International Correlation Risk☆

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Abstract

We document that the cross-sectional dispersion of conditional FX correlation is countercyclical and that currencies that perform badly (well) during periods of high dispersion yield high (low) average excess returns. We also find a negative cross-sectional association between average FX correlations and average option-implied FX correlation risk premiums. Our findings show that while investors in spot currency markets require a positive risk premium for exposure to high-dispersion states, FX option prices are consistent with investors being compensated for the risk of low-dispersion states. To address our empirical findings, we propose a no-arbitrage model that features unspanned FX correlation risk.

JEL classification: F31, G15

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1. Introduction

It is well known that stock return correlations are countercyclical and correlation risk is priced, arguably due to the reduction of diversification benefits that occurs when stock return correlations increase. However, existing literature has largely ignored the foreign exchange (FX) market. In this paper, we explore the properties of FX correlations using both spot and options market data and we propose a reduced-form no-arbitrage model that is consistent with our empirical findings.

First, we document the empirical properties of conditional FX correlations. We consider exchange rates against the U.S. dollar (USD) and show that there exists substantial cross-sectional heterogeneity in the average conditional correlation of FX pairs. Furthermore, using several business cycle proxies, we find that the cross-sectional dispersion of FX correlations is countercyclical: FX pairs with high (low) average correlation become more (less) correlated in adverse economic times. We exploit the cyclical properties of conditional FX correlation by defining an FX correlation dispersion measure, FXC, and sort currencies into portfolios based on the beta of their returns with respect to innovations in FXC, denoted by ΔFXC. We find that currencies with low ΔFXC betas have high average excess returns, whereas currencies with high ΔFXC betas yield low excess returns, suggesting that FX correlation risk has a negative price in spot FX markets. In particular, in our benchmark sample of G10 currencies, HML^C, a currency portfolio with a short position in the high ΔFXC beta currencies and a long position in the low ΔFXC beta currencies, generates a highly significant average annual excess return of 6.42% with a Sharpe ratio of 0.82.

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We continue our empirical investigation by using currency option prices to extract conditional FX correlation dynamics under the risk-neutral measure. We calculate FX correlation risk premiums, defined as the difference between conditional FX correlations under the risk-neutral measure and the physical measure, and we find a strongly negative cross-sectional association between average FX correlations and average FX correlation risk premiums: FX pairs characterized by low (high) average correlations tend to exhibit positive (negative) correlation risk premiums. Thus, the cross-sectional dispersion of FX correlations is on average lower under the risk-neutral measure than under the physical measure. We also document a very strong negative time-series association between FX correlations and FX correlation risk premiums for almost all FX pairs. As regards cyclicality, FX pairs with high average correlation risk premiums have countercyclical correlation risk premiums, whereas pairs with low correlation risk premiums have procyclical premiums. Thus, bad states amplify the magnitude of FX correlation risk premiums, increasing their cross-sectional dispersion.

We rationalize our empirical findings with a no-arbitrage model of exchange rates. The main tension we address is between the physical and the risk-neutral measure FX correlation dynamics. Under the physical measure, the negative association between ΔFXC betas and currency returns suggests that U.S. investors require a positive risk premium for being exposed to states in which the cross section of FX correlations *widens*. However, FX options are priced in a way that suggests that U.S. investors worry about states in which the cross section of FX correlations *tightens*, as the risk-neutral measure FX correlation dispersion is on average lower than its physical measure counterpart. To address this apparent contradiction, we propose a model in which FX correlation risk is not spanned by exchange rates: the pricing kernel of U.S. investors is exposed to shocks that affect conditional FX correlations, but not exchange rates themselves.

In the model, each country's stochastic discount factor (SDF) is exposed to two global shocks, as well as a single country-specific shock. Importantly, countries have heterogeneous loadings on the first global shock, but identical loadings on the second global shock. As a result, the absence of arbitrage in international financial markets suggests that exchange rates are exposed only to the first global shock, whereas the second global shock cancels out and does not affect exchange rates at all. The steady-state cross-sectional distribution of conditional FX correlations is determined by the cross section of exposures to the first global shock: on average, the USD exchange rates of foreign countries with similar exposure to the first global shock (called similar FX pairs) are more correlated than FX pairs of countries with dissimilar global risk exposure (called dissimilar FX pairs). Crucially, the cross section of conditional FX correlations exhibits time variation due to the fact that conditional FX correlations are determined by the relative importance of country-specific risk and global risk, which varies over time. When the relative magnitude of country-specific SDF shocks increases, the countries' heterogeneous exposure to the first global shock becomes less important quantitatively, and the cross section of conditional FX correlations tightens, with high correlation FX pairs becoming less correlated and low correlation FX pairs more correlated. Conversely, a relative increase in the magnitude of global risk increases the correlation of similar FX pairs and decreases the correlation of dissimilar FX pairs, widening the cross section of conditional FX correlations.

In turn, the relative magnitude of country-specific and global risk is determined by the relative magnitude of the local pricing factor, which prices country-specific risk and is exposed to the second global shock, and the global pricing factor, which prices global risk and is exposed to the first global shock. When the second global shock has an adverse realization, the local pricing factor increases, tightening the cross section of conditional FX correlations; conversely, when the second global shock has a positive realization, the cross section of conditional FX correlation becomes more dispersed. The reverse occurs for realizations of the first global shock: its adverse (positive) realizations increase (decrease) the global pricing factor, widening (tightening) the cross section of FX correlations. Thus, the cross section of conditional FX correlations is driven by both global shocks. In the model, both shocks are priced, but not symmetrically: U.S. investors price the second shock more severely than the first, so they attach a high price to states characterized by large relative values of the local pricing factor. Since those are exactly the states in which the cross-sectional dispersion of FX correlation is tight, our model is able to match the cross sectional properties of average correlation risk premiums implied by FX option prices.

As regards spot FX markets, recall that exchange rate risk does not span FX correlation risk, as exchange rates are unaffected by the second global shock. This lack of spanning allows our model to generate a negative relation between ΔFXC betas and currency returns: investing in exchange rates draws compensation solely for exposure to the first global shock and, since negative realizations of that shock lead to a widening of the cross section of FX correlations, investors require high returns for holding negative ΔFXC beta currencies, which depreciate when the cross section of conditional FX correlations becomes more dispersed.

In sum, conditional FX correlation, which can be indirectly traded using currency options, is exposed to two global shocks. U.S. investors price the second global shock more severely than the first one, so FX correlation risk premiums reflect the desire of currency option holders to primarily avoid states with negative realizations of the second shock—those are the states characterized by a tightening of the cross-sectional dispersion of FX correlation, and currency option prices reveal that feature. On the other hand, investing in foreign currency exposes investors only to the first global shock, so currency risk premiums reflect solely FX investors' desire to avoid the corresponding bad states—those states are characterized by a widening of the cross-sectional dispersion of FX correlation, and currency risk premiums compensate investors for exposure to those states. Thus, it is the lack of spanning of FX correlation risk by exchange rates and currency returns, and in particular the lack of exposure of exchange rates to the second global shock, that allows our model to jointly address the empirical properties of FX correlations, currency risk premiums and FX correlation risk premiums.

A simulated version of our model generates realized FX correlations, implied FX correlations and FX correlation risk premiums that match the cross-sectional and time-series properties of their empirical counterparts, all the while fitting the standard exchange rate, interest rate and inflation moments.

Related literature: This paper is part of the literature addressing the salient empirical properties of FX markets. Our model builds on the work of Lustig, Roussanov and Verdelhan (2011, 2014) and Verdelhan (2015); their models feature global SDF shocks, common across countries, and local SDF shocks, independent across countries. Importantly, they assume that the price of country-specific shocks is uncorrelated across countries, as local pricing factors are perfectly negatively correlated with the corresponding country-specific shocks. We show that allowing for cross-country comovement of the local pricing factors is crucial for explaining the joint behavior of FX correlations under the physical and the risk-neutral measure.

Our model assumes ex ante heterogeneity across countries regarding their exposure to global shocks. Recent international finance models that address the cross section of currency risk premiums by assuming ex ante heterogeneity across countries include Hassan (2013), Tran (2013), Backus, Gavazzoni, Telmer and Zin (2013), Colacito and Croce (2013), Colacito, Croce, Gavazzoni and Ready (2015), and Ready, Roussanov and Ward (2016). In all models, high (low) interest rate currencies are risky (hedges) because they depreciate (appreciate) in bad global states. This is because high interest rate countries are those with low exposure to global risk: small countries, countries with smooth non-traded output, countries with very procyclical monetary policy, commodity producers, or countries with low exposure to global long-run endowment shocks, depending on the model.

Finally, our paper is related to the literature on currency options. Whereas most of that literature focuses on crash risk, especially in the context of the FX carry trade—see, for example, Farhi, Fraiberger, Gabaix, Ranciere and Verdelhan (2015), Jurek (2014) and Chernov, Graveline and Zviadadze (2016)—our aim is to use option prices to study the properties of FX correlation risk premiums.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 reports our empirical findings regarding the cross-sectional and time-series properties of FX correlations, as well as the pricing of correlation risk in currency markets. Our empirical findings concerning FX correlation risk premiums are presented in Section 4. Section 5 introduces our no-arbitrage model, and Section 6 concludes. The Appendix contains details on the construction of the realized and implied FX correlation measures, results on the price of FX correlation risk, and model details, including details on the model calibration and simulation. Additional results and robustness checks are deferred to an Online Appendix.

2. Data

Our benchmark sample period starts in January 1996 and ends in December 2013, and is dictated by the availability of the currency options data.

Spot and forward exchange rates: To calculate physical measure FX moments, we use daily spot exchange rates from WM/Reuters obtained through Datastream. From the same source, we also collect one-month forward rates to calculate forward discounts.

Following the extant literature (see, e.g., Fama, 1984), we work with log spot and log one-month forward exchange rates, denoted $s_t^i = \ln(S_t^i)$ and $f_t^i = \ln(F_t^i)$, respectively; both are expressed in units of foreign currency per USD.[1] We use the U.S. dollar as the base currency, so superscript i always denotes the foreign currency. Monthly log excess returns from holding the foreign currency i are computed as $rx_{t+1}^i = f_t^i - s_{t+1}^i$. Our benchmark sample comprises the nine G10 foreign currencies (AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK) from January 1996 to December 2013. For robustness checks, we also consider the longer January 1984 to December 2013 sample period. Before the introduction of the EUR in January 1999, we use the German Mark (DEM) in its place.

Table 1 presents the properties of the G10 currency excess returns. In line with the literature on the FX carry trade, we find that currencies with high (low) nominal interest rates tend to yield high (low) average dollar excess returns: the NZD and the AUD are characterized by high nominal interest rates, as well as high average excess returns, while the reverse is true for the JPY and the CHF.

[Insert Table 1 here.]

For robustness, we extend the cross section of currencies and consider two additional currency sets: developed and emerging market currencies. The developed country sample, apart from the G10 currencies, includes the currencies of Austria, Belgium, Denmark, Finland, France, Greece, Italy, Ireland, Netherlands, Portugal, and Spain. The full sample includes all the developed country currencies, along with the currencies of the Czech Republic, Hungary, India, Indonesia, Kuwait, Malaysia, Mexico, Philippines, Poland, Singapore, South Africa, South Korea, Taiwan, and Thailand.[2]

Currency options: We use daily over-the-counter (OTC) G10 currency options data from J. P. Morgan. In addition to the nine currency pairs versus the U.S. dollar, we also have options data for all 36 cross rates. The options used in this study are plain-vanilla European calls and puts, with five option series per currency pair. Specifically, we focus on the one-month maturity and a total of five different strikes: at-the-money (ATM), 10-delta and 25-delta calls, as well as 10-delta and 25-delta puts.

3. Exchange rate correlations

In this section, we document that the cross-sectional dispersion of conditional FX correlation is countercyclical. Following that observation, we construct an FX correlation dispersion measure, FXC, and sort currencies into portfolios based on their return exposure to FXC innovations, denoted by ΔFXC. We find a negative association between ΔFXC betas and currency excess returns, suggesting that currency exposure to FX correlation risk is compensated with a positive risk premium.

3.1. Properties of exchange rate correlations

We use daily spot exchange rates to calculate conditional FX correlations under the physical measure. In particular, we proxy the conditional one-month correlation of each FX pair at time t with its realized correlation over a rolling

[1] WM/Reuters forward rates are available from 1997 onwards. For 1996, we either use forward rates from alternative sources or we construct 'implied' forward rates using the interest rate differential between the U.S. and the foreign country using interest rate data from Datastream, exploiting the fact that covered interest rate parity holds during normal conditions. We verify that our results are robust to using the WM/Reuters data only.

[2] We start with the same set of currencies used in Lustig, Roussanov and Verdelhan (2011). However, we exclude some currencies, such as the Hong Kong dollar, as they are pegged to the USD. We also exclude the Danish krone after the introduction of the EUR.

three-month window of past daily observations. Appendix A provides the details. In the remainder of the paper, we will often refer to physical measure conditional FX correlation as realized FX correlation, to distinguish it from the option-implied risk-neutral measure FX correlation (implied FX correlation).[3]

The first two columns of Table 2 report the time-series mean and standard deviation of the conditional FX correlation of each of the 36 G10 FX pairs. The mean conditional correlation is positive for all 36 FX pairs, indicating that all pairs of USD exchange rates exhibit positive comovement on average. The cross-sectional average of the conditional correlation means is 0.45, but there is substantial cross-sectional heterogeneity: the means range from almost zero (CAD/JPY with 0.05, indicating that fluctuations in the relative price of the CAD and the JPY against the USD are almost disconnected), to almost one (CHF/EUR with 0.89).[4] Furthermore, conditional FX correlations exhibit considerable variability across time: the cross-sectional average of the standard deviation of conditional FX correlations is 0.23, ranging from 0.09 (EUR/NOK pair) to 0.34 (AUD/JPY pair), suggesting non-trivial swings in the degree of exchange rate comovement across time for all FX pairs.

[Insert Table 2 here.]

Given the time variation in conditional FX correlations, it is worth exploring whether that time variation is cyclical and, if so, whether there is any cross-sectional heterogeneity in its properties. To that end, we consider the comovement of conditional FX correlations with market variables that are well-known to exhibit countercyclical behavior. The market variables we consider are a global equity volatility measure ($GVol$), a global funding illiquidity measure (GFI), the TED spread (TED), and the VIX (VIX). $GVol$ is constructed as in Lustig, Roussanov and Verdelhan (2011). GFI is constructed following the methodology of Hu, Pan and Wang (2013), but calculated using an international sample of government bond securities as in Malkhozov, Mueller, Vedolin and Venter (2016). TED is the spread between the three-month USD LIBOR and the three-month Treasury Bill rate and is available in FRED. VIX is backed out from options on the S&P 500 stock index and available from the CBOE. TED and VIX are U.S.-specific measures, but are often used as global market indicators. $GVol$ and GFI are calculated using international data in local currencies. For each FX pair and each market measure, we define the cyclicality measure to be the unconditional correlation of the market variable with the conditional correlation of the FX pair. Thus, we calculate four FX correlation cyclicality measures for each exchange rate pair, each corresponding to a market variable. We present the cyclicality measures for the 36 G10 FX pairs in the first four columns of Table 3.

[Insert Table 3 here.]

As seen in the table, we find substantial cross-sectional heterogeneity regarding the cyclicality properties of conditional FX correlations. To determine whether there is a cross-sectional pattern, we plot each cyclicality measure of the 36 FX pairs against their average conditional correlation; Panels A to D in Figure 1 present the plots for the four cyclicality measures. Each panel also presents the line of best fit from the corresponding cross-sectional regression. We report the details of the four cross-sectional regressions in Panel A of Table 4: for each regression, we document the point estimate of the slope coefficient, its asymptotic t-statistic, and the 95% bootstrapped confidence interval (2.5 and 97.5 bootstrap percentiles), as well as the regression R^2. The asymptotic t-statistic is calculated using White (1980) standard errors that adjust for cross-sectional heteroskedasticity, while the bootstrapped confidence interval accounts

[3] For robustness, we also proxy the conditional one-month correlation of each FX pair at time t with its realized correlation over a rolling one-month window of past daily observations, as well as with its realized correlation during the one-month ahead period, i.e. from t to $t + 1$. Our empirical results are robust to those alternative specifications. We report some of our findings for correlation risk premiums using the alternative realized correlation proxies in the Online Appendix.

[4] Beginning September 2011, the Swiss National Bank imposed a cap in the relative value of the CHF by establishing a floor of 1.2 CHF per EUR. The average correlation between the CHF/USD exchange rate and the EUR/USD exchange rate in the period before the cap (0.887) is almost identical to their average correlation during the cap period (0.895). Given that the cap does not seem to have changed the behavior of the CHF, we choose to retain the CHF in our sample after September 2011. We have verified that removing the CHF during the cap period does not materially affect our results.

for potential small sample effects. All four slope coefficients are positive and statistically significant at the 5% level using either the asymptotic or the bootstrapped distribution, suggesting a positive cross-sectional association between average conditional FX correlation and FX correlation cyclicality. Indeed, Figure 1 shows that the FX pairs with high average correlation tend to exhibit countercyclical correlations, whereas the FX pairs with low average correlation are characterized by procyclical FX correlations.[5]

[Insert Figure 1 and Table 4 here.]

Our findings imply that in periods characterized by adverse economic conditions or market stress, the cross section of conditional FX correlations widens, as high correlation FX pairs become more correlated and low correlation FX pairs become less correlated. To further explore the time-series properties of the cross-sectional dispersion in conditional FX correlation, we construct a conditional FX correlation dispersion measure, called FXC, as follows: each period t, we sort all FX pairs in deciles on their conditional correlation, calculate the average conditional correlation for the top and bottom deciles (which consist of four FX pairs each), and take the difference between the top and the bottom decile averages to be our dispersion measure at t, FXC_t. Due to the time variation in conditional FX correlations, there is turnover in both the top and bottom deciles; to eliminate composition effects, we also compute an alternative dispersion measure (FXC^{UNC}) by considering top and bottom deciles of FX pairs formed using average conditional correlations.

We plot the time series of the level of the two FX correlation dispersion measures in Panel A of Figure 2.[6] The correlation between FXC and FXC^{UNC} is 0.86, indicating that the two measures are very similar. Indeed, during the financial crisis the two measures are almost perfectly correlated, as there is little turnover in the extreme deciles of FX conditional correlation. To evaluate the cyclicality properties of the FX correlation dispersion measures, we explore their association with the market variables we use to measure the cyclicality of FX correlations. For reference, in Panel B of Figure 2 we plot the (standardized) market variables. Panel A of Table 5 reports the unconditional correlations between our two FX correlation dispersion measures and the market variables, in the January 1996 to December 2013 sample period, along with their bootstrap standard errors. Both dispersion measures—FXC and FXC^{UNC}—have a positive correlation with all four market variables; in all eight cases, bootstrap confidence intervals (which account for non-normality in small samples and are not reported in Table 5) indicate that the correlation is statistically significant at the 1% level. Panel B repeats the same exercise for the longer January 1984 to December 2013 period; again all eight correlations of interest are positive and significant at the 1% level.

[Insert Figure 2 and Table 5 here.]

3.2. Correlation risk and the cross section of currency returns

We can now explore how exposure to FX correlation risk relates to currency returns. To do so, we sort currencies into portfolios based on the exposure (beta) of currency excess returns to innovations in our dispersion measure FXC; innovations between t and $t+1$ are denoted by ΔFXC_{t+1} and are defined as the average of changes (first differences) in conditional FX correlation for the FX pairs that belong to the top decile in period t minus the corresponding average for the bottom decile.[7] Our currency portfolios are rebalanced monthly: each month t we calculate rolling ΔFXC return betas using the last 36 monthly observations. Hence, each month t currency portfolios are formed using only information available at time t.

We sort the nine G10 currencies into three portfolios; the first portfolio (Pf1^{C}) contains the currencies with the lowest ΔFXC betas while the last portfolio (Pf3^{C}) contains the highest ΔFXC beta currencies. Of particular interest

[5] We also calculate the cross-sectional correlation coefficient between average FX correlations and each of the four cyclicality measures; the cross-sectional correlation coefficients are 0.37 for GVol, 0.57 for GFI, 0.70 for TED and 0.38 for VIX.

[6] The Online Appendix presents additional results using alternative construction methods for FXC. We find that our portfolio results are robust to those alternative specifications.

[7] Innovations in FXC are not the first differences in FXC, as the composition of the deciles changes over time. On the other hand, since the FX pairs used to calculate FXC^{UNC} are fixed, innovations in FXC^{UNC} can be simply defined as first differences in the level of the factor.

is the HML^C portfolio, which takes a long position in $\mathrm{Pf3^C}$ and a short position in $\mathrm{Pf1^C}$. Panel A of Table 6 reports the summary statistics for the three ΔFXC-beta-sorted currency portfolios, as well as the HML^C portfolio. Notably, average portfolio returns are monotonically decreasing in the ΔFXC beta: ΔFXC is a priced currency risk factor. As a result, the average return to HML^C is negative and highly statistically significant: shorting the HML^C portfolio yields an annualized average excess return of 6.42% with a t-statistic of 3.47, and an associated Sharpe ratio of 0.82.

[Insert Table 6 here.]

Our finding of a strongly negative return for HML^C is robust to different sample periods. In particular, we consider following periods: January 1996 to July 2007, January 1984 to December 2013, and January 1984 to July 2007; two of those periods end before the recent financial crisis. Our findings are reported in Panels B to D of Table 6. Consistent with our results for the benchmark period, we find an inverse relation between exposure to the FX correlation factor ΔFXC and average currency portfolio excess returns in each of the three periods. Excluding the financial crisis increases the average excess return of shorting the HML^C portfolio to 7.35%, with an associated Sharpe ratio of 1.10 (Panel B). On the other hand, return differences across portfolios somewhat attenuate when the sample period is extended back to January 1984 (Panels C and D), but shorting the HML^C portfolio still yields highly significant annualized average excess returns (3.72% and 3.45%, respectively). Overall, our results are very robust to different sample periods and do not appear to be driven by the recent financial crisis.

For further robustness, we also explore extended cross sections of currencies: in particular, we consider a sample that includes other developed country currencies (called the developed country sample) and a sample that includes the entirety of the developed sample and also some emerging currencies (called the full sample).[8] For each of the two extended samples, we construct four ΔFXC-beta-sorted portfolios. Figure 3 presents the average excess returns of ΔFXC-beta-sorted currency portfolios for each of three sets of currencies (G10, all countries and developed countries) and each of the four periods discussed above. We find a consistently negative association between average portfolio excess returns and exposure to correlation risk, with negative average HML^C returns across the board. Furthermore, average HML^C returns are significant at the 5% level for all currency and period samples, with the sole exception of the samples starting in 1984 for the full set of currencies. For the benchmark period from January 1996 to December 2013, the average annualized return of shorting HML^C in the developed country sample is 5.46% (with a t-statistic of 2.42) and the associated Sharpe ratio is 0.57. For the full cross section of currencies, shorting HML^C yields 4.04% on average (with a t-statistic of 1.97) and a Sharpe ratio of 0.46.

