test assets on K pricing factors (element (i, k) is test asset i's loading on factor k), $K \times 1$ vector γ are the market prices of risk or risk premiums of the K factors, and $E[x]$ is the mean of variable x.

We estimate the model using the sequentially efficient general method of moments (GMM) (Hansen 1982; Cochrane 2005; Shanken and Zhou 2007). We denote first-stage (consistent but inefficient) estimates of parameters b by $\widehat{b}$, and sequentially efficient second-stage estimates by $\widehat{\widehat{b}}$. We use the following $K + (2 + K)N$ moment conditions,

$$g(b) = \begin{pmatrix} E[F_t - \mu] \\ E[\begin{pmatrix} 1 \\ F_t \end{pmatrix} \otimes (R_t - \alpha - \beta F_t)] \\ E[R_t - \gamma_0 1_{\{N\times 1\}} - \beta\gamma] \end{pmatrix} = \begin{pmatrix} 0_{\{K\times 1\}} \\ 0_{\{(1+K)N\times 1\}} \\ 0_{\{N\times 1\}} \end{pmatrix}$$

to estimate the $K + (1 + K)(1 + N)$ parameters $b = [\mu', \alpha', vec(\beta)', \gamma_0, \gamma']'$. $\otimes$ is the Kronecker product. F_t is the $K \times 1$ vector of the K factor realizations at time t, and μ is the corresponding $K \times 1$ vector of expected factor realizations. $N \times 1$ vector $\alpha = E[R_t - \beta F_t]$ are abnormal returns of the N test assets in the first set of N time-series equations. $vec(\beta)$ is an $NK \times 1$ vector of all elements in the factor loadings matrix β. $\gamma_0 1_{\{N\times 1\}} = E[R_t - \beta\gamma]$ is the common mispricing across the second set of N cross-sectional pricing equations. $1_{\{N\times 1\}}$ 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 heteroscedasticity following Newey and West (1987) when constructing the covariance matrix of the parameter estimates. Details about the estimation are in Appendix A.1.

3.2 Testable restrictions and model assessment

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

Second, if factor k is traded, then the pricing model implies that the factor premium has to be equal to its expected excess return $\gamma_k = \mu_k$. We use the t-test statistic $\frac{\widehat{\widehat{\gamma}}_k - \widehat{\widehat{\mu}}_k}{\sqrt{Var(\widehat{\widehat{\gamma}}_k - \widehat{\widehat{\mu}}_k)}}$ with $Var(\widehat{\widehat{\gamma}}_k - \widehat{\widehat{\mu}}_k) = Var(\widehat{\widehat{\gamma}}_k) + Var(\widehat{\widehat{\mu}}_k) - 2Cov(\widehat{\widehat{\gamma}}_k$

$, \widehat{\hat{\mu}}_k)$ to test whether $\widehat{\hat{\gamma}}_k - \widehat{\hat{\mu}}_k$ is statistically significantly different from zero. If it is significantly different from zero, then we reject the model.

Third, we check whether the estimated common pricing error $\widehat{\hat{\gamma}}_0$ in the cross-sectional pricing equations is statistically significantly different from zero using the *t*-test statistic $\frac{\widehat{\hat{\gamma}}_0}{\sqrt{Var(\widehat{\hat{\gamma}}_0)}}$. If $\widehat{\hat{\gamma}}_0$ is significantly different from zero, then we reject the model.

Fourth, we test whether the estimated abnormal returns $\widehat{\hat{\alpha}}^* = E[R_t] - \widehat{\hat{\gamma}}_0 1_{\{N\times 1\}} - \widehat{\beta}\widehat{\hat{\gamma}}$ in the *N* cross-sectional pricing equations are jointly statistically significantly different from zero. We use $\widehat{\hat{\alpha}}^{*\prime} Cov(\widehat{\hat{\alpha}}^*)^{-1}\widehat{\hat{\alpha}}^*$ as the test statistic, which is χ^2 distributed with $N-K$ degrees of freedom. A large test statistic is a rejection of the model.

Fifth, we test whether the estimated abnormal returns $\widehat{\hat{\alpha}} = E[R_t - \widehat{\hat{\beta}} F_t]$ in the *N* time-series pricing equations are jointly statistically significantly different from zero. Our test statistic is $\frac{T-N-K}{NT}\widehat{\hat{\alpha}}' Cov(\widehat{\hat{\alpha}})^{-1}\widehat{\hat{\alpha}} \sim F_{N,T-N-K}$. A large test statistic is a rejection of the model. This test is only possible if all pricing factors in the model are traded because in the time-series equations factor risk premiums are estimated using average excess returns of the factors.

Sixth, and finally, we report the R^2 of the *N* cross-sectional pricing equations. R^2 provides an indication of how well the model explains average returns in the cross-section, but it is not a formal test to reject a model. Accordingly, we do not place much weight on this criterion.

3.3 Composition of *CSCAR*

Before we present our GMM estimation and test results, we will discuss the portfolio composition of *CSCAR*. Table B1 provides summary statistics of the portfolio weights θ_t^{CSCAR} of *CSCAR*. *CSCAR* is similar to *CAR* in the sense that on average it takes long (short) positions in currencies with positive (negative) forward discounts. Indeed, the cross-sectional correlation $Corr(\theta_i^{CSCAR}, fd_i)$ between the average portfolio weight $\theta_i^{CSCAR} = \frac{1}{T}\sum_t \theta_{i,t}^{CSCAR}$ and the average forward discount $fd_i = \frac{1}{T}\sum_t fd_{i,t}$ is 0.93 for our data of 15 developed and 0.92 for our data of 29 developed and emerging currencies. Though, this correlation is large for average quantities, the portfolio weights are changing through time and the cross-sectional correlation in month *t*, $Corr_t(\theta_{i,t}^{CSCAR}, fd_{i,t})$ is often much smaller. On average the correlation is only 0.66 for the data of 15 and 0.63 for 29 currencies, and in some months it even turns negative. Accordingly, one must sort currencies according to forward discounts when constructing *CSCAR*, and the covariance matrix between exchange rate growths plays a crucial role as well.

Moreover, unlike that of *CAR*, the portfolio composition of *CSCAR* is far from an equally weighted scheme, and portfolio weights vary through time. The skewness of the unconditional distribution of portfolio weights is predominantly positive (negative) for currencies with positive (negative) average forward discounts. That is, weights take more extreme positive (negative) values for currencies with large (small) average forward discounts.

Portfolio weights vary through time because of the substantial time-series variation in exchange rate forward discounts and the conditional covariance matrix. The variation in forward discounts is considerable, but we observe that forward discounts are converging toward zero (especially for developed currencies) and appear more stable in more recent times.

We further document that the average FX market volatility measured by $\tilde{VOL}_t$ (see Section 2.2 or Menkhoff et al. 2012) and the average correlation between exchange rate growths are changing substantially through time. The average correlation is calculated as $\rho_t = \frac{1}{N}\sum_{i=1}^{N} \rho_{i,t}$ in month t, where $\rho_{i,t} = \frac{1}{N-1} \sum_{j \neq i} Corr_t(\Delta x_{i,t}, \Delta x_{j,t})$ is the average correlation of exchange rate growth i with all other exchange rate growths j, and we estimate the conditional correlation $Corr_t(\Delta x_{i,t}, \Delta x_{j,t})$ between exchange rate growths i and j in month t using daily exchange rate growths within the month. While forward discounts and the average correlation vary through time we do not observe a particular relationship to NBER recession periods. In stark contrast, FX market volatility spikes during the financial crisis in 2007–2008.

Finally, we find again a strong time-series variation in the percentage of eigenvalues (and corresponding eigenvectors), that we retain after we diagonalize the covariance matrix Ω_t and construct the robust version of the inverted covariance matrix $\tilde{\Omega}_t^{-1}$. There is a negative correlation of -0.4 for our data of 15 currencies and -0.66 for 29 currencies between the percentage of eigenvalues retained and the average correlation between exchange rate growths. This finding is intuitive: we need few (many) PCs to explain the common variation in exchange rate growths if the average correlation is far from (close to) zero.

The portfolio weights of $CSCAR$ are functions of the forward discounts and the covariance matrix. Thus, the notional value $\sum_i ||\theta_{i,t}^{CSCAR}||$, leverage $\sum_i \theta_{i,t}^{CSCAR}$ and turnover $\sum_i ||\theta_{i,t} - \theta_{i,t-1}||$ of $CSCAR$ vary significantly through time. This time series illustrates the market timing of $CSCAR$; that is, it increases (reduces) its risk exposure and trades more aggressively (conservatively) when the absolute size of the forward discounts is large (small) and covariances are small (large). We observe that all three measures generally approach zero in more recent times, which is mostly driven by the narrower forward discount spreads.

3.4 *CSCAR* as a single pricing factor

We first test the single-factor $CSCAR$ pricing model. This is the main result of our paper. Table B2 summarizes our five tests to evaluate the model when we use data from 15 developed (panel A) and 29 developed and emerging currencies (panel B). For each data set, we estimate the model using seven different sets of test assets and report the results in separate columns. The first column with the heading "5 IntP" uses only the five forward-discount-sorted portfolios as test assets. These forward-discount-sorted portfolios are popular test assets in the literature. In the column labeled "5 MomP & 5 ValP" we estimate our model using the 5 portfolios sorted on past currency returns and the 5 portfolios sorted on real exchange rates. "Fifteen assets" tests our model using *IntP*, *MomP*, and *ValP* together. "Six DB & 4 FXCB" uses the 6 portfolios sorted based on dollar beta and the 4 portfolios sorted based on ΔFXC beta. "Twenty-five assets" uses 25 *IntP*, *MomP*, *ValP*, *DB*, and *FXCB* portfolios together to test our model. "Eleven assets" uses the 11 traded factors $DDOL$, CAR_{VM}, $SCAR$, $NSCAR$, $NSCAR_{VM}$, $SCAR_{CV,}$ $VSCAR$, $CECAR$, $CSCAR$, $CSCAR_{CR}$, and $CSCAR_{CV.}$ "Thirty-six assets" uses all test assets combined to estimate and test our model. If we use 10 or less test assets, then the power is low and it is difficult to reject any hypothesis.[7] In our discussion we emphasize the case of all 36 assets as the power of the tests is the highest.

The results of our five tests are as follows. First, we estimate a sizable implied annual risk premium $\widehat{\gamma}_{CSCAR}$ for $CSCAR$ in the cross-section of FX market returns. For the case of 36 test assets, $\widehat{\gamma}_{CSCAR}$ is 7.14% for the data set of 15 developed currencies and 10.57% for the set of 29 currencies. These estimates are highly statistically significant with t-statistics of 4.21 and 5.39. Thus, $CSCAR$ is an important factor to price FX market returns in the cross-section. The estimates are similar (and differences are well within common confidence bounds) for the diverse sets of test assets and across both the data of 15 developed and the set of 29 currencies. $\widehat{\gamma}_{CSCAR}$ is always statistically significant, except when we use 6 *DB* and 4 *FXCB* as test assets. This is attributed to the large estimation errors and low power when we have few test assets.

Second, $\widehat{\gamma}_{CSCAR}$ is not statistically significantly different from the historical average return $\widehat{\mu}_{CSCAR}$. The point estimate of $\widehat{\mu}_{CSCAR}$ is 8.4% when we use data of 15 developed currencies and 10.83% when we use 29 currencies. These point estimates are close to the implied premium $\widehat{\gamma}_{CSCAR}$, especially for the set of 36 test assets and 29 currencies. This result is important because $CSCAR$ is itself a traded asset and thus has to be correctly priced. We confirm this finding in all sets of test assets for both 15 and 29 currencies, except for the case of 11 test assets when we use 15 currencies. In this case $\widehat{\gamma}_{CSCAR}$ is 2% smaller than $\widehat{\mu}_{CSCAR}$, which is significant at the 10% level with a p-value of 5.2%.

Third, we do not find a common pricing error $\widehat{\gamma}_0$ in the cross-sectional pricing equations. For the case of 36 test assets, $\widehat{\gamma}_0$ is 0.71% per year for 15

[7] Results for the estimation using 5 MomP, 5 ValP, 6 DB, or 4 FXCB separately are available on request. These estimates are not interesting as the power is too low for any meaningful test.

developed currencies and 0.03% for 29 currencies, neither is significant. Depending on the set of test assets and the set of currencies, the point estimate of $\widehat{\gamma}_0$ varies between -1.34% and 2.56% per year. The point estimates are only significant on the 10% level in two cases of 11 test assets and 15 currencies, or 6 *DB* and 4 *FXCB* test assets and 29 currencies.

Fourth, in all specifications the abnormal returns $\widehat{\widehat{\alpha}}^*$ in the cross-sectional pricing equations are not jointly statistically significantly different from zero, except for the case of 36 test assets and 29 currencies when the *p*-value is 8%. Note that the test statistic is substantially smaller than similar statistics for other models that we test in the subsequent sections. Therefore, while not perfect, the single-factor *CSCAR* model explains the cross-section of average returns better than the alternative models. Further note that transaction costs and capital controls can be an issue for emerging currencies. For instance, Maurer, Pezzo, and Taylor (2020) demonstrate the importance of transaction costs for FX trading strategies and show that an optimization over costs is required to efficiently tackle the problem.

Fifth, the joint test results of the abnormal returns $\widehat{\widehat{\alpha}}$ in the time-series pricing equations are similar to the joint tests of the abnormal returns in the cross-section. This is not surprising given that the point estimate of the implied risk premium of *CSCAR* is close to its historical average return. The *p*-value of the *F*-test is always well above 10% for all sets of test assets.

Sixth, and finally, Figures C1 and C2 compare the model-implied expected returns and the average historical returns of each test asset. The model captures the cross-section of average returns well. The *DB* portfolios are the only potential complication. Three of the six *DB* portfolios have significant abnormal returns in the single *CSCAR* model. However, none of these abnormal returns is significant at the 1% level.

