International Correlation Risk^{*}

Philippe MuellerAndreas StathopoulosLondon School of Economics†USC Marshall School of Business‡

Andrea Vedolin

London School of Economics[§]

Abstract

This paper provides novel evidence of priced correlation risk in foreign exchange markets. In the time-series, we find that the correlation risk premium, defined as the risk-neutral and physical correlation, is 15% per year on average. In the cross-section, global correlation risk carries a risk premium of -1%. In particular, we find that currencies with a high (low) exposure to correlation risk, i.e., that perform badly (well) during periods of high correlation, have high (low) returns on average. Correlation risk can thus explain carry trade returns. To address our empirical findings, we show in a general equilibrium model with external habit formation and home bias in preferences that time-varying correlation is driven by stochastic risk aversion. Currencies that provide a hedge against adverse shocks in global risk aversion are currencies that appreciate when conditional exchange rate correlation is high.

JEL Classification Codes: F31, G12, G13.Keywords: Carry Trade, Correlation Risk, Habit, International Finance, Exchange Rates.First Version: December 2011.This Version: June 16, 2012.

^{*}Philippe Mueller and Andrea Vedolin acknowledge financial support from STICERD at LSE. We would like to thank Dante Amengual, Andrew Ang, Joe Chen, Mike Chernov, Dobrislav Dobrev, Anh Le, Ivan Shaliastovich, Adrien Verdelhan and seminar participants of LUISS Guido Carli, Rome, University of Lund, University of Piraeus, University of Bern, Stockholm School of Economics, Federal Reserve Board, University of Essex, London School of Economics, Chicago Booth Finance Symposium 2011, 6th End of Year Meeting of the Swiss Economists Abroad, Duke/UNC Asset Pricing Conference, UCLA-USC Finance Day 2012, the Bank of Canada – Banco de España Workshop on "International Financial Markets", and the Financial Econometrics Conference at the University of Toulouse for thoughtful comments. We very much welcome comments, including references that we have inadvertently overlooked.

[†]Department of Finance, Houghton Street, WC2A 2AE London, UK, Email: p.mueller@lse.ac.uk [‡]Marshall School of Business, Los Angeles, CA 90089, USA, Email: astathop@marshall.usc.edu

[§]Department of Finance, Houghton Street, WC2A 2AE London, UK, Email: a.vedolin@lse.ac.uk

Recent research has established that a significant component of currency risk premia constitutes compensation for exposure to global risk. Motivated by this finding, we provide novel evidence of priced correlation risk in foreign exchange (FX) markets and propose economic underpinnings. In this paper, we first empirically establish that FX correlation risk is priced and we then link FX correlation risk to global risk aversion using a multi-country general equilibrium model featuring external habit formation.

Scores of papers have documented that asset return correlation is stochastic and behaves counter-cyclically. While most of the academic focus has been on equities, very little is known about FX markets. This is surprising given that the FX market is second to none in terms of turnover. When investing in currencies, it seems important to understand how currency volatilities and correlations move over time in order to manage and allocate risks effectively. This paper fills this gap by quantifying priced FX correlation risk.

To achieve this, we take both a time-series and cross-sectional perspective. Our first contribution is to provide evidence of a large correlation risk premium in currency markets. We find that the size of the estimated correlation risk premium, defined as the difference between the risk-neutral and the objective measure exchange rate correlation, is around 15%. On average, the implied correlation is 56%, whereas the realized correlation is 41%. The correlation risk premium is almost always positive, which implies that it provides a hedge against bad states of the world.

Second, we proceed by quantifying the price of FX correlation risk in the cross-section of currencies using a portfolio sorting approach, following the recent international finance literature (see e.g. Lustig and Verdelhan, 2007, Lustig, Roussanov, and Verdelhan, 2011; Menkhoff, Sarno, Schmeling, and Schrimpf, 2011; and Burnside, 2011). To this end, we construct an FX correlation risk factor, defined as the cross-sectional average of conditional exchange rate correlations, and we sort currencies into four portfolios according to their exposure to that factor. Intuitively, if the factor is counter-cyclical and correlation risk is priced in currency markets, then currencies with low FX correlation betas (i.e. currencies that co-move weakly with FX correlation) should yield higher returns, whereas low correlation risk currencies (i.e. currencies that appreciate strongly when FX correlation increases and, thus, hedge against FX correlation risk) should yield lower returns. Our results confirm that intuition: We show that investing in the portfolio with the highest relative correlation risk exposure (i.e. the portfolio consisting of the currencies that have negative FX correlation betas and, thus, depreciate when FX correlation increases) while shorting the portfolio with the lowest correlation risk exposure generates an average annual excess return between 3% (all countries) and 5% (developed countries) with Sharpe ratios of 0.36 and 0.5, respectively. We address the forward premium puzzle by showing that carry trade returns can be explained by the high exposure to the FX correlation risk factor. Following the Fama and MacBeth (1973), we estimate a negative price of FX correlation risk of -1% per annum. Furthermore, we show that high (low) interest rate currencies have negative (positive) FX correlation betas and, therefore, depreciate (appreciate) in bad states of the world, when global risk aversion is high. As a result, high interest rate currencies have positive risk premia, whereas low interest rate currencies have low or negative risk premia.

It is natural to assume that volatility and correlation are highly correlated, which leads to the question whether correlation contains information over and above what is contained in volatility. To address this, we first perform a double sort on volatility and correlation. We show that the return differential documented when sorting only on correlation is not subsumed by exposure to volatility. Conditioning on volatility, the order of magnitude of the correlation spread portfolios is nearly the same as for the univariate correlation sort. We also study whether exposure to correlation risk can explain the return differential from volatility sorted portfolios. We find that the correlation risk factor emerges as the dominant risk factor as it carries a price of risk which is larger than the one from volatility.

To address our empirical findings, we explore the implications of time variation in conditional risk aversion for currency risk premia. We consider a multi-country, multigood general equilibrium model in which preferences are characterized by external habit formation (Menzly, Santos and Veronesi, 2004) and home bias, as in Stathopoulos (2011, 2012). In the model, currency risk premia compensate investors mainly for exposure to global risk aversion fluctuations and agents are willing to accept lower returns for assets that have negative global risk aversion betas and, thus, provide a hedge against increases in global risk aversion. Consequently, the price of the global risk aversion factor is negative. We also show that global risk aversion is positively associated with conditional exchange rate second moments. Hence, currencies that hedge against adverse global risk aversion fluctuations can be empirically identified as currencies that appreciate when conditional exchange rate second moments are high. Finally, we show that our model is able to link currency risk premia to real interest rate differentials and, thus, address the forward premium puzzle. If real interest rates are procyclical, which is true if the precautionary savings motive is sufficiently strong, being long a high interest rate currency and short a low interest rate currency (i.e. engaging in the carry trade) is tantamount to having a high exposure to the global risk aversion factor, i.e., holding a holding a position with a negative global risk aversion beta. As a result, investors require a high compensation in terms of expected return in order to engage in the carry trade.

Related Literature: This paper builds on the extant literature on the risk-return relationship of excess returns in currency markets. Lustig, Roussanov, and Verdelhan (2012) identify two new risk factors: the average forward discount of the US dollar against developed market currencies and the return to the carry trade portfolio itself. They then study the predictive content of these two factors and find that the average forward discount is the best predictor of average currency excess returns even when controlling for the forward discount. While Lustig, Roussanov, and Verdelhan (2012) focus on currency portfolios, Verdelhan (2011) finds high R^2 from regressions of individual currency risk premia on the average dollar factor. Using quantile regressions, Cenedese, Sarno, and Tsiakas (2012) find that higher (lower) average currency excess return variance (correlation) leads to larger losses (gains) in the carry trade. Menkhoff, Sarno, Schmeling, and Schrimpf (2011) study whether currency excess returns can be explained by a compensation for global currency volatility risk. Mancini, Ranaldo, and Wrampelmeyer (2012) study the impact of FX liquidity on carry returns, and Adrian, Etula, and Shin (2010) present evidence that funding liquidity of U.S. intermediaries predict exchange rates well. In their paper, funding liquidity proxies for risk aversion of dollar-funded intermediaries.

Our paper is also part of the recent literature that addresses the failure of the expectations hypothesis for exchange rates. Brunnermeier, Nagel, and Pedersen (2009), Farhi, Fraiberger, Gabaix, Ranciere and Verdelhan (2009), Jurek (2009), Burnside, Eichenbaum, Kleshchelski and Rebelo (2011) and Farhi and Gabaix (2011) emphasize the importance of disaster risk for currency risk premia, Yu (2011) studies the effect of investor sentiment, while Colacito and Croce (2009, 2010) and Bansal and Shaliastovich (2011) explore the implications of long-run risk in currency markets. Martin (2011) studies the failure of the UIP in a two country economy with two goods and heterogeneity in country size. Evans (2012) shows in an open economy DSGE model that risk shocks are a significant driver of exchange rate dynamics. The paper closest to ours is Verdelhan (2010): he proposes a two-country, single-good model with trade frictions and time-varying risk aversion generated by external habit formation and illustrates the importance of procyclical real interest rates for addressing the forward premium puzzle. In our multi-country model, we endogenize consumption and focus on the relationship between global risk aversion and conditional exchange rate second moments.

Finally, different versions of our theoretical setup have been used to address the Brandt, Cochrane and Santa-Clara (2006) international risk sharing puzzle (Stathopoulos, 2011) and the portfolio home bias puzzle (Stathopoulos, 2012); our paper extends the insights of that body of work by considering the effects of time variation in risk aversion for currency returns.

The remainder of the paper is organized as follows. Section I. describes the data and details how we construct the correlation risk factor. Section II. describes how we build the currency portfolios and contains the empirical results with regards to priced correlation risk in currency markets. Section III. sets up a multi country model with external habit which we calibrate in Section IV.. And Section V. concludes. Proofs are deferred to the Appendix and additional results and robustness checks are gathered in an Online Appendix.

I. Data and Risk Factor Construction

We start by describing the data and how to construct the currency correlation risk factor. We use daily option prices on the most heavily traded currency pairs to construct a forward looking measure of correlation risk and high frequency data on the underlying spot exchange rates to calculate the realized counterparts. Our data runs from January 1999 to December 2010.