[Insert Figure 3 here.]

Finally, given the significant excess returns to the HML^C portfolio, we attempt to determine the market price of FX correlation risk. We follow the extant literature and consider a linear pricing model with two traded factors: the first factor is the dollar factor DOL, defined as the simple average of all available FX excess returns and shown by Lustig, Roussanov and Verdelhan (2011) to act as a level factor for currency returns, and the second factor is HML^C, the return difference between the high and low ΔFXC beta portfolios for the sample of G10 currencies. Our estimates for the market price of HML^C range from -51 to -67 basis points per month, depending on the set of test assets, so HML^C acts as a slope factor for pricing currency risk. The results are presented in detail in Appendix B.

4. Exchange rate correlation risk premiums

In this section, we document the cross-sectional and time-series properties of FX correlation risk premiums (CRP) and explore the relation between FX correlation risk premiums and FX correlations.

[8]The full list of currencies in each sample is given in Section 2 of the paper.

4.1. The cross-sectional properties of correlation risk premiums

In consistence with the literature on variance and correlation risk premiums in other asset classes, we define FX correlation risk premiums as the difference between expected conditional FX correlations under the risk-neutral ($\mathbb{Q}$) and the physical ($\mathbb{P}$) measure:

$$\mathrm{CRP}_{t,T}^{i,j} \equiv \mathrm{E}_t^{\mathbb{Q}}\left(\int_t^T \rho_u^{i,j} du\right) - \mathrm{E}_t^{\mathbb{P}}\left(\int_t^T \rho_u^{i,j} du\right). \tag{1}$$

We only consider one-month premiums, i.e. $T = t + 1$, as the maturity of the FX options we use to derive risk-neutral measure moments is one month.[9]

To calculate the risk-neutral (implied) conditional FX correlation, we follow the literature on model-free measures of implied volatility and covariance using daily FX option prices. The details of the calculations are presented in Appendix C. Given the availability of FX options, we calculate correlation risk premiums for each of the 36 FX pairs formed using the nine G10 exchange rates against the USD. For each FX pair not involving the EUR, our sample period starts in January 1996 and ends in December 2013, for a total of 216 monthly observations. For the EUR, the options data start in January 1999.

The time-series mean and standard deviation of the implied FX correlations of each of the 36 G10 FX pairs are reported in Table 2. The cross-sectional average of implied FX correlation means is 0.48, slightly higher than its physical measure counterpart (0.45). Importantly, there is less heterogeneity in conditional FX correlation means under the risk-neutral measure than under the physical measure: the lowest implied FX correlation mean is 0.14 (CAD/JPY pair) and the highest is 0.88 (CHF/EUR pair), whereas realized correlation means range from 0.05 to 0.89. The volatility of implied FX correlations is of the same order of magnitude as the volatility of realized FX correlations, with standard deviations ranging from 0.07 to 0.34 and their cross-sectional average being 0.19.

Finally, the last five columns of Table 2 present the descriptive statistics for FX correlation risk premiums. From left to right, we report the time-series mean and standard deviation of the correlation risk premium of each FX pair, followed by the asymptotic t-statistic and the bootstrapped 95% confidence interval of the CRP mean. CRP means exhibit considerable cross-sectional heterogeneity, with their size and sign varying greatly across FX pairs: they range from −0.069 (CAD/SEK) to 0.099 (JPY/NOK), with the cross-sectional average being 0.016. Roughly two thirds of CRP means are positive and one third are negative; overall, three quarters of the means are significant at the 5% level according to either the asymptotic or the bootstrapped distribution.[10] Furthermore, correlation risk premiums are very volatile: despite the fact that premiums are much smaller than either realized or implied FX correlations, CRP standard deviations are of the same order of magnitude as those of realized or implied correlations (ranging from 0.06 to 0.22, with a cross-sectional average of 0.14), suggesting that there is substantial time variation in the disparity between physical measure and risk-neutral measure FX correlations.

To explore whether average FX correlation risk premiums exhibit a cross-sectional pattern, we plot the average CRP of all G10 exchange rate pairs against their average realized correlations. Figure 4 presents the scatterplot, along with the line of best fit. The cross-sectional correlation between average FX correlation risk premiums and average FX realized correlations is −0.55. For example, the AUD/JPY pair, characterized by a very low average realized FX correlation (0.16), has a positive and highly significant average CRP of 0.083. On the other hand, the AUD/NZD pair has a very high average realized correlation (0.76) and a negative and significant average premium (−0.016). A cross-sectional regression of average correlation risk premiums on average realized correlations yields a statistically significant slope coefficient of −0.144.[11] The strongly negative cross-sectional association between average realized

[9] Variance risk premiums are defined analogously as the difference in expected conditional FX variance between the risk-neutral and the physical measure. A brief discussion of their summary statistics, as well as the summary statistics of physical measure (realized) and risk-neutral measure (implied) FX variance, is deferred to the Online Appendix. Inter alia, FX variance is studied in Cenedese, Sarno and Tsiakas (2014), who find that a high cross-sectional average of currency excess return variance predicts carry trade losses.

[10] In terms of size, the maximum FX correlation risk premium we find is about half of the equity correlation risk premium reported by Driessen, Maenhout and Vilkov (2009).

[11] Its asymptotic t-statistic, calculated using White (1980) standard errors, is −5.80 and the bootstrapped 95% confidence interval is [−0.154, −0.076].

FX correlations and average FX correlation risk premiums is what generates the tighter cross-sectional distribution of average implied FX correlations versus that of realized FX correlations that we discussed earlier.

[Insert Figure 4 here.]

The relative tightness of the cross-sectional distribution of conditional FX correlation under the risk-neutral measure implies a potential tension regarding the pricing of FX correlation risk. On the one hand, the negative association between ΔFXC betas and currency excess returns suggests that U.S. investors require a risk premium for being exposed to states in which FXC increases, i.e. in which the cross section of FX correlations widens. However, FX options are priced in a way that indicates that U.S. investors price states in which the cross section of FX correlations tightens. In the next section, we will address this tension by proposing a no-arbitrage model that features unspanned FX correlation risk.

4.2. The time-series properties of correlation risk premiums

We now turn to the time-series properties of implied FX correlations and FX correlation risk premiums. The first four columns of Table 7 provide summary statistics on the time-series association between realized and implied FX correlations: for each FX pair, we report the unconditional correlation coefficient between the two time series, as well as its asymptotic t-statistic and its 95% bootstrapped confidence interval. Realized and implied correlations exhibit substantial comovement across time for all FX pairs, with the unconditional correlations between the two ranging from 0.28 to 0.92, all being statistically significant, and the cross-sectional mean being 0.79.

[Insert Table 7 here.]

The last four columns of Table 7 report descriptive statistics on the unconditional correlation between realized FX correlations and FX correlation risk premiums. We find that the cross-sectional average of those unconditional correlation coefficients is -0.52 across the 36 G10 FX pairs, suggesting that elevated FX correlation is typically associated with lower than usual CRP, i.e., with a lower than usual disparity between the physical measure and the risk-neutral measure FX correlation. This association is pervasive and robust: 35 of the 36 unconditional correlation coefficients are negative, with all but one of them being statistically significant.

Finally, to assess the cyclicality of correlation risk premiums, we construct CRP cyclicality measures. As we did for FX correlations, we define our CRP cyclicality measures to be the unconditional correlations between FX correlation risk premiums and the four market variables we used before. The last four columns of Table 3 report the four CRP cyclicality measures for each of the 36 G10 FX pairs, and Panels A to D of Figure 5 plot those cyclicality measures against average FX correlation risk premiums. We find a positive cross-sectional association: FX pairs with high average CRP have countercyclical correlation risk premiums, whereas pairs with low average CRP have procyclical premiums. The regression results in Panel B of Table 4 suggest that this positive cross-sectional association is statistically significant for all four cyclicality measures.[12] Thus, the cross-sectional dispersion in FX correlation risk premiums is countercyclical: in bad times, the premiums of FX pairs with high average CRP increase and the premiums of FX pairs with low average CRP decline, widening the cross-sectional distribution of FX correlation risk premiums.

[Insert Figure 5 here.]

5. A no-arbitrage model of exchange rates

In this section, we introduce a reduced-form, no-arbitrage model of exchange rates that is consistent with our empirical findings. Our model builds on the reduced-form models in Lustig, Roussanov and Verdelhan (2011, 2014)

[12] We also calculate the cross-sectional correlation coefficient between average CRP and each of the four CRP cyclicality measures; the cross-sectional correlation coefficients are 0.47 for GVol, 0.79 for GFI, 0.69 for TED, and 0.58 for VIX.

and Verdelhan (2015). In contrast to those models, which assume that innovations in the price of country-specific shocks are uncorrelated across countries, we assume that local risk is priced identically across countries. This assumption implies a lack of spanning of FX correlation risk by exchange rates, a feature that is crucial in jointly explaining the behavior of FX correlations and FX correlation risk premiums.

5.1. Model setup

The global economy comprises $I + 1$ countries ($i = 0, 1, \dots, I$), each with a corresponding currency. Without loss of generality, we will call country $i = 0$ the domestic country and countries $i = 1, ..., I$ the foreign countries. We assume that financial markets are frictionless and complete, so that there is a unique stochastic discount factor (SDF) for each country, but that frictions in the international market for goods induce non-identical stochastic discount factors across countries. In particular, the log SDF of country i, denoted by m^i, is exposed to two global shocks, u^w and u^g, and a country-specific (local) shock u^i, and satisfies

$$-m^i_{t+1} = \alpha + \chi z_t + \varphi z^w_t + \sqrt{\kappa z_t} u^i_{t+1} + \sqrt{\gamma^i z^w_t} u^w_{t+1} + \sqrt{\delta z_t} u^g_{t+1}, \tag{2}$$

where z and z^w is the local and the global pricing factor, respectively. Both pricing factors are common to all countries. Notably, countries are ex ante heterogeneous only with regard to their exposure γ to the first global shock u^w; all other SDF parameters are identical across countries. As we will see, differences in γ capture an exchange rate fixed effect that generates, inter alia, cross-sectional differences in average FX correlations. In our model, global risk exposure γ is exogenous.[13].

The local pricing factor z prices both the local shock u^i and the second global shock u^g: in all countries, the price of the local shock is $\sqrt{\kappa z_t}$ and the price of the second global shock is $\sqrt{\delta z_t}$. On the other hand, the first global shock u^w is differentially priced across countries, with its price in country i being $\sqrt{\gamma^i z^w_t}$.

The two pricing factors are stationary processes. The local pricing factor z is driven by the second global shock u^g, and has law of motion

$$\Delta z_{t+1} = \lambda(\bar{z} - z_t) - \xi \sqrt{z_t} u^g_{t+1}. \tag{3}$$

Thus, the local pricing factor is a square root process, reverting to its unconditional mean of $\bar{z}$ at speed λ. Importantly, the local pricing factor is countercyclical, as adverse u^g shocks increase its value.

The global pricing factor z^w is driven by the global shock u^w; it is also a square root process, with law of motion

$$\Delta z^w_{t+1} = \lambda^w(\bar{z}^w - z^w_t) - \xi^w \sqrt{z^w_t} u^w_{t+1}, \tag{4}$$

which also implies countercyclical pricing of risk. To ensure that both pricing factors are strictly positive, we impose the Feller conditions $2\lambda\bar{z} > \xi^2$ and $2\lambda^w\bar{z}^w > (\xi^w)^2$. All parameters except α, χ and φ are strictly positive and all shocks are i.i.d. standard normal.

Finally, the inflation process for country i is given by

$$\pi^i_{t+1} = \bar{\pi} + \zeta z^w_t + \sqrt{\sigma}\eta^i_{t+1}. \tag{5}$$

Expected inflation rates are time varying and identical across countries. However, realized inflation rates differ across countries, as inflation shocks η^i are i.i.d. standard normal. Conditional inflation variance is constant and equal to σ and inflation shocks are unpriced, so the model does not feature any inflation risk premiums. As a result, all the salient economic mechanisms in the model arise from real variables, as nominal variables inherit all the conditional properties of their nominal counterparts. For that reason, we will discuss the model intuition using real variables and will consider nominal variables only in the simulation section.

[13]Richer models that endogenize unconditional cross-sectional differences in global risk exposure include Hassan (2013), Tran (2013), Backus, Gavazzoni, Telmer and Zin (2013), Colacito, Croce, Gavazzoni and Ready (2015) and Ready, Roussanov and Ward (2016).

5.2. The properties of conditional FX moments

We denote the real log exchange rate between foreign currency i and the domestic currency by q^i (units of foreign currency per unit of domestic currency, in real terms). As a result of financial market completeness, real exchange rate changes equal the SDF differential between the two countries,

$$\Delta q^i_{t+1} = m^0_{t+1} - m^i_{t+1}, \tag{6}$$

which implies that real exchange rate changes can be decomposed into a part driven by country-specific shocks and a part that reflects exposure to global risk:

$$\Delta q^i_{t+1} = \sqrt{\kappa z_t} u^i_{t+1} - \sqrt{\kappa z_t} u^0_{t+1} + \left(\sqrt{\gamma^i} - \sqrt{\gamma^0} \right) \sqrt{z^w_t} u^w_{t+1}. \tag{7}$$

If the foreign country has a higher (lower) exposure γ to global shock u^w than the domestic country, its currency appreciates (depreciates) against the domestic currency when a negative u^w realization occurs. On the other hand, exposure to the second global shock u^g drops out of exchange rate changes since all countries have the same loading on u^g, and, thus, the only global shock that affects exchange rate changes directly is u^w. Therefore, in the remainder of the paper, global FX risk always refers to the first global shock u^w.

We now turn to conditional FX moments. The conditional variance of changes in the log real exchange rate i is increasing in both the local pricing factor z and the global pricing factor z^w:

$$var_t \left(\Delta q^i_{t+1} \right) = 2\kappa z_t + \left(\sqrt{\gamma^i} - \sqrt{\gamma^0} \right)^2 z^w_t. \tag{8}$$

The first effect arises from the country-specific component of stochastic discount factors: given the independence of local shocks across countries, the higher the impact of local shocks on the SDF, the more the two SDFs diverge and, hence, the more volatile the exchange rate is. The second effect arises from the global component of SDFs: the higher the difference in global risk exposure between country i and the domestic country, and the more severely global risk exposure is priced, the more volatile the real exchange rate is.

The conditional covariance of changes in log real exchange rates i and j is

$$cov_t \left(\Delta q^i_{t+1}, \Delta q^j_{t+1} \right) = \kappa z_t + D^{i,j} z^w_t, \tag{9}$$

where we define the constant $D^{i,j}$ as follows:

$$D^{i,j} \equiv \left(\sqrt{\gamma^i} - \sqrt{\gamma^0} \right) \left(\sqrt{\gamma^j} - \sqrt{\gamma^0} \right). \tag{10}$$

We call exchange rate pairs (i, j) that satisfy $D^{i,j} > 0$ "similar" and exchange rate pairs that satisfy $D^{i,j} < 0$ "dissimilar". Thus, similar exchange rates correspond to foreign countries which both have either more or less exposure to global risk than the domestic country, whereas dissimilar exchange rates correspond to pairs of foreign countries in which one country has higher, and the other country lower, exposure to global risk compared with the domestic country.

The first component of conditional FX covariance is due to the common exposure of the two exchange rates to the domestic local shock, as the two exchange rates are mechanically positively correlated through their relation to the domestic SDF. When z increases, this "domestic currency effect" becomes more prevalent, increasing the covariance between the two exchange rates, as both foreign currencies appreciate or depreciate together against the domestic currency.

The second component captures FX comovement that arises from exposure to global FX risk. Foreign countries with similar exposure to the global shock u^w (i.e. countries that satisfy $D^{i,j} > 0$) have exchange rates that covary more than the exchange rates of countries that have dissimilar exposure to global FX risk. Furthermore, fluctuations in z^w have different effects on conditional FX covariance, depending on the type of the FX pair: an increase in the global pricing factor amplifies the importance of exposure to global risk and, thus, increases the conditional covariance of similar exchange rates and reduces the covariance of dissimilar exchange rates.

We can now turn to conditional FX correlations. As happens for FX covariances, country heterogeneity in exposure to the global shock u^w generates cross-sectional heterogeneity in average conditional FX correlations: similar FX pairs have higher correlations on average than dissimilar ones. Furthermore, the time variation in the pricing factors z^w and z introduces time variation in the conditional correlation of both similar and dissimilar FX pairs and, thus, in the cross-sectional distribution of conditional FX correlation.

To illustrate the effects of the two pricing factors on conditional FX correlations, we consider a world of $I = 3$ foreign countries. Countries 1 and 2 are less exposed to global FX risk than the domestic country, while country 3 is more exposed than the domestic country. This implies that the FX pair (1,2) is similar whereas FX pair (1,3) is dissimilar. To ensure symmetry, we set the values of the country exposures to global risk such that the condition $D^{1,2} = -D^{1,3} > 0$ is satisfied.

[Insert Figure 6 here.]

We first consider the impact of the global pricing factor z^w; the left panels of Figure 6 present the results. In particular, Panels A, C and E plot conditional FX correlations as a function of z^w for different values of the local pricing factor ($z = 0.2\overline{z}$, $\overline{z}$ and $5\overline{z}$, depicted with circles, solid lines and squares, respectively). Panel A refers to the similar exchange rate pair (1,2), Panel C to the dissimilar exchange rate pair (1,3) and Panel E plots the difference in the conditional FX correlations of the two FX pairs. An increase in the global pricing factor z^w raises the relative importance of exposure to the global shock u^w, amplifying similarities and dissimilarities: similar FX pairs (Panel A) become more correlated, whereas dissimilar FX pairs (Panel C) become less correlated. When $z^w \to \infty$, similar exchange rates become perfectly positively correlated and dissimilar exchange rates become perfectly negatively correlated. Taken together, these results imply that the disparity in conditional FX correlation across exchange rate pairs is increasing in z^w (Panel E).

We now turn to the effects of the local pricing factor z. The results are presented in the right panels of Figure 6; Panels B, D and F plot the sensitivity of conditional FX correlations to the value of the local pricing factor z for different values of the global pricing factor ($z^w = 0.2\overline{z}$, $\overline{z}$ and $5\overline{z}$), with Panel B referring to the similar FX pair, Panel D to the dissimilar FX pair and Panel F to the difference in the two pairs' conditional FX correlations. Recall that an increase of the local pricing factor z increases both the variance of all exchange rates and the covariance of all exchange rate pairs, due to the domestic currency effect. However, the impact of that effect on FX correlation depends on the type of the FX pair. When $z \to \infty$ the correlation of all FX pairs converges to 0.5. This happens because all cross-sectional differences in global risk exposure become second-order and what ultimately drives FX comovement is the domestic currency effect. In particular, the limit behavior of log exchange rate changes is described by

$$\Delta q^i_{t+1} \to \sqrt{\kappa z_t} u^i_{t+1} - \sqrt{\kappa z_t} u^0_{t+1}, \tag{11}$$

so exposure to the domestic local shock, which accounts for half of the conditional FX variance and generates all the FX comovement, pushes all FX correlations towards 0.5. Due to the domestic currency effect, when the local pricing factor increases, the importance of similar or dissimilar exposure to global risk is attenuated. As a result, the conditional correlation of similar exchange rates declines (Panel B), whereas the conditional correlation of dissimilar exchange rates increases (Panel D), leading to a tightening of the cross section of conditional FX correlations (Panel F).

In sum, the cross-sectional dispersion of conditional FX correlations is increasing in the global pricing factor z^w and decreasing in the local pricing factor z. Given that z^w increases after negative u^w shocks and z increases after negative u^g shocks, that implies that changes in FXC reflect both u^w shocks (with a positive sign) and u^g shocks (with a negative sign). Empirically, we have seen that FXC is strongly positively correlated with four market variables that reflect credit risk, illiquidity and stock market volatility, suggesting that those variables identify exposure to the first global shock u^w, rather than to the second global shock u^g. Therefore, those business cycle variables can be proxied in our model by z^w.

5.3. Correlation risk and the cross section of FX returns

The USD excess return for investing in the currency of country i satisfies:

$$rx^i_{t+1} - E_t(rx^i_{t+1}) = -\Delta q^i_{t+1} + E_t(\Delta q^i_{t+1}) = -\sqrt{\kappa z_t}u^i_{t+1} + \sqrt{\kappa z_t}u^0_{t+1} - \left(\sqrt{\gamma^i} - \sqrt{\gamma^0}\right)\sqrt{z^w_t}u^w_{t+1}, \tag{12}$$

so FX excess returns are not exposed to u^g risk. As a result, the conditional risk premium that the domestic investor receives for investing in foreign currency i (including the Jensen term) is

$$rp^i_t \equiv E_t\left(rx^i_{t+1}\right) + \frac{1}{2}var_t(rx^i_{t+1}) = -cov_t(m^0_{t+1}, -\Delta q^i_{t+1}) = \kappa z_t + \left(\sqrt{\gamma^0} - \sqrt{\gamma^i}\right)\sqrt{\gamma^0}z^w_t. \tag{13}$$

FX risk premiums have two components: a part that compensates domestic investors for the fact that investing in a foreign currency essentially entails shorting the country-specific component of the domestic SDF, and a part that reflects compensation for exposure to the global shock u^w. The first component is identical across currencies, so all cross-sectional variation in FX risk premiums is solely due to heterogeneity in exposure to u^w, i.e. heterogeneity in γ. In particular, the compensation provided by currency i for exposure to u^w shocks is decreasing in the country loading γ^i. For example, if $\gamma^i < \gamma^0$, then currency i depreciates against the domestic currency when a bad realization of the global shock u^w occurs. Given that $\gamma^0 > 0$, i.e., that a bad realization of u^w increases domestic marginal utility, domestic investors require a positive risk premium in order to hold currency i. Conversely, currencies of countries with high exposure to u^w ($\gamma^i > \gamma^0$) have a negative premium for global FX risk, as they provide a hedge to domestic investors.