To conclude, we report strong evidence in favor of the single-factor *CSCAR* model. The risk premium of *CSCAR* is large and significant when we estimate it in the cross-section of FX returns. Our estimate is robust to the choice of the set of test assets or whether we use data of 15 developed or 29 developed and emerging currencies. Furthermore, we do not find robust evidence to reject the single-factor *CSCAR* model. The risk premium estimated in the cross-section is not statistically different from the historical average return of *CSCAR*; the common pricing error in the cross-sectional pricing equations is not significantly different from zero; and abnormal returns are neither jointly significant in the cross-sectional pricing equations nor in the times-series equations.

3.5 Importance of covariance and spread adjustments

In Tables B3 to B6 we show that models with various alterations of the single *CSCAR* model are rejected. Therefore, we argue that both the covariance and spread adjustments are critical for *CSCAR* to price the cross-section of FX market returns.

In every table, we present three model specifications. For each model, we present results for the cases of 25 (columns 1 to 3) and 36 test assets (columns 4 to 6) using data of 15 developed currencies. In the Internet Appendix, we show that our results are similar for the larger set of 29 developed and emerging currencies. In addition to the five tests described in Section 3.2, in the last two rows we also report the abnormal returns of *CSCAR* as a test asset according to the model under investigation. If the abnormal return is not statistically significantly different from zero, then the model spans *CSCAR* and contains all its relevant information for pricing. In contrast, if the abnormal return is significant, then *CSCAR* contains important risk not captured by the model. We find that the abnormal return of *CSCAR* is positive and significant in all models.

CAR: Columns 1 and 4 in Table B3 report the results of the well-known *DOL*-*CAR* two factor model. Recall that *CSCAR* adjusts *CAR* by taking into account the covariance matrix and size of the forward discounts. Thus, comparing the *DOL*-*CAR* model to the *CSCAR* model reveals the importance of these adjustments for pricing. Confirming the results in the literature, Tables B3 shows that *DOL* is not priced in the cross-section, and *CAR* has a significant risk premium between 4.06% and 4.36%, depending on the set of test assets we use for the estimation. The implied risk premium for *CAR* is not significantly different from its historical average returns. In all specifications we are able to reject the model, i.e., $\widehat{\widehat{\gamma}}_0$ or the abnormal returns in the cross-section $\widehat{\widehat{\alpha}}^*$ or the time-series $\widehat{\widehat{\alpha}}$ are statistically significantly different from zero. In the case of 36 test assets the abnormal returns in the cross-section and time-series equations are large, and we reject the hypothesis that they are jointly equal to zero with p-values less than 0.1%. This confirms the results in the literature that the *DOL*-*CAR* model is not able to explain expected returns if we consider assets different from forward-discount-sorted portfolios. In the last two rows, we report the abnormal returns of *CSCAR* in the *DOL*-*CAR* model. The abnormal return of *CSCAR* is 5.42% in the cross-sectional equation and 6.51% in the time-series equation. The t-statistics are between 3.67 and 4.69. These large abnormal returns confirm that *CSCAR* is not spanned by the *DOL* and *CAR* factors.

Finally, in Figure C3, we compare the *DOL*-*CAR* model-implied expected returns to the historical average returns of our 36 test assets. The model fails to explain about half of the test assets; that is, the abnormal returns are statistically significantly different from zero. The model does a good job of explaining the *IntP*, *ValP*, *MomP*, and *FXCB* portfolios as none of the abnormal returns is significant. The *DOL*-*CAR* model is unable to explain the average returns of all the *DB* portfolios and all 11 test assets, which include several variations of $(CS)CAR$. Most of the abnormal returns of these test assets are significant at the 1% level. This is in stark contrast to the single-factor *CSCAR* model illustrated in Figures C1 and C2. The model is able to explain the cross-section of average returns.

We conclude that the covariance and spread adjustments are important in explaining the cross-section of average returns of a broad set of test assets.

DDOL: Columns 2 and 5 in Table B3 show that the rejection of the *DOL-DDOL* model is similar to that of the *DOL-CAR* model. The implied risk premium of *DDOL* changes when we use 25 versus 36 test assets to estimate the model. We reject the hypothesis that the abnormal returns are jointly equal to zero in the cross-sectional and time-series equations. Finally, abnormal returns of *CSCAR* are large (at 6.66% and 7.43%) and highly statistically significant, suggesting that *DOL-DDOL* does not span *CSCAR*.

NSCAR: *NSCAR* chooses portfolio weights proportional to the forward discounts but keeps the notional value of the factor constant through time. Thus, a model with *NSCAR* informs us of whether a spread adjustment of *CAR* is enough to explain the cross-section of average returns. Columns 3 and 6 in Table B3 report the results. Overall, we see only modest improvements of *DOL-NSCAR* over the *DOL-CAR* model. For the case of 25 test assets the model does a reasonable job to explain the cross-section of expected returns but we still reject (with a *p*-value of 8%) the join hypothesis that abnormal returns in the cross-sectional or time-series dimensions are equal to zero. Therefore, the spread adjustment makes some progress (though the model is still imperfect) to capture the risks of the *MomP*, *ValP*, *DB* and *FXCB* portfolios. In the case of 36 test assets, the corresponding *p*-values are less than 1%, and the model is clearly rejected (similar to the *DOL-CAR* model). We find again that *DOL* and *NSCAR* do not span *CSCAR*; that is, the abnormal returns of the *CSCAR* are always positive and significant, at 5.36% and 5.60%.

$\mathbf{CAR}_{VM}$ and $\mathbf{NSCAR}_{VM}$: A natural question is whether we need the entire covariance matrix to adjust *CAR* or whether managing the volatility as suggested by Fleming, Kirby, and Ostdiek (2001) and Moreira and Muir (2016) is sufficient. We investigate the ability of CAR_{VM} and $NSCAR_{VM}$ as pricing factors. Remember that these two factors differ from *CAR* and *NSCAR* because of the market timing being based on the current volatility, a fact that has implications on the unconditional return distribution and our unconditional tests. Columns 1, 2, 4 and 5 in Table B4 suggest that managing the volatility of *CAR* or *NSCAR* does not significantly improve the *DOL-CAR* model. The $DOL\text{-}CAR_{VM}$ and $DOL\text{-}NSCAR_{VM}$ models appear to explain the cross-section of average returns in the case of 25 test assets but are rejected in the case of 36 test assets. In particular, in both models we reject the hypothesis that the abnormal returns in the cross-sectional and time-series equations are jointly equal to zero with p-values less than 1%. Finally, $CSCAR$ has again highly significant abnormal returns between 5.27% and 6.10% in both models, which means that $CSCAR$ is not spanned by these factors. We conclude that a volatility-managed carry (CAR or $SCAR$) factor does not explain the cross-section of FX returns and it is important to account for the entire covariance matrix.

Eight-factor model: In columns 3 and 6 in Table B4, we test whether a model that includes the MOM and VAL factors in addition to DOL, and the above discussed CAR, CAR_{VM}, $NSCAR$, and $NSCAR_{VM}$ factors can explain the cross-section of FX returns. Not surprisingly, the model is not rejected in the case of 25 test assets. However, we still reject the eight-factor model in the case of 36 test assets based on the fact that abnormal returns in the cross-sectional and time-series equations are not jointly equal to zero. The p-values are always less than or equal to 1%. Moreover, the abnormal return of $CSCAR$ is positive and significant (at 3.94% and 4.76%), suggesting that the eight factors are not able to span all the priced risk contained in $CSCAR$. Thus, momentum, value, and the volatility of the carry are not sufficient to capture the information contained in the covariance and spread adjustments of $CSCAR$.

SCAR and VSCAR: Similar to $NSCAR$ and $NSCAR_{VM}$, $SCAR$ and $VSCAR$ are the spread-adjusted versions of CAR. In addition to the spread adjustment, $SCAR$ times the market based on the size of the forward discounts. In addition to the market timing of $SCAR$, $VSCAR$ accounts for the variances of all currency returns but ignores the correlations. Thus, $SCAR$ and $CSCAR$ only differ because of the covariance adjustment, while $VSCAR$ and $CSCAR$ only differ because of the correlation matrix of exchange rate growths. While we estimate significant risk premiums for $SCAR$ and $VSCAR$, we still reject both models. Columns 1, 2, 4, and 5 in Table B5 report the results. For the $SCAR$ model, abnormal returns in the cross-sectional and time-series equations are jointly different from zero for the cases of 25 and 36 test assets. For the $VSCAR$ model, we cannot reject the model in the case of 25 test assets. However, we always reject $VSCAR$ model when we use our set of 36 test assets. For both the $SCAR$ and $VSCAR$ models, abnormal returns for $CSCAR$ are sizable and significant, ranging between 4.05% and 6.22%. We conclude that the covariance adjustment is key to explain the cross-section of returns. Moreover, the correlation structure between exchange rate growths is important and accounting only for exchange rate growth variances is not sufficient.

CECAR: In contrast to the above analysis, where we confirm that the covariance adjustment is important, we further investigate the importance of the spread adjustment. $CECAR$ accounts for the covariance matrix in the same way as *CSCAR* but does not account for the size of the forward discounts. Columns 3 and 6 in Table B5 report the results. The *CECAR* factor is compensated with a significant risk premium in the cross-section, though the size of the premium substantially varies with the set of test assets. In the case of 25 test assets the rejection of the model is marginal. In the case of 36 test assets the abnormal returns in the cross-sectional and time-series equations are jointly different from zero and we reject the model with *p*-values less than 1%. Moreover, the abnormal returns of *CSCAR* are significant (at 5.16% and 5.98%), and, thus, *CECAR* fails to capture the priced risks contained in *CSCAR*. We conclude that fully accounting for the forward discount is important and the covariance adjustment itself is not sufficient.

CSCAR$_{CR}$ and CSCAR$_{CV}$: To investigate the importance of *CSCAR*'s market timing (i.e., the time variation in the notional value), we test $CSCAR_{CR}$ and $CSCAR_{CV}$ as pricing factors. Recall that the portfolio compositions of $CSCAR_{CR}$, $CSCAR_{CV}$, and *CSCAR* are identical up to the notional value. $CSCAR_{CR}$ is constructed to keep the notional value, and $CSCAR_{CV}$ is constructed to keep the conditional volatility constant through time. Note that the constant notional value does not imply a constant conditional volatility because the volatility in FX markets is heteroscedastic. The time variation in the notional value affects the unconditional distribution of returns and has important implications for our model tests. It is not clear ex ante and eventually an empirical question whether the market timing of *CSCAR* or $CSCAR_{CV}$ or no market timing as in $CSCAR_{CR}$ is desirable for pricing assets. Columns 1, 2, 4 and 5 in Table B6 report the results. Both $CSCAR_{CR}$ and $CSCAR_{CV}$ are compensated by large and significant risk premiums. Neither of the two models can be rejected in the case of 25 test assets, but we reject both models in the case of 36 test assets because abnormal returns in the cross-sectional and time-series equations are jointly significantly different from zero. Moreover, in both models the abnormal returns of *CSCAR* are significant, (ranging between 2.79% and 4.96%), suggesting that *CSCAR* carries important information that is not spanned by the $CSCAR_{CR}$ and $CSCAR_{CV}$ factors.

CSCAR$_{\text{full}}$: To construct *CSCAR*, we diagonalize the covariance matrix Ω_t and remove small eigenvalues and corresponding eigenvectors to obtain a robust version of the inverse of the covariance matrix $\tilde{\Omega}_t^{-1}$ (see details in Section 2.1). This approach helps to mitigate estimation errors in the covariance matrix and avoid near-arbitrage opportunities.[8] $CSCAR_{\text{full}}$ uses the "full" covariance matrix Ω_t; that is, it does not remove the small eigenvalues.

[8] There exist other methods to obtain robust estimates of the covariance matrix. For instance, the shrinkage estimator of Ledoit and Wolf (2003) is an alternative approach. We find that our approach to diagonalize the covariance matrix and remove small eigenvalues and eigenvectors yields more desirable results. Results using shrinkage estimator are available on request.

Therefore, comparing $CSCAR_{\text{full}}$ to $CSCAR$ informs us whether the diagonalization and removing small eigenvalues is relevant. Columns 3 and 6 in Table B6 report the results. Similar to $CSCAR$, $CSCAR_{\text{full}}$ is priced in the cross-section of returns and has a large and significant risk premium. The implied risk premium is larger than the historical average return of $CSCAR_{\text{full}}$. We reject the $CSCAR_{\text{full}}$ model because the abnormal returns in the cross-sectional and time-series equations are jointly significantly different from zero in all model estimations. Finally, we find that $CSCAR$ has a positive and significant abnormal return (at 5.53% and 7.65%), and, thus, $CSCAR_{\text{full}}$ does not capture all the information contained in $CSCAR$. We conclude that diagonalizing the covariance matrix Ω_t and removing small eigenvalues and corresponding eigenvectors to construct a robust version of the inverse of the covariance matrix, that is, $\tilde{\Omega}_t^{-1}$, is critical for $CSCAR$ to correctly price the cross-section of FX market returns.

To conclude, we confirm that both the covariance and forward discount adjustments are important for $CSCAR$ to price the cross-section of FX market returns. This finding is important for future empirical and theoretical research. First, empirical research could analyze the structure of the covariance matrix and relate patterns in the exchange rate growth covariation to economic fundamentals. Second, many theoretical models focus on forward discounts without investigating the pricing implications of exchange rate growth variances and correlations. Our results reveal the importance of analyzing the economic mechanism that relates the covariance matrix to expected returns in FX markets.

3.6 FX market volatility, correlations, illiquidity, and crash risk

So far, we have established that covariance and spread adjustments to the carry trade are important to obtain a factor that is able to consistently price the cross-section of FX returns. Next, we investigate whether other factors that capture FX market volatility, correlations, illiquidity, or crash risk contain the same information or whether our proposed mean-variance adjustments are special.