A. Data Description

High Frequency Currency Data: The high frequency spot exchange rates Euro, Japanese Yen, British Pound, and Swiss Franc, all vis-à-vis the U.S. Dollar, are from Olsen & Associates. Given that the high liquidity in foreign exchange markets prevents triangular arbitrage opportunities in the five most heavily traded currencies, calculating the remaining cross rates using the four exchange rates is common practice. The raw data contains all interbank bid and ask indicative quotes for the exchange rates for the nearest even second. After filtering the data for outliers, the log price at each 5 minute tick is obtained by linearly interpolating from the average of the log bid and log ask quotes for the two closest ticks. As options are traded continuously throughout the day, this results in a total of 288 observations over a 24 hour period.¹

Currency Option Data: We use daily over-the-counter (OTC) currency options data from JP Morgan for the four currency pairs EURUSD, JPYUSD, GBPUSD, and CHFUSD plus the six cross rates (i.e., we have have options data on a total of ten exchange rates). The use of OTC option data has several advantages over exchange traded option data. First, the trading volume in the OTC FX options market is several times larger than the corresponding volume on exchanges such as the Chicago Mercantile Exchange. As a consequence, this leads to more competitive quotes in the OTC market. Second, the conventions for writing and quoting options in the OTC markets have several features that are appealing when performing empirical studies: Every day,

¹We follow the empirical literature and take five minute intervals opposed to higher frequencies to mitigate the effect of spurious serial correlation due to microstructure noise (see Andersen and Bollerslev, 1998).

new option series with fixed times to maturity and fixed strike prices, defined by sticky deltas, are issued. In comparison, the time to maturity of exchange-traded option series gradually declines with the approaching expiration date, and the moneyness continually changes as the underlying exchange rate moves. Therefore, the OTC option data allows for better comparability over time, as the series' main characteristics do not change from day to day. The options used in this study are plain-vanilla European calls and puts and encompass 5 option series per exchange rate: We consider a one month maturity and a total of five different strikes: at-the-money (ATM), 10-delta call and 25-delta call, 10-delta-put and 25-delta put.

Spot and Forward Rates: To form our portfolios, we use daily data for spot exchange rates and one month forward rates versus the U.S. dollar obtained from Datastream. We start from daily data in order to construct the correlation risk exposure. In line with the previous literature (see Fama, 1984), we work with the log spot and one month forward exchange rates, denoted as $s_t^i = \ln(S_t^i)$ and $f_t^i = \ln(F_t^i)$, respectively. We use the U.S. dollar as the home currency and thus the superscript *i* always denotes the foreign currency. Our total sample consists of 21 countries: Australia, Canada, Czech Republic, Denmark, Euro, Finland, Hungary, India, Japan, Kuwait, Mexico, New Zealand, Norway, Philippines, Singapore, South Africa, Sweden, Switzerland, Taiwan, Thailand, and the United Kingdom.² We also run a separate analysis using only developed countries, which are: Australia, Canada, Denmark, Euro, Finland, Japan, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom.

Carry Portfolios: At the end of each period t, we allocate currencies into four portfolios based on their forward discounts at the end of period t. Sorting on forward discounts is the same as sorting on interest rate differentials since covered interest parity holds closely in the data at the frequency analyzed in this paper. We re-balance portfolios at the end of each month. This is repeated month by month. Currencies are ranked from low to high interest rate differentials. Portfolio 1 contains currencies with the lowest interest rate (or smallest forward discounts) and portfolio 4 contains currencies with the

 $^{^{2}}$ These are the same countries as in Lustig, Roussanov, and Verdelhan (2011), minus the 10 Euro countries and Hong Kong, Indonesia, Malaysia, Poland, Saudi Arabia and South Korea for which we do not have a full sample of forward rates.

highest interest rates (or largest forward discounts). Monthly excess returns for holding foreign currency *i* are computed as: $rx_{t+1}^i \approx f_t^i - s_{t+1}^i$.

We follow Lustig, Roussanov, and Verdelhan (2011) and build a long-short factor based on carry trade portfolios (HML). We also build a zero-cost dollar portfolio (DOL), which is an equally weighted average of the different currency portfolios, i.e. the average return of a strategy that consists of borrowing money in the U.S. and investing in the global money markets outside the U.S.

[Insert Table 1 approximately here.]

Summary statistics of the carry trade, HML, and DOL factor are presented in Table 1. In line with previous findings, there is a monotonic increase from the lowest to the highest forward discount sorted portfolio. The unconditional average excess return from holding an equally weighted average carry portfolio is 4% per annum. The HML portfolio is highly profitable with an average return of 9.2% and a Sharpe ratio of 1.19.

B. Construction of Realized and Implied Volatility and Correlation Measures

In the following, we construct both realized and implied correlation measures for different currency pairs. For the former, we use high frequency data on the underlying spot exchange rates and for the latter we rely on options written directly on these exchange rates.

B.1. Realized Variance and Correlation

Currencies are traded continuously throughout the day all over the world. To match the time when we measure the daily option prices, we record the daily spot exchange rate at 4pm GMT. Overall, we have 288 intra-day currency returns over five minute intervals (from 4pm today to 4pm the next day):

$$r_{k,5\min} = \ln\left(S_k\right) - \ln(S_{k-5\min}).$$

We follow Andersen, Bollerslev, Diebold, and Labys (2000) and compute the realized variance by summing the squared 5-minute frequency returns over the day:³

$$RV_t = \sum_{k=1}^K r_{k,5\min}^2.$$

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

$$RCov_t^{i,j} = \sum_{k=1}^K r_{k,5\min}^i r_{k,5\min}^j.$$

The realized correlation is then simply the ratio between the realized covariance and the product of the respective standard deviations:

$$RCorr_t^{i,j} = RCov_t^{i,j} / \sqrt{RV_t^i} \sqrt{RV_t^j}.$$

We use realized measures observable at time t to proxy for the expectation under the physical measure for the period T - t.

B.2. Implied Variance and Correlation

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

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

where S_t is the underlying spot exchange rate and P(K,T) and C(K,T) are the put and call prices with maturity date T and strike K, respectively. Since, in practice, the number of traded options for any underlying asset is finite, the available strike price series

 $^{^{3}}$ We also use more refined measures of realized variance for robustness checks. The results, however, are not sensitive to how we measure the expected variance under the physical measure.

is a finite sequence as well. The calculation of the model-free implied variance employs the whole cross-section of option prices: For each maturity T, all five strikes are taken into account. These are quoted in terms of the corresponding delta of the option. To convert the quoted delta-strikes into dollar strike prices, we use the option prices from the Garman and Kohlhagen (1983) model and solve for the delta of the corresponding option. The corresponding spot rates are extracted from the high-frequency dataset in accordance with the exact time of the daily options quote, i.e. at 4pm GMT. The riskfree interest rates for USD, EUR, JPY, GBP, and CHF are represented by the London Interbank Offered Rates (LIBOR). To approximate the integral in equation (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 due to the fact that there is no continuum of options available. We find that both errors are extremely small using currency options. 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.⁴ We require all cross rates for three currencies, S_t^i , S_t^j , and S_t^{ij} . The absence of triangular arbitrage then yields:⁵

$$S_t^{ij} = S_t^i / S_t^j$$

Taking logs, we derive the following relationship:

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

⁴Brandt and Diebold (2006) use the same approach to construct realized covariances of exchange rates from range based volatility estimators.

⁵Recent studies report that the average violation of triangular arbitrage is about 1.5 basis points with an average duration of 1.5 seconds (see Kozhan and Tham, 2012). We note however that most papers that study violations of triangular arbitrage use indicative quotes, which only give an approximate price at which a trade can be executed. Executable prices can differ from indicative prices by a few 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. In our data, we find that triangular arbitrage is less than 1 basis point, we therefore conclude that these violations are not affecting the calculated quantities.

Finally, taking variances yields:

$$\int_{t}^{T} \left(\sigma_{u}^{ij}\right)^{2} du = \int_{t}^{T} \left(\sigma_{u}^{i}\right)^{2} du + \int_{t}^{T} \left(\sigma_{u}^{j}\right)^{2} du - 2 \int_{t}^{T} \gamma_{u}^{i,j} du,$$

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

$$\int_{t}^{T} \gamma_{u}^{i,j} du = \frac{1}{2} \int_{t}^{T} \left(\sigma_{u}^{i}\right)^{2} du + \frac{1}{2} \int_{t}^{T} \left(\sigma_{u}^{j}\right)^{2} ds - \frac{1}{2} \int_{t}^{T} \left(\sigma_{u}^{ij}\right)^{2} du.$$

Using the standard replication arguments, we find that:

$$E_{t}^{\mathbb{Q}}\left(\int_{t}^{T}\gamma_{u}^{i,j}du\right) = e^{r(T-t)}\left(\int_{t}^{S_{t}^{i}}\frac{1}{K^{2}}\mathrm{P}^{i}(K,T)dK + \int_{S_{t}^{i}}^{\infty}\frac{1}{K^{2}}\mathrm{C}^{i}(K,T)dK - \int_{t}^{S_{t}^{j}}\frac{1}{K^{2}}\mathrm{P}^{j}(K,T)dK + \int_{S_{t}^{j}}^{\infty}\frac{1}{K^{2}}\mathrm{C}^{j}(K,T)dK - \int_{t}^{S_{t}^{i,j}}\frac{1}{K^{2}}\mathrm{C}^{ij}(K,T)dK\right).$$

$$(2)$$

The model-free implied correlation can then be calculated using expression (2) and the model-free implied variance expression (1):⁶

$$E_t^{\mathbb{Q}}\left(\int_t^T \rho_u^{i,j} du\right) \equiv \frac{E_t^{\mathbb{Q}}\left(\int_t^T \gamma_u^{i,j} ds\right)}{\sqrt{E_t^{\mathbb{Q}}\left(\int_t^T \left(\sigma_u^i\right)^2 du\right)}}\sqrt{E_t^{\mathbb{Q}}\left(\int_t^T \left(\sigma_u^j\right)^2 du\right)}}.$$
(3)

Tables 2 and 3 provide summary statistics of the realized and implied volatility and correlation together with their corresponding risk premia while Figures 1 and 2 graph the measures over time. On average, implied volatility exceeds realized volatility for the Japanese Yen but realized volatility is larger on average than the implied counterpart for the Euro, British Pound and the Swiss Franc. Implied and realized volatility are not very time varying except for a huge spike in October 2008.

⁶Our expression for implied correlation does not necessary imply that the correlation is bounded between -1 and 1. One way to ensure that the absolute implied correlations stay below one would be to impose a normalization in the spirit of the Dynamic Conditional Correlation model of Engle (2002). As in the data, we do not find implied correlations exceeding 1, we do not apply this normalization.

[Insert Figures 1 and 2 and Tables 2 and 3 approximately here.]

Figure 2 reveals that both realized and implied correlation remain quite stable until 2006 but then suddenly drop for most currency pairs. It is also interesting to note that the conditional correlations are mostly positive except for the Euro and British Pound vis-à-vis the Japanese Yen, a typical safe haven currency. One feature that is common to all currency pairs is that correlations exhibit high volatility during the recent financial crisis.