We can now turn to the determinants of the ΔFXC loadings of FX returns. We have seen that fluctuations in FXC, the cross-sectional dispersion in conditional FX correlation, reflect innovations in both the global pricing factor z^w (which are scaled multiples of the global shock u^w) and in the local pricing factor z^w (scaled multiples of the global shock u^g). Importantly, both kinds of innovations are priced and have opposite effects on ΔFXC, so it is not trivial to establish whether a positive loading of an asset return on ΔFXC should be associated with a positive or a negative risk premium: assets should earn a negative premium for a positive loading on ΔFXC that arises from exposure to u^w, and a positive premium for a positive loading that arises from exposure to u^g. However, there is no ambiguity in the case of FX returns, as the only global innovations to which they are exposed are u^w shocks. As a result, the conditional loading of FX returns on ΔFXC has the same sign as their conditional loading on Δz^w, so in the interests of tractability we can consider the latter. We have:

$$\frac{cov_t(rx^i_{t+1}, \Delta z^w_{t+1})}{var_t(\Delta z^w_{t+1})} = \frac{cov_t(\left(\sqrt{\gamma^0} - \sqrt{\gamma^i}\right)\sqrt{z^w_t}u^w_{t+1}, -\xi^w\sqrt{z^w_t}u^w_{t+1})}{var_t(-\xi^w\sqrt{z^w_t}u^w_{t+1})} = \frac{\sqrt{\gamma^i} - \sqrt{\gamma^0}}{\xi^w}. \tag{14}$$

Thus, countries i with a higher SDF exposure γ^i to global risk u^w than the domestic country have FX excess returns with a positive conditional loading on ΔFXC; conversely, the FX returns of countries with $\gamma^i < \gamma^0$ have a negative loading on ΔFXC. Given the negative cross-sectional association between γ and currency risk premiums, those loadings imply a negative risk premium for high ΔFXC beta exchange rates and a positive premium for low ΔFXC beta exchange rates, in line with our empirical findings.

We finish with a note on the cross-sectional relation between interest rates and currency risk premiums. In the model, the real interest rate of country i is given by

$$r^i_t = \alpha + \left(\chi - \frac{1}{2}\kappa - \frac{1}{2}\delta\right)z_t + \left(\varphi - \frac{1}{2}\gamma^i\right)z^w_t, \tag{15}$$

so all cross-sectional heterogeneity in interest rates is due to cross-sectional differences in global risk exposure γ: in all periods, countries with high (low) exposure to global FX risk have a relatively low (high) interest rate, due to a stronger (weaker) precautionary savings motive. As a result, high interest rate currencies are associated with low γs and, thus, high risk premiums.

5.4. The properties of correlation risk premiums

We now turn to FX correlation risk premiums. To explore their properties, we first need to characterize the law of motion of the pricing factors under the risk-neutral measure. From the perspective of the domestic investor, the risk-neutral measure law of motion for the global pricing factor z^w is

$$\Delta z^w_{t+1} = \lambda^w(\overline{z}^w - z^w_t) + \xi^w \sqrt{\gamma^0} z^w_t - \xi^w \sqrt{z^w_t} u^{w,\mathbb{Q}}_{t+1}, \tag{16}$$

so the drift adjustment is positive and equal to $\xi^w \sqrt{\gamma^0} z^w_t$. We can rewrite the equation above as a square root process,

$$\Delta z^w_{t+1} = \lambda^{w,\mathbb{Q}}(\overline{z}^{w,\mathbb{Q}} - z^w_t) - \xi^w \sqrt{z^w_t} u^{w,\mathbb{Q}}_{t+1}, \tag{17}$$

where $\lambda^{w,\mathbb{Q}} \equiv \lambda^w - \xi^w \sqrt{\gamma^0}$ and $\overline{z}^{w,\mathbb{Q}} \equiv \frac{\lambda^w}{\lambda^{w,\mathbb{Q}}} \overline{z}^w$. Thus, under the risk-neutral measure the global pricing factor z^w has a higher unconditional mean ($\overline{z}^{w,\mathbb{Q}} > \overline{z}^w$) and is more persistent ($\lambda^{w,\mathbb{Q}} < \lambda^w$) than under the physical measure. Similarly, the risk-neutral measure law of motion for the local pricing factor z is given by

$$\Delta z_{t+1} = \lambda^{\mathbb{Q}}(\overline{z}^{\mathbb{Q}} - z_t) - \xi \sqrt{z_t} u^{g,\mathbb{Q}}_{t+1}, \tag{18}$$

where $\lambda^{\mathbb{Q}} \equiv \lambda - \xi \sqrt{\delta}$ and $\overline{z}^{\mathbb{Q}} \equiv \frac{\lambda}{\lambda^{\mathbb{Q}}} \overline{z}$, so the local pricing factor also has a higher unconditional mean and is more persistent under the risk-neutral measure than under the physical measure. Notably, the drift adjustment of the two factors depends crucially on the volatility parameters ξ^w and ξ, which determine the sensitivity of the pricing factors to shocks u^w and u^g respectively, and on the exposure parameters γ^0 and δ, which regulate the pricing of shocks u^w and u^g, respectively, for the domestic agent. The higher ξ is relative to ξ^w, and the higher δ is relative to γ^0, the higher the drift adjustment of the local pricing factor is relative to the adjustment of the global pricing factor, as the shocks to the former are more highly priced compared with the shocks to the latter.

Note that for the global pricing factor we have

$$E^{\mathbb{Q}}_t(z^w_{t+s}) = \left(1 - (1 - \lambda^{w,\mathbb{Q}})^s\right) \overline{z}^{w,\mathbb{Q}} + (1 - \lambda^{w,\mathbb{Q}})^s z^w_t \tag{19}$$

under the risk-neutral measure, compared to

$$E^{\mathbb{P}}_t(z^w_{t+s}) = (1 - (1 - \lambda^w)^s) \overline{z}^w + (1 - \lambda^w)^s z^w_t \tag{20}$$

under the physical measure, for $s > 0$. Given the higher steady-state value and higher persistence of the global pricing factor under the risk-neutral measure, the wedge $E^{\mathbb{Q}}_t(z^w_{t+s}) - E^{\mathbb{P}}_t(z^w_{t+s})$ is always positive and increasing in z^w_t.[14] Exactly the same is true for the local pricing factor z. Thus, the implied conditional FX correlations are calculated using higher expected values for both z and z^w than their physical counterparts; this stems from the fact that states characterized by high values of z and z^w are bad states and, thus, receive an elevated probability weight under the risk-neutral measure. The expression for FX correlation risk premiums is derived in Appendix D. Intuitively, the wedge between implied and physical FX correlations is determined by the wedge in the expected values of z and z^w between the two measures, i.e. by the wedge between the risk-neutral and physical measure conditional distributions of z and z^w.

Of particular relevance is the case in which the domestic agent prices fluctuations in the local pricing factor z more heavily than fluctuations in the global pricing factor z^w, i.e. when $\xi \sqrt{\delta} >> \xi^w \sqrt{\gamma^0}$. In that case, the domestic investor risk-adjusts by assigning higher probabilities to states in which z has elevated values; states in which z^w is high also receive elevated importance under the risk-neutral measure, but risk adjustment mainly involves paying attention to high z states. This risk adjustment has implications both for the cross section and the time series of FX correlation risk premiums.

We start with the cross-sectional implications. When investors price z shocks more heavily then z^w shocks, risk adjustment involves paying elevated attention to states in which the cross-sectional dispersion of FX correlation

[14] In particular, the wedge is an affine function of z^w_t, with both the constant and the slope coefficient being positive. The constant is positive due to the fact that the function $f(x) = \frac{1-(1-x)^s}{x}$ for $s > 1$ is decreasing in x for $x \in (0, 1)$.

tightens: recall that, as seen in Figure 6, high z states are associated with lower than usual FX correlations for similar FX pairs and higher than usual FX correlations for dissimilar pairs. Therefore, focusing attention on high z states generates implied FX correlations that are on average lower than physical FX correlations for similar FX pairs. As a result, similar FX pairs (which have high average FX correlations) have negative average FX correlation risk premiums. Conversely, dissimilar FX pairs (which have low average FX correlations) have higher implied FX correlations than physical FX correlations on average and, thus, positive average FX correlation risk premiums. Thus, our model generates a negative cross-sectional association between average FX correlations and average FX correlation risk premiums, in line with the empirical findings presented in Figure 4.

We now turn to the time-series properties of FX correlation risk premiums. First, we consider similar FX pairs. As discussed in Section 5.2, the correlation of similar FX pairs is increasing in the global pricing factor z^w. Although this is true for both implied and physical FX correlations, implied FX correlations are less sensitive to z^w than their physical counterparts. Panel A of Figure 6 provides a useful visualization; circles plot FX correlation as a function of z^w conditional on a low z value ($z = 0.2\overline{z}$), while squares plot FX correlation as a function of z^w conditional on a high z value ($z = 5\overline{z}$). As can be easily seen, the high z curve (squares) is much flatter than the low z one (circles) in the region of the state space in which the economy spends most of the time (values of z^w between 0 and $2\overline{z}^w$). Since risk adjustment puts more weight to high z states, implied FX correlations are less sensitive to z^w than physical correlations for similar FX pairs. This sensitivity differential means that implied FX correlations increase less than physical correlations in high z^w states (empirically mapped to recessions), reducing the correlation risk premiums of similar FX pairs in those states. Conversely, implied FX correlations drop less than physical FX correlations in low z^w states (booms), increasing the correlation risk premiums of similar FX pairs. In short, the model implies that similar FX pairs have procyclical FX correlation risk premiums and, since they also have countercyclical conditional correlations, the time series correlation between FX correlations and FX correlation risk premiums is negative for similar FX pairs. Similarly, we can use Panel C of Figure 6 to show that dissimilar FX pairs have countercyclical FX correlation risk premiums, which also implies a negative time series correlation between FX correlations and FX correlation risk premiums for those FX pairs. In short, our model is able to address the key empirical time-series properties of FX correlation risk premiums presented in Table 7 and Figure 5.

In short, conditional FX correlation, which can be indirectly traded using currency options, is exposed to both u^w and u^g innovations. If the domestic agent is pricing z shocks (i.e. u^g innovations) more severely than z^w shocks (u^w innovations), then FX correlation risk premiums largely reflect the desire of currency option holders to avoid high z states, which feature a tightening of the cross-sectional dispersion of FX correlation. On the other hand, investing in foreign currency exposes investors only to u^w innovations, so currency risk premiums reflect solely the desire to avoid high z^w states, which are characterized by a widening of the cross-sectional dispersion of FX correlation. Thus, the lack of spanning of FX correlation risk by currency returns, and in particular the lack of exposure of exchange rates to u^g innovations, allows the model to jointly address the empirical properties of FX correlations, FX correlation risk premiums, and currency risk premiums.

5.5. *Model simulation*

Finally, we assess the quantitative performance of our model and show that it can match key FX correlation moments, as well as the standard interest rate and exchange rate moments.

To illustrate the importance of unspanned FX correlation risk, we consider a nesting model; both our model and the Lustig, Roussanov and Verdelhan (2014) model are special cases of that nesting model. The law of motion of the local pricing factor of country i, z^i, in the nesting model is

$$\Delta z^i_{t+1} = \lambda(\overline{z} - z^i_t) - \xi \sqrt{z^i_t}\left(\sqrt{\rho} u^g_{t+1} + \sqrt{1-\rho} u^i_{t+1}\right), \tag{21}$$

where $0 \leq \rho \leq 1$, so z^i is driven by both the global shock u^g and the local shock u^i. The nesting model allows for imperfect comovement of (and, thus, for heterogeneity in) local pricing factors across countries. As a result, countries can have different conditional loadings on the global innovation u^g and the exposure to u^g now enters the expression for real exchange rate changes:

$$\Delta q^i_{t+1} = E_t(\Delta q^i_{t+1}) + \sqrt{\kappa z^i_t} u^i_{t+1} - \sqrt{\kappa z^0_t} u^0_{t+1} + \left(\sqrt{\gamma^i} - \sqrt{\gamma^0}\right) \sqrt{z^w_t} u^w_{t+1} + \sqrt{\delta}\left(\sqrt{z^i_t} - \sqrt{z^0_t}\right) u^g_{t+1}. \tag{22}$$

If $\rho = 1$ and all local pricing factors have the same initial value, then all local pricing factors are identical and we retrieve our model, which features unspanned risk. On the other hand, if $\rho = 0$ we retrieve the model in Lustig, Roussanov and Verdelhan (2014), which features independent local pricing factors and in which FX correlation is fully spanned by exchange rates.[15]

Since our empirical results focus on G10 exchange rates, we simulate our model assuming a global economy with ten countries, the United States and $I = 9$ foreign countries. We simulate the model for different values of ρ, and we run two types of simulations: small-sample and large-sample. For a given value of ρ, a small-sample simulation consists of 1,000 simulation paths of 216 monthly observations each, matching the size of our empirical sample. For each simulated moment, the point estimate and the standard error of the moment is, respectively, the moment average across the 1,000 simulations and the moment standard deviation across those simulations. We also calculate the 95% confidence interval for each moment using the 2.5 and 97.5 percentiles of the moment in the cross-section of the 1,000 simulation paths. The output of our small-sample simulations is reported in Tables 9 and 10 and Figure 11, to be discussed below. All other simulation results refer to large-sample simulations: for a given value of ρ, a large-sample simulation consists of a single path of 50,000 monthly observations. The calibration and simulation details are discussed in Appendix E and the values of our model parameters can be found in Table 8.

Our quantitative analysis starts with the benchmark model, which features perfectly correlated local pricing factors ($\rho = 1$). Table 9 reports empirical and simulated moments for inflation rates, interest rates and exchange rates. For each empirical moment, we report the value of the moment in our sample, as well as its bootstrap standard error. The latter equals the standard deviation of the moment across 1,000 block bootstrap samples of 216 monthly observations each, with a block length of three monthly observations. As we can see, all moments are matched reasonably well.

[Insert Tables 8 and 9 here.]

We can now consider FX correlation moments; the first two columns of Table 10 contrast the empirical moments (first column) with the benchmark model moments (second column). Our model generates a non-trivial cross-sectional spread in average physical and implied FX correlations, in line with the empirical evidence, and is able to closely match their cross-sectional mean. One weakness of the model regards the magnitude of FX correlation risk premiums: the model-implied premiums are lower (in absolute terms) than their empirical counterparts, so the cross-sectional mean of average premiums in the model, while positive, is lower than the empirical mean (0.71% in the model, compared with 1.58% in the data) and the model is unable to match the wide cross-sectional dispersion in average correlation risk premiums that is observed empirically. Notably though, the model is able to successfully generate both positive and negative FX correlation risk premiums, as in the data. The model is also able to match the almost perfect positive cross-sectional association between average realized and average implied FX correlations (0.98 in the data, 1.00 in the model) and, crucially, the strongly negative cross-sectional association between average realized correlations and average CRP. Indeed, in the simulated data, FX pairs with high average FX correlation have negative average CRP and FX pairs with low average FX correlation have positive average CRP, which is consistent with the empirical evidence; Figure 7 provides a graphical illustration of that feature by plotting the average model-implied CRP against the average model-implied FX correlation for all 36 FX pairs. As regards time-series properties, the model generates a perfect time-series correlation between realized and implied correlation for all FX pairs, replicating the very high average correlation (0.79) observed in the data, and a negative time-series correlation between realized correlation and CRP (−0.77), also in line with the empirical evidence (−0.52).

[15] The empirical spanning properties of FX correlation are explored in the Online Appendix.

[Insert Table 10 and Figure 7 here.]

In our model, exchange rates are only exposed to the first global shock u^w, so bad states for investors in foreign currencies are those characterized by high values of the global pricing factor z^w. Thus, we explore the cyclicality of FX correlations and FX correlation risk premiums in the model by mapping the countercyclical market variables we used in the empirical part of our paper to z^w; our aim is to match the empirical cyclicality findings in Figures 1 and 5. To do so, we follow the same two-step approach we use for our empirical data: first, we calculate the correlation cyclicality measure of each exchange rate pair, equal to the time-series correlation of its conditional FX correlation with z^w, and we then calculate the cross-sectional correlation of the FX correlation cyclicality measures with average FX correlations (36 observations, one for each FX pair). We find that the FX correlation cyclicality measures range from −0.73 to 0.73 across FX pairs and that their cross-sectional correlation with average FX correlations is strongly positive (0.75), suggesting that high correlation FX pairs have countercyclical correlations whereas low correlation pairs have procyclical correlations, in line with empirical evidence. Then, we repeat the same exercise for correlation risk premiums: we find that the FX CRP cyclicality measures range from −0.78 to 0.79 and that their cross-sectional correlation with average CRP is positive (0.81), again in line with the data.

Our model assumes only one dimension of ex ante heterogeneity across countries, their exposure γ to the global shock u^w. That heterogeneity generates cross-sectional differences in average FX correlations, average interest rates and average currency excess returns and, thus, engenders cross-sectional linkages among those three measures. In particular, the model implies that average correlations across FX pairs are positively associated with both the product of the corresponding foreign currencies' average interest rate differentials $E(r^i - r^0)E\left(r^j - r^0\right)$ and the product of their average currency excess returns $E(rx^i)E(rx^j)$. Those cross-sectional associations in simulated data are presented in Figure 8: Panel A illustrates the relation between average FX correlations and the product of average nominal interest rate differentials, while Panel B shows the relation between average FX correlations and the product of average currency excess returns. In support of our model, we find that both those model-implied positive cross-sectional associations are present in the empirical data: in the sample of G10 exchange rates, the cross-sectional correlation of average nominal FX correlations with the product of corresponding nominal interest rate differentials is 0.35 and the correlation with the product of average currency excess returns is 0.42.

[Insert Figures 8 and 9 here.]

Finally, we consider the asset pricing implications of the model. First, we focus on nominal interest rate-sorted currency portfolios; we sort the nine currencies into three portfolios and report the annualized average excess return of each portfolio in Panel A of Figure 9. The model generates a strong carry trade effect, with the return on the FX carry portfolio having an annualized average excess return of 2.79%. In congruence with the extant literature, the Lustig, Roussanov and Verdelhan (2011) HML^{FX} factor is priced in the cross section of simulated interest rate sorted portfolios: our low, medium, and high interest rate currency portfolios have HML^{FX} betas of −0.41, 0.06, and 0.59, respectively.

Next, we consider currency portfolios sorted on their ΔFXC beta; their annualized average excess returns are presented in Panel B of Figure 9. The annualized average excess return for the currency portfolio that is long currencies with low ΔFXC beta and short currencies with a high ΔFXC beta is 1.27%, suggesting a negative price for exposure to FX correlation risk, consistent with our empirical findings. It is worth noting that the Lustig, Roussanov and Verdelhan (2011) HML^{FX} factor is priced in the cross section of ΔFXC-beta-sorted currency portfolio returns, with the low, medium, and high ΔFXC beta portfolios having an HML^{FX} beta of 0.32, 0.06, and −0.15, respectively. Furthermore, there is a negative cross-sectional association between nominal interest rates and ΔFXC betas: the low, medium and high ΔFXC beta portfolio has an average interest rate differential (against the domestic country) of 0.81%, 0.16% and −0.43%, respectively.

For comparison, we now turn to the case of non-identical local pricing factors across countries ($0 \leq \rho < 1$). First, consider the behavior of conditional FX variance and covariance: conditional FX variance is given by

$$var_t\left(\Delta q^i_{t+1}\right) = \kappa z^i_t + \kappa z^0_t + \left(\sqrt{\gamma^i} - \sqrt{\gamma^0}\right)^2 z^w_t + \delta\left(\sqrt{z^i_t} - \sqrt{z^0_t}\right)^2, \tag{23}$$

whereas conditional FX covariance is

$$cov_t\left(\Delta q^i_{t+1}, \Delta q^j_{t+1}\right) = \kappa z^0_t + D^{i,j} z^w_t + \delta\left(\sqrt{z^i_t} - \sqrt{z^0_t}\right)\left(\sqrt{z^j_t} - \sqrt{z^0_t}\right). \tag{24}$$

When the local pricing factors differ across countries, exchange rates are more volatile than in the benchmark model, as differential exposure to u^g increases SDF disparity. As regards FX covariance, exposure to u^g risk has one key difference compared to exposure to u^w: country exposure to u^w is regulated by the fixed parameter γ and thus is constant over time, so FX pairs are either always similar or always dissimilar regarding their u^w exposure, whereas the exposure of each country i to u^g is determined by $\sqrt{\delta z^i}$, so it is unconditionally equal across countries, but time-varying, implying that each FX pair can switch between being similar and being dissimilar with respect to u^g exposure over time.

To understand the behavior of the cross-section of conditional FX correlations, we study the properties of the conditional correlations of similar and dissimilar FX pairs in the special case of independent local pricing factors ($\rho = 0$); the intuition is similar for other values of ρ less than 1. Similar to Figure 6, Figure 10 illustrates the effect of z^w and z^0 on conditional FX correlations in a world of three foreign countries: countries 1 and 2 are less exposed to the first global shock u^w than the domestic country, while country 3 is more exposed.

[Insert Figure 10 here.]

The left panels of Figure 10 depict conditional FX correlations as a function of the global pricing factor z^w holding all local pricing factors (domestic and foreign) constant at their common steady-state value $\bar{z}$. Not surprisingly, the impact of changes in the global pricing factor z^w is the same as in the model with identical local pricing factors: as z^w increases, similarities and dissimilarities in exposure to global risk get amplified. Thus, the cross-sectional dispersion in FX correlation is increasing in z^w (Panel E).

The right panels of Figure 10 present conditional FX correlations as a function of the domestic local pricing factor z^0, assuming that the global pricing factor z^w and all foreign local pricing factors are equal to their steady-state values. As we see, the relation between z^0 and conditional FX correlation is not monotonic. For small values of z^0, conditional FX correlation is high for both similar and dissimilar FX pairs (Panel B and Panel D, respectively): in those states, all FX pairs are similar regarding their exposure to u^g, as the loading of all foreign countries is higher than the domestic loading. As the value of z^0 increases, conditional FX correlation decreases, since the component of FX correlation arising from exposure to u^g is attenuated. When z^0 reaches $\bar{z}$, all local factors have identical values, so exposure to u^g does not affect FX moments, as it drops out of exchange rates. Finally, for large values of z^0, all FX pairs are again similar regarding their exposure to u^g, this time because the domestic loading is higher than all foreign loadings, so all FX pairs are highly correlated. Indeed, it can be shown that as $z^0 \to \infty$, all FX pairs become conditionally perfectly correlated. In sum, the cross-sectional dispersion of FX correlation is not monotonic in z^0 (Panel F).

The business cycle behavior of FXC, the cross-sectional dispersion of conditional FX correlation, depends on the relative importance of z^w and z^0 for FX correlation determination. The higher the correlation among the local pricing factors, the lower the importance of u^g exposure (and thus z^0) for conditional FX correlation, so high (low) values of ρ are associated with high (low) comovement between FXC and z^w. Panel A of Figure 11 plots the correlation of FXC with z^w against different values of ρ: we plot both the point estimate (solid line) and the 95% confidence interval (shaded area). Notably, only very high values of ρ lead to empirically plausible and statistically significant correlation between FXC and z^w. In particular, the correlation between FXC and z^w hovers around zero for almost the entirety of the ρ state space—even for $\rho = 0.95$, the correlation between the two measures is only 0.02. That correlation jumps to 0.60 for $\rho = 1$, with an associated 95% confidence interval of [0.27,0.83], underscoring the importance of extremely high local pricing factor comovement.