Menkhoff et al. (2012) show the importance of the unexpected changes in FX market volatility (*VOL*) in pricing currency returns. Karnaukh, Ranaldo, and Soederlind (2015) and Mancini, Ranaldo, and Wrampelmeyer (2013) document the importance of illiquidity (*ILL*) in explaining returns. Related to crash risk, Rafferty (2012) introduces an FX skewness (*SKEW*) factor, Lettau, Maggiori, and Weber (2014) construct a stock market downside risk (*DSR*) factor, and He, Kelly, and Manela (2017) show that an intermediary capital risk factor (*INT*) is priced in the cross-section of interest-rate-sorted currency portfolios. Finally, Mueller, Stathopoulos, and Vedolin (2017) and Verdelhan (2018) propose an FX correlation dispersion (*HMLC*) factor and a dollar beta (*HMLDB*) factor to address time variations in correlations across currencies. In the following, we show that none of these factors is able to explain the cross-section of FX market returns, and these factors do not span the *CSCAR* factor.

VOL, ILL, SKEW, DSR, INT: In Tables B7 and B8, we test whether volatility, illiquidity, or crash risk factors explain the cross-section of our 25 and 36 test assets and whether *CSCAR* is simply picking up these risks. *VOL*, *ILL*, *SKEW*, and *DSR* are not traded, and, thus, we cannot test whether the implied risk premium is equal to the historical average return and whether abnormal returns in the time-series equations are jointly zero. Only the *SKEW* factor has a robust and significant market price in the cross-section. Either all other factors have consistently insignificant market prices or the implied risk premium varies across sets of test assets and currencies. Note that these findings are not inconsistent with the literature. We consider a much larger set of test assets (i.e., sets of 25 or 36 test assets, while the literature focuses on only the five *IntP*), and thus, the bar for the factors to succeed is higher than that for the original papers that introduce these factors. The abnormal returns are always (for 25 or 36 test assets) statistically significantly different from zero for all model specifications. Therefore, we reject all models without exception. Finally, the abnormal returns of *CSCAR* are always large and highly statistically significant (ranging between 5.83% and 6.97%), which implies that the priced risks captured by *CSCAR* are not explained by *VOL*, *ILL*, *SKEW*, *MKT*, *DSR*, or *INT*.

HMLBD, HMLC: Table B9 reports the results for *CAR*-*HMLDB* and *DOL*-*HMLC*, which are the two-factor models proposed by Verdelhan (2018) and Mueller, Stathopoulos, and Vedolin (2017), respectively. These models are designed to capture FX correlation risk. The abnormal returns in the cross-section of the 25 test assets are jointly significantly different from zero and we reject the *CAR*-*HMLDB* model. We also reject *CAR*-*HMLDB* (with *p*-values less than 1%) if we use our set of 11 portfolios or our complete set of 36 test assets. Moreover, we always reject the *HMLC* model independent of the set of test assets or currencies as the abnormal returns are always significantly different from zero both in the cross-section or in the time-series equations.[9]

[9] Note that average returns of the *HMLC* portfolio are not robust across our sets of developed and emerging currencies. $\widehat{\mu}_{HMLC}$ is -2% for the 15 developed currencies and 0.2% for the 29 currencies (results concerning 29 currencies being reported in the Internet Appendix). At first, this seems at odds with the -6.4% reported by Mueller, Stathopoulos, and Vedolin (2017). However, their sample comprises G10 currencies from 1996 to 2013. In our data, $\widehat{\mu}_{HMLC}$ is -4.7% for 15 currencies and -1% for 29 currencies during the same period. Moreover, they report an average return of -3.7% for the period from 1984 to 2013, while in our data $\widehat{\mu}_{HMLC}$ is -2.4% for 15 developed currencies and -0.2% for 29 currencies. Therefore, our estimates of $\widehat{\mu}_{HMLC}$ in our analysis differ from those of Mueller, Stathopoulos, and Vedolin (2017) because of the sample period, and, more importantly, the performance of *HMLC* appears to depend on the set of currencies. In comparison, our estimates of $\widehat{\mu}_{HMLDB}$ are in line with the estimates by Verdelhan (2018). The average return is 4.3% for developed and emerging currencies from 1988 to 2016 in the data on Adrien Verdelhan's website. In our data, $\widehat{\mu}_{HMLDB}$ is 4.1% for 15 developed currencies and 4.2% for 29 currencies from 1988 to 2016. In our main analysis, $\widehat{\mu}_{HMLDB}$ is 3.9% for 15 developed currencies and 3.7% for 29 currencies.

Finally, the abnormal returns of *CSCAR* are always positive and statistically different from zero (ranging from 5.04% to 8.19%), suggesting that neither the dollar beta nor FX correlation dispersion factors captures the priced risks of *CSCAR*.

We conclude that *CSCAR* captures important information to price the cross-section of FX market returns, and these risks are not explained by FX volatility, correlation, illiquidity or crash risks. The finding that crash risk does not explain the cross-section of returns reinforces the findings by Daniel, Hodrick, and Lu (2014), Bekaert and Panayotov (2020), and Maurer, To, and Tran (2020). These papers construct profitable currency trading strategies with returns that cannot be explained by crash risks and question the idea that crash risks are important for pricing in FX markets.

3.7 Predictability of FX market returns

The conditional covariance matrix (i.e., the variances and the correlation structure of currency returns) and the forward discounts are both critical to correctly price the cross-section of FX market returns. Since the forward discounts and the conditional covariance matrix vary through time, *CSCAR* dynamically adjusts its notional value and leverage in response to these changes. This is essentially market timing, and we demonstrate above that it is an integral feature for *CSCAR* to succeed in our tests, that is, factors that are proportional to *CSCAR* at time t but differ in their market timing are rejected in our tests, while the *CSCAR* single-factor model cannot be rejected. To provide additional support, in this section, we provide evidence that *CSCAR* is able to predict future returns, volatility and illiquidity in FX markets. The intuition is that if the conditional covariance matrix and forward discounts are important determinants of conditional expected returns (i.e., pricing) and if they vary through time, then FX market returns should be predictable. We further show that global FX market volatility does not predict returns, which emphasizes the importance of the information contained in the correlation matrix and forward discounts and the difference between *CSCAR* and a volatility-managed carry factor in the spirit of Della Corte, Sarno, and Tsiakas (2009), Daniel, Hodrick, and Lu (2014), Fleming, Kirby, and Ostdiek (2001) and Moreira and Muir (2016).

For N currencies (plus the USD as the base), we have $\frac{N\times(N-1)}{2}$ elements in the covariance matrix and N forward discounts. It is not practical to keep track of so many state variables. However, the portfolio weights of *CSCAR* are functions of the covariance matrix and forward discounts. Thus, *CSCAR* summarizes the information of these state variables in terms of its portfolio holdings, and the variables we are particularly interested in are *CSCAR*'s notional value $\sum_i ||\theta_{i,t}^{CSCAR}||$, its leverage $\sum_i \theta_{i,t}^{CSCAR}$ and its turnover $\sum_i ||\theta_{i,t} - \theta_{i,t-1}||$. Intuitively, a large (small) notional value indicates that absolute values of forward discounts are large (small) relative to the covariance matrix. Moreover, if $CSCAR$ is the optimal investment strategy, then the leverage summarizes the "attractiveness" of risky assets relative to the risk-free asset. Finally, the turnover summarizes how much the covariance matrix and forward discounts (and thus, portfolio weights of $CSCAR$) change from month to month. Therefore, changes in the notional value, leverage and turnover characterize changes in the conditional covariance matrix and forward discounts. We use these three measures to capture the variation of the original state variables. As we saw in Section 3.3, there is a substantial variation in these three time series.

Our hypothesis is that the covariance matrix and forward discounts are important state variables and conditional expected returns depend on these state variables. Since we observe a substantial time-series variation in these variables, then conditional expected FX market returns and volatility should vary through time and returns and volatility should be predictable. As a preview, we find strong evidence that FX market returns, volatility and illiquidity are predictable.

We run predictive regressions,

$$Y_{t,t+h} = c_{const} + c_{trend}t + \sum_j c_j x_{j,t} + \varepsilon_t,$$

where the dependent variable $Y_{t,t+h} = \frac{1}{h}\sum_{\tau=1}^{h} Y_{t+\tau}$ is the average realization of Y over the subsequent h months after month t, t captures any time trend, $x_{j,t}$ is the realization of predictor j in month t, ε_t is white noise, and c_{const}, c_{trend} and c_j are the regression coefficients.

Our first three predictors are the notional value, leverage, and turnover of $CSCAR$. We further investigate the predictive power of the sign of the median forward discount $x_{4,t} = sign(median\{fd_{i,t}\})$. This measure is identical to the conditioning variable used to construct $DDOL$, that is, if the median forward discount is positive (negative) $DDOL$ takes a long (short) position in DOL. Additionally, we use global FX market volatility $x_{5,t} = \tilde{VOL}_t$ and global FX market illiquidity $x_{6,t} = ILL_t$ as predictors. The dependent (predicted) variables Y are the future global FX market volatility $\tilde{VOL}$ and illiquidity $\tilde{ILL}$, and future returns of $CSCAR_{CR}$, HML, DOL, $D\text{-}DOL$, MOM, and VAL.[10] We consider prediction horizons h of 1, 6, 12, and 18 months; that is, we test whether our predictors x_j are able to explain 1-month and up to 18-month-ahead realizations of our dependent variables Y.

Table B10 reports the results of our predictive regressions for 15 developed currencies. The notional value of $CSCAR$ is significantly correlated with future FX market volatility, illiquidity and returns of $CSCAR_{CR}$, CAR, $DDOL$, and MOM. For returns of DOL and VAL, there is evidence of

10 If we are able to predict the returns of $CSCAR_{CR}$, then we can also predict the returns of $CSCAR$ because the two factors only differ with respect to the notional value. Results are available on request.

predictability at longer horizons of 6 to 18 months. The notional value also predicts volatility and illiquidity at a short horizon. We find similar statistically significant coefficients for the leverage of $CSCAR$. The turnover of $CSCAR$ has some power to predict volatility and illiquidity but there is no robust evidence to predict returns. The sign of the median forward discount consistently predicts the return of DOL and illiquidity, but we find no robust evidence that it has the power to predict volatility or returns of the other factors. Finally, past volatility has the power to predict future volatility and similarly past illiquidity well forecasts future illiquidity. Volatility and illiquidity do not have a robust correlation with future FX market returns.

The adjusted R^2 of the predictive regressions is impressive. At the 1-month horizon we are able to forecast between 53% and 59% of the variation in FX market volatility and illiquidity. At the 6-, 12- and 18-month horizons the adjusted R^2 decreases monotonically to 15%-32%. The adjusted R^2 to predict returns of $CSCAR_{CR}$ at the 1-month horizon is 3.85%. It increases to 19.5% at the 18-month horizon. At the 1-month horizon, the adjusted R^2 to forecast returns of CAR are 2.22%, DOL 5.12%, $DDOL$ 1.37%, MOM 0.05%, and VAL -0.05%. R^2 increases to 9.52% for CAR, 25.7% for DOL, 27.01% for $DDOL$, 0.11% for MOM, and 7.62% for VAL at the 18-month horizon.

The difference in the predictive power between the notional value and the leverage of $CSCAR$ and the global FX market volatility emphasizes the difference between the covariance and spread adjustment of the carry versus a volatility-managed carry factor in the spirit of Della Corte, Sarno, and Tsiakas (2009), Daniel, Hodrick, and Lu (2014), Fleming, Kirby, and Ostdiek (2001), and Moreira and Muir (2016). $CSCAR$ is timing the market in response to changes in forward discounts, volatility, and correlations, all of which are important. In contrast, volatility-managed factors are only responding to changes in volatility.

In summary, we take the predictive power of the notional value and the leverage of $CSCAR$ as evidence that $CSCAR$ is able to forecast future expected returns and risks in FX markets. FX market volatility or illiquidity do not have the same predictive power. This is consistent with our previous finding that both the covariance and spread adjustments are important determinants of conditional expected returns and that the correlation structure between exchange rate growths is critical to price FX market returns. This is an important finding for future empirical research to identify economic fundamentals that drive the time-series variation in the conditional covariance matrix and forward discounts. Our finding also informs theoretical research to focus on economic mechanisms responsible for a time-series variation in the conditional covariance matrix of exchange rate growths and forward discounts.

4. Model

To conceptually illustrate the intuition and properties of the pricing factor based on covariances and spreads, we analyze $CSCAR$ in the tractable international asset pricing framework of Lustig, Roussanov, and Verdelhan (2014) (while relegating the technical derivations to the Internet Appendix). Specifically, we consider the benchmark model of Mueller, Stathopoulos, and Vedolin (2017), and perform a comparative analysis on their international correlation risk factor and the $CSCAR$ factor within that model. We extend their analysis by explicitly computing the model-implied portfolio composition of the two risk factors. The computation maps the empirical factors to their theoretical counterparts in the model, and helps elucidate $CSCAR$ from a perspective of the current literature in international finance.

4.1 Model and asset pricing quantities

We adopt and briefly describe the model setup of Mueller, Stathopoulos, and Vedolin (2017) that belongs to the no-arbitrage log-normal setting of Lustig, Roussanov, and Verdelhan (2014). We relegate the technical derivations to the Internet Appendix. The international correlation risk factor is formulated in a benchmark complete-market setting of $N+1$ countries indexed by $i \in \{0, \ldots, N\}$, where $i = 0$ designates the domestic (U.S.) country. Country i's SDF is given,

$$\log \frac{M_{i,t+1}}{M_{i,t}} = m_{i,t+1} = -\alpha - \chi z_t - \phi z_t^w - \sqrt{\kappa z_t} u_{t+1}^i - \sqrt{\gamma^i z_t^w} u_{t+1}^w - \sqrt{\delta z_t} u_{t+1}^g, \quad (1)$$

in which u_{t+1}^w and u_{t+1}^g are two independent global shocks, and u_t^i country-specific independent shock. Local and global state variables (or, pricing factors), z_t and z_t^w, capture the local and global mean-reverting dynamics of the prices of risks. The first global shock u_{t+1}^w has (permanent) heterogeneous prices of risk in different currencies determined by common z_t^w and (permanent) heterogeneous positive loadings $\{\gamma^i\}$ (Lustig, Roussanov, and Verdelhan, 2014).