B.3. Global Correlation Risk

To construct our global correlation risk factor, we average implied correlation over all different currency pairs at any given day.⁷ We prefer to use implied as opposed to the realized quantities as they provide a more forward-looking measure of risk. We show in the Online Appendix, that all results go through using realized measures of correlation.

As explained above, we have options on EUR, GBP, JPY and CHF versus the USD and currency options for the ten cross pairs of the five currencies. This allows us to calculate six correlation measures. Hence,

$$IC_{t,T}^{G} = 1/6 \times \sum_{i=1}^{4} \sum_{j>i} IC_{t,T}^{ij},$$
(4)

where IC_{t}^{ij} is the implied correlation for currency pair *i* and *j*. In a similar vein, we construct a global volatility risk factor by taking the average of the implied volatilities, i.e. $\text{IV}_{t,T}^{G} = 1/4 \times \sum_{i=1}^{4} \text{IV}_{t,T}^{i}$ where IV_{t}^{i} is the implied volatility for exchange rate *i*. The two time series are plotted in Figure 3.

[Insert Figure 3 approximately here.]

⁷A priori it is not clear how to construct a global risk factor and in principle, we could calculate principal components and use the first principal component to represent global correlation risk. As the unconditional correlation between the average and the first principal component is 99%, we prefer to use the average as it is the simplest measure. Throughout, we use an equal weighted average to represent a global risk factor and obviously one could think about more elaborate ways to construct an average. We explore a turnover weighted average in the Online Appendix and show that the two methods lead to the same results.

The global volatility factor shows a distinct spike in October 2008 where global volatility increases from 8% to almost 30%. Interestingly, the spike coincides with the all time high in the equity market index implied volatility VIX. The global correlation factor is more volatile with a spike right after the financial crisis. The correlation risk factor started at around 40% in the early 2000 and almost doubled until 2008 and since then is on a downward spiral. Overall, the global volatility risk factor shows little movement except for at the most recent crisis whereas the global correlation risk factor seems to move much more.

For our empirical analysis, we use innovations of the aforementioned FX correlation and volatility factors, defined as the residuals after fitting an AR(1) process for the correlation and variance risk factors. We denote them by ΔIC^G and ΔIV^G , respectively.⁸

II. Empirical Analysis

In this section, we study the price of correlation risk in two ways. First, we quantify in the time-series the size of correlation risk premia for different currency pairs, where we define a correlation risk premium as the difference between the risk-neutral and physical expectations of the currencies' correlation. Secondly, we study the empirical relation between the global correlation risk proxy and the risk-return profile of currency portfolios in the cross-section. If correlation risk is indeed priced in currency markets, then sorting currencies according to their exposure to correlation risk should yield a significant spread in average returns. We start by sorting a cross-section of different currencies according to their exposure to correlation risk. We then ask whether our proposed risk factor can explain carry trade returns. To this end, we run time series regressions of each portfolio's excess return on a set of potential risk factors. Using these

⁸We run portfolio sorts with both first differences and the AR(1) innovations and find that the results remain robust to the method chosen.

factor betas, we assess the price of correlation risk using the two-stage methodology from Fama and MacBeth (1973).

A. Correlation Risk Premia

In the following, we quantify the size of variance and correlation risk premia in FX markets using the implied and realized measures presented in the previous section. Following the literature, the variance and correlation risk premia are defined as the difference between the risk-neutral and physical expectations of the variance and correlation, respectively. Thus, $\text{VRP}_{t,T}^i$, the (T-t)-period variance risk premium for the log exchange rate s^i at time t is defined as: $\text{VRP}_{t,T}^i \equiv E_t^{\mathbb{Q}} \left(\int_t^T (\sigma_u^i)^2 du \right) - E_t^{\mathbb{P}} \left(\int_t^T (\sigma_u^i)^2 du \right)$, where $(\sigma_u^i)^2$ is the variance of exchange rate s^i at time u. In a similar vein, the expression for the correlation risk premium between exchange rates s^i and s^j , $\text{CRP}_{t,T}^{i,j}$, is defined as:

$$CRP_{t,T}^{i,j} \equiv E_t^{\mathbb{Q}} \left(\int_t^T \rho_u^{i,j} du \right) - E_t^{\mathbb{P}} \left(\int_t^T \rho_u^{i,j} du \right)$$

$$\equiv \frac{E_t^{\mathbb{Q}} \left(\int_t^T \gamma_u^{i,j} du \right)}{\sqrt{E_t^{\mathbb{Q}} \left(\int_t^T (\sigma_u^i)^2 du \right)} \sqrt{E_t^{\mathbb{Q}} \left(\int_t^T (\sigma_u^j)^2 du \right)}}$$

$$= \frac{E_t^{\mathbb{P}} \left(\int_t^T \gamma_u^{i,j} du \right)}{\sqrt{E_t^{\mathbb{P}} \left(\int_t^T (\sigma_u^j)^2 du \right)} \sqrt{E_t^{\mathbb{P}} \left(\int_t^T (\sigma_u^j)^2 du \right)}},$$
(5)

where $\rho_t^{i,j}$ and $\gamma_t^{i,j}$ are the conditional correlation and covariance between the two exchange rates, respectively. In the following, we will concentrate on one month premia only, i.e. T = t + 1.

The summary statistics of the risk premia are reported in Panel C of Tables 2 and 3. Different from the equity index market, we find that variance risk premia in FX markets are small on average and statistically not different from zero. We also note that the variance risk premia are left skewed, which could be due to the implicit crash risk in FX currency markets (see Brunnermeier, Nagel, and Pedersen, 2009). This is also evident from the figures where we see that the variance risk premia experience large and sudden negative crashes, especially during the early years of 2000. One possible reason for the

small size of the variance risk premia could also be due to the high volatility of the series themselves: The risk premia switch sign quite often and display large jumps – mostly negative ones in the 2000 and a positive one during the most recent financial crisis. This echoes the findings of Chernov, Graveline, and Zviadadze (2012) who report large jumps in the implied volatility of currency options.

In contrast, correlation risk premia are mostly positive and economically large: The average correlation risk premium is 14%, which is comparable to what is observed in the equity market.⁹ Interestingly, the correlation risk premia are mostly positive in the period up to 2008 and then turn negative for most of the currency pairs. There are also noteworthy cross-sectional differences across different currency pairs. The large negative drop in implied correlations coincides with the huge increase in the FX implied volatility and VIX after the Lehman default in September 2008. For example for the EURJYP and GBPJPY exchange rates, the implied correlation drops from +26% to -24% and +12% to -40%, respectively, while the associated risk premia drops from +53% to -5% and +42% to -17%, respectively.

Overall, we conclude that the compensation for correlation risk in the time-series is economically relevant for all currency pairs. In the following, we study the price of correlation risk in the cross-section of currency portfolios.

B. Correlation Risk Sorted Portfolios

We first construct monthly portfolios sorted according to the correlation risk exposure. Intuitively, we expect those currencies to yield lower returns that hedge well against correlation risk, whereas we expect currencies that have a high exposure to correlation risk yield high returns on average.

At the end of each period t, we build four currency portfolios based on the correlation risk exposure of the respective currencies. We estimate pre-ranking betas from rolling regressions of currency excess returns on the global correlation risk using 36 month

⁹Driessen, Maenhout, and Vilkov (2009) estimate that the correlation risk premium on the S&P 100 is approximately 18%, with an average realized correlation of 29% and an average implied correlation of 47%. Buraschi, Trojani, and Vedolin (2011) report similar numbers.

windows that end in period t - 1 (as in Lustig, Roussanov, and Verdelhan, 2011 and Menkhoff, Sarno, Schmeling, and Schrimpf, 2011):

$$rx_{t+1}^i = \alpha^i + \beta_t^{i,\text{IC}} \Delta \text{IC}_t^G + \epsilon_t^i$$

where rx_{t+1}^i is the one month excess return of currency *i*, defined as $rx_{t+1}^i \equiv f_t^i - s_{t+1}^i$ and ΔIC_t^G denotes innovations in the correlation risk factor. This gives the currencies' exposure to global correlation risk and only uses information up to time *t*. We repeat the same regressions using the volatility risk factor. Descriptive portfolio statistics for the correlation sorting are reported in Table 4. To save space, we defer the results for the volatility sorting to the Online Appendix.

[Insert Table 4 approximately here.]

In Panel A of Table 4 we report summary statistics for the correlation risk sorted currency portfolios for all countries and in Panel B we report the statistics for the developed countries only. Correlation sorted portfolios yield quite attractive Sharpe ratios between 0.56 and 0.69, respectively. Investing in currencies with high correlation betas leads to significantly lower returns compared to investing in low correlation beta currencies. Longing low correlation beta currencies and shorting the high correlation beta currencies yields an average return of more than 3% and an annualized Sharpe ratio of 0.37. When we move to Panel B, the results improve further. The difference between the low correlation risk exposure currencies and high correlation risk exposure currencies is more than 5% per annum with a Sharpe ratio of 0.54. There is also a strikingly monotone increase in estimated slope coefficients. Estimates are negative and large for currencies with low exposure and positive for high exposure currencies. The table also shows pre-formation forward discounts for the portfolios. The average forward discount is monotonically decreasing, which mirrors the findings for the carry trade portfolios (see Table 1).

C. Factor Mimicking Portfolios

The portfolio sorting exercise has provided some evidence that global correlation risk is priced in the cross-section of currency returns. In a next step, we assess the crosssectional price of correlation risk. To this end, we estimate a factor premium on the mimicking correlation factor, denoted by FIC. Following Ang, Hodrick, Xing, and Zhang (2006), we construct a factor-mimicking portfolio of correlation innovations. This allows us to naturally asses the factor prices of correlation risk vis-à-vis other factors.

To this end, we regress innovations in the global correlation and volatility risk proxies on the four excess carry return portfolios:

$$\Delta \mathrm{IC}_t^G = c + b' \mathbf{r} \mathbf{x}_t + u_t,$$

where $\mathbf{r}\mathbf{x}_t$ is the vector of excess returns. The factor mimicking portfolio excess return is then the product of the estimated slope coefficients and the excess returns, i.e. $FIC_t \equiv \hat{b}'\mathbf{r}\mathbf{x}_t$.

In the first step of the Fama and MacBeth (1973) regressions, we estimate betas using the full sample, in the second stage, we use the cross-sectional regressions to estimate the factor premia. Panel B of Table 5 shows the premia. The price of the dollar trade risk factor is positive, in line with previous findings. In contrast, the price of correlation risk is -0.08% per month and statistically significant. The negative factor price is in line with our previous findings that portfolios, which co-move positively with correlation innovations require lower risk premia. The question then is which portfolios provide a good hedge against correlation risk? To this end, we look at the factor betas for the different currency portfolios. The results are reported in Table 5, Panel A.