We now turn to correlation risk premiums; the details are reported in Appendix D. In the special case of independent local pricing factors ($\rho = 0$), the domestic investor only prices z^0 and z^w shocks, whereas innovations in the foreign local pricing factors are foreign-specific shocks that do not enter the domestic investor's SDF and, thus, are unpriced. In that case, the risk-neutral measure overweighs states in which z^w and z^0 have elevated values. Assuming, as we did for our benchmark model, that the domestic agent prices local shocks more harshly than global shocks, risk adjustment mainly entails paying attention to high z^0 states. As seen in Panels B and D of Figure 10, those states are characterized by high conditional FX correlations for both similar and dissimilar FX pairs. Thus, pricing states in which the domestic pricing factor z^0 has a high value tends to generate higher implied than physical FX correlations, and thus positive correlation risk premiums, for all FX pairs.

The simulated FX moments of the model with independent local pricing factors ($\rho = 0$) are reported in the third column of Table 10. The cross-section of average physical FX correlations is much tighter now than in the benchmark model, as exchange rate exposure to u^g ameliorates the importance of differences in u^w exposure across countries; the same is true for implied FX correlations. Average FX correlation risk premiums are small for all FX pairs, and, consistent with the discussion above, are positive: the left tail (i.e., the 2.5 percentile) of average CRP is 0.00%, whereas the right tail (i.e., the 97.5 percentile) is 0.08% and statistically significant. Furthermore, the model generates no cross-sectional association between average FX correlations and average FX correlation risk premiums, at odds with the empirical evidence. This is because the exposure to u^g, which tends to increase the correlation of all FX pairs, similar and dissimilar, as z^0 increases, and thus generates positive CRP for all FX pairs, offsets the effects of the exposure to u^w, which tends to decrease the correlation of similar FX pairs and increase the correlation of dissimilar FX pairs as z^0 increases, and thus generates negative CRP for similar FX pairs and positive CRP for dissimilar FX pairs. Lastly, the model with $\rho = 0$ fails to match the empirical time-series properties of FX correlation risk premiums: on average, the time series of simulated physical FX correlations and FX CRP are almost uncorrelated, at odds with the strongly negative correlation that characterizes their empirical counterparts.

To explore the behavior of FX correlation risk premiums for intermediate values of ρ, Panel B of Figure 11 plots the correlation coefficient of average FX correlations and average CRP for $\rho = \{0, 0.05, ..., 0.95, 1\}$. As the value of ρ increases, and thus the local pricing factors become more correlated across countries, the cross-sectional correlation between average FX correlations and average FX correlation risk premiums tends to decline. We find that high values of ρ are needed for this correlation to become statistically significant. In particular, the cross-sectional correlation is negative and significant at the 5% level only for ρ values of 0.65 and higher. Taken together, Panels A and B of Figure 11 show that only very high values of ρ can jointly satisfy the physical and the risk-neutral measure properties of FX correlations.

A weakness of our benchmark model, which imposes the polar condition of $\rho = 1$, is that the cross-sectional rank of interest rates (nominal and real) is fixed across time, as cross-sectional interest rate disparity is only generated by the fixed parameter γ. In reality, the cross-sectional ranking of interest rates is time-varying, so this feature of the model is not realistic and precludes matching salient empirical findings, such as the "dollar carry trade" explored in Lustig, Roussanov and Verdelhan (2014). However, we can show that a very small relaxation of the assumption of identical local pricing factors allows the model to generate realistic cross-sectional properties of interest rates without compromising the desirable features of the benchmark model for FX correlations.

Consider the average interest rate differential between the foreign countries and the domestic country (AFD, average forward discount):

$$AFD_t = \frac{1}{I}\sum_{i=1}^{I} r_t^i - r_t^0 = \left(\chi - \frac{1}{2}\kappa - \frac{1}{2}\delta\right)\left(\frac{1}{I}\sum_{i=1}^{I} z_t^i - z_t^0\right) + \frac{1}{2}\left(\gamma^0 - \frac{1}{I}\sum_{i=1}^{I}\gamma^i\right) z_t^w. \tag{25}$$

Notably, the expression above is valid for both nominal and real interest rate differentials. If the local pricing factor is identical across countries ($\rho = 1$), then the first term drops out and the AFD solely reflects fluctuations in the global pricing factor z^w, never changing sign. However, if the local pricing factors differ across countries ($0 \le \rho < 1$), then the AFD can change sign across time, as it reflects fluctuations both in z^w and the local pricing factors. In the special, and empirically plausible—if the domestic country is the United States—case that the domestic SDF loading on global risk

u^w is close to the average foreign loading ($\gamma^0 \simeq \frac{1}{I}\sum_{i=1}^{I}\gamma^i$), the sign of the AFD each period is determined by the sign of the local pricing factor differential. Assuming that the precautionary savings motive dominates the intertemporal smoothing motive ($\chi < \frac{1}{2}\kappa + \frac{1}{2}\delta$) and that the number of foreign countries I is large enough so that the average of the foreign local pricing factors is always close to their common steady-state value $\overline{z}$,

$$\frac{1}{I}\sum_{i=1}^{I} z_t^i \rightarrow \overline{z}, \tag{26}$$

then the AFD is positive (negative) when the domestic local pricing factor z^0 is higher (lower) than its steady-state value. In that case, a domestic investor engaging in the dollar carry trade, i.e. investing in foreign currencies when $AFD > 0$ and shorting them when $AFD < 0$, takes (insures) FX risk when the domestic pricing factor z^0 is transitorily high (low).

To show that our model can address the salient cross-sectional properties of interest rates, we simulate the model setting $\rho = 0.999$, keeping all other parameters at their Table 8 values. In simulated data, this ρ value implies an average cross-sectional correlation of 0.999 for the local pricing factors. We find that the model with $\rho = 0.999$ preserves the key FX correlation features of the benchmark model; the simulated moments are presented in the last column of Table 10. As regards the dollar carry trade, its empirical annualized return for the G10 currencies from January 1996 to December 2013 is 5.26% using the nominal AFD and 3.48% using the real AFD. In the model, the two strategies are identical, yielding an annualized return of 1.82%, so the model undershoots both empirical returns. On the other hand, the model is able to almost perfectly match the turnover of interest rate-sorted currency portfolios: it generates a monthly turnover of 0.049, virtually identical to the empirical turnover of 0.047 observed in the G10 sample from January 1996 to December 2013.

6. Conclusion

We document that FX correlations become more cross-sectionally dispersed in adverse economic states, and construct an FX correlation dispersion measure, denoted by FXC and defined as the difference between the conditional correlation of the most and least conditionally correlated FX pairs. We then sort currencies into portfolios based on their exposure to FXC innovations and show that the spread between high and low ΔFXC beta currency portfolios is economically and statistically significant (6.42% annually), suggesting that investors want to be compensated for investing in currencies that perform badly during periods of increased cross-sectional dispersion in conditional FX correlations. Then, defining the FX correlation risk premium as the difference between the FX correlation under the risk-neutral and the physical probability measures, we find a strongly negative cross-sectional association between average FX correlations and average FX correlation risk premiums: FX pairs with high average correlation exhibit low (or negative) average correlation risk premiums, while the opposite is true for FX pairs with low average correlations.

We rationalize our empirical findings with a no-arbitrage model of exchange rates that is able to jointly match the salient properties of FX correlations under both the physical and the risk-neutral measure. Our findings suggest that a possible avenue for richer no-arbitrage models that feature endogenously determined stochastic discount factors and aim to explain the dynamics of FX correlation is the incorporation of unspanned risk; in that class of models, any shock that affects countries' SDF identically (and thus does not enter exchange rates) and causes the cross section of FX correlation to tighten, can potentially address the apparent inconsistency between the behavior of FX correlations under the physical measure and under the risk-neutral measure. That said, we stress that unspanned risk is not the only possible avenue to be explored; alternative economic mechanisms, including market segmentation or other frictions in financial markets, may also play a role in addressing our empirical findings.

Appendix A. Realized FX moments

We use daily spot exchange rates to calculate measures of realized FX moments. $\Delta s_t^i = \ln\left(S_t^i\right) - \ln(S_{t-1}^i)$ denotes the daily log change for exchange rate i. The annualized realized FX variance observed at t is then calculated as follows:

$$\mathrm{RV}_t = \frac{252}{K} \sum_{k=0}^{K-1} \Delta s_{t-k}^2, \tag{A.1}$$

where K refers to a three month window to estimate the rolling realized variances. Following Bollerslev, Tauchen and Zhou (2009), we use this rolling estimate to proxy for the expected variance over the next month.

In a similar spirit, we derive the annualized realized covariance between exchange rates i and j:

$$\mathrm{RCov}_t^{i,j} = \frac{252}{K} \sum_{k=0}^{K-1} \Delta s_{t-k}^i \Delta s_{t-k}^j. \tag{A.2}$$

Finally, the realized FX correlation is defined as the ratio of corresponding realized FX covariance and the product of the respective FX standard deviations:

$$\mathrm{RC}_t^{i,j} = \mathrm{RCov}_t^{i,j} / \sqrt{\mathrm{RV}_t^i}\sqrt{\mathrm{RV}_t^j}. \tag{A.3}$$

Appendix B. The price of FX correlation risk

We consider the following two-factor model:

$$\mathrm{E}[rx^i] = \beta_i^{DOL}\lambda^{DOL} + \beta_i^{HML^C}\lambda^{HML^C}, \tag{B.1}$$

where rx^i denotes the excess return in levels (i.e., corrected for the Jensen term). To estimate the factor prices λ^{DOL} and λ^{HML^C} we follow the two-stage procedure of Fama and MacBeth (1973): first, we run a time-series regression of excess returns on the factors and then we run a cross-sectional regression of average excess returns on factor betas. We do not include a constant in the cross-sectional regression of the second stage.[16]

Panel A in Table 11 reports the first-stage regression results. We consider 15 test assets: three currency portfolios sorted on exposure to ΔFXC (Pf1$^{\mathrm{C}}$, Pf2$^{\mathrm{C}}$ and Pf3$^{\mathrm{C}}$), three currency portfolios sorted on forward discounts (called "carry portfolios" and denoted by Pf1$^{\mathrm{F}}$, Pf2$^{\mathrm{F}}$ and Pf3$^{\mathrm{F}}$) and nine individual G10 exchange rates. As expected, the HML^C betas of the ΔFXC-beta-sorted portfolios are monotonically increasing. On the other hand, the HML^C betas of the carry portfolios are monotonically decreasing, with low (high) interest rate currencies having a positive (negative) HML^C beta. Finally, the HML^C betas for the individual G10 currencies are highly negatively correlated with their average excess returns over the sample period, with the correlation coefficient being −0.92.

Panel B presents the second-stage results for various sets of test assets. Set (1) includes only the three ΔFXC-beta-sorted portfolios (Pf1$^{\mathrm{C}}$ to Pf3$^{\mathrm{C}}$) and the three carry portfolios (Pf1$^{\mathrm{F}}$ to Pf3$^{\mathrm{F}}$), while Set (2) contains the test assets of Set (1) along with the nine individual G10 currencies. For both sets, we report the point estimates of the prices of risk, along with their standard errors (in parentheses) and Shanken (1992)-corrected standard errors (in brackets). We also report the R^2 of each second-stage regression. We find a significantly negative price of correlation risk: λ^{HML^C} is −0.58% (−0.54%) per month for Set (1) (Set (2)). Those estimates are not significantly different from the average HML^C return of −0.54% per month. The second-stage R^2 is very high for both regressions (0.99 and 0.93, respectively).

[Insert Table 11 here.]

[16] The dollar factor *DOL* essentially acts a constant; see Lustig, Roussanov and Verdelhan (2011).

For robustness, we also consider additional developed and emerging country currencies. Set (3) of test assets includes four ΔFXC-beta-sorted and four forward-discount-sorted portfolios, using all developed country currencies. Set (4) includes four ΔFXC-beta-sorted and four forward-discount-sorted portfolios, using the full set of currencies. The second-stage results are provided in Panel B of Table 11. We find that the λ^{HML^C} estimates are in line with our benchmark results: the price of correlation risk is estimated at -0.51% and -0.67% per month in Sets (3) and (4), respectively, with both estimates being statistically significant at the 5% level. The regression R^2 is 0.90 for Set (3) and 0.81 for Set (4).[17]

We have shown that our traded correlation risk factor HML^C acts as a slope factor regarding the pricing of currency risk. A natural question that arises regards the relation between HML^C and the Lustig, Roussanov and Verdelhan (2011) carry trade factor HML^{FX}, which reflects the returns to a portfolio that invests in high interest rate currencies and shorts low interest rate currencies, as HML^{FX} has also been shown to act as a slope factor. Empirically, the two factors are strongly negatively correlated: using monthly data from January 1996 to December 2013, the correlation coefficient between the two time series is -0.66, suggesting that they capture similar sources of risk.

The highly negative association between HML^{FX} and HML^C is fully consistent with our proposed no-arbitrage model. In the model, the excess return to the carry trade portfolio is defined as

$$HML^{FX}_{t+1} = \frac{1}{N}\sum_{i\in HF} rx^i_{t+1} - \frac{1}{N}\sum_{i\in LF} rx^i_{t+1}, \tag{B.2}$$

with high interest rate (low γ, according to the model) currencies in set HF and low interest rate (high γ) currencies in set LF. Provided that currency portfolios contain enough currencies so that the local shocks average zero, HML^{FX} innovations are perfectly positively correlated with the global shock u^w:

$$HML^{FX}_{t+1} - E_t\left(HML^{FX}_{t+1}\right) = \frac{1}{N}\left(\sum_{i\in LF}\sqrt{\gamma^i} - \sum_{i\in HF}\sqrt{\gamma^i}\right)\sqrt{z^w_t}u^w_{t+1}. \tag{B.3}$$

Thus, HML^{FX} returns capture exposure to the global shock u^w, which is the only global shock priced in currency markets.

On the other hand, FXC innovations capture both kinds of global shocks, u^w and u^g, so they provide a very noisy measure of the part of FX correlation risk that is priced in foreign exchange markets. It follows that HML^{FX} will always have better pricing ability than ΔFXC in the cross section of currency returns. To get a cleaner measure of u^w innovations, we can consider FX return differentials, which are only exposed to u^w shocks. In particular, consider portfolio HML^C, which is long currencies with high ΔFXC loading and short currencies with low ΔFXC loading. Its return is

$$HML^{C}_{t+1} = \frac{1}{N}\sum_{i\in HC} rx^i_{t+1} - \frac{1}{N}\sum_{i\in LC} rx^i_{t+1}, \tag{B.4}$$

with high-ΔFXC-loading (i.e. high γ) currencies in set HC and low-ΔFXC-loading (low γ) currencies in set LC. Provided that the long and the short positions of the portfolio contain enough currencies so that the local shocks cancel out, the return innovations of the HML^C portfolio are perfectly negatively correlated with the global shock u^w:

$$HML^{C}_{t+1} - E_t\left(HML^{C}_{t+1}\right) = \frac{1}{N}\left(\sum_{i\in LC}\sqrt{\gamma^i} - \sum_{i\in HC}\sqrt{\gamma^i}\right)\sqrt{z^w_t}u^w_{t+1}. \tag{B.5}$$

Therefore, HML^C return innovations are perfectly negatively correlated with HML^{FX} return innovations, as they both reflect u^w shocks and, thus, should have the same explanatory power for the cross section of FX returns: high γ currencies, which hedge u^w risk, have low interest rates, high HML^C betas, low HML^{FX} betas and low risk premiums, whereas low γ (i.e. high interest rate, low HML^C beta, high HML^{FX} beta) currencies have high risk premiums.[18]

[17] To conserve space, we defer the first-stage regression results for the test assets in Sets (3) and (4) to the Online Appendix. Furthermore, the Online Appendix contains price of risk estimates using FXC innovations, a non-traded factor, in lieu of HML^C returns, a traded factor; we find that FXC innovations also have a negative price in the cross section of currency returns.

[18] In the Online Appendix, we also discuss the relation between our FX correlation risk factor and the FX volatility risk factor of Menkhoff, Sarno, Schmeling and Schrimpf (2012).

Appendix C. Implied FX moments

We follow Demeterfi, Derman, Kamal and Zou (1999) and Britten-Jones and Neuberger (2000) to obtain a model-free measure of implied volatility. They show that if the underlying asset price is continuous, then the risk-neutral expectation over a horizon $T-t$ of total return variance is defined as an integral of option prices over an infinite range of strike prices:

$$\mathrm{E}_t^{\mathbb{Q}}\left(\int_t^T \left(\sigma_u^i\right)^2 du\right) = 2e^{r(T-t)}\left(\int_0^{S_t} \frac{1}{K^2}\mathrm{P}(K,T)\,dK + \int_{S_t}^{\infty} \frac{1}{K^2}\mathrm{C}(K,T)\,dK\right), \tag{C.1}$$

where S_t is the underlying spot exchange rate, $\mathrm{P}(K,T)$ and $\mathrm{C}(K,T)$ are the respective put and call option prices with maturity date T and strike price K, and r is the continuously compounded interest rate of the quote currency.[19] In practice, the number of traded options for any underlying asset is finite; hence the available strike price series is a finite sequence. Calculating the model-free implied variance involves the entire cross section of option prices: for each maturity T, all five strikes are taken into account. These are quoted in terms of the option delta. In addition, we use daily spot rates and one-month Eurocurrency (LIBOR) rates from Datastream. Following the conventions in the FX market, we use the use the Garman and Kohlhagen (1983) valuation formula to extract the relevant strike prices and to calculate the corresponding option prices.[20]

To approximate the integral in equation (C.1), we adopt a trapezoidal integration scheme over the range of strike prices covered by our dataset. Jiang and Tian (2005) report two types of implementation errors: (i) truncation errors due to the non-availability of an infinite range of strike prices, and (ii) discretization errors that arise due to the unavailability of a continuum of available options. We find that both errors are extremely small when currency options are used. For example, the size of the errors totals only half a percentage point in terms of volatility.

Model-free implied correlations are constructed from the available model-free implied volatilities.[21] For the construction we require all cross rates for three currencies, S_t^i, S_t^j, and S_t^{ij}, i.e. the two exchange rates against the domestic (base) currency and the exchange rate between the two foreign currencies. The absence of triangular arbitrage then implies that:[22] $S_t^{ij} = S_t^i/S_t^j$. Taking logs, we derive the following equation:

$$\ln\left(\frac{S_T^{ij}}{S_t^{ij}}\right) = \ln\left(\frac{S_T^i}{S_t^i}\right) - \ln\left(\frac{S_T^j}{S_t^j}\right). \tag{C.2}$$

Finally, taking variances yields:

$$\int_t^T \left(\sigma_u^{ij}\right)^2 du = \int_t^T \left(\sigma_u^i\right)^2 du + \int_t^T \left(\sigma_u^j\right)^2 du - 2\int_t^T \gamma_u^{i,j} du, \tag{C.3}$$

where $\gamma_t^{i,j}$ denotes the covariance of returns between domestic currency FX pairs i and j. Solving for the covariance term, we obtain:

$$\int_t^T \gamma_u^{i,j} du = \frac{1}{2}\int_t^T \left(\sigma_u^i\right)^2 du + \frac{1}{2}\int_t^T \left(\sigma_u^j\right)^2 ds - \frac{1}{2}\int_t^T \left(\sigma_u^{ij}\right)^2 du. \tag{C.4}$$

[19] In particular, Britten-Jones and Neuberger (2000) show that the risk-neutral expected integrated return variance is fully specified by a continuum of call and put options, provided that the price of the underlying asset is a diffusion process. However, recent empirical evidence shows that jump risk may be present in the FX market, see, e.g., Chernov, Graveline and Zviadadze (2016), Jurek (2014), and Farhi, Fraiberger, Gabaix, Ranciere and Verdelhan (2015). In the Online Appendix, we show that our analysis is robust to the presence of jumps.

[20] See, e.g., Wystup (2006) for the specifics of FX options conventions.

[21] Brandt and Diebold (2006) use the same approach to construct realized covariances of exchange rates from range-based volatility estimators. Our construction methodology relies on state prices being sufficiently similar for the different agents (countries).

[22] Recent studies report that the average violation of triangular arbitrage is about 1.5 basis points with an average duration of 1.5 seconds (Kozhan and Tham (2012)). However, most papers examining violations of triangular arbitrage use indicative quotes, which give only an approximate price at which a trade can be executed. Executable prices can differ from indicative prices by several basis points. Using executable FX quotes, Fenn, Howison, McDonald, Williams and Johnson (2009) report that triangular arbitrage is less than 1 basis point and the duration less than 1 second. Our data also indicate that triangular arbitrage is less than 1 basis point. We therefore conclude that these violations have no effect on calculated quantities.