As markets are complete, currency i's exchange rate against the USD equals the ratio of SDFs, $X_{i,t} = \frac{M_{i,t}}{M_{0,t}}$, where $X_{i,t}$ denotes the amount of USD per unit of currency i,

$$\log \frac{X_{i,t+1}}{X_{i,t}} = m_{i,t+1} - m_{0,t+1} = \sqrt{\kappa z_t}(u_{t+1}^0 - u_{t+1}^i) + \left(\sqrt{\gamma^0} - \sqrt{\gamma^i}\right)\sqrt{z_t^w} u_{t+1}^w, \quad (2)$$

As a result, the covariances of exchange rates are implied in the model,

$$\Omega_{ii,t} = Var_t\left(\log\frac{X_{i,t+1}}{X_{i,t}}\right) = 2\kappa z_t + D_{ii}z_t^w,$$
$$\Omega_{ij,t} = Var_t\left(\log\frac{X_{i,t+1}}{X_{i,t}}, \log\frac{X_{j,t+1}}{X_{j,t}}\right) = \kappa z_t + D_{ij}z_t^w, \tag{3}$$

wherein the ratio $\frac{z_t}{z_t^w}$ of state variables characterizes the disparity of the international correlation in FX markets. Countries of similar (dissimilar) loadings γ^i have lower (higher) correlations of their exchange rates against the USD when this ratio is higher. The short-term risk-free rate is given by the conditional expected growth rate, $r_{i,t} = -\log E_t\left[\frac{M_{i,t+1}}{M_{i,t}}\right]$. In the absence of arbitrages, the covered interest rate parity (CIP) holds between spot and forward exchange rates, $X_{i,t}(1+r_{0,t}) = F_{i,t}(1+r_{i,t})$, so the exchange rate forward discount equals the interest rate differential,

$$fd_{i,t} = \log\frac{X_{i,t}}{F_{i,t}} = r_{i,t} - r_{0,t} = \frac{1}{2}(\gamma^0 - \gamma^i)z_t^w. \tag{4}$$

We consider a net-zero currency strategy of long currency i, short USD from t to $t+1$. Given complete markets (2) and CIP (4), the realized and conditional expected returns in USD of this strategy are

$$CT_{i,t+1} \equiv \log\frac{X_{i,t+1}}{X_{i,t}} + fd_{i,t}$$
$$= \sqrt{\kappa z_t}(u_{t+1}^0 - u_{t+1}^i) + (\sqrt{\gamma^0} - \sqrt{\gamma^i})\sqrt{z_t^w}u_{t+1}^w + \frac{1}{2}(\gamma^0 - \gamma^i)z_t^w, \tag{5}$$
$$ECT_{i,t} \equiv E_t[CT_{i,t+1}] = fd_{i,t} = r_{i,t} - r_{0,t}. \tag{6}$$

This result shows that the exchange rate forward discount is an unbiased predictor of the future currency return.

Empirically, the international correlation risk factor is constructed as follows. First, currency pairs $\{ij\}$ are sorted into 10 bins (deciles) based on the conditional correlation $\rho_t\left(\frac{X_{i,t+1}}{X_{i,t}}, \frac{X_{j,t+1}}{X_{j,t}}\right)$ of the exchange rates. The disparity in the international correlation FXC_t is measured by the difference between the average conditional correlation in the top and bottom deciles. The exposure β_{FXC}^k of a currency k to the international correlation risk factor is quantified by the slope coefficient in the regression of the exchange rate growth $\frac{X_{k,t+1}}{X_{k,t}}$ on the innovations $\Delta FXC_{t+1} \equiv FXC_{t+1} - FXC_t$. Finally, the mimicking portfolio $HMLC_t$ of the international correlation risk factor is constructed by sorting currencies into bins based on their exposures $\{\beta_{FXC}^k\}$, and taking equally weighted long positions in currencies in the top ($FXCB_4$) and short positions in currencies in the bottom ($FXCB_1$) bin. The realized return of the mimicking portfolio $HMLC_{t+1}$ from t to $t+1$ is

$$HMLC_{t+1} = \sum\nolimits_{i \in FXCB_4} CT_{i,t+1} - \sum\nolimits_{i \in FXCB_1} CT_{i,t+1},$$

$$\text{or} \begin{cases} \theta_i^{HMLC} = 1 \text{ if } i \in FXCB_4, \\ \theta_i^{HMLC} = -1 \text{ if } i \in FXCB_1, \end{cases} \tag{7}$$

where $CT_{i,t+1}$ denotes the realized currency return (5), and θ_i^{HMLC} the portfolio weight (up to a normalization constant).

The realized return of the $CSCAR$-mimicking portfolio is

$$CSCAR_{t+1} = \sum_{i=1}^{N} \theta_{i,t}^{CSCAR} CT_{i,t+1}, \text{ with } \theta_{i,t}^{CSCAR} = (\Omega_t^{-1} fd_t)_i, \tag{8}$$

where Ω_t is the exchange rate conditional covariance matrix (3), and fd_t the forward discounts (4).

By construction, $HMLC$ (7) always assigns an equal absolute (long or short) weight to every currency that contributes to the strategy (i.e., currencies in the top and bottom terciles), and zero weight to other currencies. Conceptually, currencies contributing to $HMLC$ are determined based on the covariation between the movements in currency k's values $X_{k,t+1}$ and in the international correlation FXC_{t+1}. As u_{t+1}^w is the only shock common to these movements, the composition of $HMLC$ (7) depends principally on the exposures of currency values and the international correlation to the first global shock u_{t+1}^w. On the other hand, $CSCAR$ (8) allows for weights distributed among all available currencies, depending on the covariance matrix Ω_t (3) as well as the forward discount fd_t (4). Both global, u_{t+1}^w, and country-specific shocks, $\{u_{t+1}^i\}$, contribute to the covariance matrix, and the composition of $CSCAR$ (8). These differences in the portfolio weight determination implies different factor returns and pricing properties of $HMLC$ and $CSCAR$.

4.2 Factor prices and pricing power of factors

We formalize the comparative analysis of factors based on the international correlation ($HMLC$) and on covariances and spreads ($CSCAR$) by examining their market-based factor prices and pricing powers.

4.2.1 Market-based factor prices. The price of a risk factor quantifies the required excess return to bear the risk of the factor, that is, the factor's risk-adjusted return or Sharpe ratio. We first consider a market-based perspective, in which factor prices are determined by a pricing kernel constructed from currency strategies in the FX market. This pricing kernel is the unique projector of the SDF on the space of currency returns (Hansen and Jagannathan 1991).

In the model, the forward discounts equal the conditional expected currency returns (6). Note that the conditional covariance matrix Ω_t of exchange rate growths $\frac{X^i_{t+1}}{X_{t+1}}$ is also the conditional covariance matrix of realized currency returns $CT_{i,t+1}$ (5). Hence, the $N \times 1$ portfolio weight vector (8) of $CSCAR$ can be written as

$$\theta_t^{CSCAR} = \Omega_t^{-1} E_t[CT_{t+1}] = Var_t(CT_{t+1}, CT_{t+1})^{-1} E_t[CT_{t+1}],$$

where $N \times 1$ vector CT_{t+1} denotes a N realized currency returns $\{CT_{i,t+1}\}$, $i \in \{1, \ldots, N\}$. This expression shows that θ_t^{CSCAR} are the optimal weights of the mean-variance efficient portfolio in FX markets. As a result, $CSCAR$ delivers the highest Sharpe ratio among all FX strategies, including $HMLC$ and the standard carry factor CAR. $CSCAR$ perfectly negatively correlates with and represents the Hansen-Jagannathan minimum-variance, that is, the unique pricing kernel linear in currency returns. Since $HMLC$ is another currency strategy, this result implies that in the USD denomination, $HMLC$ offers a lower Sharpe ratio and a higher pricing error than $CSCAR$ in pricing FX returns.

4.2.2 Pricing power in two specific limits. The above finding on the optimality of $CSCAR$ in pricing assets on the FX markets represents the U.S. SDF projected on the return space of currency strategies. $CSCAR$ therefore has the highest correlation with the U.S. SDF among all currency strategies.

In the current model, as SDFs of all countries are specified (1), we can directly compute, verify, and analyze the model-implied correlation between the U.S. SDF and $HMLC$ and $CSCAR$ factors. This analysis exhibits how information about first and second moments of currency returns are combined to formulate $CSCAR$, in difference with the formulation of $HMLC$ and CAR. It also reconfirms the outperformance of $CSCAR$ over other FX factors explicitly in two limits of interest, namely, the large and small international correlation parity $\frac{z_t^w}{z_t}$ (3). Note that the correlation between a factor and SDF can be either positive (hedge factor) or negative (risk factor). In what follows we are interested in the absolute value of this correlation.

Small international correlation disparity: In this limit, we can obtain a power series expansion in the small ratio $\frac{z_t^w}{z_t}$ for all pricing quantities in the model. In the leading order of approximation, the conditional correlation between a factor return $F_{t+1} \in \{CSCAR_{t+1}, HMLC_{t+1}\}$ and the U.S. SDF is

$$Corr_t\left(F_{t+1}, \frac{M_{0,t+1}}{M_{0,t}}\right) = -\frac{\sum_{i=1}^{N} \theta_{i,t}^F}{\sqrt{1+\frac{\delta}{\kappa}}\sqrt{[\sum_{i=1}^{N} \theta_{i,t}^F]^2 + \sum_{i=1}^{N} (\theta_{i,t}^F)^2}}, \tag{9}$$

where $\theta_{i,t}^F$ denotes the portfolio composition of factor F_{t+1}.

The international correlation risk factor assigns equal weights but with opposite signs to the contributing currencies in the top and bottom terciles (7). As a result, the sum of portfolio weights associated with $HMLC$, and hence, its correlation (9) with the U.S. SDF approach zero in the limit of small international correlation disparity, $Corr_t\left(HMLC_{t+1}, \frac{M_{0,t+1}}{M_{0,t}}\right) \approx 0$. Intuitively, when there is little disparity in international correlation, a strategy based on the correlation disparity like $HMLC$ receives little signal, resulting in a factor of weak pricing power in that limit.

In contrast, as $CSCAR$ assigns heterogeneous weights to all currencies, the sum of $CSCAR$ portfolio weights and its correlation with the U.S. SDF remain nonzero in the limit of small international correlation disparity $|Corr_t\left(CSCAR_{t+1}, \frac{M_{0,t+1}}{M_{0,t}}\right)| > 0$. Intuitively, this is because $CSCAR$ employs signals from both FX covariances and spreads, the latter is characterized by forward discounts (6) and remain strictly heterogeneous across different foreign currencies i.[11] The resultant $CSCAR$ correlates more strongly with the U.S. SDF and has a stronger pricing power in the USD denomination than does $HMLC$ in the limit of small international correlation disparity.

Large international correlation disparity: In this limit, we can also explicitly compare the performance of $HMLC$ and $CSCAR$. Intuitively, when $z_t^w \gg z_t$, the exposure of a currency i to the international correlation disparity FXC_{t+1} is determined principally by the loading differential $(\sqrt{\gamma^0} - \sqrt{\gamma^i})$ in the dominant term in (5). As a result, $HMLC$ (7) assigns largest (long and short) weights to currencies that has extreme (largest and smallest) loadings γ^i. However, the composition of $HMLC$ is confined to a set of equal absolute weights. Such a constraint places a lower bound on the volatility that $HMLC$ can achieve, therefore an upper bound on its Sharpe ratio because all currency premiums remain finite in the limit of $z_t^w \gg z_t$. A similar argument applied on the carry strategy shows that the Sharpe ratio of CAR is also subject to an upper bound.

In the same limit, the dynamics of all exchange rates are dominated by the common global shock u_{t+1}^w (2). Hence, exchange rates in every pair X_i, X_j are either almost perfectly correlated (if $\gamma^i - \gamma^0$ and $\gamma^j - \gamma^0$ have the same sign) or almost perfectly negatively correlated (if $\gamma^i - \gamma^0$ and $\gamma^j - \gamma^0$ have different

11 State variable z_t^w is a common multiplicative factor in (4), so it does not influence the heterogeneity in the forward discounts and the associated portfolio weights of $CSCAR$.

signs). By taking appropriate positions in these highly (positively or negatively) correlating currencies, one can formulate currency strategies of very small volatilities. Because heterogeneous currency premiums (6), (4) do not cancel each other in this formulation, these currency strategies have a high Sharpe ratio. This argument shows that *CSCAR*, as a mean-variance optimal strategy in FX markets, necessarily has a high Sharpe ratio, and thus, strictly dominates the limited Sharpe ratios of *HMLC* and *CAR* established earlier in the same limit. The following proposition summarizes the comparative statics of *HMLC* and *CSCAR* in the benchmark model of the international correlation.

Proposition 1.

(i) *CSCAR* represents the unique minimum-variance pricing kernel of FX markets, hence, offers the highest Sharpe ratio in the USD denomination among all traded currency strategies.

(ii) *CSCAR* has a higher correlation with the model's full U.S. SDF, hence, a higher power in pricing traded financial assets than *HMLC* in the USD denomination in both limits of large and small FX correlation disparity.

(iii) As we explained earlier, the general optimality result (i) implies a specific result (ii) in the benchmark model. Several further observations that place *CSCAR* in light of a broader class of models are in order.