[Insert Table 5 approximately here.]

Low interest rate currencies have a high correlation beta and thus provide a good hedge against correlation risk as they have a large negative exposure to correlation risk. On the other hand, high interest rate currencies have negative FX correlation factor betas and, as a result, command high FX correlation risk premia. Furthermore, the estimated coefficients are highly significant for the dollar factor (DOL), which is not surprising given earlier results in Lustig, Roussanov, and Verdelhan (2011).

D. What Does Correlation Tell Us Beyond Volatility?

Prima facie, it is hard to disentangle correlation from volatility, as the former depends on the latter. However, recent papers show that the compensation for volatility risk is often really compensation for correlation risk (see e.g. Driessen, Maenhout, and Vilkov, 2009) and that for example the hedging demand for correlation risk often dominates that for volatility. Buraschi, Porchia, and Trojani (2010) for example find in an inter-temporal portfolio optimization setting with time-varying correlations that the correlation hedging component can be up to seven times larger than the hedging component due to volatility. In the following, we study the relative pricing power of correlation beyond volatility. We do this in two ways, first, we perform a double sorted portfolio strategy, then we estimate the price of correlation risk using volatility sorted portfolios as test assets.

Since volatility and correlation are intimately linked, which could potentially lead to multi-collinearity issues, we use innovations in correlation and the orthogonalized component of volatility.¹⁰ In our double-sorting exercise, we sort currencies into two bins based independently on volatility and correlation. For each of the four portfolios formed, we report subsequent annualized returns. The results from sorting on volatility and correlation are reported in Table 6, Panel A. The number of currencies in each portfolio are reported in parentheses below the returns. We abstain from doing a double sort using developed countries only as there would be too few currencies available.

Reading across Panel A of Table 6, we find that holding volatility constant, correlation continues to be negatively related to subsequent returns for both low and high levels of volatility. For the low volatility sorted currencies, the low minus high portfolio yields 3.41% per annum, which corresponds to the magnitude of the return differential in

¹⁰We note, however, that changes in volatility, IV^G and changes in correlation, IC^G are very little correlated with -15%.

univariate sorted portfolios in Table 4. In the high volatility regime, the spread portfolio leads to slightly lower returns of almost 2%.

To shed more light on the question whether correlation subsumes some of the compensation to volatility, we run the same exercise as in Section II. C., but replace the carry portfolios as test assets with volatility sorted portfolios. We also construct a correlation and volatility factor mimicking factor using these assets, which we label \widetilde{FIC} and \widetilde{FIV} , respectively. We report the estimated factor betas and prices of volatility and correlation in Panel B and Panel C of Table 6, respectively.

Low volatility currencies have a high beta whereas high volatility currencies have a low beta. This means that if volatility is high (i.e. like during the recent financial crisis), the low volatility currencies provide a good hedge, on the other hand, the high volatility currencies command high risk premia. The estimated prices of risk are both highly statistically significant: The price of correlation risk is 0.10% per month which corresponds to 1.2% per year.

Overall, the results in Table 6 imply that, on average, correlation risk is priced in the cross-section of currency returns beyond the explanatory power of volatility. Consistent with the evidence presented in Menkhoff, Sarno, Schmeling, and Schrimpf (2011), we find that currencies with a lower exposure to volatility have higher returns.

[Insert Table 6 approximately here.]

E. The Link Between Global Correlation Risk and Risk Aversion

The previous results show that global FX correlation is priced in the time-series and cross-section of currency returns, implying that it acts as a proxy for priced global systematic risk. In the context of time-varying conditional risk aversion, global risk aversion would constitute such a global priced factor. To evaluate the connection between our two FX factors and global risk aversion, we construct a proxy for the global surplus consumption ratio, defined as a real GDP-weighted average of all individual countries' surplus consumption ratio. Following Wachter (2006), the country i surplus

consumption ratio is proxied by a weighted moving average of past consumption growth, $\sum_{k=1}^{40} \beta^k \Delta c_{t-k}$, where Δc is real per capita consumption growth and $\beta = 0.97$. We find that the unconditional correlation between our global surplus consumption proxy and the FX correlation risk factor is -0.44.

Another empirical proxy for conditional risk aversion could be consumer confidence (see Baele, Bekaert, and Inghelbrecht, 2010). To proxy for global consumer confidence, we take data from the Michigan Consumer Confidence and the European Economic Sentiment Indicator and average these two series.¹¹ We find that this average has an unconditional correlation of -50% with our global correlation risk factor.

Overall, these numbers support a positive link between global conditional risk aversion and the second moments of exchange rates. In the following section, we propose a general equilibrium model that formalizes that link.

III. Model

We study a multi-country general equilibrium model in which preferences are characterized by external habit and home bias. In the model we posit, global risk aversion is intimately linked to second moments of foreign exchange. We then test whether our model can replicate the empirical facts which we have established in the data.

A. Model Details

A.1. Endowments and Preferences

The world economy comprises n + 1 countries, indexed by *i*: the domestic country (i = 0) and *n* foreign countries (i = 1, ..., n), each of which is populated by a single representative agent. There are n + 1 distinct perishable goods in the world economy, indexed by *j*, and each agent is initially endowed with a claim on the entirety of the world endowment of the corresponding good. Uncertainty in the economy is represented by a filtered probability space $(\Omega, \mathcal{F}, \mathbf{F}, P)$, where $\mathbf{F} = \{\mathcal{F}_t\}$ is the filtration generated

¹¹The first time-series can be downloaded from the St. Louis Fed Economic Database and the latter from the webpage of the European Commission Economic Databases and Indicators.

by the standard *m*-dimensional Brownian motion \mathbf{B}_t , $t \in [0, \infty)$, augmented by the null sets. The world endowment stream of good j is denoted by $\{\tilde{X}_t^j\}$; all endowment processes are Itô processes satisfying:

$$d\log \widetilde{X}_t^j = \mu^{j,X} dt + \sigma^{j,X'} \mathbf{dB}_t, \ j = 0, 1, \dots, n$$

with $\sigma^{j,X} \neq \mathbf{0}$ for all j. Without loss of generality, the global numéraire is the domestic consumption basket, to be defined below. Since all goods are frictionlessly traded internationally, the price of each good, in units of the global numéraire, is the same in all countries; the numéraire price of good j is Q^{j} .

Representative agent i has expected discounted utility:

$$E_0\left[\int_0^\infty e^{-\rho t}\log(C_t^i-H_t^i)dt\right],$$

where $\rho > 0$ is her subjective discount rate, C^i is her level of consumption and H^i is the time-varying level of consumption habit. Consumption is expressed in units of a composite good, the domestic consumption basket, defined as:

$$C^{i} \equiv \left(\prod_{j=0}^{n} \left(X^{i,j}\right)^{a^{i,j}}\right),\,$$

where $X^{i,j}$ is the quantity of good j that agent i consumes. The preferences of agent i with respect to the n + 1 goods are described by the vector of preference parameters $\alpha^i = [a^{i,0}, a^{i,1}, ..., a^{1,n}]$ such that $\sum_{j=0}^n a^{i,j} = 1$ and $a^{i,j} > 0$ for all i and j. This specification allows for cross-country heterogeneity in consumption preferences, including consumption home bias. We collect the preference parameters in the preference matrix \mathbf{A} , such that $\mathbf{A} = [a_{i,j}] = a^{i-1,j-1}$.

The habit level of agent i is external. Instead of specifying the law of motion for the habit level H^i , we specify the law of motion for the inverse surplus consumption ratio

 $G^i = \frac{C^i}{C^i - H^i}$. Specifically, we assume that the inverse surplus consumption ratio solves the stochastic differential equation:

$$dG_t^i = \varphi \left(\bar{G} - G_t^i \right) dt - \delta \left(G_t^i - l^i \right) \left(\frac{dC_t^i}{C_t^i} - E_t \left(\frac{dC_t^i}{C_t^i} \right) \right)$$

as in Menzly, Santos and Veronesi (2004). The inverse surplus consumption ratio G^i is a stationary process, reverting to its long-run mean of \overline{G} at speed φ . Furthermore, innovations in G^i are perfectly negatively correlated with innovations in the consumption growth of agent *i*. The parameter $\delta > 0$ scales the size of the innovation in G^i vis-à-vis the innovation in consumption growth. The parameter $l \geq 1$ is the lower bound of the inverse surplus ratio G^i . Importantly, the sensitivity of the inverse surplus consumption ratio to consumption growth innovations is increasing in G^i , which implies large conditional variability of the surplus consumption ratio in bad states of the world. The local curvature of the utility function is then given by:

$$-\frac{u_{CC}(C_t^i, H_t^i)}{u_C(C_t^i, H_t^i)}C_t^i = G_t^i$$

In a slight abuse of terminology, we will refer to G^i as the conditional risk aversion of country i in the remainder of this paper.

A.2. Financial Markets, Prices and Exchange Rates

Financial markets are dynamically complete and frictionless, so agents are able to optimally share risk. As a result, there is a unique state-price density for cash flows expressed in units of the global numéraire, denoted by Λ . The numéraire state-price density satisfies the law of motion:

$$\frac{d\Lambda_t}{\Lambda_t} = -r_t dt - \eta_t' \mathbf{dB}_t,$$

where r is the real risk-free rate and η is the market price of risk. Given financial market completeness, each agent i maximizes her utility subject to the following static budget constraint:

$$E_0\left[\int_0^\infty \frac{\Lambda_t}{\Lambda_0} C_t^i P_t^i dt\right] \le E_0\left[\int_0^\infty \frac{\Lambda_t}{\Lambda_0} \widetilde{X}_t^i Q_t^i dt\right].$$

Each country *i* has a local numéraire, which is the local consumption basket C^i . The price of C^i in units of the global numéraire is:

$$P_t^i = \prod_{j=0}^n \left(\frac{Q_t^j}{a^{i,j}}\right)^{a^{i,j}}$$

and is defined as the minimum expenditure required to buy a unit of C^i . Given that the global numéraire is the domestic consumption basket (the domestic local numéraire), it holds that $P_t^i = 1$ for all t.

Cash flows expressed in units of the local numéraire of country i are priced by Λ^{i} , the local state-price density, which has law of motion:

$$\frac{d\Lambda_t^i}{\Lambda_t^i} = -r_t^i dt - \eta_t^{i\prime} \mathbf{dB}_t,$$

where r^i is the real risk-free rate in units of the local numéraire and η^i is the local market price of risk. Since the global numéraire is the domestic local numéraire, it holds that $\Lambda = \Lambda^0$, $r = r^0$ and $\eta = \eta^0$.