Using the standard replication arguments, we find that:

$$
\begin{aligned}
\mathrm{E}_t^{\mathbb{Q}}\left(\int_t^T \gamma_u^{i,j}\, du\right) &= e^{r(T-t)}\Bigg(\int_t^{S_t^i} \frac{1}{K^2}\mathrm{P}^i(K,T)\, dK + \int_{S_t^i}^{\infty} \frac{1}{K^2}\mathrm{C}^i(K,T)\, dK \\
&\quad + \int_t^{S_t^j} \frac{1}{K^2}\mathrm{P}^j(K,T)\, dK + \int_{S_t^j}^{\infty} \frac{1}{K^2}\mathrm{C}^j(K,T)\, dK \\
&\quad - \int_t^{S_t^{ij}} \frac{1}{K^2}\mathrm{P}^{ij}(K,T)\, dK - \int_{S_t^{ij}}^{\infty} \frac{1}{K^2}\mathrm{C}^{ij}(K,T)\, dK\Bigg).
\end{aligned} \tag{C.5}
$$

The model-free implied correlation can then be calculated using expression (C.5) and the model-free implied variance expression (C.1):

$$
\mathrm{E}_t^{\mathbb{Q}}\left(\int_t^T \rho_u^{i,j} du\right) \equiv \frac{\mathrm{E}_t^{\mathbb{Q}}\left(\int_t^T \gamma_u^{i,j} ds\right)}{\sqrt{\mathrm{E}_t^{\mathbb{Q}}\left(\int_t^T \left(\sigma_u^i\right)^2 du\right)}\sqrt{\mathrm{E}_t^{\mathbb{Q}}\left(\int_t^T \left(\sigma_u^j\right)^2 du\right)}}. \tag{C.6}
$$

Appendix D. FX correlation risk premiums in the model

For period $[t, T]$, the expected variance of the changes in the log exchange rate i is given by

$$
E_t^{\mathbb{Q}}\left(\sum_{s=0}^{T-t-1} var_{t+s}\left(\Delta q_{t+s+1}^i\right)\right) = \sum_{s=0}^{T-t-1} E_t^{\mathbb{Q}}\left[2\kappa z_{t+s} + \left(\sqrt{\gamma^i} - \sqrt{\gamma^0}\right)^2 z_{t+s}^w\right], \tag{D.1}
$$

and the expected covariance of the changes in log exchange rates i and j is

$$
E_t^{\mathbb{Q}}\left(\sum_{s=0}^{T-t-1} cov_t\left(\Delta q_{t+1}^i, \Delta q_{t+1}^j\right)\right) = \sum_{s=0}^{T-t-1} E_t^{\mathbb{Q}}\left[\kappa z_{t+s} + \left(\sqrt{\gamma^i} - \sqrt{\gamma^0}\right)\left(\sqrt{\gamma^j} - \sqrt{\gamma^0}\right) z_{t+s}^w\right]. \tag{D.2}
$$

For the local pricing factor we have

$$
E_t^{\mathbb{Q}}(z_{t+s}) = \left(1 - (1-\lambda^{\mathbb{Q}})^s\right)\overline{z}^{\mathbb{Q}} + (1-\lambda^{\mathbb{Q}})^s z_t \equiv A_s^{\mathbb{Q}} + B_s^{\mathbb{Q}} z_t \tag{D.3}
$$

under the risk-neutral measure and

$$
E_t(z_{t+s}) = (1 - (1-\lambda)^s)\,\overline{z} + (1-\lambda)^s z_t \equiv A_s + B_s z_t \tag{D.4}
$$

under the physical measure, with $A_s^{\mathbb{Q}} > A_s$ and $B_s^{\mathbb{Q}} > B_s$ for all $s > 0$. A similar notation can be used for the global pricing factor z^w. For $X_s = \{A_s, B_s, A_s^{\mathbb{Q}}, B_s^{\mathbb{Q}}, A_s^w, B_s^w, A_s^{w,\mathbb{Q}}, B_s^{w,\mathbb{Q}}\}$, we respectively define $X = \{A, B, A^{\mathbb{Q}}, B^{\mathbb{Q}}, A^w, B^w, A^{w,\mathbb{Q}}$ and $B^{w,\mathbb{Q}}\}$ as $X \equiv \sum_{s=0}^{T-t-1} X_s$.

The expected FX correlation is defined as the ratio of the corresponding expected FX covariance over the product of the square root of the two FX variances, as in the empirical section of our paper. Thus, the FX correlation risk premium can be written as

$$
\begin{aligned}
CRP_t^{i,j} &= \frac{\kappa\left(A^{\mathbb{Q}} + B^{\mathbb{Q}} z_t\right) + D^{i,j}\left(A^{w,\mathbb{Q}} + B^{w,\mathbb{Q}} z_t^w\right)}{\sqrt{2\kappa\left(A^{\mathbb{Q}} + B^{\mathbb{Q}} z_t\right) + \left(\sqrt{\gamma^i} - \sqrt{\gamma^0}\right)^2\left(A^{w,\mathbb{Q}} + B^{w,\mathbb{Q}} z_t^w\right)}\sqrt{2\kappa\left(A^{\mathbb{Q}} + B^{\mathbb{Q}} z_t\right) + \left(\sqrt{\gamma^j} - \sqrt{\gamma^0}\right)^2\left(A^{w,\mathbb{Q}} + B^{w,\mathbb{Q}} z_t^w\right)}} &\text{(D.5)} \\
&\quad - \frac{\kappa\left(A + B z_t\right) + D^{i,j}\left(A^w + B^w z_t^w\right)}{\sqrt{2\kappa\left(A + B z_t\right) + \left(\sqrt{\gamma^i} - \sqrt{\gamma^0}\right)^2\left(A^w + B^w z_t^w\right)}\sqrt{2\kappa\left(A^{\mathbb{Q}} + B^{\mathbb{Q}} z_t\right) + \left(\sqrt{\gamma^j} - \sqrt{\gamma^0}\right)^2\left(A^w + B^w z_t^w\right)}}. &\text{(D.6)}
\end{aligned}
$$

Thus, the magnitude of the correlation risk premium depends on the difference between the risk-neutral measure parameters $A^{\mathbb{Q}}$, $B^{\mathbb{Q}}$, $A^{w,\mathbb{Q}}$ and $B^{w,\mathbb{Q}}$ and the physical measure parameters A, B, A^w and B^w. When the domestic agent prices fluctuations in the local pricing factor more heavily than fluctuations in the global pricing factor, i.e., when $\xi\sqrt{\delta} >> \xi^w\sqrt{\gamma^0}$, then

$$
\left(A^{\mathbb{Q}} + B^{\mathbb{Q}} z_t\right) - (A + B z_t) >> \left(A^{w,\mathbb{Q}} + B^{w,\mathbb{Q}} z_t^w\right) - (A^w + B^w z_t^w), \tag{D.7}
$$

implying that the risk adjustment for the local pricing factor z is quantitatively larger than the risk adjustment for the global pricing factor z^w as regards FX correlation. The implications of such risk adjustment for the cross-sectional and time-series properties of FX correlation risk premiums are discussed in the main text.

As regards the nesting model, the law of motion for the global pricing factor z^w under the risk-neutral measure is identical to its risk-neutral measure law of motion in the model with identical pricing factors, given in equation (17), whereas the law of motion of the domestic local pricing factor z^0 is

$$\Delta z^0_{t+1} = \lambda^{0,\mathbb{Q}}(\bar{z}^{0,\mathbb{Q}} - z^0_t) - \xi \sqrt{z^0_t}\left(\sqrt{\rho}u^{g,\mathbb{Q}}_{t+1} + \sqrt{1-\rho}u^{0,\mathbb{Q}}_{t+1}\right), \tag{D.8}$$

where $\bar{z}^{0,\mathbb{Q}} \equiv \frac{\lambda}{\lambda^{0,\mathbb{Q}}}\bar{z}$ and $\lambda^{0,\mathbb{Q}} = \lambda - \xi\left(\sqrt{\rho}\sqrt{\delta} + \sqrt{1-\rho}\sqrt{\kappa}\right)$, as both components of the innovations in z^0 are priced by the domestic investor. For the foreign local pricing factors z^i with $i = 1, ..., I$, the risk-neutral measure law of motion is

$$\Delta z^i_{t+1} = \lambda(\bar{z} - z^i_t) + \xi\sqrt{\rho}\sqrt{\delta}\sqrt{z^i_t}\sqrt{z^0_t} - \xi\sqrt{z^i_t}\left(\sqrt{\rho}u^{g,\mathbb{Q}}_{t+1} + \sqrt{1-\rho}u^{i,\mathbb{Q}}_{t+1}\right), \tag{D.9}$$

as the domestic investor prices only the global component $\sqrt{\rho}u^g$ of the foreign local pricing factor innovations, but not their local component $\sqrt{1-\rho}u^i$.

Appendix E. Model calibration and simulation

Excluding ρ, the nesting model has 14 + (I + 1) parameters in total: five common SDF parameters (α, χ, ϕ, κ, and δ), $I + 1$ heterogeneous parameters (the loading γ^i for each country), six common pricing factor parameters—three for the local pricing factor (λ, $\bar{z}$ and ξ) and three for the global pricing factor (λ^w, $\bar{z}^w$ and ξ^w) —and three common inflation parameters ($\bar{\pi}$, ζ and σ).

To calibrate our benchmark model, we impose $\rho = 1$ and then largely follow Lustig, Roussanov, and Verdelhan (2011, 2014). First, we reduce the set of parameters by imposing the constraint that the loadings γ^i are equally spaced across the foreign countries. In particular, we assume that the first foreign country has loading γ^{min}, the last foreign country has loading γ^{max}, and each intermediate foreign country $i = 2, ..., I-1$ has loading $\gamma^i = \gamma^{min} + \frac{i-1}{I-1}(\gamma^{max} - \gamma^{min})$. To generate a large effect of the local pricing factor, in line with our model, we first set $\delta = 40$ and $\lambda = 0.25$; the latter value ensures that the local pricing factor z is stationary under both the physical and the risk-neutral measure. Furthermore, we set γ^{min} to 0.20 (instead to 0.18, as in the Lustig, Roussanov and Verdelhan (2014) calibration), in order to achieve a more realistic cross-sectional dispersion in interest rates and FX correlations; in unreported results, using 0.18 does not affect our results substantially. All the other parameters, with the exception of χ, ξ, ξ^w and $\bar{\pi}$, are set equal to the corresponding values in Lustig, Roussanov and Verdelhan (2014). Notably, the calibration in Lustig, Roussanov and Verdelhan (2014) targets specific interest rate, inflation, and exchange rate moments, but does not involve any moments related to FX correlations or FX correlation risk premiums. Finally, we set χ, ξ, ξ^w and $\bar{\pi}$ using GMM as follows. We target three moments: the cross-sectional average of the time-series mean and variance of the real interest rates of the ten countries, and the cross-sectional average of the time-series mean of the inflation rates of the ten countries. In the estimation, we leave $\bar{\pi}$ unconstrained, but constrain the ratio of $\frac{\xi}{\xi^w}$ to equal 2.43, which is the parameter ratio in the Lustig, Roussanov and Verdelhan (2014) calibration. The values of our calibrated parameters are reported in Table 8. Regarding the calibration data, we proxy interest rate differentials against the USD by the corresponding forward discounts, while the nominal USD interest rate is set to the Fama-French 1-month Treasury Bill rate. Inflation in each country is calculated using the corresponding CPI, and real interest rates are calculated as the difference between nominal interest rates and inflation rates.

Finally, we simulate the model for different values of ρ. We consider two types of simulations: small-sample and large-sample. For a given value of ρ, a small-sample simulation consists of 1,000 simulation paths of 5,216 monthly observations each, initialized at the steady-state values $\bar{z}$ and $\bar{z}^w$; to reduce the effect of initial conditions, we discard the first 5,000 observations, so we are left with 216 observations for each path, allowing us to study the small-sample properties of the moments of interest. For a given value of ρ, a large-sample simulation consists of a single path of 55,000 monthly observations, initialized at the steady-state values $\bar{z}$ and $\bar{z}^w$; again, we discard the first 5,000 observations, and calculate moments using the last 50,000 observations. For both kinds of simulations, conditional FX moments (realized and implied) are calculated using conditional expectations over a period of 21 days (i.e. one month) into the future, with the model parameters appropriately adjusted to the daily frequency; at each period, conditional expectations are calculated using averages across 100 simulations, with the exception of the benchmark model ($\rho = 1$), in which case we use closed-form expressions for the conditional expectations.

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Table 1. Summary statistics: G10 currencies

The table reports summary statistics for the G10 currencies. For each foreign currency i we report the mean, standard deviation, Sharpe ratio, skewness, and kurtosis of USD excess returns $f_t^i - s_{t+1}^i$, and the mean forward discount $f_t^i - s_t^i$. Excess returns are annualized and expressed in percentage points. Panel A: monthly data from January 1996 through December 2013. Panel B: monthly data from January 1984 through December 2013. In both panels, before January 1999 we use the DEM in the place of the EUR.

Panel A: January 1996–December 2013

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
Mean	3.01	1.12	-0.39	-0.46	1.37	-2.74	1.17	3.73	0.22
StDev	12.78	8.50	10.91	10.25	8.50	10.78	11.15	13.09	11.22
Sharpe ratio	0.24	0.13	-0.04	-0.05	0.16	-0.25	0.11	0.29	0.02
Skewness	-0.60	-0.60	0.13	-0.15	-0.50	0.48	-0.36	-0.37	-0.08
Kurtosis	5.29	7.26	4.40	3.80	4.73	5.22	4.10	4.85	3.61
$f_t - s_t$	2.12	-0.04	-2.00	-0.60	0.91	-3.01	0.98	2.70	-0.10

Panel B: January 1984–December 2013

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
Mean	2.96	1.15	1.21	1.60	2.43	0.14	2.99	4.88	2.34
StDev	12.08	7.15	11.93	11.14	10.37	11.38	11.05	13.25	11.36
Sharpe ratio	0.24	0.16	0.10	0.14	0.23	0.01	0.27	0.37	0.21
Skewness	-0.72	-0.65	0.00	-0.21	-0.23	0.32	-0.48	-1.01	-0.46
Kurtosis	5.62	8.90	3.56	3.43	5.36	4.26	4.20	9.41	4.44
$f_t - s_t$	3.12	0.77	-1.83	-0.61	1.89	-2.64	2.23	4.15	1.60

Table 2. Summary statistics: FX correlations and FX correlation risk premiums.
The table reports means and standard deviations for realized and implied FX correlations (RC and IC, respectively), as well as FX correlation risk premiums (CRP) for all FX pairs. Correlation risk premiums are defined as the difference between the implied and realized correlations. Realized correlations are calculated using past daily log exchange rate changes over a three month window. Implied correlations are calculated from daily option prices on the underlying exchange rates. The last two columns report the bootstrapped 95% confidence interval (using the 2.5 and 97.5 percentiles). Monthly data from January 1996 to December 2013 (options data for EUR start in January 1999).

		RC		IC		CRP				
FX pair		Mean	Std	Mean	Std	Mean	Std	t-stat	2.5%	97.5%
AUD	CAD	0.471	0.25	0.430	0.27	-0.041	0.15	-4.07	-0.060	-0.023
AUD	CHF	0.357	0.27	0.405	0.20	0.048	0.15	4.73	0.028	0.068
AUD	EUR	0.450	0.28	0.544	0.16	0.019	0.09	2.81	0.006	0.031
AUD	GBP	0.422	0.24	0.453	0.19	0.031	0.12	3.86	0.014	0.046
AUD	JPY	0.155	0.34	0.238	0.26	0.083	0.16	7.58	0.062	0.103
AUD	NOK	0.467	0.26	0.431	0.29	-0.036	0.20	-2.64	-0.064	-0.010
AUD	NZD	0.755	0.16	0.739	0.15	-0.016	0.08	-2.97	-0.026	-0.005
AUD	SEK	0.474	0.25	0.480	0.20	0.005	0.13	0.61	-0.012	0.022
CAD	CHF	0.233	0.28	0.283	0.21	0.050	0.15	4.94	0.031	0.070
CAD	EUR	0.307	0.30	0.405	0.19	0.024	0.13	2.45	0.005	0.044
CAD	GBP	0.281	0.27	0.307	0.23	0.025	0.15	2.34	0.004	0.044
CAD	JPY	0.054	0.26	0.136	0.19	0.082	0.16	7.33	0.060	0.104
CAD	NOK	0.340	0.28	0.341	0.28	-0.002	0.18	-0.17	-0.028	0.022
CAD	NZD	0.413	0.23	0.352	0.34	-0.061	0.22	-4.19	-0.092	-0.035
CAD	SEK	0.352	0.26	0.287	0.29	-0.069	0.17	-5.96	-0.094	-0.047
CHF	EUR	0.888	0.13	0.875	0.12	-0.010	0.08	-1.69	-0.020	0.002
CHF	GBP	0.580	0.19	0.605	0.15	0.025	0.11	3.32	0.010	0.039
CHF	JPY	0.405	0.26	0.456	0.18	0.051	0.14	5.15	0.032	0.070
CHF	NOK	0.726	0.16	0.731	0.12	0.006	0.11	0.73	-0.009	0.021
CHF	NZD	0.358	0.23	0.370	0.20	0.012	0.16	1.06	-0.010	0.033
CHF	SEK	0.707	0.16	0.712	0.13	0.004	0.10	0.58	-0.010	0.017
EUR	GBP	0.644	0.15	0.683	0.10	0.003	0.08	0.54	-0.009	0.015
EUR	JPY	0.324	0.27	0.364	0.20	0.067	0.15	5.84	0.046	0.089
EUR	NOK	0.825	0.09	0.798	0.07	-0.025	0.06	-5.20	-0.035	-0.016
EUR	NZD	0.440	0.23	0.501	0.17	0.005	0.12	0.55	-0.013	0.022
EUR	SEK	0.816	0.11	0.817	0.08	-0.022	0.06	-4.64	-0.031	-0.012
GBP	JPY	0.217	0.26	0.293	0.19	0.076	0.15	7.29	0.056	0.095
GBP	NOK	0.577	0.16	0.638	0.12	0.059	0.16	5.39	0.038	0.080
GBP	NZD	0.415	0.23	0.404	0.22	-0.011	0.14	-1.15	-0.029	0.006
GBP	SEK	0.560	0.16	0.598	0.13	0.037	0.13	4.26	0.021	0.053
JPY	NOK	0.248	0.26	0.347	0.21	0.099	0.16	9.22	0.079	0.119
JPY	NZD	0.146	0.32	0.233	0.24	0.087	0.18	7.09	0.063	0.111
JPY	SEK	0.241	0.27	0.294	0.20	0.052	0.16	4.95	0.033	0.072
NOK	NZD	0.449	0.22	0.413	0.27	-0.036	0.20	-2.65	-0.064	-0.011
NOK	SEK	0.796	0.10	0.780	0.11	-0.016	0.08	-2.93	-0.026	-0.006
NZD	SEK	0.439	0.23	0.403	0.27	-0.036	0.18	-2.89	-0.060	-0.013

Table 3. Cyclicality of realized FX correlations and FX correlation risk premiums.
The table reports the unconditional correlation of realized correlations (RC cyclicality) and correlation risk premiums (CRP cyclicality) with four market variables: the global equity volatility measure used in Lustig, Roussanov and Verdelhan (2011) ($GVol$), the global funding illiquidity measure of Malkhozov, Mueller, Vedolin and Venter (2016) (GFI), the TED spread (TED), and the CBOE VIX (VIX). Unconditional correlations are calculated using monthly data from January 1996 through December 2013 (options data for EUR start in January 1999).

FX pair		RC cyclicality				CRP cyclicality			
		$GVol$	GFI	TED	VIX	$GVol$	GFI	TED	VIX
AUD	CAD	0.174	-0.016	-0.081	0.168	-0.090	-0.203	-0.029	-0.180
AUD	CHF	-0.110	-0.342	-0.241	-0.180	0.068	0.116	0.024	0.062
AUD	EUR	0.100	-0.217	-0.079	0.008	0.040	0.007	-0.076	0.060
AUD	GBP	0.016	-0.207	-0.047	-0.102	0.004	0.062	-0.070	0.053
AUD	JPY	-0.328	-0.488	-0.365	-0.395	0.077	0.162	0.110	0.082
AUD	NOK	0.143	-0.145	-0.037	0.089	-0.096	-0.113	-0.328	-0.116
AUD	NZD	0.298	-0.125	0.014	0.287	-0.107	0.036	-0.016	-0.138
AUD	SEK	0.121	-0.161	-0.084	0.050	-0.141	-0.017	-0.115	-0.125
CAD	CHF	-0.099	-0.251	-0.223	-0.164	0.120	0.099	0.167	0.103
CAD	EUR	0.070	-0.133	-0.106	-0.009	-0.056	-0.014	0.076	-0.031
CAD	GBP	0.042	-0.060	-0.021	-0.041	0.090	-0.156	-0.150	0.066
CAD	JPY	-0.284	-0.405	-0.322	-0.383	0.050	0.097	0.065	0.063
CAD	NOK	0.102	-0.065	-0.063	0.053	-0.038	-0.151	-0.132	-0.043
CAD	NZD	0.166	-0.005	-0.060	0.174	0.084	-0.321	-0.182	-0.018
CAD	SEK	0.134	-0.025	-0.066	0.069	-0.078	-0.091	-0.187	-0.028
CHF	EUR	-0.221	-0.107	-0.030	-0.250	0.330	0.122	0.178	0.308
CHF	GBP	-0.159	-0.323	-0.256	-0.265	0.069	0.114	0.113	0.087
CHF	JPY	-0.146	-0.063	-0.028	-0.223	0.069	0.114	0.002	0.133
CHF	NOK	-0.269	-0.045	-0.130	-0.276	0.103	-0.019	0.098	0.130
CHF	NZD	-0.106	-0.241	-0.256	-0.114	0.142	-0.026	-0.031	0.084
CHF	SEK	-0.186	-0.221	-0.013	-0.265	0.037	-0.050	0.059	0.025
EUR	GBP	0.105	-0.155	-0.137	-0.018	-0.216	-0.137	-0.043	-0.184
EUR	JPY	-0.281	-0.178	-0.215	-0.301	0.173	0.228	0.190	0.208
EUR	NOK	-0.064	0.137	0.026	-0.056	-0.063	-0.062	0.032	-0.042
EUR	NZD	0.135	-0.106	-0.057	0.104	-0.002	-0.111	-0.205	-0.022
EUR	SEK	0.077	-0.169	0.077	-0.025	-0.177	-0.107	0.058	-0.186
GBP	JPY	-0.353	-0.412	-0.368	-0.433	0.158	0.213	0.149	0.166
GBP	NOK	0.026	-0.041	-0.118	-0.041	-0.038	-0.010	0.058	0.017
GBP	NZD	0.059	-0.099	0.000	-0.007	0.001	-0.196	-0.227	0.006
GBP	SEK	0.097	-0.163	-0.065	0.006	-0.211	0.013	-0.028	-0.128
JPY	NOK	-0.340	-0.219	-0.303	-0.354	0.199	0.212	0.262	0.226
JPY	NZD	-0.327	-0.361	-0.352	-0.317	0.064	0.077	0.129	0.008
JPY	SEK	-0.343	-0.314	-0.224	-0.399	0.224	0.256	0.121	0.253
NOK	NZD	0.163	-0.059	-0.028	0.161	-0.062	-0.179	-0.301	-0.101
NOK	SEK	0.156	0.030	0.141	0.144	-0.086	-0.022	-0.105	-0.047
NZD	SEK	0.171	-0.065	-0.054	0.144	-0.118	-0.154	-0.284	-0.154

Table 4. Cross-sectional FX cyclicality regressions.

Panel A presents the output of cross-sectional regressions of average realized FX correlations on each of the four FX correlation cyclicality measures. Panel B presents the output of cross-sectional regressions of average FX correlation risk premiums on each of the four FX CRP cyclicality measures. Each panel reports the regression slope coefficients, their t-statistics, their bootstrapped 95% confidence intervals, and the regression R^2s. For Panel A (Panel B) results, each FX correlation cyclicality measure (FX CRP cyclicality measure) is defined as the unconditional correlation of realized FX correlation (FX CRP) with a given market variable. The market variables are the global equity volatility measure used in Lustig, Roussanov and Verdelhan (2011) ($GVol$), the global funding illiquidity measure of Malkhozov, Mueller, Vedolin and Venter (2016) (GFI), the TED spread (TED), and the CBOE VIX (VIX). The cyclicality measures are calculated using monthly data from January 1996 through December 2013 (options data for EUR start in January 1999) and are reported in Table 3. The t-statistics (in parentheses) are calculated using White (1980) standard errors.