4.2.3 Discussion. First, the second global shock u^g_{t+1} has an identical price in all currencies (1). This eliminates u^g_{t+1} from exchange rates (2), generates a negative relationship between currency returns and exposures β_{FXC} to the international correlation risk, and is a key feature of the benchmark model by Mueller, Stathopoulos, and Vedolin (2017). This feature also implies that exchange rates highly (positively or negatively) correlate in the limit of a large FX correlation disparity, implying that the well-diversified *CSCAR* factor achieves a superior Sharpe ratio. In retrospect, working with the benchmark model enables an illustration of *CSCAR*'s efficiency and outperformance versus the model's characteristic factor *HLMC*, while upholding the same key feature of the FX correlation risk.

Second, beyond the benchmark model, the more general framework by Lustig, Roussanov, and Verdelhan (2014) replaces a single z_t by multiple country-specific local state variables $\{z^i_t\}$. Such a diverse set of country-specific shocks not only weakens the relationship and interpretation of a FX correlation risk factor with currency returns but also enriches the implications for efficiency of FX strategies. Conceptually, forward discounts cease to exactly equal currency risk premiums,

$$E_t[CT_{i,t+1}] = fd_{i,t} - \chi(z^i_t - z^0_t), \tag{10}$$

or *CSCAR* is not strictly the minimum-variance SDF in FX markets. Practically, however, the calibration in Lustig, Roussanov, and Verdelhan

(2014) shows that parameter χ, that is, the difference between currency risk premiums and forward discounts, is not significantly different from zero when the model is confronted by FX data. Furthermore, when the global state variable z_t^w dominates the local counterparts $\{z_t^i\}$, this difference is also small. Either case indicates the efficiency and optimality of $CSCAR$ as (approximately) the Hansen-Jagannathan SDF projector on the FX market return space. Third, $CSCAR$'s construction centers on the combined efficiency of spreads and covariances. With respect to spreads, strategies examined in Lustig, Roussanov, and Verdelhan (2014) and Mueller, Stathopoulos, and Vedolin (2017), including the carry, dollar carry, unconditional HML carry,[12] and the FX correlation $HMLC$ (7), all assign equal weights to the currencies contributing to these strategies. $CSCAR$'s portfolio weights vary quantitatively with currencies' spreads and keep $CSCAR$'s expected excess return away from zero in states where signals from FX correlations are weak as in the premise of Proposition 1. With respect to covariances, whenever FX markets have enough assets to reasonably diversify the portfolio risks $CSCAR$ delivers a high Sharpe ratio.

In sum, a necessary (and sufficient) condition for the dominance of $CSCAR$ over other FX factors is that forward discounts equal expected currency premiums. In the no-arbitrage multifactor framework of Lustig, Roussanov, and Verdelhan (2014), parametric values calibrated from FX data do not statistically significantly rule out this equality. Importantly, in this framework, the same model parameters enter the model-implied forward discounts and expected currency premiums, which justifies the employment of the former as a signal to achieve the efficiency and pricing power in FX markets via the construction of the $CSCAR$.

5. Conclusion

We adjust the Carry (CAR) factor to account for the covariance matrix of exchange rate growths (covariance adjustment) and the size of forward discounts (spread adjustment). We call this factor the Covariance- and Spread-adjusted Carry ($CSCAR$).

Using various sets of test assets and data of 15 developed and 29 developed and emerging currencies from 1984 to 2016, we find that that the single-factor $CSCAR$ model is able to price the cross-section of average FX market returns. In contrast, carry factors that do not use all the information of the covariance matrix and forward discounts are unable to price the cross-section

[12] The carry is the usual portfolio strategy taking long (short) positions in foreign currencies against the USD based on whether foreign interest rates are higher (lower) than the U.S. interest rate. The dollar carry takes a long (short) position in an equally weighted basket of foreign currencies against the USD when the average of foreign interest rates is higher (lower) than the U.S. interest rate. The unconditional HML carry is similar to the carry, but is based on the time-series averages of interest rates, and hence, do not feature rebalancing of the portfolios.

of FX returns. Moreover, popular single- and multifactor models do not span the *CSCAR* factor and are rejected in our tests.

We further show that the conditional covariance matrix of exchange rate growths and forward discounts vary through time, and because they are important determinants of conditional expected returns (i.e., pricing), FX market returns are predictable 1 to 18 months ahead. We also document a substantial time-series variation in the conditional covariance matrix of exchange rate growths and forward discounts, and it is critical to account for this variation to price assets. Future empirical research should investigate the underlying economic fundamentals that drive this time-series variation.

A Technical Details

A.1 Sequentially Efficient GMM Estimation

This section provides details on the estimation of our factor pricing models in Section 3 using sequentially efficient GMM (Hansen 1982; Cochrane 2005; Shanken and Zhou 2007). We refer to the set of $(1+K)N$ moment conditions $E[\begin{pmatrix} 1 \\ F_t \end{pmatrix} \otimes (R_t - \alpha - \beta F_t)] = 0$ as the time-series pricing equations, and the N moment conditions $E[R_t - \gamma_0 1_{\{N\times 1\}} - \beta\gamma] = 0$ as the cross-sectional pricing equations. We first solve

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

where I_x is an identity matrix with dimension $x \times x$ and $g_T(\widehat{b}) = \frac{1}{T}\sum_{t=1}^{T} h_t(\widehat{b})$ with $h_t(\widehat{b}) = \begin{pmatrix} F_t - \mu \\ \begin{pmatrix} 1 \\ F_t \end{pmatrix} \otimes (R_t - \widehat{\alpha} - \widehat{\beta} F_t) \\ R_t - \widehat{\gamma}_0 1_{\{N\times 1\}} - \widehat{\beta}\widehat{\gamma} \end{pmatrix}$, is the sample estimate of $g(b)$. The closed-form solution of $\widehat{b}$ is

$$\widehat{\mu} = E[F_t]$$

$$\begin{pmatrix} \widehat{\alpha}' \\ \widehat{\beta} \end{pmatrix} = E\left[\begin{pmatrix} 1 \\ F_t \end{pmatrix}\begin{pmatrix} 1 & F_t' \end{pmatrix}\right]^{-1} E\left[\begin{pmatrix} 1 \\ F_t \end{pmatrix} R_t'\right]$$

$$\begin{pmatrix} \widehat{\gamma}_0 \\ \widehat{\gamma} \end{pmatrix} = \left[\begin{pmatrix} 1_{1\times N} \\ \widehat{\beta}\prime \end{pmatrix}\begin{pmatrix} 1_{N\times 1} & \widehat{\beta} \end{pmatrix}\right]^{-1} \begin{pmatrix} 1_{1\times N} \\ \widehat{\beta}' \end{pmatrix} E[R_t],$$

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 μ, $\begin{pmatrix} \alpha \\ \beta \end{pmatrix}$, and $\begin{pmatrix} \gamma_0 \\ \gamma \end{pmatrix}$. Therefore, the point estimate of $\widehat{b}$ is identical to the estimate in two-stage time-series and cross-sectional regressions (Fama and MacBeth 1973). The covariance matrix of $\widehat{b}$ and $g_T(\widehat{b})$ are estimated as follows:

$$Cov(\widehat{b}) = \frac{1}{T}[A_1 D(\widehat{b})]^{-1} A_1 S(\widehat{b})([A_1 D(\widehat{b})]^{-1} A_1)'$$

$$Cov(g_T(\widehat{b})) = \frac{1}{T}\Big(I_{(2+K)N} - D(\widehat{b})[A_1 D(\widehat{b})]^{-1} A_1) S(\widehat{b})(I_{(2+K)N} - D(\widehat{b})[A_1 D(\widehat{b})]^{-1} A_1)',$$

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

$$D(\widehat{b}) = \frac{\partial g_T(\widehat{b})}{\partial \widehat{b}'} = \begin{pmatrix} -I_K & 0 & 0 & 0 & 0 \\ 0 & -I_N & -E[F_t'] \otimes I_N & 0 & 0 \\ 0 & -E[f_t] \otimes I_N & -E[F_t \otimes F_t'] \otimes I_N & 0 & 0 \\ 0 & 0 & -\widehat{\gamma}' \otimes I_N & -1_{\{N\times 1\}} & -\widehat{\beta} \end{pmatrix},$$

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

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

with $L = T^{1/4}$. Note that the estimate $S(\widehat{b})$ takes into account cross- and autocorrelations and heteroscedasticity. In a second step, we solve

$$A_2 g_T(\widehat{\widehat{b}}) = 0 \text{ with } A_2 = \begin{pmatrix} I_K & 0 & 0 \\ 0 & I_{(1+K)N} & 0 \\ 0 & 0 & D^*(\widehat{\widehat{b}})' S^*(\widehat{b})^{-1} \end{pmatrix},$$

where the $N \times (1+K)$ matrix $D^*(\widehat{\widehat{b}}) = (-1_{\{N\times 1\}} \quad -\widehat{\widehat{\beta}})$ is the $N \times (1+K)$ lower, right submatrix of $D(\widehat{b})$, and $S^*(\widehat{b})$ is the $N \times N$ lower, right submatrix of $S(\widehat{b})$. We only adjust the weights on the set of the N cross-sectional pricing equations using the information of the first-stage error covariance matrix $S(\widehat{b})$. This is the idea of sequentially efficient GMM. The alternative weighting matrix $\tilde{A}_2 = D(\widehat{b})' S(\widehat{b})^{-1}$ is theoretically more efficient than A_2, but in practice inverting the matrix $S(\widehat{b})$ can be difficult to do, and estimation errors can lead to nonrobust results. Shanken and Zhou (2007) show that more robust estimates are obtained with sequentially efficient GMM, that is, estimating (μ, α, and) β in a consistent but inefficient way, and then, given the estimates $\widehat{\beta}$, estimate γ_0 and γ using an efficient weighting matrix. The closed-form solution of $\widehat{b}$ is

$$\widehat{\widehat{\mu}} = \widehat{\mu}, \widehat{\widehat{\alpha}} = \widehat{\alpha}, \widehat{\widehat{\beta}} = \widehat{\beta}$$

$$\left(\widehat{\widehat{\gamma}}_0 \, \widehat{\widehat{\gamma}}\right) = -\left(D^*(\widehat{\widehat{b}})' S^*(\widehat{b})^{-1} D^*(\widehat{\widehat{b}})\right)^{-1} D^*(\widehat{\widehat{b}})' S^*(\widehat{b})^{-1} E[R_t].$$

$Cov(\widehat{\widehat{b}})$ and $Cov(g_T(\widehat{\widehat{b}}))$ are analogous to $Cov(\widehat{b})$ and $Cov(g_T(\widehat{b}))$ simply be replacing A_1 by A_2 and $\widehat{b}$ by $\widehat{\widehat{b}}$. $Cov(\widehat{\widehat{\alpha}})$ is given by the $N \times N$ submatrix between rows $K+1$ and $K+N$ and columns $K+1$ and $K+N$ of $Cov(\widehat{\widehat{b}})$. $Var(\widehat{\widehat{\gamma}}_0)$ is equal to the element on row $K+(1+K)N+1$ and column $K+(1+K)N+1$ of $Cov(\widehat{\widehat{b}})$. $Var(\widehat{\widehat{\gamma}}_k)$ is the element on row $K+(1+K)N+1+k$ and column $K+(1+K)N+1+k$ of $Cov(\widehat{\widehat{b}})$. $Var(\widehat{\widehat{\mu}}_k)$ is equal the element on row k and column k of $Cov(\widehat{\widehat{b}})$. $Cov(\widehat{\widehat{\mu}}_k, \widehat{\widehat{\gamma}}_k)$ is equal to the element on row k and column $K+(1+K)N+1+k$ of $Cov(\widehat{\widehat{b}})$. $Cov(\widehat{\widehat{\alpha}}^*)$, with $\widehat{\widehat{\alpha}}^* = E[R_t] - \widehat{\widehat{\gamma}}_0 1_{\{N\times 1\}} - \widehat{\widehat{\beta}}\widehat{\widehat{\gamma}}$, is the $N \times N$ lower, right submatrix of $Cov(g_T(\widehat{\widehat{b}}))$.