Real exchange rates express the relative values of local numéraires. Specifically, the time t real exchange rate S^i (for i = 1, ..., n) is the price of the domestic consumption basket expressed in units of the consumption basket of foreign country i:

$$S_t^i = \frac{P_t^0}{P_t^i} = \frac{1}{P_t^i},$$
 (6)

so an increase of S^i denotes real appreciation of the domestic consumption basket. Notably, real exchange rate dynamics reflect cross-country preference heterogeneity:

$$S_t^i = \prod_{j=0}^n \left(\frac{(a^{i,j})^{i,j}}{(a^{0,j})^{0,j}} \right) \prod_{j=0}^n \left(Q_t^j \right)^{a^{0,j} - a^{i,j}}.$$

Purchasing power parity holds only if the two countries' preferences are identical $(a^{i,j} = a^{0,j})$ for all goods j, so that the two consumption baskets have the same composition. In the case of preference heterogeneity, purchasing power parity is violated and the real exchange rate varies across time.

It can easily be shown that the real exchange rate satisfies:

$$S_t^i = \frac{\Lambda_t}{\Lambda_t^i},\tag{7}$$

so that arbitrage opportunities are precluded in international financial markets. As a result, the dynamics for S^i is:

$$\frac{dS_t^i}{S_t^i} = \left[\left(r_t^i - r_t \right) + \eta_t^{i\prime} \left(\eta_t^i - \eta_t \right) \right] dt + \left(\eta_t^i - \eta_t \right)^{\prime} \mathbf{dB}_t.$$

Real exchange rate volatility arises from the differential exposure of the two local pricing kernels to endowment shocks, encoded in the vector $\eta^i - \eta$. In the presence of heterogeneous exposure to endowment shocks, uncovered interest rate parity does not hold, since there exists a non-zero currency risk premium:

$$E_t\left(\frac{dS_t^i}{S_t^i}\right) = \left[\left(r_t^i - r_t\right) + \eta_t^{i\prime}\left(\eta_t^i - \eta_t\right)\right]dt.$$

B. Equilibrium

In Appendix A, we show that the competitive equilibrium solution is equivalent to the solution of the planner's problem:

$$\max_{\left\{X_t^{i,j}\right\}} E_0\left[\int_0^\infty e^{-\rho t}\left(\sum_{i=0}^n \mu^i \log\left(C_t^i - H_t^i\right)\right) dt\right],$$

subject to the family of resource constraints:

$$\widetilde{X}_{t}^{j} = \sum_{i=0}^{n} X_{t}^{i,j}$$
, for $j = 0, ..., n$,

for all t, where μ^i , i = 0, ..., n is the welfare weight of country i. Without loss of generality, we normalize the welfare weights to sum to one: $\sum_{i=0}^{n} \mu^i = 1$.

C. Local State-Price Densities

In equilibrium, the state-price density of the local numéraire of country i is given by the discounted marginal utility of the local consumption basket, scaled by the welfare weight μ^i :

$$\Lambda^i_t = e^{-\rho t} \mu^i \frac{G^i_t}{C^i_t}.$$
(8)

Therefore, the country i risk-free rate is:

$$r_t^{i,C} = \rho + \mu_t^{i,C} + \varphi \left(\frac{G_t^i - \bar{G}}{G_t^i}\right) - \left(1 + \delta \left(\frac{G_t^i - l}{G_t^i}\right)\right) \sigma_t^{i,C'} \sigma_t^{i,C},$$

where $\mu_t^{i,C}$ is the conditional mean of the consumption growth rate of country *i*. The risk-free rate is determined by the interaction of two forces, the desire for marginal utility intertemporal smoothing and the precautionary savings motive. An increase in G^i increases current marginal utility, enhancing the agent's desire to consume more, and save less, now. However, it also increases the desire for precautionary savings. The relative strength of the two effects is determined by the preference parameters φ and δ : An increase in φ , the speed of mean-reversion of conditional risk aversion, increases the importance of the smoothing motive, as it raises the probability that future marginal utility will be lower, while an increase in δ , the sensitivity of risk aversion changes to consumption shocks, increases the conditional variability of marginal utility and, therefore, the agent's incentive to accumulate precautionary savings.

The local market price of risk is given by:

$$\eta_t^i = \left(1 + \delta\left(\frac{G_t^i - l}{G_t^i}\right)\right) \sigma_t^{i,C},$$

and has two familiar components. The first component is the conditional sensitivity of the price of risk to consumption growth variability and is increasing in conditional risk aversion G_t^i . In the absence of external habit formation, the sensitivity would be constant and equal to one, the relative risk aversion implied by log utility. However, external habit formation induces time variation in conditional risk aversion and, thus, to the sensitivity of the price of risk. The second component, conditional consumption growth volatility, is determined by the degree of optimal international risk sharing, which, in turn, depends on the interaction between preference home bias and external habit formation.

D. Global Risk Factors

It is shown in Appendix A that the global numéraire state-price density is increasing in global conditional risk aversion and decreasing in global consumption expenditure:

$$\Lambda_t = e^{-\rho t} \frac{G_t^W}{\mathcal{C}_t^W}.$$
(9)

Global conditional risk aversion G^W is defined to be the welfare-weighted average of all countries' conditional risk aversions,

$$G_t^W \equiv \sum_{i=0}^n \mu^i G_t^i.$$

Global consumption expenditure is:

$$\mathcal{C}_t^W \equiv \sum_{i=0}^n \left(C_t^i P_t^i \right) = \sum_{i=0}^n \left(\widetilde{X}_t^j Q_t^j \right).$$

and, given market clearing, equals the value of the global endowment.

We will focus on the properties of the excess currency return, defined as the return of the foreign money market account in units of the domestic numéraire in excess of the domestic risk-free rate:

$$dR_t^i = \eta_t' \left(\eta_t - \eta_t^i\right) dt + \left(\eta_t - \eta_t^i\right)' \mathbf{dB}_t.$$

The currency risk premium is determined by the exposure of the currency return to the two global risk factors:

$$E_t\left(dR_t^i\right) = -E_t\left(dR_t^i\frac{d\Lambda_t}{\Lambda_t}\right) = \lambda_t^C\beta_t^{i,C} + \lambda_t^G\beta_t^{i,G}.$$

The price of the exposure to global consumption expenditure innovations is positive, as bad states of the world are associated with low global consumption expenditure, while the price of the exposure to global risk aversion innovations is negative, as bad states entail high global conditional risk aversion:

$$\lambda_t^C \equiv var_t \left(\frac{d\mathcal{C}_t^W}{\mathcal{C}_t^W}\right), \, \lambda_t^G \equiv -var_t \left(\frac{dG_t^W}{G_t^W}\right).$$

IV. Calibration and Simulation Results

In this section, we evaluate the ability of our model to match the salient features of the data. Specifically, we first show that our model is able to generate conditional exchange rate correlation that is positively associated with conditional conditional global risk aversion, justifying the use of conditional exchange rate correlation as a risk factor in the empirical part of our paper. We then establish that the main driver of cross-sectional variation in currency risk premia is differential exposure to the correlation risk factor and show that, given procyclical real interest rates, differences in exposure can generate a carry trade effect.

A. Calibration and Model Moments

We simulate a global economy of 22 countries, the domestic one and 21 foreign ones, at the monthly frequency. The log endowment growth processes are specified to be symmetric and have constant first and second moments:

$$d\log \widetilde{X}_t^j = \mu dt + \sigma^j \mathbf{dB}_t, \ j = 0, 1, \dots, 21,$$

where σ^j is a 22 × 1 vector such that $\sigma^j[j, 1] = \sigma$ and $\sigma^j[j', 1] = \sigma\tilde{\rho}$ for all $j' \neq j$. Regarding preferences, we specify the preference matrix **A** so that the domestic country (US) is more home-biased and larger than the foreign countries consistently with the data; all foreign countries are symmetric. Specifically, we set

$$\mathbf{A} = \begin{bmatrix} 0.8700 & 0.0062 & \dots & 0.0062 \\ 0.0506 & 0.6000 & \dots & 0.0175 \\ \dots & \dots & \dots & \dots \\ 0.0506 & 0.0175 & 0.0175 & 0.6000 \end{bmatrix}$$

so the domestic and foreign country home bias is 0.87 and 0.6, respectively, and the domestic country has an equilibrium welfare weight $\mu^0 = 0.28$.¹² The other calibration parameters are reported in Table 7. Notably, we set the parameter of conditional risk aversion mean-reversion, φ , equal to 0.03, so conditional risk aversion is very persistent and, thus, the inter-temporal smoothing component of the risk-free rate is weak. On the other hand, we set δ , the sensitivity parameter of conditional risk aversion to consumption growth shocks to 120, implying a strong precautionary savings motive.

[Insert Table 7 approximately here.]

B. The Impact of Endowment Shocks

C. The Effect of Global Risk Aversion

Importantly, the calibrated parameters generate conditional real exchange rate correlation that is increasing in global risk aversion. Figure 4 shows the dependence of several moments of interest on global risk aversion, assuming country risk aversions are identical $(G_t^i = G_t^W \text{ for all } i)$; the horizontal axis measures the value of G_t^i , ranging from 20 to 50,

¹²The preference matrix **A** is calibrated using annual data from 1999 to 2010 on GDP, imports of goods and services and exports of goods services from the IMF International Financial Statistics. The US preference home bias parameter, 0.87, is calibrated to match the time-series average of the US openness ratio 0.5(Imports+Exports)/GDP which is 0.13. The foreign preference home bias parameter, 0.6, corresponds to the cross-sectional average of 20 countries' (all the foreign countries in our empirical analysis, bar Singapore) average openness ratio. Finally, the domestic welfare weight corresponds to the US share of global GDP over the sample period.

while the vertical axis measures different moments. Eliminating all cross-sectional heterogeneity in conditional risk aversion allows us to abstract from cross-country insurance effects and focus exclusively on the forces that shape optimal international risk sharing. Given that all countries have access to complete financial markets, countries are able to achieve the optimal level of international risk sharing. However, given preference home bias, optimal risk sharing is not identical to perfect consumption pooling: there is a tension between the desire to share risk, which would imply perfect consumption pooling under preference homogeneity, and preference home bias, which induces consumption home bias.

[Insert Figure 4 approximately here.]

Panels A and C of Figure 4 present the conditional variance of consumption growth rates and SDFs; we report the variance for the domestic country and for any of the foreign countries. Increased global risk aversion generates two opposing effects on conditional SDF volatility η^i : increased international risk sharing decreases the conditional variance of consumption growth rates (Panel A), which tends to reduce η^i but the reduction in consumption risk is not enough to balance the increase in the sensitivity component of the SDF, so conditional SDF variance increases (Panel C). Panels B and D present the conditional correlation of consumption growth rates and SDFs across countries; we report the correlation between the domestic country and any of the foreign countries, as well as between any two foreign countries. As global risk aversion increases, the desire to share risk becomes stronger: as a result, cross-country consumption growth (Panel B) and SDF correlations (Panel D) increase, sharply initially, more slowly afterwards.