Panel A: Average RC and RC cyclicality					
	Slope	t-stat	2.5%	97.5%	R^2
$GVol$	0.404	(2.45)	0.064	1.000	0.14
GFI	0.867	(5.14)	0.176	1.054	0.32
TED	1.151	(7.31)	0.348	1.638	0.50
VIX	0.409	(2.66)	0.148	0.892	0.15
Panel B: Average CRP and CRP cyclicality					
	Slope	t-stat	2.5%	97.5%	R^2
$GVol$	0.166	(2.66)	0.007	0.199	0.22
GFI	0.249	(9.00)	0.108	0.284	0.63
TED	0.203	(6.61)	0.073	0.263	0.48
VIX	0.201	(3.80)	0.065	0.233	0.34

Table 5. Unconditional correlation of FX correlation dispersion measures and market variables.
The table reports the correlation coefficients between the FX correlation dispersion measures FXC and FXC^{UNC} and four market variables: the global equity volatility measure used in Lustig, Roussanov and Verdelhan (2011) ($GVol$), the global funding illiquidity measure of Malkhozov, Mueller, Vedolin and Venter (2016) (GFI), the TED spread (TED), and the CBOE VIX (VIX). Panel A: monthly data from January 1996 through December 2013. Panel B: monthly data from January 1984 through December 2013. In both panels, we report bootstrap standard errors in parentheses.

Panel A: January 1996–December 2013

	FXC^{UNC}	$GVol$	GFI	TED	VIX
FXC	0.86	0.35	0.48	0.42	0.45
	(0.02)	(0.08)	(0.06)	(0.07)	(0.07)
FXC^{UNC}		0.26	0.44	0.41	0.39
		(0.10)	(0.07)	(0.07)	(0.08)
$GVol$			0.53	0.59	0.81
			(0.08)	(0.08)	(0.04)
GFI				0.57	0.61
				(0.07)	(0.07)
TED					0.43
					(0.09)

Panel B: January 1984–December 2013

	FXC^{UNC}	$GVol$	GFI	TED	VIX
FXC	0.89	0.22	0.32	0.26	0.21
	(0.01)	(0.06)	(0.05)	(0.05)	(0.07)
FXC^{UNC}		0.21	0.33	0.28	0.19
		(0.06)	(0.05)	(0.05)	(0.07)
$GVol$			0.12	0.41	0.79
			(0.07)	(0.08)	(0.03)
GFI				0.61	0.18
				(0.04)	(0.08)
TED					0.41
					(0.09)

Table 6. ΔFXC**-beta-sorted currency portfolios.**
The table reports summary statistics for the excess returns of three G10 currency portfolios sorted on exposure to ΔFXC, the innovations to the FX correlation dispersion measure FXC. Portfolio 1 (Pf1^{C}) contains the three currencies with the lowest pre-sort ΔFXC betas, whereas Portfolio 3 (Pf3^{C}) contains the three currencies with the highest pre-sort ΔFXC betas. HML^C, denotes the portfolio that has along position in the high correlation beta currencies (Pf3^{C}) and a short position in the low correlation beta currencies (Pf1^{C}). Monthly data: for Panel A from January 1996 through December 2013, for Panel B from January 1996 through July 2007, for Panel C from January 1984 through December 2013, and for Panel D from January 1984 through July 2007.

Panel A: January 1996–December 2013

	Pf1^{C}	Pf2^{C}	Pf3^{C}	HML^C
Mean	4.04	0.99	-2.38	-6.42
Std	10.26	9.11	7.86	7.83
t-stat	1.67	0.46	-1.28	-3.47
Skewness	-0.66	0.06	0.01	0.44
Kurtosis	6.57	3.53	3.09	4.75
Sharpe Ratio	0.39	0.11	-0.30	-0.82

Panel B: January 1996–July 2007

	Pf1^{C}	Pf2^{C}	Pf3^{C}	HML^C
Mean	3.84	0.74	-3.51	-7.35
Std	7.34	8.07	7.56	6.68
t-stat	1.78	0.31	-1.58	-3.74
Skewness	0.17	0.49	0.11	-0.01
Kurtosis	3.35	3.10	2.76	2.92
Sharpe Ratio	0.52	0.09	-0.46	-1.10

Panel C: January 1984–December 2013

	Pf1^{C}	Pf2^{C}	Pf3^{C}	HML^C
Mean	4.37	1.58	0.65	-3.72
Std	9.62	9.44	8.87	8.37
t-stat	2.48	0.92	0.40	-2.43
Skewness	-0.43	-0.24	-0.26	0.06
Kurtosis	6.09	3.73	3.96	3.71
Sharpe Ratio	0.45	0.17	0.07	-0.44

Panel D: January 1984–July 2007

	Pf1^{C}	Pf2^{C}	Pf3^{C}	HML^C
Mean	4.36	1.61	0.91	-3.45
Std	8.00	9.05	9.00	8.02
t-stat	2.64	0.87	0.49	-2.09
Skewness	0.18	-0.22	-0.28	-0.19
Kurtosis	3.81	3.79	4.04	3.13
Sharpe Ratio	0.54	0.18	0.10	-0.43

Table 7. Time-series correlations of FX correlations and FX correlation risk premiums.
The table reports the time-series correlations between realized FX correlations (RC) and implied FX correlations (IC), and between realized FX correlations and FX correlation risk premiums (CRP), for all FX pairs. In addition to the correlation estimates, we report their t-statistics and 95% bootstrapped confidence intervals. FX correlation risk premiums are defined as the difference between the implied and realized FX correlations. Realized FX correlations are calculated using past daily log exchange rate changes over a three month window. Implied FX correlations are calculated from daily option prices on the underlying exchange rates. Monthly data from January 1996 to December 2013 (options data for EUR start in January 1999).

FX pair		Correlation RC/IC				Correlation RC/CRP			
		Mean	t-stat	2.5%	97.5%	Mean	t-stat	2.5%	97.5%
AUD	CAD	0.843	22.88	0.800	0.875	-0.102	-1.49	-0.243	0.046
AUD	CHF	0.844	22.97	0.805	0.877	-0.695	-14.15	-0.756	-0.627
AUD	EUR	0.923	32.09	0.901	0.941	-0.714	-13.63	-0.782	-0.638
AUD	GBP	0.876	26.54	0.844	0.905	-0.656	-12.71	-0.732	-0.566
AUD	JPY	0.892	28.89	0.855	0.922	-0.695	-14.13	-0.764	-0.610
AUD	NOK	0.744	16.09	0.679	0.807	-0.213	-3.15	-0.317	-0.091
AUD	NZD	0.872	26.01	0.833	0.906	-0.457	-7.52	-0.646	-0.212
AUD	SEK	0.870	25.82	0.840	0.902	-0.618	-11.49	-0.723	-0.490
CAD	CHF	0.856	24.22	0.827	0.885	-0.684	-13.73	-0.756	-0.594
CAD	EUR	0.864	22.93	0.822	0.899	-0.702	-13.21	-0.785	-0.602
CAD	GBP	0.825	21.24	0.776	0.869	-0.518	-8.82	-0.640	-0.371
CAD	JPY	0.777	18.03	0.708	0.829	-0.680	-13.57	-0.737	-0.622
CAD	NOK	0.780	18.18	0.723	0.838	-0.316	-4.85	-0.465	-0.168
CAD	NZD	0.784	18.48	0.730	0.838	0.161	2.39	0.011	0.308
CAD	SEK	0.813	20.34	0.766	0.856	-0.137	-2.01	-0.241	-0.024
CHF	EUR	0.846	21.27	0.717	0.946	-0.603	-10.12	-0.743	-0.278
CHF	GBP	0.816	20.63	0.757	0.862	-0.640	-12.17	-0.715	-0.554
CHF	JPY	0.835	22.19	0.788	0.874	-0.733	-15.76	-0.785	-0.665
CHF	NOK	0.725	15.42	0.632	0.816	-0.671	-13.23	-0.763	-0.525
CHF	NZD	0.724	15.35	0.661	0.783	-0.532	-9.19	-0.619	-0.428
CHF	SEK	0.757	16.94	0.668	0.832	-0.560	-9.88	-0.683	-0.386
EUR	GBP	0.774	16.38	0.707	0.837	-0.592	-9.82	-0.697	-0.463
EUR	JPY	0.858	22.35	0.811	0.898	-0.760	-15.65	-0.813	-0.704
EUR	NOK	0.704	13.27	0.628	0.776	-0.632	-10.90	-0.773	-0.379
EUR	NZD	0.770	16.17	0.703	0.830	-0.467	-7.06	-0.597	-0.329
EUR	SEK	0.721	13.93	0.659	0.786	-0.549	-8.78	-0.697	-0.326
GBP	JPY	0.824	21.30	0.770	0.867	-0.713	-14.87	-0.778	-0.634
GBP	NOK	0.282	4.30	0.077	0.448	-0.711	-14.79	-0.767	-0.647
GBP	NZD	0.812	20.32	0.773	0.852	-0.350	-5.47	-0.498	-0.199
GBP	SEK	0.644	12.31	0.575	0.717	-0.615	-11.41	-0.747	-0.462
JPY	NOK	0.795	19.15	0.743	0.837	-0.572	-10.21	-0.657	-0.473
JPY	NZD	0.831	21.83	0.777	0.875	-0.680	-13.55	-0.746	-0.603
JPY	SEK	0.825	21.34	0.775	0.865	-0.699	-14.29	-0.762	-0.627
NOK	NZD	0.699	14.29	0.630	0.764	-0.157	-2.32	-0.267	-0.051
NOK	SEK	0.701	14.36	0.643	0.761	-0.347	-5.42	-0.521	-0.148
NZD	SEK	0.750	16.58	0.684	0.805	-0.158	-2.34	-0.253	-0.053

Table 8. Parameter values.
The table reports the calibrated parameter values used for the model simulations. All countries share the same parameter values except for γ: γ^0 is the parameter for the domestic country, whereas the values for the foreign γ^i, $i = 1, ..., 9$, are equally spaced on the interval $[\gamma^{min}, \gamma^{max}]$.

SDF parameters

α	χ	ϕ	κ	δ	γ^0	γ^{min}	γ^{max}
0.0076	19.4551	0.06	0.04	40	0.36	0.20	0.49

Pricing factor parameters

λ	$\bar{z}$	ξ	λ^w	$\bar{z}^w$	ξ^w
0.25	0.0077	0.0393	0.01	0.0209	0.0162

Inflation parameters

$\bar{\pi}$	ζ	σ
-0.0039	0.25	0.0037^2

Table 9. Simulated moments (benchmark model): interest rates, inflation, and exchange rates.
The table reports empirical moments (first column) and simulated moments (second column) for the model with identical local pricing factors (benchmark model). For each empirical moment, the table reports the value of the moment in the sample and the moment bootstrap standard error (in parentheses). Bootstrapping involves 1,000 block bootstrap samples of 216 monthly observations each, with a block length of three observations. For each simulated moment, the table reports the point estimate and the standard error (in parentheses); the former is the moment average across 1,000 simulations, while the latter is the moment standard deviation across those simulations. The first panel reports the annualized mean and standard deviation of the U.S. real interest rate and the cross-sectional average of the mean and standard deviation of foreign real interest rates. The second panel reports the cross-sectional average of real exchange rate volatility and autocorrelation. The third panel reports the annualized mean and standard deviation of U.S. inflation and the cross-sectional average of the mean and standard deviation of foreign inflation. The fourth panel reports the annualized mean and standard deviation of the U.S. nominal interest rate and the cross-sectional average of the mean and standard deviation of foreign nominal interest rates. The fifth panel reports the cross-sectional average of nominal exchange rate volatility and autocorrelation.

Moment	Data	Model
$E\left(r^{U.S.}\right)$	0.28%	0.74%
	(0.46%)	(1.96%)
$Std\left(r^{U.S.}\right)$	1.35%	1.08%
	(0.13%)	(0.17%)
$E_{\text{cross}}\left(E\left(r^{FGN}\right)\right)$	1.15%	0.94%
	(0.19%)	(1.85%)
$E_{\text{cross}}\left(Std\left(r^{FGN}\right)\right)$	1.19%	1.08%
	(0.03%)	(0.17%)
$E_{\text{cross}}\left(Std\left(\Delta q_{t+1}\right)\right)$	10.82%	9.52%
	(0.59%)	(0.73%)
$E_{\text{cross}}\left(AC\left(\Delta q_{t+1}\right)\right)$	-0.01	0.00
	(0.05)	(0.04)
$E\left(\pi^{U.S.}\right)$	2.32%	1.83%
	(0.33%)	(3.86%)
$Std\left(\pi^{U.S.}\right)$	1.27%	1.59%
	(0.14%)	(0.29%)
$E_{\text{cross}}\left(E\left(\pi^{FGN}\right)\right)$	1.56%	1.85%
	(0.17%)	(3.84%)
$E_{\text{cross}}\left(Std\left(\pi^{FGN}\right)\right)$	1.12%	1.59%
	(0.04%)	(0.28%)
$E\left(r^{NOM,U.S.}\right)$	2.60%	2.58%
	(0.25%)	(2.09%)
$Std\left(r^{NOM,U.S.}\right)$	0.62%	1.11%
	(0.02%)	(0.20%)
$E_{\text{cross}}\left(E\left(r^{NOM,FGN}\right)\right)$	2.70%	2.77%
	(0.15%)	(2.20%)
$E_{\text{cross}}\left(Std\left(r^{NOM,FGN}\right)\right)$	0.44%	1.13%
	(0.02%)	(0.21%)
$E_{\text{cross}}\left(Std\left(\Delta s_{t+1}\right)\right)$	10.76%	9.69%
	(0.62%)	(0.72%)
$E_{\text{cross}}\left(AC\left(\Delta s_{t+1}\right)\right)$	0.01	0.00
	(0.06)	(0.04)

Table 10. Simulated moments: FX correlations and FX correlation risk premiums.
The table reports empirical moments (first column) and simulated moments for the model with $\rho = 1$, $\rho = 0$ and $\rho = 0.999$ (second, third and fourth column, respectively). All moments refer to nominal exchange rates. For each empirical moment, the table reports the value of the moment in the sample and the moment bootstrap standard error (in parentheses). Bootstrapping involves 1,000 block bootstrap samples of 216 monthly observations each, with a block length of 3 observations. For each simulated moment, the table reports the point estimate and the standard error (in parentheses); the former is the moment average across 1,000 simulations, while the latter is the moment standard deviation across those simulations. The first panel reports the cross-sectional mean and the 2.5 and 97.5 percentiles of average realized FX correlations, respectively. The second panel reports the cross-sectional mean and the 2.5 and 97.5 percentiles of average implied FX correlations. The third panel reports the cross-sectional mean and the 2.5 and 97.5 percentiles of average FX CRP. The fourth panel reports the cross-sectional correlation between average realized and average implied FX correlation and the cross-sectional correlation between average realized FX correlation and average FX CRP. The fifth panel reports the cross-sectional average of the correlation between realized and implied FX correlation and the cross-sectional average of the correlation between realized FX correlation and FX CRP.

Moment	Data	Model		
		$\rho = 1$	$\rho = 0$	$\rho = 0.999$
$2.5\%_{\text{cross}}\,(E(RC))$	0.09	0.01	0.30	0.06
	(0.03)	(0.17)	(0.04)	(0.15)
$E_{\text{cross}}\,(E(RC))$	0.45	0.39	0.40	0.40
	(0.02)	(0.04)	(0.03)	(0.04)
$97.5\%_{\text{cross}}\,(E(RC))$	0.86	0.66	0.49	0.64
	(0.01)	(0.06)	(0.03)	(0.05)
$2.5\%_{\text{cross}}\,(E(IC))$	0.17	0.03	0.30	0.09
	(0.02)	(0.16)	(0.04)	(0.15)
$E_{\text{cross}}\,(E(IC))$	0.48	0.40	0.40	0.41
	(0.01)	(0.04)	(0.03)	(0.04)
$97.5\%_{\text{cross}}\,(E(IC))$	0.85	0.65	0.49	0.63
	(0.01)	(0.05)	(0.03)	(0.05)
$2.5\%_{\text{cross}}\,(CRP)$	-6.62%	-0.89%	0.00%	-0.71%
	(1.41%)	(0.18%)	(0.03%)	(0.16%)
$E_{\text{cross}}\,(CRP)$	1.58%	0.71%	0.04%	0.56%
	(0.57%)	(0.20%)	(0.02%)	(0.16%)
$97.5\%_{\text{cross}}\,(CRP)$	9.43%	2.75%	0.08%	2.23%
	(1.20%)	(0.55%)	(0.03%)	(0.48%)
$corr_{\text{cross}}\,(E(RC), E(IC))$	0.98	1.00	1.00	1.00
	(0.01)	(0.00)	(0.00)	(0.00)
$corr_{\text{cross}}\,(E(RC), E(CRP))$	-0.55	-0.99	0.00	-0.99
	(0.10)	(0.01)	(0.22)	(0.00)
$E_{\text{cross}}\,(corr(RC, IC))$	0.79	1.00	1.00	1.00
	(0.02)	(0.00)	(0.00)	(0.00)
$E_{\text{cross}}\,(corr(RC, CRP))$	-0.52	-0.77	-0.02	-0.80
	(0.03)	(0.13)	(0.03)	(0.10)

Table 11. Estimating the price of correlation risk.

The table reports the results for the estimation of the market price of correlation risk. Panel A reports factor betas and Newey and West (1987) standard errors (in parentheses) for the first stage regressions for various test assets. The test assets are: three currency portfolios (Pf^C) sorted on exposure to the correlation risk factor ΔFXC (excess return moments for which are reported in Table 6), three currency portfolios (Pf^F) sorted on interest rate differentials, and the nine individual G10 currencies. Panel B reports the Fama and MacBeth (1973) factor prices and standard errors (in parentheses); Shanken (1992)-corrected standard errors are reported in brackets. We consider four sets of test assets. Set (1) only includes the three ΔFXC-beta-sorted and the three interest-rate-sorted portfolios from Panel A, while Set (2) also includes the nine individual G10 currencies. Set (3) includes four ΔFXC-beta-sorted and four interest-rate-sorted currency portfolios, using all developed country currencies. Set (4) includes four ΔFXC-beta-sorted and four interest-rate-sorted currency portfolios, using the full set of currencies. The first-stage beta estimates for Sets (3) and (4) are provided in the Online Appendix. Monthly data from January 1996 through December 2013. Regression R^2s are also provided.

Panel A: Factor betas

	α		DOL		HML^C		R^2
$Pf1^C$	-0.01	(0.07)	1.03	(0.05)	-0.52	(0.03)	0.40
$Pf2^C$	-0.02	(0.09)	1.11	(0.06)	0.00	(0.04)	0.10
$Pf3^C$	-0.03	(0.07)	1.03	(0.05)	0.48	(0.03)	-0.20
$Pf1^F$	-0.06	(0.10)	0.98	(0.06)	0.33	(0.06)	-0.12
$Pf2^F$	-0.03	(0.08)	1.03	(0.04)	-0.05	(0.04)	0.12
$Pf3^F$	0.03	(0.09)	1.16	(0.07)	-0.32	(0.06)	0.30
AUD	-0.09	(0.13)	1.20	(0.08)	-0.52	(0.08)	0.39
CAD	-0.04	(0.11)	0.66	(0.07)	-0.19	(0.07)	0.17
CHF	0.04	(0.14)	1.24	(0.08)	0.31	(0.07)	-0.05
EUR	-0.09	(0.11)	1.22	(0.07)	0.07	(0.05)	0.08
GBP	0.10	(0.13)	0.75	(0.09)	0.08	(0.06)	0.03
JPY	0.04	(0.22)	0.63	(0.12)	0.57	(0.10)	-0.25
NOK	0.03	(0.13)	1.24	(0.09)	0.02	(0.08)	0.11
NZD	0.06	(0.15)	1.27	(0.08)	-0.39	(0.11)	0.32
SEK	-0.10	(0.11)	1.29	(0.07)	-0.05	(0.06)	0.14

Panel B: Factor prices

	λ^{DOL}			λ^{HML^C}			R^2
Set (1)	0.09	(0.15)	[0.15]	-0.58	(0.15)	[0.15]	0.99
Set (2)	0.09	(0.15)	[0.15]	-0.54	(0.20)	[0.20]	0.93
Set (3)	0.13	(0.15)	[0.15]	-0.51	(0.17)	[0.18]	0.90
Set (4)	0.15	(0.14)	[0.14]	-0.67	(0.22)	[0.23]	0.81

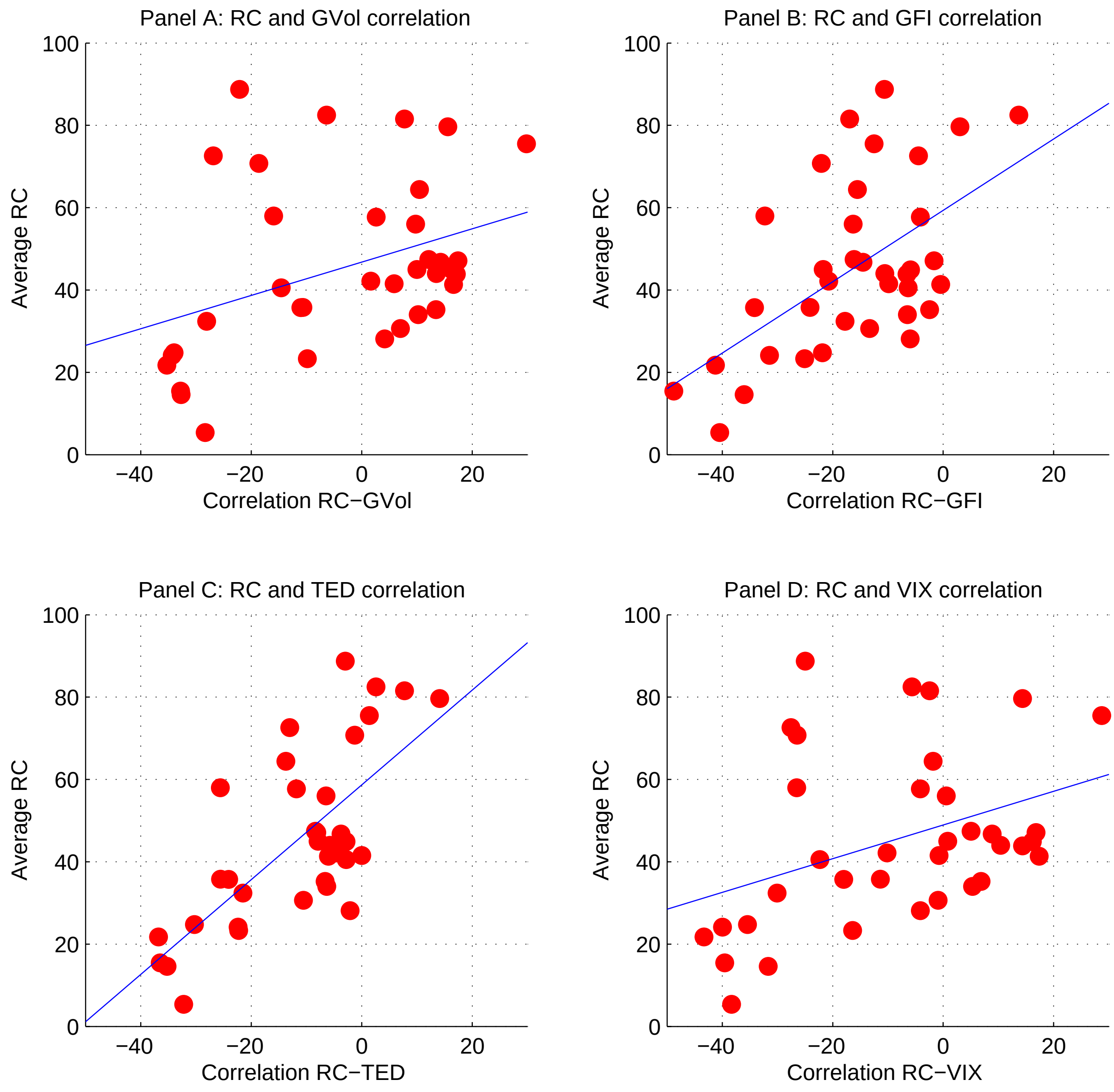

Fig. 1. Average realized FX correlations and FX correlation cyclicality.