B. Tables

Table B1
Portfolio weights of *CSCAR*

A. Fifteen developed currencies

	Mean	Median	SD	Skew	Kurt	Min	Max	fd_i
Italy	0.227	0.064	0.470	1.712	8.798	−1.249	2.574	4.03
Norway	0.217	0.076	0.410	2.832	13.518	−0.333	2.999	2.10
United Kingdom	0.174	0.113	0.329	0.626	8.008	−1.489	1.659	1.76
New Zealand	0.170	0.106	0.266	2.597	14.936	−0.435	2.163	3.84
Australia	0.132	0.111	0.243	−0.275	4.674	−0.916	0.787	3.19
Sweden	0.039	0.020	0.315	−2.198	31.438	−2.739	1.777	1.46
Belgium	0.033	0.042	0.287	0.160	6.008	−1.082	1.208	0.67
Denmark	0.007	−0.026	0.244	2.010	17.325	−1.180	1.927	0.74
Canada	0.002	−0.020	0.318	0.763	8.972	−1.619	1.450	0.80
France	−0.043	−0.026	0.211	−0.637	9.917	−1.215	0.903	1.55
Euro	−0.073	−0.051	0.124	−2.600	22.313	−1.013	0.466	−0.29
Netherlands	−0.088	−0.050	0.198	−1.294	7.618	−1.006	0.568	−0.68
Germany	−0.123	−0.057	0.246	−2.061	8.537	−1.362	0.305	−0.93
Switzerland	−0.197	−0.137	0.278	0.221	16.500	−1.836	1.968	−1.72
Japan	−0.258	−0.198	0.301	−1.576	6.502	−1.624	0.508	−2.49

B. Twenty-nine developed and emerging currencies

	Mean	Median	SD	Skew	Kurt	Min	Max	fd_i
Mexico	0.339	0.163	0.503	1.620	5.645	−0.747	2.423	6.40
Portugal	0.333	0.291	0.322	0.913	4.001	−0.327	1.465	5.36
Brazil	0.311	0.273	0.285	1.215	5.394	−0.350	1.355	9.26
Greece	0.311	0.266	0.397	2.662	13.622	−0.174	2.274	4.78
Spain	0.237	0.193	0.292	0.183	5.980	−1.082	1.351	4.85
Iceland	0.210	0.135	0.238	1.358	4.797	−0.127	1.119	6.08
South Africa	0.199	0.124	0.328	1.829	8.273	−0.642	1.751	6.55
Hungary	0.190	0.105	0.341	1.625	9.036	−1.101	1.845	5.65
New Zealand	0.155	0.093	0.272	1.995	11.105	−0.505	1.946	3.84
Italy	0.108	0.039	0.353	1.128	6.177	−1.092	1.643	4.03
United Kingdom	0.067	0.023	0.294	1.144	11.850	−1.490	1.977	1.76
Norway	0.050	0.006	0.315	3.223	21.944	−1.112	2.466	2.10
Australia	0.049	0.023	0.240	0.338	5.951	−0.896	1.337	3.19
Belgium	0.030	0.027	0.205	−0.152	3.754	−0.648	0.597	0.67
Ireland	0.018	−0.009	0.266	0.128	5.002	−0.985	0.920	2.03
Poland	0.016	−0.010	0.192	2.099	16.545	−0.708	1.302	2.51
Taiwan	0.009	−0.007	0.223	2.440	14.521	−0.629	1.270	−0.85
South Korea	0.001	0.008	0.202	−0.277	4.068	−0.664	0.578	1.27
Canada	−0.006	−0.011	0.320	0.639	9.263	−1.406	1.821	0.80
Czech Republic	−0.023	−0.024	0.258	0.492	6.443	−1.028	1.029	0.87
Sweden	−0.023	−0.003	0.278	−1.317	14.880	−2.076	1.463	1.46
Denmark	−0.034	−0.036	0.180	2.228	18.435	−0.755	1.440	0.74
Euro	−0.061	−0.045	0.103	−0.064	8.376	−0.457	0.481	−0.29
Singapore	−0.069	−0.021	0.237	−2.614	17.841	−1.870	0.696	−1.17
France	−0.088	−0.062	0.210	−1.978	12.296	−1.314	0.540	1.55
Netherlands	−0.126	−0.105	0.192	−0.448	9.120	−1.035	0.811	−0.68
Germany	−0.133	−0.099	0.210	−2.233	12.339	−1.344	0.300	−0.93
Switzerland	−0.180	−0.111	0.263	−1.086	5.899	−1.437	0.682	−1.72
Japan	−0.206	−0.163	0.276	−1.470	7.036	−1.794	0.352	−2.49

Summary statistics of portfolio weights $\theta_t^{CSCAR} = \tilde{\Omega}_t^{-1} fd_t$.
CSCAR incorporates information from both the robust covariance matrix of exchange rate growths and the forward discounts. fd_t is the vector of forward discounts of all exchange rates against the USD, and $\tilde{\Omega}_t$ is a robust version of the conditional covariance matrix Ω_t of all exchange rate growths at the end of month t. fd_i (in the last column) is the average annualized forward discount in percentage points of the exchange rate between currency i and USD. The data of 15 developed countries (panel A) and 29 developed and emerging currencies (panel B) are from January 1984 to February 2016.

Table B2
Single-factor *CSCAR* pricing model

A. Fifteen developed currencies

	5 IntP	5 Mom P & 5 ValP	15 Assets	6 DB & 4 FXCB	25 assets	11 assets	36 assets
$\widehat{\gamma}_0$	0.68	−1.02	−0.85	1.06	0.85	1.62*	0.71
	(.36)	(-.51)	(-.51)	(.62)	(.77)	(1.87)	(1.44)
$\widehat{\gamma}_{CSCAR}$	9.01*	9.39**	9.59***	10.49	8.34***	6.40***	7.14***
	(2.48)	(2.48)	(3.23)	(.93)	(3.13)	(3.59)	(4.21)
R^2 (%)	90.48	35.46	45.55	15.22	31.47	83.69	53.33
$\widehat{\gamma}_{CSCAR} - \widehat{\mu}_{CSCAR}$	0.61	1.00	1.20	2.09	−0.06	−2.00*	−1.26
	(.20)	(.31)	(.54)	(.20)	(.03)	(2.20)	(1.32)
Joint test of cross-sectional regression $\widehat{\alpha}^* = 0$:							
χ^2-test	0.69	14.61	15.98	8.75	27.07	10.45	45.57
(p-value)	(.95)	(.10)	(.31)	(.46)	(.30)	(.40)	(.11)
Joint test of time-series regression $\widehat{\alpha} = 0$:							
F-test	0.17	1.46	1.06	1.09	1.03	1.38	1.19
(p-value)	(.97)	(.15)	(.39)	(.37)	(.43)	(.18)	(.22)

B. Twenty-nine developed and emerging currencies

	5 IntP	5 MomP & 5 ValP	15 assets	6 DB & 4 FXCB	25 assets	11 assets	36 assets
$\widehat{\gamma}_0$	−0.39	−1.08	−1.34	2.56*	1.32	0.33	0.03
	(-.22)	(-.52)	(-.83)	(2.26)	(1.43)	(.67)	(.10)
$\widehat{\gamma}_{CSCAR}$	10.22*	11.71**	12.07***	5.62	10.44***	9.68***	10.57***
	(2.42)	(2.42)	(3.30)	(.74)	(3.32)	(4.44)	(5.39)
R^2 (%)	53.88	29.59	44.91	6.65	29.27	96.07	77.39
$\widehat{\gamma}_{CSCAR} - \widehat{\mu}_{CSCAR}$	−0.61	0.87	1.24	−5.21	−0.39	−1.15	−0.26
	(.18)	(.19)	(.42)	(.76)	(.16)	(1.54)	(.19)
Joint test of cross-sectional regression $\widehat{\alpha}^* = 0$:							
χ^2-test	7.25	11.36	17.18	11.41	31.07	11.53	47.39*
(p-value)	(.12)	(.25)	(.25)	(.25)	(.15)	(.32)	(.08)
Joint test of time-series regression $\widehat{\alpha} = 0$:							
F-test	1.44	1.19	1.19	1.49	1.21	1.03	1.20
(p-value)	(.21)	(.30)	(.28)	(.14)	(.22)	(.42)	(.21)

Estimates of the cross-sectional pricing equation $E[R_t] = \gamma_0 1_{\{N\times 1\}} + \beta\gamma$ using sequentially efficient GMM for *CSCAR* as a single pricing factor. Appendix A.1 provides details about the estimation. *CSCAR* factor return, $\sum_i \theta_{i,t}^{CSCAR} CT_{i,t+1}, \theta_t^{CSCAR} = \tilde{\Omega}_t^{-1} fd_t$, incorporate the information of both robust covariation between exchange rate growths and the forward discounts. R^2 is the model fit of the cross-sectional pricing equation. χ^2-test is the joint test statistic of $\alpha_i^* = 0$ for all test assets $i \in \{1, \ldots, N\}$. F-test is the joint test statistic of $\alpha_i = 0$ for all test assets $i \in \{1, \ldots, N\}$. *t*-statistics are in parentheses below coefficient estimates, and *p*-values are below the χ^2- and F-test statistics. Errors are estimated taking into account auto- and cross-sectional correlations and heteroscedasticity according to Newey and West (1987). The data are our set of 15 developed countries (panel A) and 29 developed and emerging currencies (panel B) from January 1984 to February 2016.
*$p < 1$;
**$p < .05$;
***$p < .01$.

Table B3

Carry and dollar carry (without market timing)

Fifteen developed currencies	25 Test assets			Thirty-six test assets		
$\widehat{\gamma}_0$	3.46**	0.27	1.35	1.69***	1.12**	1.09**
	(2.64)	(.19)	(1.06)	(3.48)	(2.26)	(2.37)
$\widehat{\gamma}_{DOL}$	−2.96	−0.39	−1.46	−1.44	−0.78	−0.75
	(−1.52)	(−.20)	(−.76)	(−.93)	(−.53)	(−.50)
$\widehat{\gamma}_{CAR}$	4.36**			4.06**		
	(2.47)			(2.50)		
$\widehat{\gamma}_{DDOL}$		5.13**			3.82**	
		(2.58)			(2.55)	
$\widehat{\gamma}_{NSCAR}$			4.84***			3.71***
			(2.96)			(2.96)
R^2 (%)	19.83	25.11	35.30	38.58	40.64	45.77
$\widehat{\gamma}_{DOL} - \widehat{\mu}_{DOL}$	−4.66***	−2.08	−3.15**	−3.13**	−2.48*	−2.44*
	(3.02)	(1.27)	(2.08)	(2.63)	(2.01)	(2.00)
$\widehat{\gamma}_{CAR} - \widehat{\mu}_{CAR}$	−0.87			−1.16		
	(.94)			(.96)		
$\widehat{\gamma}_{DDOL} - \widehat{\mu}_{DDOL}$		0.04			−1.27	
		(.02)			(1.44)	
$\widehat{\gamma}_{NSCAR} - \widehat{\mu}_{NSCAR}$			−0.92			−2.06**
			(.78)			(2.05)
Joint test of cross-sectional regression $\widehat{\alpha}^* = 0$:						
χ^2-test	39.75**	37.25**	33.13*	63.26***	62.26***	59.21***
(p-value)	(.02)	(.03)	(.08)	(.00)	(.00)	(.00)
Joint test of time-series regression $\widehat{\alpha} = 0$:						
F-test	1.52*	1.39	1.21	1.93***	1.74***	1.74***
(p-value)	(.05)	(.10)	(.23)	(.00)	(.01)	(.01)
Abnormal return of CSCAR in the cross-section (α^*_{CSCAR}) and time-series (α_{CSCAR}):						
α^*_{CSCAR}				5.42***	6.66***	5.36***
				(3.67)	(4.16)	(3.50)
α_{CSCAR}				6.51***	7.43***	5.60***
				(4.69)	(4.62)	(4.23)

This table reports estimates of the cross-sectional pricing equation $E[R_t] = \gamma_0 1_{\{N\times 1\}} + \beta\gamma$ using sequentially efficient GMM. *CAR* is the equally weighted Carry factor; *NSCAR* further adjusts for the spread in forward discounts at a constant notional value; *DOL* invests equally in all foreign currencies against the USD; and *DDOL* takes a long or short position in *DOL* depending on the median forward discount. R^2 is the model fit of the cross-sectional pricing equation. The χ^2-test is the joint test statistic of $\alpha_i^* = 0$ for all test assets $i \in \{1, \ldots, N\}$. The F-test is the joint test statistic of $\alpha_i = 0$ for all test assets $i \in \{1, \ldots, N\}$. *t*-statistics are in parentheses below the coefficient estimates. Errors are estimated taking into account auto- and cross-sectional correlations and heteroscedasticity according to Newey and West (1987). The data are our set of 15 developed countries from January 1984 to February 2016.

*p <0.1;
**p <0.05;
***p <0.01.

Table B4
Managing volatility

Fifteen developed currencies	Twenty-five test assets			Thirty-six test assets		
$\widehat{\gamma}_0$	2.96**	0.70	−1.09	1.19**	1.20**	0.91
	(2.41)	(.54)	(-.64)	(2.40)	(2.57)	(1.23)
$\widehat{\gamma}_{DOL}$	−2.49	−1.02	1.54	−1.10	−0.93	0.09
	(−1.32)	(−.51)	(.66)	(−.74)	(−.63)	(.05)
$\widehat{\gamma}_{DDOL}$			6.81***			4.43**
			(3.03)			(2.65)
$\widehat{\gamma}_{CAR}$			4.58**			3.76**
			(2.39)			(2.15)
$\widehat{\gamma}_{CAR_{VM}}$	10.39**		11.86*	3.45*		3.93*
	(2.62)		(1.85)	(1.82)		(1.87)
$\widehat{\gamma}_{NSCAR}$			5.82**			4.21***
			(2.66)			(3.07)
$\widehat{\gamma}_{NSCAR_{VM}}$		17.20***	16.53**		6.32**	6.96**
		(3.77)	(2.22)		(2.45)	(2.56)
$\widehat{\gamma}_{MOM}$			1.56			0.96
			(1.44)			(1.00)
$\widehat{\gamma}_{VAL}$			4.80***			3.78***
			(3.31)			(2.77)
R^2 (%)	32.26	43.37	61.60	34.55	38.35	52.56
Joint test of cross-sectional regression $\widehat{\alpha}^* = 0$:						
χ^2-test	32.36*	26.38	14.40	70.18***	68.96***	52.82***
(p-value)	(.09)	(.28)	(.64)	(.00)	(.00)	(.00)
Joint test of time-series regression $\widehat{\alpha} = 0$:						
F-test	1.47*	1.40*	0.84	1.93***	1.94***	1.71***
(p-value)	(.07)	(.10)	(.68)	(.00)	(.00)	(.01)
Abnormal return of CSCAR in the cross-section (α^*_{CSCAR}) and time-series (α_{CSCAR}):						
α^*_{CSCAR}				6.10***	5.56***	4.76***
				(4.02)	(3.46)	(3.43)
α_{CSCAR}				5.27***	5.40***	3.94***
				(4.14)	(3.97)	(3.56)

This table reports estimates of the cross-sectional pricing equation $E[R_t] = \gamma_0 1_{\{N\times 1\}} + \beta\gamma$ using sequentially efficient GMM. Details about the estimation are in Appendix A.1. CAR is the equally weighted Carry factor; the volatility-managed CAR_{VM} adjusts for the variance of CAR's return; $NSCAR$ adjusts for the spread in forward discounts at a constant notional value; the volatility-managed $NSCAR_{VM}$ adjusts for the variance of $NSCAR$'s return; DOL invests equally in all foreign currencies against the USD; $DDOL$ takes a long or short position in DOL depending on the median forward discount; MOM (momentum) sorts currencies based on the past performance; and VAL (value) sorts currencies based on the real exchange rate. R^2 is the model fit of the cross-sectional pricing equation. The χ^2-test is the joint test statistic of $\alpha_i^* = 0$ for all test assets $i \in \{1, \ldots, N\}$. The F-test is the joint test statistic of $\alpha_i = 0$ for all test assets $i \in \{1, \ldots, N\}$. t-statistics are in parentheses below the coefficient estimates. Errors are estimated taking into account auto- and cross-sectional correlations and heteroscedasticity according to Newey and West (1987). The data are our set of 15 developed countries from January 1984 to February 2016.
*p <0.1;
**p <0.05;
***p <0.01.