Panels E, F, G and H present the second moments of real exchange rates and their determinants. The amount of non-shared risk between the domestic country and foreign country i can be decomposed into the amount of aggregate risk and the proportion of the aggregate risk that is not shared. The amount of aggregate risk of the domestic country and foreign country i is defined as:

$$RP_t^{i,0} \equiv var_t \left(\frac{d\Lambda_t^i}{\Lambda_t^i}\right) + var_t \left(\frac{d\Lambda_t^0}{\Lambda_t^0}\right) = \eta_t^{i\prime} \eta_t^i + \eta_t^{0\prime} \eta_t^0$$

The proportion of aggregate risk that is shared is given by the Brandt, Cochrane and Santa-Clara (2006) international risk sharing index:

$$RS_t^{i,0} = 1 - \frac{\left(\sigma_t^i\right)^2}{var_t\left(\frac{d\Lambda_t^i}{\Lambda_t^i}\right) + var_t\left(\frac{d\Lambda_t^0}{\Lambda_t^0}\right)} = 1 - \frac{\left(\eta_t^i - \eta_t^0\right)'\left(\eta_t^i - \eta_t^0\right)}{\eta_t^{i\prime}\eta_t^i + \eta_t^{i\prime}\eta_t^0}$$

The index ranges between 0, in which case there is no risk sharing between the two countries, and 1, in which case risk sharing between the two countries is perfect. Thus, conditional exchange rate volatility is the product of the proportion of aggregate risk not shared times the amount of aggregate risk:

$$(\sigma_t^i)^2 = (1 - RS_t^{i,0})RP_t^{i,0}$$

As global risk aversion increases, the decrease in consumption risk is not enough to offset the effect of the increase of global risk aversion, so the pricing component of the non-shared risk between the domestic and the foreign country increases (Panel G). On the other hand, increased international risk sharing decreases the risk sharing component (Panel H). The risk pricing component is the dominant one, leading to an increase of the conditional variance of exchange rates (Panel E).

Similarly, conditional exchange rate covariance can be written as:

$$\gamma_t^{i,j} = \frac{1}{2}(1 - RS_t^{i,0})RP_t^{i,0} + \frac{1}{2}(1 - RS_t^{j,0})RP_t^{j,0} - \frac{1}{2}(1 - RS_t^{i,j})RP_t^{i,j}$$

so it depends on all bilateral risk pricing $(RP^{i,0}, RP^{j,0}, RP^{i,j})$ and risk sharing $(RS^{i,0}, RS^{j,0}, RS^{i,j})$ terms.

As before, the risk pricing term of the non-shared risk between any two foreign countries $(RP^{i,j})$ is increasing in global risk aversion (Panel G) and dominates the decreasing risk sharing term (Panel H), so the conditional exchange rate covariance $\gamma^{1,2}$ is also increasing in global risk aversion (Panel E). Importantly, the US is calibrated as a relatively large and home-biased country, two characteristics that have opposing effects on the dependence of conditional real exchange rate correlation on global risk aversion: the former (latter) tends to generate conditional real exchange rate correlation which is decreasing (increasing) in global risk aversion. In our calibration, the relative home-bias effect dominates and conditional exchange rate correlation is increasing in global risk aversion.

D. Sorting on Conditional Global Risk Aversion Betas

As discussed previously, risk premia compensate investors for exposure to two priced global risk factors, the global consumption expenditure factor and the global risk aversion factor. In our calibration, the price of the latter risk factor is an order of magnitude higher than the price of the former one. This result is typical in models that rely on the variability of the surplus consumption ratio in order to generate substantial volatility in the SDF, given smooth consumption growth. As a result, the cross-section of currency returns largely mirrors the cross-section of global risk aversion betas.

Table 8 illustrates that point: we do a monthly sort of the 21 foreign currencies into 4 portfolios according to their conditional global risk aversion beta, with Portfolio 1 containing the currencies in the lowest $\beta^{i,G}$ quartile and Portfolio 4 containing the currencies in the highest $\beta^{i,G}$ quartile. As expected, there is a monotonic negative relationship between global risk aversion betas and average currency portfolio returns: the riskiest portfolio, Portfolio 1, which has the lowest risk aversion beta and, thus, the highest adverse exposure to the global risk aversion factor outperforms Portfolio 4, which provides the best hedge against global risk aversion, by about 10% in annual terms.

[Insert Table 8 approximately here.]

E. Sorting on Forward Discounts

Finally, we explore the ability of our model to address the forward premium puzzle, as illustrated in Table 1. Table 9 reports the summary statistics on portfolios sorted on interest rate differentials (forward discounts): Portfolio 1 contains currencies ranked in the bottom forward discount quantile (low interest rate currencies), while Portfolio 4 contains the high interest rate currencies. Since the cross-section of currency risk premiums is largely determined by the cross-section of global risk aversion betas, Table 9 implies that high (low) interest rate currencies have low (high) global risk aversion betas, i.e. that they depreciate (appreciate) in bad states of the world, when global risk aversion is high.

[Insert Table 9 approximately here.]

To understand the connection between global risk aversion betas and risk-free rates, we can abstract from the second-order consumption growth terms and write the global risk aversion beta of currency return i as:

$$\beta_t^{i,G} = \frac{cov_t \left(dR_t^i, \frac{dG_t^W}{G_t^W} \right)}{var_t \left(\frac{dG_t^W}{G_t^W} \right)} \simeq \frac{cov_t \left(\frac{dG_t^i}{G_t^i} - \frac{dG_t^W}{G_t^W}, \frac{dG_t^W}{G_t^W} \right)}{var_t \left(\frac{dG_t^W}{G_t^W} \right)} = \rho_t \left(\frac{dG_t^i}{G_t^i}, \frac{dG_t^W}{G_t^W} \right) \frac{\sigma_t \left(\frac{dG_t^i}{G_t^W} \right)}{\sigma_t \left(\frac{dG_t^W}{G_t^W} \right)} - 1$$

If international risk sharing is sufficiently high in equilibrium, Stathopoulos (2011) shows that the growth rate of conditional risk aversion is very correlated across countries, so the correlation term above is close to 1 and we can write

$$\beta_t^{i,G} \simeq \frac{\sigma_t \left(\frac{dG_t^i}{G_t^i}\right)}{\sigma_t \left(\frac{dG_t^W}{G_t^W}\right)} - 1$$

Since the conditional volatility of the growth rate of conditional risk aversion is increasing in the level of conditional risk aversion, the expression above suggests that the currencies of countries with high conditional risk aversion compared to the rest of the world will tend to have a positive $\beta^{i,G}$ and, thus, provide a hedge against increases in global risk aversion, while the currencies of countries with low relative conditional risk aversion will tend to be very exposed to adverse fluctuations of global risk aversion (negative $\beta^{i,G}$) and, thus, will command high risk premia.

After establishing a positive relationship between the cross-section of global risk aversion betas and the cross-section of conditional risk aversion levels, we need to establish a negative relationship between the level of conditional risk aversion and the level of the risk-free rate in each country. As Verdelhan (2010) shows, such a negative relationship arises if the precautionary savings motive dominates the intertemporal smoothing motive and, as a result, real interest rates are procyclical.¹³ In short, if real interest rates are procyclical, low interest rate currencies provide a conditional hedge against increases of global risk aversion, whereas high interest rate currencies are conditionally riskier. As mentioned in a previous section, the cyclical behavior of the real interest rate depends on the relative strength of the intertemporal smoothing motive vis-a-vis the precautionary savings motive and, thus, largely on the values of the preference parameters φ and δ .

Our calibration parameters imply a dominant precautionary savings motive. As a result, the high interest rate currency portfolio (Portfolio 4) contains the currencies of low conditional risk aversion countries and, thus, is very exposed to global risk aversion risk, while the low interest rate portfolio (Portfolio 1) contains the currencies of high risk aversion countries and thus, provides a good hedge against increases in global risk aversion and has a negative average return.

¹³Ang, Bekaert, and Wei (2008) and Ang and Ulrich (2012) provide both theoretical and empirical support for procyclical real interest rates in the U.S.

V. Conclusion

We show that FX correlation risk is priced in the time-series and cross-section of currency returns. We first study correlation risk premia constructed from the difference of risk-neutral and physical correlation measures. The reported correlation risk premia are large: The annualized correlation risk premia is 15% on average across different currency pairs. To study the pricing in the cross-section, we then construct an FX correlation risk factor from these implied correlations and show that its price is negative and economically significant (-1% per year). Sorting currencies into portfolios on the basis of their exposure to this FX correlation factor, we find that a strategy which is long low FX correlation beta currencies and short high FX correlation beta currencies yields attractive returns and Sharpe ratios. Furthermore, we address the forward premium puzzle by showing that high interest rate currencies are highly exposed to FX correlation risk, whereas low interest rate currencies provide a hedge against adverse FX correlation innovations.

Motivated by our empirical findings, we propose a general equilibrium model that links the conditional moments of real exchange rates with global conditional risk aversion. The success of our model hinges on two key ingredients: Time-varying risk aversion and home bias. In our calibration, hedging against increases in conditional exchange rate second moments proxies for hedging against increases in global risk aversion. We also show that risk aversion is linked to FX correlation, in particular, we find that in the presence of home bias, there is a strictly positive relationship between risk aversion and conditional correlation. Moreover, if interest rates are pro-cyclical, high interest rate currencies command high risk premia due to their high exposure to the global risk aversion factor, justifying the empirically observed violations from uncovered interest rate parity.