The figure illustrates the association between average realized FX correlations and measures FX correlation cyclicality. For each FX pair, FX correlation cyclicality is measured by the unconditional correlation between the realized FX correlation of the pair and a market variable that acts as a business cycle proxy. The market variables considered are the global equity volatility measure from Lustig, Roussanov and Verdelhan (2011) ($GVol$, Panel A), the global funding illiquidity measure (GFI, Panel B) from Malkhozov, Mueller, Vedolin and Venter (2016), the TED spread (TED, Panel C), and the CBOE VIX (VIX, Panel D). Monthly data from January 1996 to December 2013. In each panel, the line of best fit is also shown.

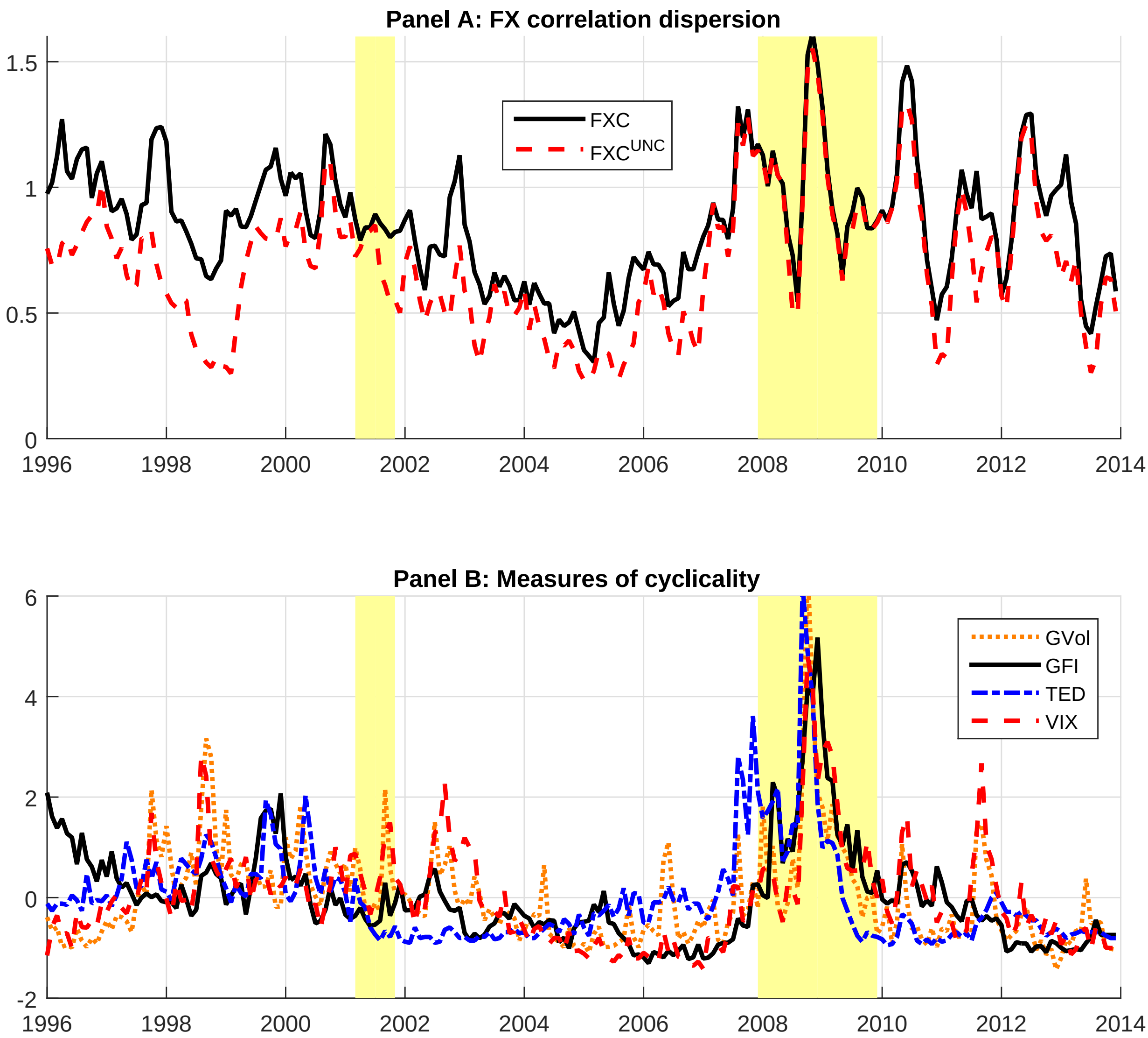

Fig. 2. FX correlation dispersion measures and market variables.

Panel A plots the time series of the two FX correlation dispersion measures, FXC and FXC^{UNC}, from January 1996 to December 2013. FXC (solid line) is calculated as the difference between the average FX correlation of high- and low-correlation FX pairs; the two groups consist of the highest and lowest deciles of realized FX correlations across all 36 G10 FX pairs, respectively, with the deciles being rebalanced every month. FXC^{UNC} (dashed line) is calculated as the difference in average correlations between the decile of high average correlation FX pairs and the decile of low average correlation FX pairs. Panel B plots the time series of the global equity volatility measure used in Lustig, Roussanov and Verdelhan (2011) ($GVol$), the global funding illiquidity measure of Malkhozov, Mueller, Vedolin and Venter (2016) (GFI), the TED spread (TED), and the CBOE VIX (VIX), from January 1996 to December 2013. All series in Panel B are standardized to have zero mean and a standard deviation of one. In both panels, the shaded areas correspond to NBER recessions.

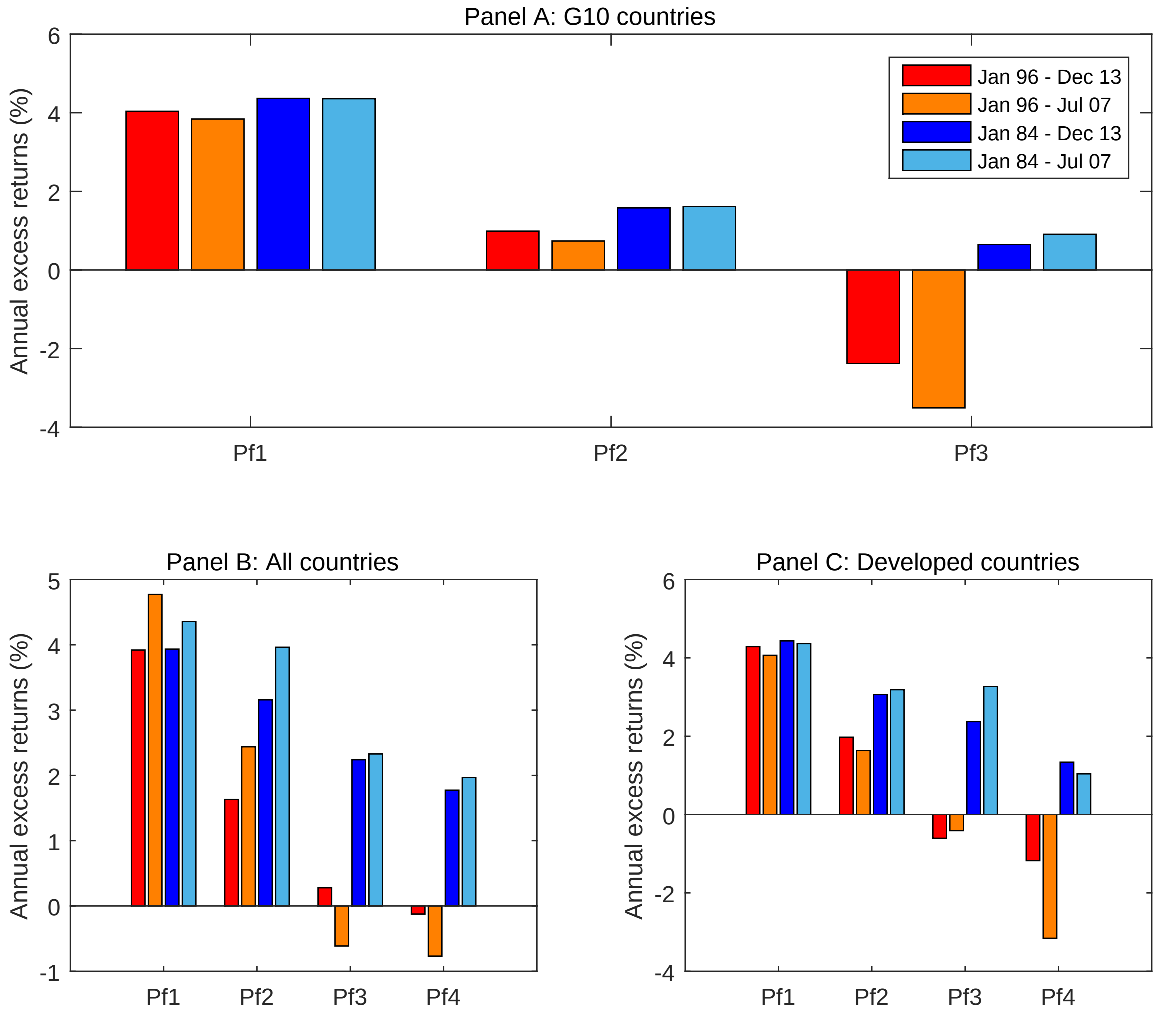

Fig. 3. Currency portfolios sorted on exposure to the FX correlation factor ΔFXC.

The figure displays annualized average excess returns of currency portfolios, for different currency and period samples. Currencies are sorted into portfolios at time t based on their exposure to ΔFXC at the end of period $t-1$; exposure is measured by regressing currency excess returns on the FX correlation risk factor ΔFXC over the preceding 36 months. Panel A presents the portfolio excess returns for the G10 set of currencies (three ΔFXC-beta-sorted currency portfolios), while Panels B and C present the portfolio excess returns for the currencies in the developed country set and in the full country set, respectively (four ΔFXC-beta-sorted currency portfolios for each set). In each panel, Portfolio 1 (Pf1) contains the currencies with the lowest pre-sort ΔFXC betas whereas Portfolio 3 or 4 (Pf3 or Pf4), depending on the set of currencies, contains the currencies with the highest pre-sort ΔFXC betas. In each panel, average annualized portfolio excess returns are reported for four sample periods: January 1996–December 2013, January 1996–July 2007, January 1984–December 2013, and January 1984–July 2007.

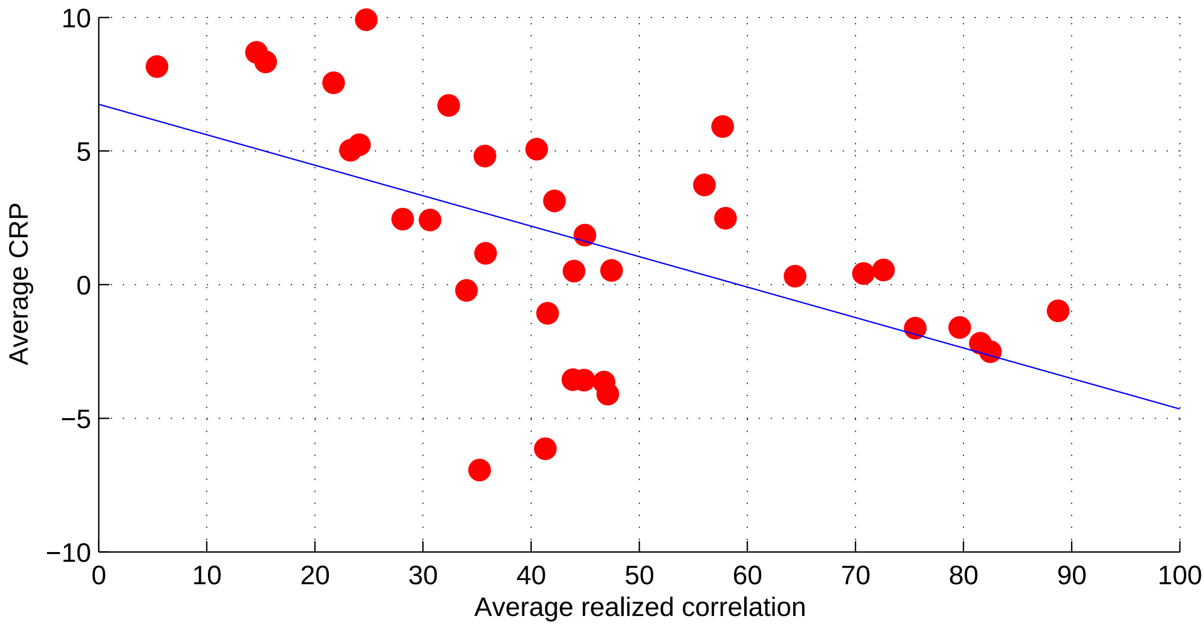

Fig. 4. Average realized FX correlations and average FX correlation risk premiums.

The figure plots the average FX correlation risk premiums for all 36 G10 exchange rate pairs against the corresponding average realized FX correlations. Average FX correlation risk premiums and average realized FX correlations are expressed in percentage points. Monthly data from January 1996 to December 2013 (options data for EUR start in January 1999). The line of best fit is also shown.

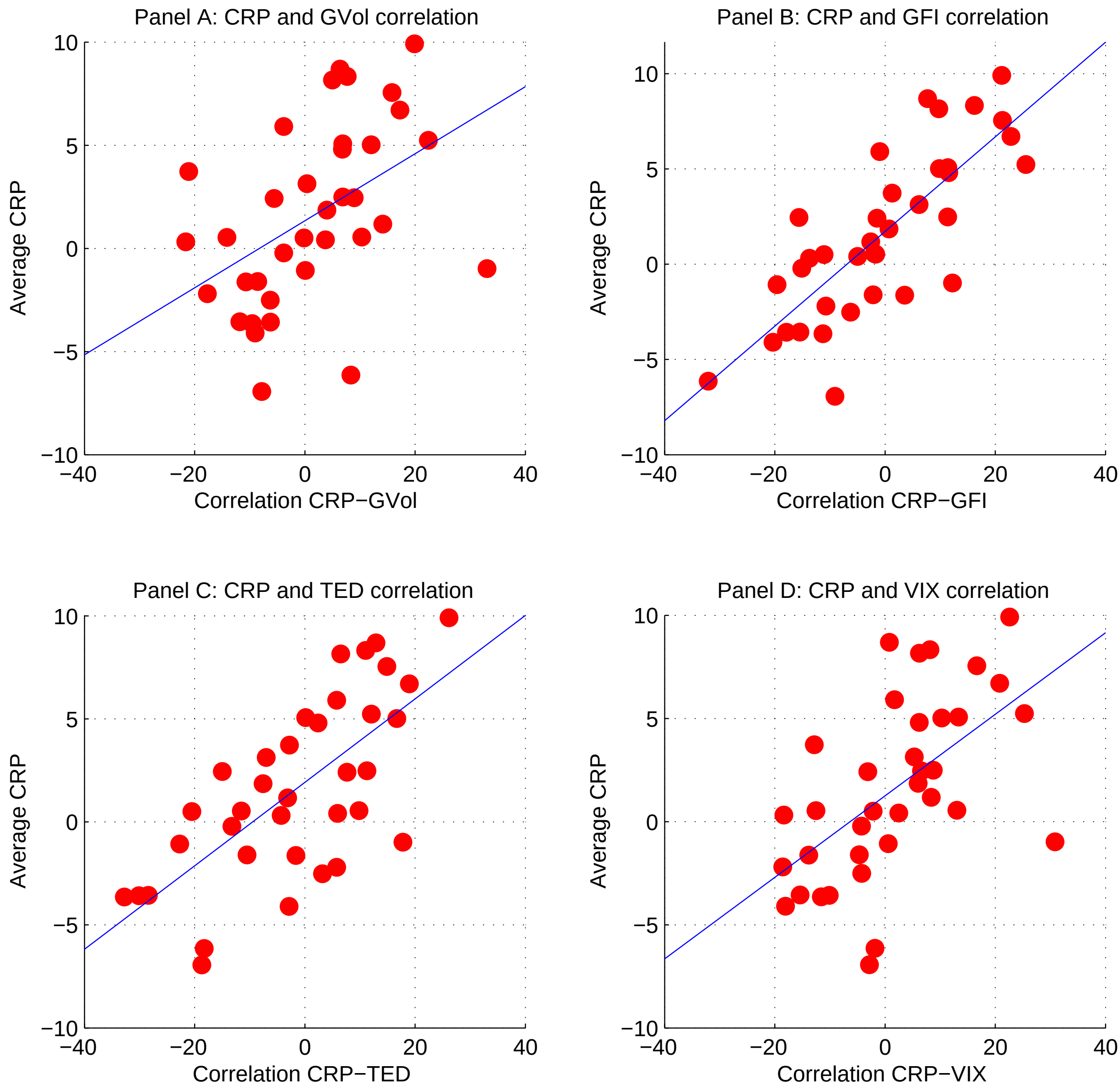

Fig. 5. Average FX correlation risk premiums and FX CRP cyclicality.

The figure illustrates the association between average FX correlation risk premiums and measures FX correlation risk premium cyclicality. For each FX pair, FX correlation risk premium cyclicality is measured by the unconditional correlation between the FX correlation risk premium of the pair and a market variable that acts as a business cycle proxy. The market variables considered are the global equity volatility measure from Lustig, Roussanov and Verdelhan (2011) ($GVol$, Panel A), the global funding illiquidity measure (GFI, Panel B) from Malkhozov, Mueller, Vedolin and Venter (2016), the TED spread (TED, Panel C), and the CBOE VIX (VIX, Panel D). Monthly data from January 1996 to December 2013 (options data for EUR start in January 1999). In each panel, the line of best fit is also shown.

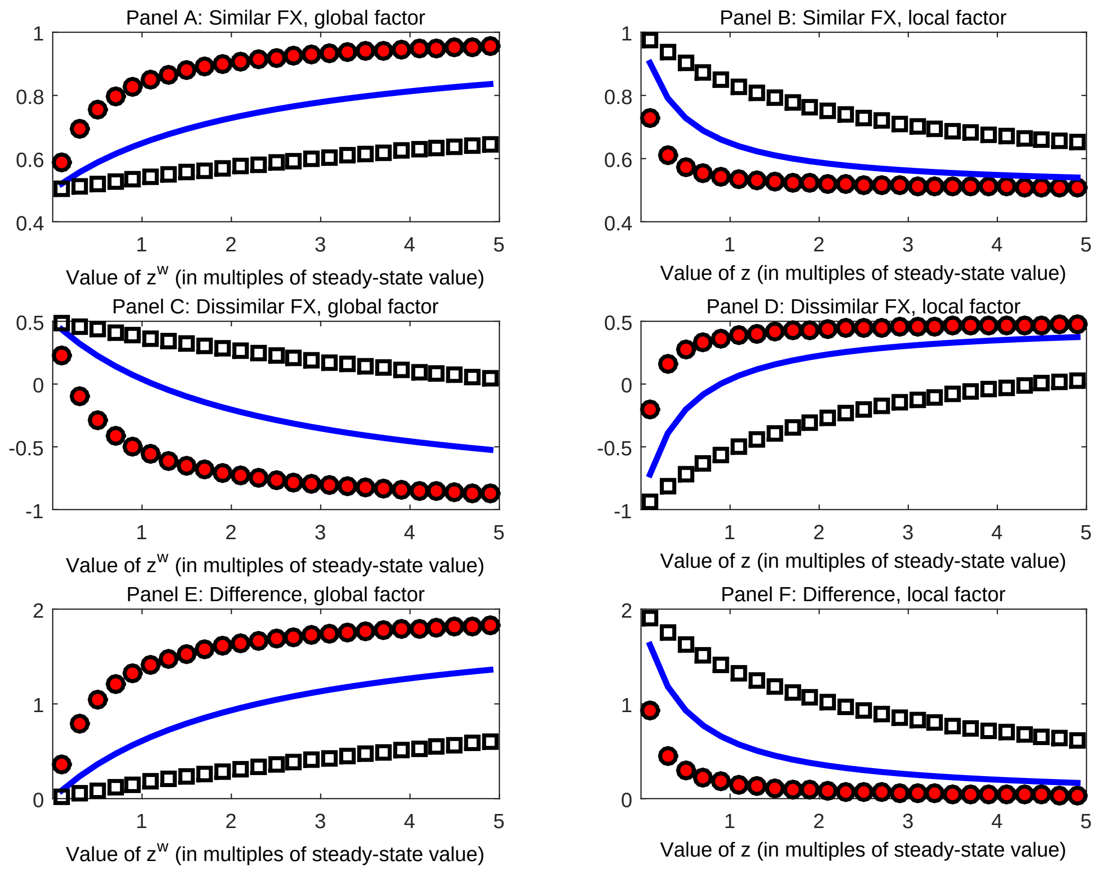

Fig. 6. Model-implied FX correlations.