Table B5

Importance of spread and covariance adjustments

Fifteen developed currencies	Twenty-five test assets			Thirty-six test assets		
$\widehat{\gamma}_0$	0.47	0.07	1.19	1.09**	0.94**	1.18**
	(.41)	(.06)	(1.08)	(2.39)	(2.03)	(2.57)
$\widehat{\gamma}_{SCAR}$	4.90**			4.30***		
	(2.18)			(2.73)		
$\widehat{\gamma}_{VSCAR}$		7.84***			7.00***	
		(2.85)			(3.83)	
$\widehat{\gamma}_{CECAR}$			10.22**			2.64
			(2.33)			(1.50)
R^2 (%)	9.43	20.93	17.49	37.39	46.12	32.92
$\widehat{\gamma}_{SCAR} - \widehat{\mu}_{SCAR}$	−1.01			−1.61		
	(.62)			(1.48)		
$\widehat{\gamma}_{VSCAR} - \widehat{\mu}_{VSCAR}$		−1.34			−2.18*	
		(.70)			(1.90)	
$\widehat{\gamma}_{CECAR} - \widehat{\mu}_{CECAR}$			3.27			−4.31***
			(.86)			(3.49)
Joint test of cross-sectional regression $\widehat{\alpha}^* = 0$:						
χ^2-test	42.04**	29.72	30.07	63.82***	53.25**	69.43***
(p-value)	(.01)	(.19)	(.18)	(.00)	(.02)	(.00)
Joint test of time-series regression $\widehat{\alpha} = 0$:						
F-test	1.53*	1.05	1.46*	1.78***	1.44*	1.89***
(p-value)	(.05)	(.41)	(.07)	(.00)	(.05)	(.00)
Abnormal return of CSCAR in the cross-section (α^*_{CSCAR}) and time-series (α_{CSCAR}):						
α^*_{CSCAR}				5.73***	4.14***	5.98***
				(3.99)	(3.24)	(4.27)
α_{CSCAR}				6.22***	4.05***	5.16***
				(4.76)	(3.50)	(4.65)

This table reports estimates of the cross-sectional pricing equation $E[R_t] = \gamma_0 1_{\{N\times 1\}} + \beta\gamma$ using sequentially efficient GMM. Details about the estimation are in Appendix A.1. *CAR* is the equally weighted Carry factor; *SCAR* adjusts for the spread in forward discounts and times the market based on the forward discounts; *VSCAR* further adjusts for the variances (but not the correlations) of currency returns; and *CECAR* adjusts for the correlations of currency returns and the sign of the forward discounts. R^2 is the model fit of the cross-sectional pricing equation. The χ^2-test is the joint test statistic of $\alpha^*_i = 0$ for all test assets $i \in \{1, \ldots, N\}$. The F-test is the joint test statistic of $\alpha_i = 0$ for all test assets $i \in \{1, \ldots, N\}$. *t*-statistics are in parentheses below coefficient estimates, and *p*-values are below the χ^2- and F-test statistics. Errors are estimated taking into account auto- and cross-sectional correlations and heteroscedasticity according to Newey and West (1987). The data are our set of 15 developed countries from January 1984 to February 2016.

*p <0.1;

**p <0.05;

***p <0.01.

Table B6

Importance of market timing and robust estimate of covariance matrix

Fifteen developed currencies	Twenty-five test assets			Thirty-six test assets		
$\widehat{\widehat{\gamma}}_0$	1.37	1.28	1.78*	1.09**	0.95**	1.34***
	(1.27)	(1.21)	(1.73)	(2.38)	(2.05)	(2.94)
$\widehat{\widehat{\gamma}}_{CSCAR_{CR}}$	7.69***			4.26**		
	(2.99)			(2.47)		
$\widehat{\widehat{\gamma}}_{CSCAR_{CV}}$		8.77***			6.33***	
		(3.29)			(3.49)	
$\widehat{\widehat{\gamma}}_{CSCAR_{\text{full}}}$			10.86			9.94*
			(1.68)			(1.98)
R^2 (%)	24.05	29.34	7.29	36.65	43.10	37.23
$\widehat{\widehat{\gamma}}_{CSCAR_{CR}} - \widehat{\widehat{\mu}}_{CSCAR_{CR}}$	1.80			−1.62		
	(.86)			(1.44)		
$\widehat{\widehat{\gamma}}_{CSCAR_{CV}} - \widehat{\widehat{\mu}}_{CSCAR_{CV}}$		0.57			−1.87*	
		(.29)			(1.71)	
$\widehat{\widehat{\gamma}}_{CSCAR_{\text{full}}} - \widehat{\widehat{\mu}}_{CSCAR_{\text{full}}}$			6.00			5.08
			(.93)			(.90)
Joint test of cross-sectional regression $\widehat{\widehat{\alpha}}^* = 0$:						
χ^2-test	31.70	28.50	48.38***	66.63***	64.01***	71.45***
(p-value)	(.13)	(.24)	(.00)	(.00)	(.00)	(.00)
Joint test of time-series regression $\widehat{\widehat{\alpha}} = 0$:						
F-test	1.35	1.16	2.09***	1.86***	1.83***	2.13***
(p-value)	(.13)	(.28)	(.00)	(.00)	(.00)	(.00)
Abnormal return of CSCAR in the cross-section (α^*_{CSCAR}) and time-series (α_{CSCAR}):						
α^*_{CSCAR}				4.82***	3.11***	5.53***
				(3.88)	(3.14)	(3.38)
α_{CSCAR}				4.96***	2.79***	7.65***
				(4.75)	(4.22)	(4.81)

This table reports estimates of the cross-sectional pricing equation $E[R_t] = \gamma_0 1_{\{N\times 1\}} + \beta\gamma$ using sequentially efficient GMM. Details about the estimation are in Appendix A.1. *CAR* is the equally weighted Carry factor; *CSCAR* adjusts for both robust covariation between exchange rate growths and the forward discounts; $CSCAR_{CR}$ further features a constant notional value and $CSCAR_{CV}$ features a constant volatility; and $CSCAR_{full}$ is similar to *CSCAR* but employs the original (nonrobust) covariation between exchange rate growths. R^2 is the model fit of the cross-sectional pricing equation. χ^2-test is the joint test statistic of $\alpha_i^* = 0$ for all test assets $i \in \{1, \dots, N\}$. F-test is the joint test statistic of $\alpha_i = 0$ for all test assets $i \in \{1, \dots, N\}$. *t*-statistics are in parentheses below coefficient estimates, and *p*-values are below the χ^2- and F-test statistics. Errors are estimated taking into account auto- and cross-sectional correlations and heteroscedasticity according to Newey and West (1987). The data are our set of 15 developed countries from January 1984 to February 2016.
*p <0.1;
**p <0.05;
***p <0.01.

Table B7
Volatility, illiquidity, and skewness

Fifteen developed currencies	Twenty-five test assets			Thirty-six test assets		
$\widehat{\gamma}_0$	3.12**	2.84**	1.78	1.58***	1.49***	1.56***
	(2.35)	(2.27)	(1.34)	(3.03)	(3.13)	(3.24)
$\widehat{\gamma}_{DOL}$	−2.80	−2.59	−1.89	−1.36	−1.34	−1.20
	(-1.44)	(-1.40)	(-1.00)	(-.89)	(-.89)	(-.83)
$\widehat{\gamma}_{VOL}$	−4.09			−1.68		
	(-.96)			(-.46)		
$\widehat{\gamma}_{ILL}$		−1.90			−1.62	
		(-.39)			(-.48)	
$\widehat{\gamma}_{SKEW}$			−13.41**			−11.72***
			(-2.69)			(-3.20)
R^2 (%)	6.41	4.56	23.90	31.66	31.68	44.25
$\widehat{\gamma}_{DOL} - \widehat{\mu}_{DOL}$	−4.49***	−4.28***	−3.58**	−3.06**	−3.03**	−2.89**
	(2.92)	(2.88)	(2.18)	(2.59)	(2.68)	(2.29)
Joint test of cross-sectional regression $\widehat{\alpha}^* = 0$:						
χ^2-test	46.57***	50.35***	37.47**	72.12***	73.46***	65.16***
(p-value)	(.00)	(.00)	(.03)	(.00)	(.00)	(.00)
Abnormal return of CSCAR in the cross-section (α^*_{CSCAR}):						
α^*_{CSCAR}				6.78***	6.97***	5.83***
				(4.45)	(4.32)	(3.81)

This table reports estimates of the cross-sectional pricing equation $E[R_t] = \gamma_0 1_{\{N\times 1\}} + \beta\gamma$ using sequentially efficient GMM. Details about the estimation are in Appendix A.1. *DOL* invests equally in all foreign currencies against the USD; *VOL* characterizes unexpected changes in the global FX market volatility; *ILL* characterizes unexpected changes in the global FX market illiquidity; and *SKEW* characterizes the global FX market skewness. R^2 is the model fit of the cross-sectional pricing equation. The χ^2-test is the joint test statistic of $\alpha_i^* = 0$ for all test assets $i \in \{1,\dots,N\}$. The F-test is the joint test statistic of $\alpha_i = 0$ for all test assets $i \in \{1,\dots,N\}$. *t*-statistics are in parentheses below coefficient estimates, and *p*-values are below the χ^2- and F-test statistics. Errors are estimated taking into account auto- and cross-sectional correlations and heteroscedasticity according to Newey and West (1987). The data are our set of 15 developed countries from January 1984 to February 2016.
*$p < 0.1$;
**$p < 0.05$;
***$p < 0.01$.

Table B8
Downside risk and intermediary capital ratio

Fifteen developed currencies	25 test assets			36 test assets		
γ_0	1.44	1.40	1.21	2.14***	1.68***	1.88***
	(1.48)	(1.41)	(1.15)	(4.07)	(3.03)	(3.44)
γ_{MKT}	11.26	7.63	9.37	−5.95	−2.62	−4.09
	(1.50)	(1.26)	(1.46)	(-1.06)	(-.49)	(-.81)
γ_{DSR}	−0.77		−1.61	3.97		3.97
	(-.21)		(-.43)	(1.27)		(1.27)
γ_{INT}		22.06**	25.53**		9.13	7.39
		(2.24)	(2.30)		(1.10)	(.91)
R^2 (%)	−11.71	19.60	28.76	8.21	16.68	25.06
$\gamma_{MKT} - E[MKT]$	3.60	−0.04	1.70	−13.61**	−10.29*	−11.76**
	(.48)	(-.01)	(.26)	(-2.43)	(-1.92)	(-2.34)
$\gamma_{INT} - E[INT]$		9.77	13.25		−3.15	−4.89
		(.99)	(1.19)		(-.38)	(-.60)
Joint test of cross-sectional regression α_j^*:						
χ^2-test ($\alpha^* = 0$)	38.18**	33.07*	30.65*	69.96***	65.68***	64.82***
(p-value)	(.02)	(.06)	(.08)	(.00)	(.00)	(.00)
Joint test of time-series regression α_j:						
F-test ($\alpha = 0$)		1.49*			2.21***	
(p-value)		(.06)			(.00)	
Abnormal return of CSCAR in the cross-section (α^*_{CSCAR}) and time-series (α_{CSCAR}):						
α^*_{CSCAR}				5.50***	6.34***	5.38***
(t-test)				(4.95)	(5.13)	(4.80)
α_{CSCAR}					8.23***	
(t-test)					(4.92)	

Estimates of the cross-sectional pricing equation $E[R_t] = \gamma_0 1_{\{N\times1\}} + \beta\gamma$ using sequentially efficient GMM. Details about the estimation are in Appendix A.1. *MKT* is the value-weighted US stock market index, *DSR* is the stock market downside risk factor, and *INT* is the traded intermediary capital risk factor. R^2 is the model fit of the cross-sectional pricing equation. χ^2-test is the joint test statistic of $\alpha_i^* = 0$ for all test assets $i \in \{1, \ldots, N\}$. F-test is the joint test statistic of $\alpha_i = 0$ for all test assets $i \in \{1, \ldots, N\}$. t-statistics are in parentheses below coefficient estimates, and p-values are below the χ^2- and F-test statistics. Errors are estimated taking into account auto- and cross-sectional correlations and heteroscedasticity according to Newey and West (1987). The data are our set of 15 developed countries from January 1984 to February 2016.
*$p < 1$;
**$p < 0.5$;
***$p < .01$.