References

- ADRIAN, T., E. ETULA, AND H. S. SHIN (2010): "Risk Appetite and Exchange Rates," Working Paper, Federal Reserve Bank of New York, No. 361.
- ANDERSEN, T., AND T. BOLLERSLEV (1998): "Answering the Skeptics: Yes, Standard Volatility Models Do Provide Accurate Forecasts," *International Economic Review*, 39, p. 885 – 905.
- ANDERSEN, T., T. BOLLERSLEV, F. DIEBOLD, AND P. LABYS (2000): "Exchange Rate Returns Standardized by Realized Volatility are (Nearly) Gaussian," *Multinational Finance Journal*, 4, p. 159 – 179.
- ANG, A., G. BEKAERT, AND M. WEI (2008): "The Term Structure of Real Rates and Expected Inflation," *Journal of Finance*, 63, p. 797 849.
- ANG, A., R. HODRICK, Y. XING, AND X. ZHANG (2006): "The Cross-Section of Volatility and Expected Returns," *Journal of Finance*, 61, p. 259 – 299.
- ANG, A., AND M. ULRICH (2012): "Nominal Bonds, Real Bonds, and Equity," Working Paper, Columbia University.
- BAELE, L., G. BEKAERT, AND K. INGHELBRECHT (2010): "The Determinants of Stock and Bond Return Comovements," *Review of Financial Studies*, 23, p. 2374 – 2428.
- BANK FOR INTERNATIONAL SETTLEMENT (2010): "Report on Global Foreign Exchange Market Activity in 2010," Triennial Central Bank Survey.
- BANSAL, R., AND I. SHALIASTOVICH (2011): "A Long-Run Risks Explanation of Predictability Puzzles in Bond and Currency Markets," Working Paper, Duke University.
- BRANDT, M., J. COCHRANE, AND P. SANTA-CLARA (2006): "International Risk Sharing Is Better Than You Think, or Exchange Rates are too Smooth," *Journal of Monetary Economics*, 53, p. 671 – 698.
- BRANDT, M. W., AND F. X. DIEBOLD (2006): "A No-Arbitrage Approach to Range-Based Estimation of Return Covariances and Correlations," *Journal of Business*, 79, p. 61 73.
- BRITTEN-JONES, M., AND A. NEUBERGER (2000): "Option Prices, Implied Price Processes, and Stochastic Volatility," *Journal of Finance*, 55, p. 839 – 866.
- BRUNNERMEIER, M., S. NAGEL, AND L. H. PEDERSEN (2009): "Carry Trades and Currency Crashes," *NBER Macroeconomics Annual 2008*, 23, p. 313 347.
- BURASCHI, A., P. PORCHIA, AND F. TROJANI (2010): "Correlation Risk and Optimal Portfolio Choice," *Journal of Finance*, 65, p. 393 – 420.
- BURASCHI, A., F. TROJANI, AND A. VEDOLIN (2011): "When Uncertainty Blows in the Orchard: Comovement and Equilibrium Volatility Risk Premia," Working Paper, London School of Economics.
- BURNSIDE, C. (2011): "Carry Trades and Risk," NBER Working Paper 17278.

- BURNSIDE, C., M. EICHENBAUM, I. KLESHCHELSKI, AND S. REBELO (2011): "Do Peso Problems Explain the Returns to the Carry Trade?," *Review of Financial Studies*, 24, p. 853 – 891.
- CENEDESE, G., L. SARNO, AND I. TSIAKAS (2012): "Average Variance, Average Correlation and Currency Returns," Working Paper, Cass Business School.
- CHERNOV, M., J. GRAVELINE, AND I. ZVIADADZE (2012): "Sources of Risk in Currency Returns," Working Paper, London School of Economics.
- COLACITO, R., AND M. M. CROCE (2009): "Six Anomalies looking for a model: A consumption based explanation of International Finance Puzzles," Working Paper, UNC.

(2010): "Risk Sharing for the Long-Run: A General Equilibrium Approach to International Finance with Recursive Preferences and Long-Run Risks," Working Paper, UNC.

- DANIELSSON, J., AND R. PAYNE (2001): "Measuring and Explaining Liquidity on an Electronic Limit Order Book: Evidence from Reuters D2000-2," Working Paper, London School of Economics.
- DEMETERFI, K., E. DERMAN, M. KAMAL, AND J. ZHOU (1999): "A Guide to Volatility and Variance Swaps," *Journal of Derivatives*, 6, p. 9 32.
- DRIESSEN, J., P. MAENHOUT, AND G. VILKOV (2009): "The Price of Correlation Risk: Evidence from Equity Options," *Journal of Finance*, 64, p. 1377 – 1406.
- ENGLE, R. F. (2002): "Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models," *Journal of Business* and Economic Statistics, 20, p. 339 – 350.
- EVANS, M. D. D. (2012): "Exchange Rate Dark Matter," Working Paper, Georgetown University.
- FAMA, E., AND J. MACBETH (1973): "Risk, Return, and Equilibrium: Empirical Tests," Journal of Political Economy, 81, p. 607 – 636.
- FAMA, E. F. (1984): "Forward and Spot Exchange Rates," Journal of Monetary Economics, 14, p. 319 – 338.
- FARHI, E., S. FRAIBERGER, X. GABAIX, R. RANCIERE, AND A. VERDELHAN (2009): "Crash Risk in Currency Markets," Working Paper, Harvard University.
- FARHI, E., AND X. GABAIX (2011): "Rare Disasters and Exchange Rates," Working Paper, Harvard University.
- FENN, D. J., S. D. HOWISON, M. MCDONALD, S. WILLIAMS, AND N. F. JOHNSON (2009): "The Mirage Of Triangular Arbitrage In The Spot Foreign Exchange Market," *International Journal of Theoretical and Applied Finance*, 12, p. 1105 – 1123.
- GARMAN, M. B., AND S. W. KOHLHAGEN (1983): "Foreign Currency Option Values," Journal of International Money and Finance, 2, p. 231 237.
- GOODHART, C., T. ITÔ, AND R. PAYNE (1995): "One Day in June, 1993: A Study of the Working of Reuters 2000-2 Electronic Foreign Exchange Trading System," NBER Technical Working Papers, 179.

- JIANG, G., AND Y. TIAN (2005): "Model-Free Implied Volatility and Its Information Content," *Review of Financial Studies*, 18, p. 1305 – 1342.
- JUREK, J. (2009): "Crash-Neutral Currency Carry Trades," Working Paper, Princeton University.
- KOZHAN, R., AND W. W. THAM (2012): "Execution Risk in High-Frequency Arbitrage," forthcoming, Managment Science.
- LUSTIG, H., N. ROUSSANOV, AND A. VERDELHAN (2011): "Common Risk Factors in Currency Markets," *forthcoming, Review of Financial Studies*.

(2012): "Countercylical Currency Risk Premia," Working Paper, UCLA.

- LUSTIG, H., AND A. VERDELHAN (2007): "The Cross-Section of Foreign Currency Risk Premia and Consumption Growth Risk," *American Economic Review*, 97, p. 89 – 117.
- MANCINI, L., A. RANALDO, AND J. WRAMPELMEYER (2012): "Liquidity in the Foreign Exchange Market: Measurement, Commonality, and Risk Premiums," *forthcoming, Journal of Finance.*
- MARTIN, I. (2011): "The Forward Premium Puzzle in a Two-Country World," Working Paper, Stanford University.
- MENKHOFF, L., L. SARNO, M. SCHMELING, AND A. SCHRIMPF (2011): "Carry Trades and Global Foreign Exchnage Volatility," *forthcoming, Journal of Finance*.
- MENZLY, L., T. SANTOS, AND P. VERONESI (2004): "Understanding Predictability," *Journal* of *Political Economy*, 112, p. 1–47.
- ROLL, R. (1984): "A Simple Implicit Measure of the Effective Bid-Ask Spread in An Efficient Market," Journal of Finance, 39, p. 1127 – 1139.
- STATHOPOULOS, A. (2011): "Asset Prices and Risk Sharing in Open Economies," Working Paper, University of Southern California.
- (2012): "Portfolio Home Bias and External Habit Formation," Working Paper, University of Southern California.
- VERDELHAN, A. (2010): "A Habit-Based Explanation of the Exchange Rate Risk Premium," Journal of Finance, 65, p. 123 – 146.
- VERDELHAN, A. (2011): "The Share of Systematic Variation in Bilateral Exchange Rates," Working Paper, MIT.
- WACHTER, J. A. (2006): "A Consumption-Based Model of the Term Structure of Interest Rates," *Journal of Financial Economics*, 79, p. 365 399.
- Yu, J. (2011): "A Sentiment-Based Explanation of the Forward Premium Puzzle," Working Paper, University of Minnesota.

Appendix A Proofs

Equilibrium Prices and Quantities:

Under the assumption of market completeness, there is a unique global numéraire state-price density, Λ , which satisfies the SDE

$$\frac{d\Lambda_t}{\Lambda_t} = -r_t dt - \eta_t' \mathbf{dB}_t$$

where r is the global numéraire risk-free rate and η is the market price of risk process.

Using Λ , the intertemporal budget constraint of agent *i* can be written in static form as follows:

$$E_0\left[\int_0^\infty \frac{\Lambda_t}{\Lambda_0} C_t^i P_t^i dt\right] \le E_0\left[\int_0^\infty \frac{\Lambda_t}{\Lambda_0} \widetilde{X}_t^i Q_t^i dt\right]$$

or

$$E_0\left[\int_0^\infty \frac{\Lambda_t}{\Lambda_0} \left(\sum_{j=0}^{n+1} X_t^{i,j} Q_t^j\right) dt\right] \le E_0\left[\int_0^\infty \frac{\Lambda_t}{\Lambda_0} \widetilde{X}_t^i Q_t^i dt\right]$$

After replacing each agent's intertemporal dynamic budget constraint with her static budget constraint, we can solve for the competitive equilibrium. The first order conditions (FOCs) of agent i are:

$$e^{-\rho t}a^i \frac{G_t^i}{X_t^{i,j}} = \frac{1}{\mu^i} \Lambda_t Q_t^j$$
, for all j

where $\frac{1}{\mu^i}$ is the Lagrange multiplier associated with the budget constraint of agent *i* holding with equality. Combining the FOCs with the market clearing conditions:

$$\sum_{k=0}^n X_t^{i,j} = \tilde{X}_t^j, \, \text{for all } j$$

we get the equilibrium consumption allocation:

$$X_t^{i,j} = \frac{a^{i,j}\mu^i G_t^i}{\sum_{k=0}^n a^{k,j}\mu^k G_t^k} \widetilde{X}_t^j$$

To calculate the Lagrange multipliers $\frac{1}{\mu^i}$, we substitute equilibrium quantities and prices in the static budget constraint of agent *i* (holding with equality). After some algebra, we get:

$$\mu^{i}\left(\varphi\bar{G}+\rho G_{0}^{i}\right)=\sum_{k=0}^{n}a^{k,i}\mu^{k}\left(\varphi\bar{G}+\rho G_{0}^{k}\right)$$

This system of equations has solutions of the form

$$\frac{\mu^i}{\mu^0} = b^i \frac{\varphi \bar{G} + \rho G_0^0}{\varphi \bar{G} + \rho G_0^i}$$

where the vector $\mathbf{b} = [b^1, b^2, ..., b^n]'$ is the unique solution of

$$\mathbf{b} = \begin{bmatrix} a^{0,1} & a^{1,1} & \dots & a^{n,1} \\ a^{0,2} & a^{1,2} & \dots & a^{n,2} \\ \dots & \dots & \dots & \dots \\ a^{0,n} & a^{1,n} & \dots & a^{n,n} \end{bmatrix} \begin{bmatrix} 1 \\ \mathbf{b} \end{bmatrix}$$

The budget constraint determines only the ratios $\frac{\mu^i}{\mu^0}$. To pin down the values for the Lagrange multipliers, we impose the normalization $\sum_{i=0}^{n} \mu^i = 1$.