The figure displays the properties of conditional real FX correlation in the model with identical local pricing factors. Panels A, C, and E plot the conditional FX correlation as a function of the global pricing factor z^w, holding the local pricing factor z constant: Panel A refers to the conditional FX correlation of the similar FX pair (1,2), Panel C refers to the conditional FX correlation of the dissimilar FX pair (1,3), and Panel E refers to the difference in conditional FX correlation between the two pairs. In each panel, the circles, solid line, and squares plot the conditional FX correlation, assuming that the local pricing factor z is equal to 0.2, 1, and 5 times its steady-state value $\bar{z}$, respectively. Panels B, D, and F plot the conditional FX correlation as a function of the local pricing factor z, holding the global pricing factor z^w constant: Panel B refers to the conditional FX correlation of the similar FX pair (1,2), Panel D refers to the conditional FX correlation of the dissimilar FX pair (1,3), and Panel F refers to the difference in conditional FX correlation between the two pairs. In each panel, the circles, solid line, and squares plot the conditional FX correlation assuming that the global pricing factor z^w is equal to 0.2, 1, and 5 times its steady-state value $\bar{z}^w$, respectively. To plot the figures, we set the model parameters equal to their calibrated values in Table 8. To ensure symmetry, we set the values of the country exposures to global FX risk such that the condition $D^{1,2} = -D^{1,3} > 0$ is satisfied; in particular, we impose $\gamma^1 = \gamma^{min}$ and $\gamma^3 = \gamma^{max}$, and set γ^2 so that the symmetry condition holds.

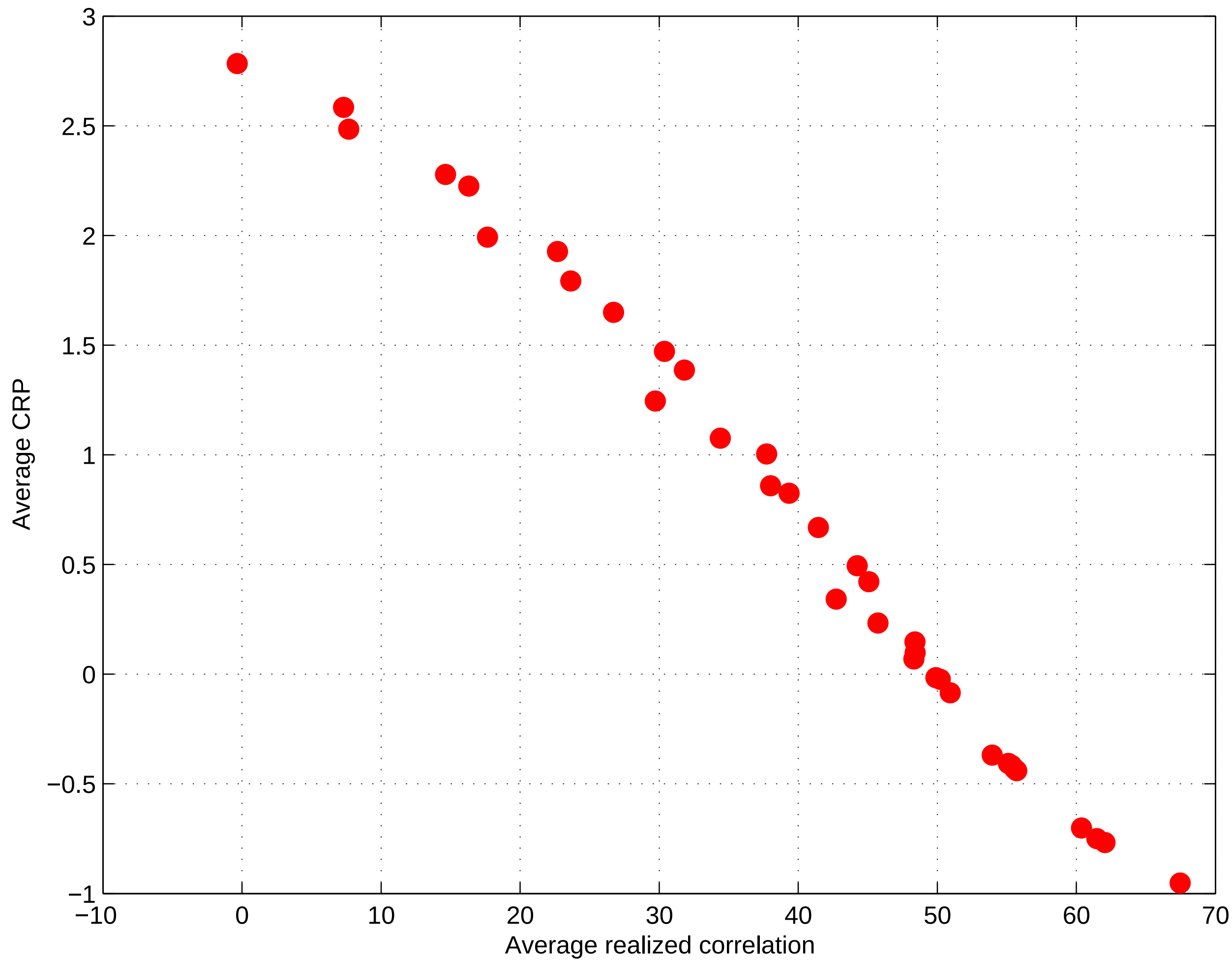

Fig. 7. Model-implied average realized FX correlations and average FX correlation risk premiums.
The figure plots the average FX correlation risk premiums for all 36 exchange rate pairs against the corresponding average realized FX correlations using simulated data for the model with identical local pricing factors ($\rho = 1$). The parameter values are reported in Table 8 and the simulation details can be found in Appendix E. Average FX correlation risk premiums and average realized FX correlations are expressed in percentage points.

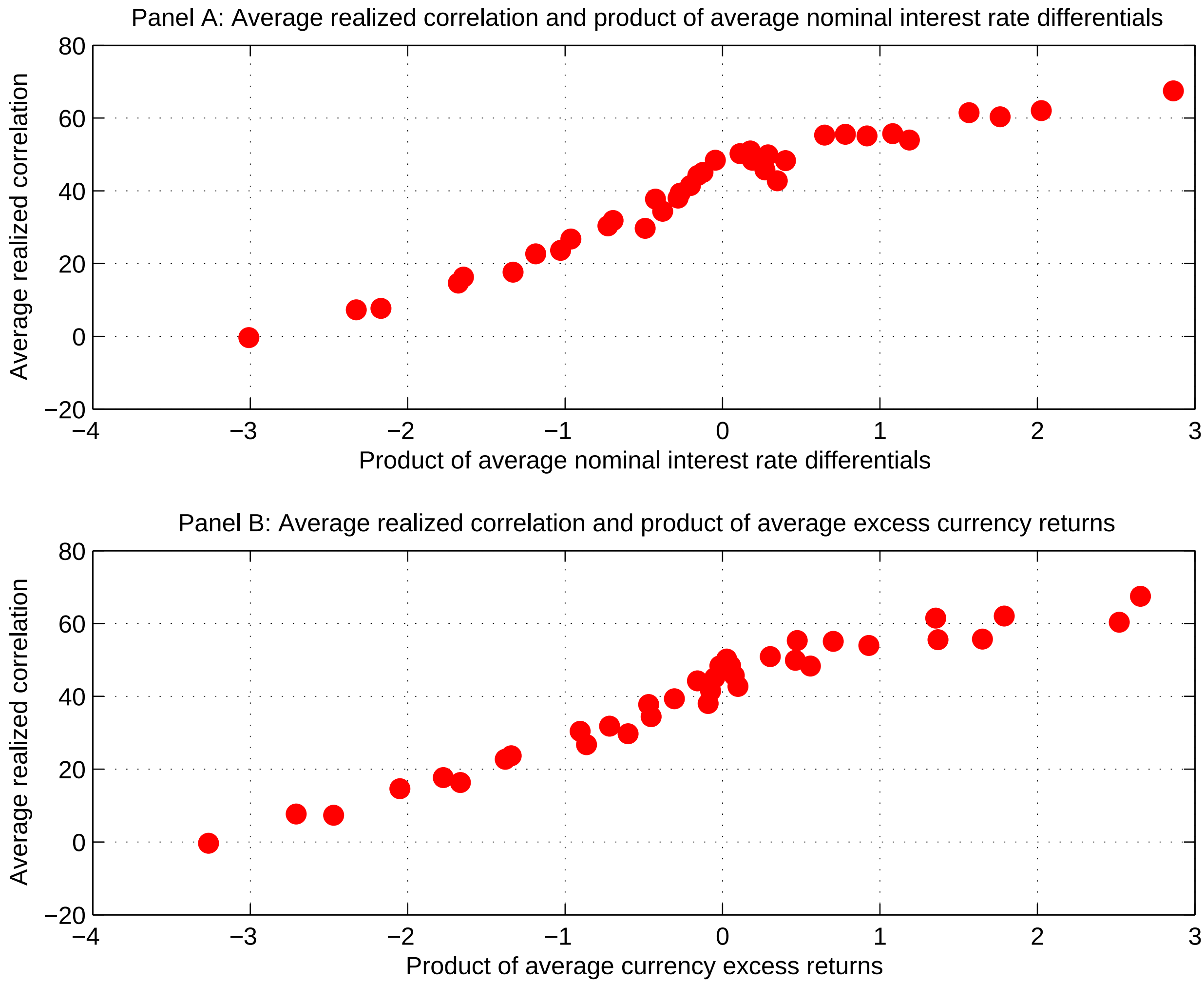

Fig. 8. Model-implied average realized FX correlations and products of average nominal interest rate differentials and average currency excess returns.

The figure plots the average realized FX correlations for all 36 exchange rate pairs against the corresponding product of average nominal interest rate differentials (Panel A) or the product of average currency excess returns (Panel B) for the model with identical local pricing factors ($\rho = 1$). The parameter values are reported in Table 8 and the simulation details can be found in Appendix E. Average realized FX correlations are expressed in percentage points and products of nominal interest rate differentials and currency excess returns in squared percentage points; nominal interest rate differentials and currency excess returns are annualized.

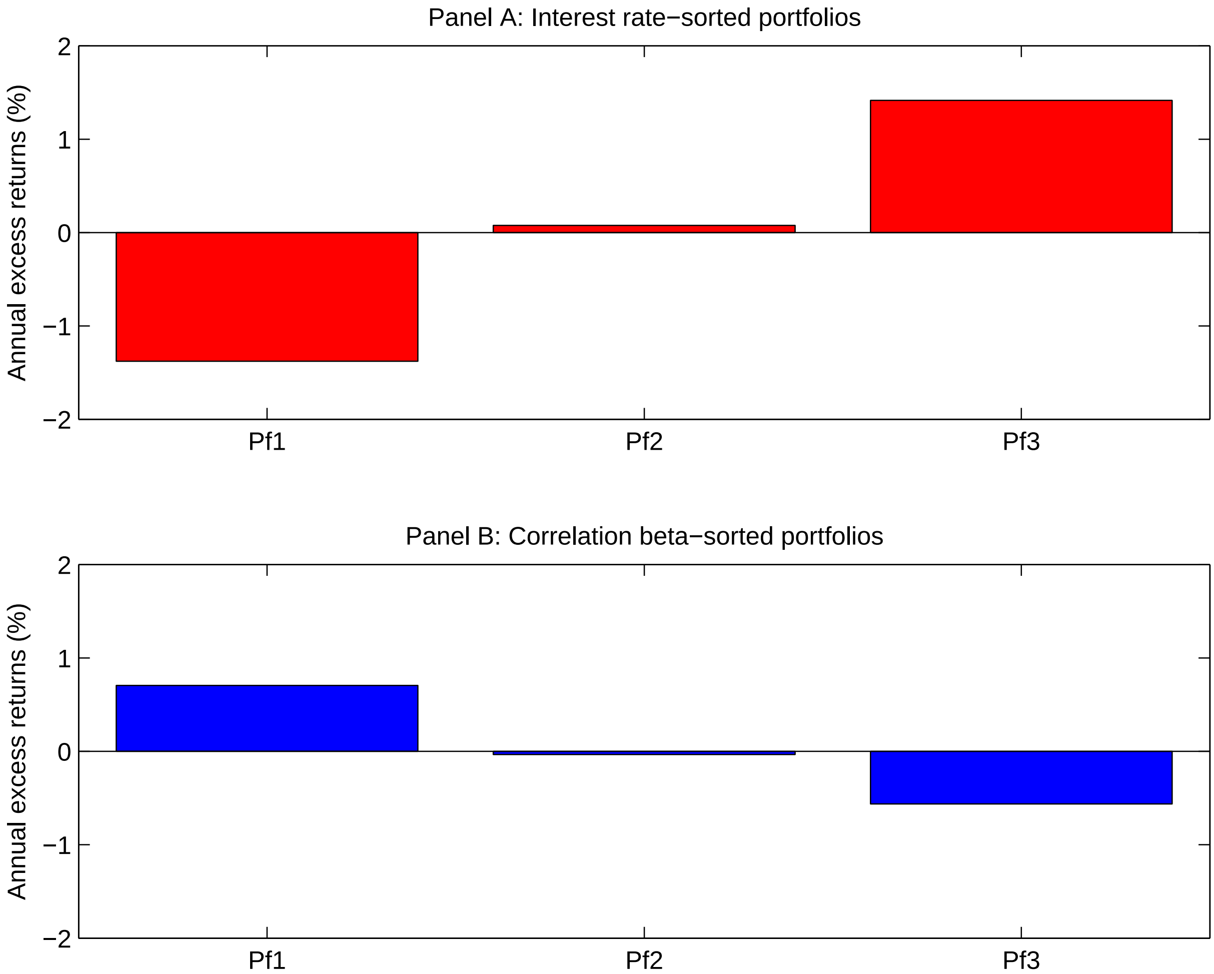

Fig. 9. Model-implied currency portfolio excess returns.
The figure displays average annualized portfolio excess returns for interest rate-sorted (Panel A) and ΔFXC beta-sorted (Panel B) currency portfolios using simulated data for the model with identical local pricing factors ($\rho = 1$). For Panel A, currencies are sorted into portfolios according to their nominal interest rate, with monthly rebalancing. Portfolio 1 (Pf1) contains low interest rate currencies whereas Portfolio 3(Pf3) contains high interest rate currencies. For Panel B, currencies are sorted into portfolios on their exposure to ΔFXC at the end of period $t-1$, with monthly rebalancing; exposure is measured by regressing currency excess returns on the correlation risk factor ΔFXC over the preceding 36 months. Portfolio 1 (Pf1) contains the currencies with the lowest pre-sort ΔFXC betas whereas Portfolio 3 (Pf3) contains the currencies with the highest pre-sort ΔFXC betas. The parameter values are reported in Table 8 and the simulation details can be found in Appendix E.

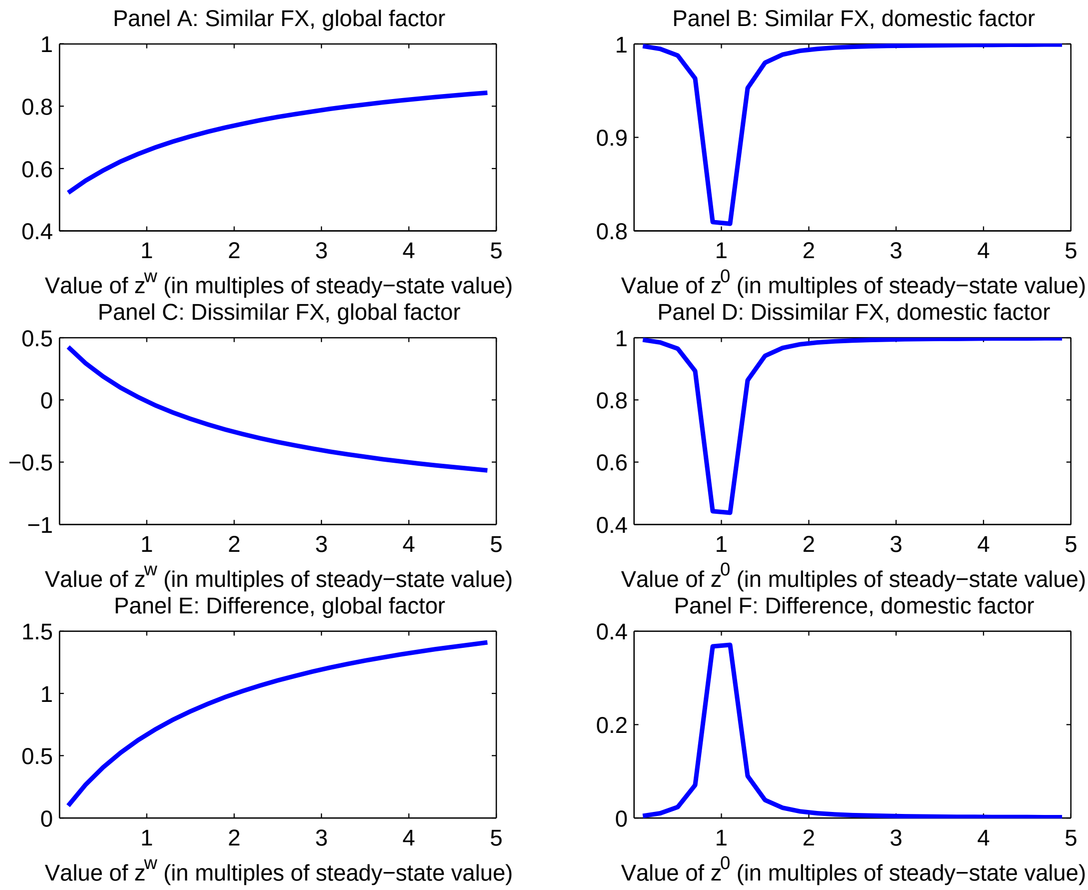

Fig. 10. Model-implied FX correlations: independent local pricing factors.

The figure displays the properties of conditional real FX correlation in the model with independent local pricing factors ($\rho = 0$). Panels A, C, and E plot the conditional FX correlation as a function of the global pricing factor z^w, holding all the local pricing factors constant at their common steady-state level $\bar{z}$: Panel A refers to the conditional FX correlation of the similar FX pair (1,2), Panel C refers to the conditional FX correlation of the dissimilar FX pair (1,3), and Panel E refers to the difference in conditional FX correlation between the two pairs. Panels B, D, and F plot the conditional FX correlation as a function of the domestic pricing factor z^0, holding the global pricing factor z^w constant at its steady-state level $\bar{z}^w$ and all the foreign local pricing factors constant at their common steady-state value $\bar{z}$: Panel B refers to the conditional FX correlation of the similar FX pair (1,2), Panel D refers to the conditional FX correlation of the dissimilar FX pair (1,3), and Panel F refers to the difference in conditional FX correlation between the two pairs. To plot the figures, we set the model parameters equal to their calibrated values in Table 8. To ensure symmetry, we set the values of the country exposures to global FX risk such that the condition $D^{1,2} = -D^{1,3} > 0$ is satisfied; in particular, we impose $\gamma^1 = \gamma^{min}$ and $\gamma^3 = \gamma^{max}$, and set γ^2 so that the symmetry condition holds.

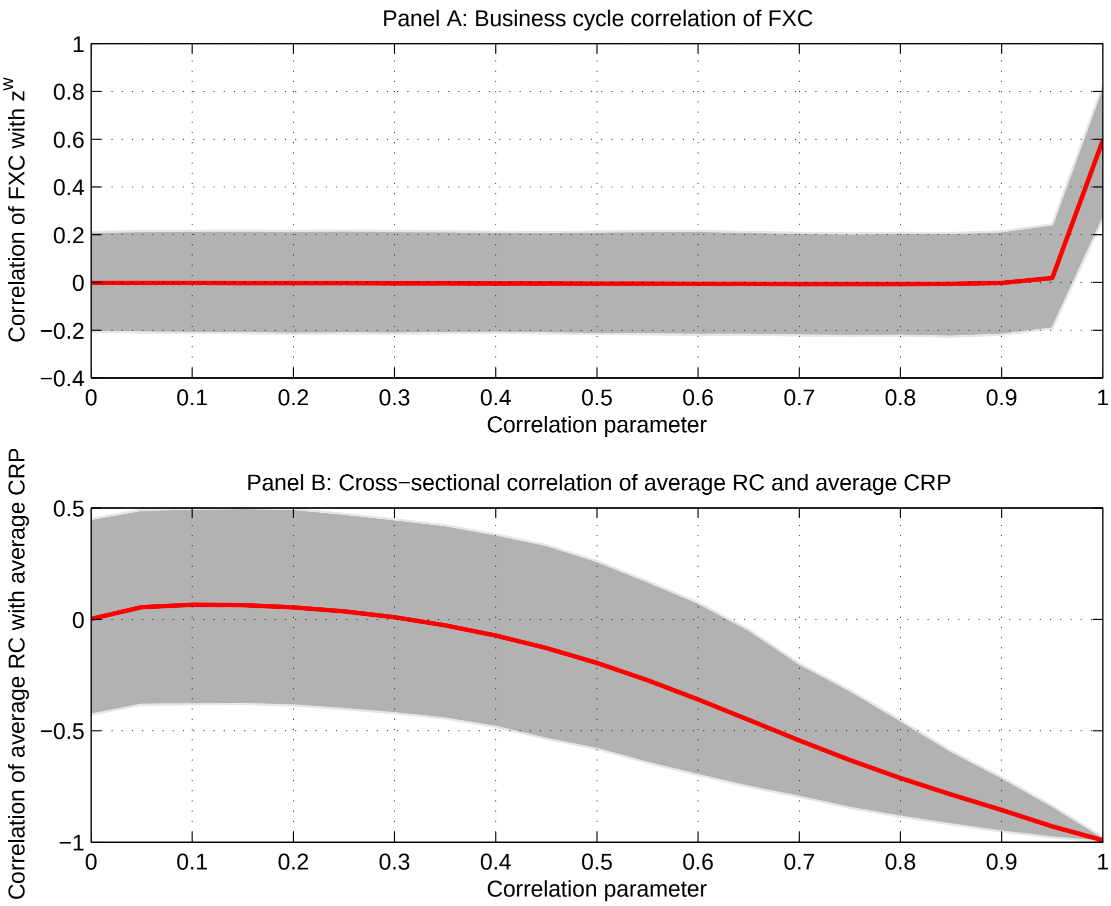

Fig. 11. Model-implied correlations as function of parameter ρ.

The figure presents the point estimates (solid line) and the 95% confidence intervals (shaded area) of correlations of interest in simulated data for different values of the correlation parameter ρ: a value of $\rho = 0$ corresponds to the model with independent local pricing factors, whereas a value of $\rho = 1$ corresponds to the benchmark model with identical local pricing factors. We consider 21 values of ρ: they range from $\rho = 0$ to $\rho = 1$, in increments of 0.05. Panel A presents the correlation between FXC, the measure of cross-sectional dispersion in conditional FX correlation, and the global pricing factor z^w. Panel B presents the cross-sectional correlation between average FX correlations and average FX correlation risk premiums across FX pairs. With the exception of parameter ρ, the parameter values are reported in Table 8. The simulation details can be found in Appendix E.