Table B9

Dollar beta and FX correlation dispersion

Fifteen developed currencies	25 test assets		11 test assets		36 test assets	
$\widehat{\gamma}_0$	2.01*	2.83**	1.90**	1.83*	1.48***	1.50***
	(1.96)	(2.27)	(2.27)	(1.99)	(3.24)	(3.15)
$\widehat{\gamma}_{DOL}$		−2.55		4.91		−1.26
		(-1.39)		(1.77)		(-.85)
$\widehat{\gamma}_{CAR}$	4.32**		4.15*		3.95**	
	(2.52)		(2.01)		(2.48)	
$\widehat{\gamma}_{HMLDB}$	2.67		4.35		2.00	
	(1.60)		(1.36)		(1.26)	
$\widehat{\gamma}_{HMLC}$		−1.08		−0.91		−0.70
		(-.72)		(-.25)		(-.50)
R^2 (%)	14.84	4.92	70.14	68.08	37.36	31.60
$\widehat{\gamma}_{DOL} - \widehat{\mu}_{DOL}$		−4.25***		3.22		−2.95**
		(2.85)		(1.24)		(2.56)
$\widehat{\gamma}_{CAR} - \widehat{\mu}_{CAR}$	−0.91		−1.08		−1.28	
	(1.00)		(.70)		(1.07)	
$\widehat{\gamma}_{HMLDB} - \widehat{\mu}_{HMLDB}$	−1.21*		0.47		−1.87**	
	(2.06)		(.17)		(2.42)	
$\widehat{\gamma}_{HMLC} - \widehat{\mu}_{HMLC}$		0.92		1.09		1.30
		(1.58)		(.32)		(1.68)
Joint test of cross-sectional regression $\widehat{\alpha}^* = 0$:						
χ^2-test	35.27**	50.71***	22.95***	24.34***	61.27***	73.87***
(p-value)	(.05)	(.00)	(.01)	(.00)	(.00)	(.00)
Joint test of time-series regression $\widehat{\alpha} = 0$:						
F-test	1.39	2.02***	3.15***	3.34***	1.80***	2.30***
(p-value)	(.10)	(.00)	(.00)	(.00)	(.00)	(.00)
Abnormal return of CSCAR in the cross-section (α^*_{CSCAR}) and time-series (α_{CSCAR}):						
α^*_{CSCAR}			5.04***	5.96***	5.54***	7.06***
			(3.71)	(4.04)	(3.89)	(4.42)
α_{CSCAR}			6.56***	8.19***	6.56***	8.19***
			(4.71)	(5.04)	(4.71)	(5.04)

Estimates of the cross-sectional pricing equation $E[R_t] = \gamma_0 1_{\{N\times 1\}} + \beta\gamma$ using sequentially efficient GMM. Details about the estimation are in Appendix A.1. *HMLDB* (dollar beta factor) is a long-short strategy based on currency loadings on the *DOL* factor, *HMLC* is a long-short strategy based on currency loadings on the FX market correlation dispersion. R^2 is the model fit of the cross-sectional pricing equation. χ^2-test is the joint test statistic of $\alpha_i^* = 0$ for all test assets $i \in \{1, \ldots, N\}$. F-test is the joint test statistic of $\alpha_i = 0$ for all test assets $i \in \{1, \ldots, N\}$. *t*-statistics are in parentheses below coefficient estimates, and *p*-values are below the χ^2- and F-test statistics. Errors are estimated taking into account auto- and cross-sectional correlations and heteroscedasticity according to Newey and West (1987). The data are our set of 15 developed countries from January 1984 to February 2016.

*$p < 1$;

**$p < 0.5$;

***$p < .01$.

Table B10
Predictive regressions

A. h = 1 month

	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8
x_1	−0.037***	−0.003***	0.341***	0.280***	0.127	0.226**	0.143**	0.170*
x_2	0.012	−0.000	−0.199	0.120	0.342	−0.580*	−0.153	−0.242
x_3	0.019***	0.002***	−0.105	0.004	−0.285**	−0.071	0.016	−0.020
x_4	0.000	−0.002**	0.216	0.058	0.401***	0.247	−0.008	−0.099
x_5	0.474***	0.013	−1.307	−1.075	−0.777	0.191	1.266	1.110
x_6	0.905**	0.688***	−2.805	1.233	−2.247	−4.452	−5.128	4.704
R^2 (%)	53.48	59.05	3.85	2.22	5.12	1.37	0.05	−0.05

B. h = 6 months

	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8
x_1	−0.011***	−0.001	0.141***	0.132***	−0.021	0.091*	0.069***	0.019
x_2	−0.001	−0.003	−0.187	0.082	0.274*	−0.109	−0.099	0.208
x_3	0.013***	0.001	−0.022	−0.018	−0.090*	−0.050	−0.015	−0.009
x_3	0.009	−0.002	0.094	0.024	0.219**	0.047	0.053	−0.073
x_5	0.307***	−0.013	0.372	0.704	0.479	0.603	−0.451	0.135
x_6	0.935**	0.564***	2.107	1.080	2.079	6.749*	−1.290	8.476***
R^2 (%)	34.46	42.52	6.62	2.01	11.87	9.00	2.75	3.74

C. h = 12 months

	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8
x_1	−0.004	−0.000	0.102***	0.085***	0.012	0.059*	0.035*	0.041
x_2	−0.015	−0.004	−0.121	0.099	0.016	−0.261**	−0.053	0.249***
x_3	0.006**	−0.000	0.023	0.027	−0.074**	0.011	−0.004	0.009
x_4	0.014*	−0.002	−0.020	−0.054	0.260***	0.164**	0.046	−0.089
x_5	0.179***	−0.021*	1.423**	1.177**	0.471	0.056	−0.138	−0.060
x_6	0.936**	0.465***	−0.132	−1.714	2.862	9.660***	−0.206	7.021***
R^2 (%)	24.45	35.40	14.36	5.10	20.16	21.47	0.45	9.94

D. h = 18 months

	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8
x_1	−0.002	−0.001	0.082***	0.063**	0.007	0.058***	0.019	0.045*
x_2	−0.015	−0.003	−0.082	0.165	−0.084	−0.204***	−0.055	0.159**
x_3	0.003	−0.001	0.053*	0.048**	−0.048*	0.024	0.006	−0.007
x_4	0.010	−0.004***	0.003	0.008	0.236***	0.110*	0.011	−0.045
x_5	0.101*	−0.023**	1.377**	1.095***	0.451	0.001	0.114	−0.171
x_6	0.849**	0.369***	0.091	−0.763	2.480	8.421***	0.442	4.744*
R^2 (%)	15.45	31.65	19.50	9.52	25.70	27.01	0.11	7.62

Predictive regression $Y_{t,t+h} = c_{const} + c_{trend}t + \sum_j c_j x_{j,t} + \varepsilon_t$. $Y_{t,t+h} = \frac{1}{h}\sum_{\tau=1}^{h} Y_{t+\tau}$ at $h =$ 1-, 6-, 12-, and 18-month horizons. Predicted quantities are global FX market volatility $\tilde{VOL}$, illiquidity $\tilde{ILL}$ and currency returns of $CSCAR_{CR}$, CAR, DOL, $DDOL$, MOM, VAL. That is, Y: $Y_1 = VOL_{t,t+h}$, $Y_2 = ILL_{t,t+h}$, $Y_3 = CSCAR_{CR,t,t+h}$, $Y_4 = CAR_{t,t+h}$, $Y_5 = DOL_{t,t+h}$, $Y_6 = DDOL_{t,t+h}$, $Y_7 = MOM_{t,t+h}$, and $Y_8 = VAL_{t,t+h}$. Predictors x_j: $x_1 = \sum_i ||\theta_{i,t}||$ (notional value of $CSCAR$), $x_2 = \sum_i \theta_{i,t}$ (total exposure to risky assets of $CSCAR$), $x_3 = \sum_i ||\theta_{i,t} - \theta_{i,t-1}||$ (turnover of $CSCAR$), $x_4 = sign(median\{fd_{i,t}\})$ (sign of median forward discount across all currencies), $x_5 = \tilde{VOL}_t$ (global FX market volatility), $x_6 = \tilde{ILL}_t$ (global FX market illiquidity). R^2 (adjusted) in percentage measures the regression fit. The data are our set of 15 developed from January 1984 to February 2016. Standard errors are calculated using Newey and West (1987) to account for heteroscedasticity and autocorrelation.
*$p < 1$;
**$p < 0.5$;
***$p < .01$.

C. Figures

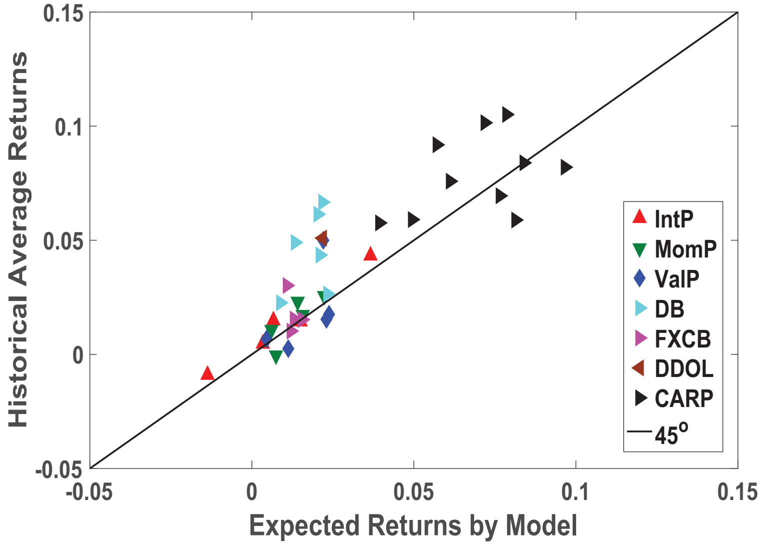

Figure C1
Single-factor *CSCAR* model fit: Developed currencies
This figure compares historical average returns and expected returns according to the single-factor CSCAR model, where we use the average return of CSCAR as the factor premium. IntP, MomP, ValP, DB, and FXCB denote, respectively, the test assets that are portfolios sorted on forward discounts, past currency returns, real exchange rates against the USD, the dollar factor, and the FX correlation dispersion. DDOL is the dynamic dollar factor, and CARP refers to the 10 optimized carry portfolios: CARV M, SCAR, NSCAR, NSCARV M, SCARCV, VSCAR, CECAR, CSCAR, CSCARCR, and CSCARCV. The data are our set of 15 developed currencies.

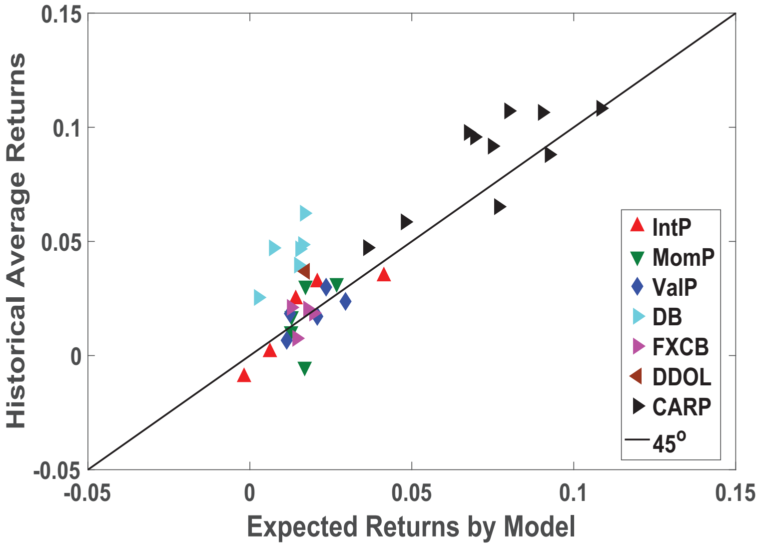

Figure C2
Single-factor *CSCAR* model fit: All currencies
This figure compares historical average returns and expected returns according to the single-factor CSCAR model, where we use the average return of CSCAR as the factor premium. IntP, MomP, ValP, DB, and FXCB denote, respectively, the test assets that are portfolios sorted on forward discounts, past currency returns, real exchange rates against the USD, the dollar factor, and the FX correlation dispersion. DDOL is the dynamic dollar factor, and CARP refers to the 10 optimized carry portfolios: CARV M, SCAR, NSCAR, NSCARV M, SCARCV, VSCAR, CECAR, CSCAR, CSCARCR, and CSCARCV. The data are our set of 29 developed and emerging currencies.

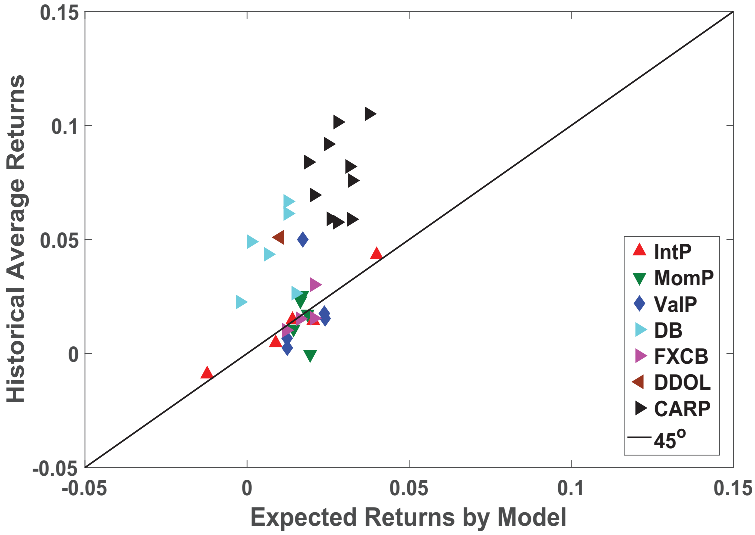

Figure C3
DOL-CAR **factor model fit: Developed currencies**
This figure compares historical average returns and expected returns according to the DOL-CAR factor model, where we use the average return of DOL-CAR as the factor premium. IntP, MomP, ValP, DB, and FXCB denote, respectively, the test assets that are portfolios sorted on forward discounts, past currency returns, real exchange rates against the USD, the dollar factor, and the FX correlation dispersion. DDOL is the dynamic dollar factor, and CARP refers to the 10 optimized carry portfolios: CARV M, SCAR, NSCAR, NSCARV M, SCARCV, VSCAR, CECAR, CSCAR, CSCARCR, and CSCARCV. The data are our set of 15 developed currencies.

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