It can easily be shown that, if the planner takes the law of motion for each agent's inverse surplus consumption ratio as exogenous, the planner's problem solution is equivalent to the competitive equilibrium solution if each country's welfare weight is set equal to μ^i .

Equilibrium consumption processes:

Since equilibrium consumption $C = [C^0, ..., C^n]'$ is a function of the vector of conditional risk aversion $G = [G^0, ..., G^n]'$, we need to solve for the fixed point that satisfies both the equilibrium consumption allocations and the law of motion for G. By the definition of the consumption baskets, we have:

$$C^{i} \equiv \left(\prod_{j=0}^{n} \left(X^{i,j}\right)^{a^{i,j}}\right), \text{ for all } i$$

so, applying Itô's lemma and equating the diffusion terms, we get, after some algebra:

$$\sigma_t^C = \left(\Psi_t^{-1} \mathbf{A}\right) \sigma_t^X$$

where σ_t^C is the $(n+1) \times m$ consumption volatility matrix

$$\sigma_t^C = \left[\begin{array}{c} \sigma_t^{0,C\prime} \\ \ldots \\ \sigma_t^{n,C\prime} \end{array} \right]$$

 σ^X_t is the $(n+1)\times m$ endowment volatility matrix

$$\sigma_t^X = \begin{bmatrix} \sigma_t^{0,X\prime} \\ \dots \\ \sigma_t^{n,X\prime} \end{bmatrix}$$

and, finally, Ψ is the $(n+1) \times (n+1)$ matrix defined as

$$\Psi_t = [\psi_{i,j}] = \psi_t^{i-1,j-1}$$

where

$$\psi_t^{i,i} \equiv 1 + \left(1 - \sum_{j=0}^n \frac{a^{i,j} a^{i,j} \mu^i G_t^i}{\sum_{k=0}^n a^{k,j} \mu^k G_t^k}\right) \delta\left(\frac{G_t^i - l}{G_t^i}\right)$$

and

$$\psi_t^{i,i'} \equiv -\left(\sum_{j=0}^n \frac{a^{i,j} a^{i',j} \mu^{i'} G_t^{i'}}{\sum_{k=0}^n a^{k,j} \mu^k G_t^k}\right) \delta\left(\frac{G_t^{i'} - l}{G_t^{i'}}\right), \ i \neq i'$$

Equilibrium consumption processes: Note that (6), (7) and (8) imply that:

$$\Lambda_t = e^{-\rho t} \mu^i \frac{G_t^i}{C_t^i} \frac{1}{P_t^i}$$

Rearranging as:

$$\Lambda_t \left(C_t^i P_t^i \right) = e^{-\rho t} \left(\mu^i G_t^i \right)$$

and summing over all countries, we get:

$$\Lambda_t \sum_{i=0}^n \left(C_t^i P_t^i \right) = e^{-\rho t} \sum_{i=0}^n \left(\mu^i G_t^i \right).$$

Expression (9) follows from the definition of global risk aversion and global consumption expenditure.

Appendix B Tables

Table 1 Summary Statistics Carry Trade Portfolios

This table reports summary statistics for portfolios sorted on time t - 1 forward discounts. We also report annualized Sharpe Ratios (SR) and the first order autocorrelation coefficient (AC(1)). Portfolio 1 contains 25% of all the currencies with the lowest forward discounts whereas Portfolio 4 contains currencies with the highest forward discounts. All returns are excess returns in USD. DOL denotes the average return of the four currency portfolios, HmL denotes a long-short portfolio that is short in Pf1 and long in Pf4. Data is sampled monthly and runs from January 1999 to December 2010.

	Pf1	Pf2	Pf3	Pf4	DOL	HML
Mean	-0.004	0.027	0.048	0.088	0.040	0.092
StDev	0.068	0.081	0.080	0.097	0.073	0.078
Skewness	0.108	-0.208	-0.120	-1.445	-0.435	-1.070
Kurtosis	2.613	3.632	4.808	9.394	4.683	6.773
SR	-0.065	0.334	0.596	0.908	0.540	1.189
AC(1)	0.10	0.07	0.18	0.28	0.19	0.29
. ,						

Table 2Summary Statistics Volatilities

This table reports summary statistics for implied and realized volatilities (i.e. the square root of variance, Panels A and B) and the variance risk premium, which is defined as the difference between the implied and realized variance (Panel C). Implied variances are calculated from daily option prices on the underlying exchange rates. Realized variances are calculated from five minute tick data on the underlying spot exchange rates. All numbers are annualized. Data runs from January 1999 to December 2010.

	EUR	JPY	GBP	CHF				
	PANEL A: IMPLIED VOLATILITY							
Mean	0.110	0.117	0.097	0.112				
Max	0.294	0.321	0.298	0.246				
Min	0.049	0.065	0.050	0.057				
StDev	0.035	0.036	0.036	0.027				
Skewness	1.943	2.052	2.808	1.659				
Kurtosis	9.602	10.215	13.087	9.127				
AC(1)	0.85	0.76	0.87	0.81				
	5 5	D						
	PANEL B:	REALIZED VOL	ATILITY					
Mean	0.110	0.116	0.097	0.115				
Max	0.319	0.349	0.347	0.251				
Min	0.049	0.042	0.050	0.054				
StDev	0.039	0.044	0.038	0.032				
Skewness	2.140	2.009	3.163	1.088				
Kurtosis	10.986	8.987	17.525	5.138				
AC(1)	0.49	0.39	0.69	0.51				
	DANDE C. I	VARIANCE RISK						
	FANEL C:	VARIANCE RISK	FREMIUM					
Mean	0.000	-0.001	-0.001	-0.002				
Max	0.030	0.037	0.024	0.024				
Min	-0.077	-0.045	-0.057	-0.056				
StDev	0.009	0.009	0.007	0.008				
Skewness	-3.923	-0.912	-3.732	-2.606				
Kurtosis	36.740	9.248	29.635	16.905				
AC(1)	0.19	0.16	0.08	0.30				

Table 3Summary Statistics Correlation

This table reports summary statistics for implied and realized correlations (Panels A and B) and the correlation risk premium, which is the difference between the implied and realized correlation (Panel C). Implied correlations are calculated from daily option prices on the underlying exchange rates. Realized correlations are calculated from five minute tick data on the underlying spot exchange rates. Data is annualized and runs from January 1999 to December 2010.

	EURJPY	EURGBP	EURCHF	JPYGBP	JPYCHF	GBPCHF
		PANEL A	: Implied Co	ORRELATION		
Mean	0.396	0.690	0.895	0.303	0.472	0.643
Max	0.689	0.863	0.986	0.661	0.412	0.877
Min	-0.241	0.370	0.541	-0.406	-0.011	0.326
StDev	0.191	0.102	0.086	0.216	0.175	0.140
Skewness	-0.667	-0.632	-2.593	-0.562	-0.683	-0.468
Kurtosis	2.957	2.978	10.435	3.218	3.051	2.344
AC(1)	0.74	0.78	0.81	0.81	0.70	0.84
()						
		PANEL B:	Realized C	ORRELATION		
					-	
Mean	0.294	0.552	0.728	0.194	0.308	0.473
Max	0.640	0.780	0.928	0.580	0.716	0.761
Min	-0.375	0.165	0.300	-0.355	-0.249	0.110
StDev	0.228	0.127	0.126	0.201	0.196	0.135
Skewness	-0.584	-0.684	-0.680	-0.342	-0.260	-0.113
Kurtosis	2.931	2.824	3.013	2.771	2.394	2.296
AC(1)	0.82	0.88	0.79	0.82	0.85	0.84
		PANEL C: C	ORRELATION	Risk Premiu	UM	
Mean	0.103	0.139	0.168	0.109	0.164	0.169
Max	0.620	0.443	0.537	0.519	0.523	0.491
Min	-0.221	-0.165	-0.049	-0.345	-0.078	-0.160
StDev	0.136	0.117	0.127	0.141	0.125	0.136
Skewness	0.681	0.258	0.809	-0.364	0.421	-0.137
Kurtosis	4.212	3.079	3.029	4.118	2.829	2.574
AC(1)	0.25	0.72	0.77	0.27	0.36	0.68

Table 4Portfolios Sorted on Betas with Correlation Risk

This table reports summary statistics for portfolios sorted on correlation risk betas, i.e. currencies are sorted according to their betas in a rolling time-series regression of individual currencies' daily excess returns on daily innovations in the correlation risk. Correlation risk is defined as the residual from an AR(1) process of implied correlation. Portfolio 1 contains currencies with the lowest betas whereas portfolio 4 contains currencies with the highest betas. LmH is long Portfolio 1 and short Portfolio 4. The mean, standard deviation, and Sharpe Ratios are annualized, the rest is per month. We also report pre-formation betas, Pre β and pre-formation forward discounts for each portfolio (in % per year). Pre-formation discounts are calculated at the end of each month prior to portfolio formation. Data runs from January 1999 to December 2010.

	Pf1	Pf2	Pf3	Pf4	LmH
	PAN	EL A: ALL	COUNTRIE	S	
Mean	0.079	0.056	0.052	0.047	0.032
StDev	0.117	0.080	0.088	0.083	0.087
Skewness	-0.764	-1.377	-0.070	0.005	-0.264
Kurtosis	5.530	8.173	2.918	3.327	3.564
SR	0.670	0.695	0.600	0.563	0.369
AC(1)	0.11	0.19	0.14	0.11	-0.01
Pre β	-23.07	-0.20	12.68	25.36	
Pre $f - s$	0.34	0.29	0.26	0.14	
	PANEL]	B: Develo	ped Count	TRIES	
Mean	0.107	0.071	0.056	0.053	0.054
StDev	0.136	0.111	0.102	0.086	0.100
Skewness	-0.586	-0.488	-0.298	0.064	-0.059
Kurtosis	4.064	5.014	4.180	2.599	3.913
SR	0.790	0.639	0.544	0.612	0.543
AC(1)	0.22	0.08	0.17	0.05	0.17
Pre β	-21.90	5.77	15.01	26.94	
Pre $f - s$	0.06	0.05	0.04	0.03	
-					

Table 5Estimating the Price of Correlation Risk

Test assets are the four carry trade portfolios based on either all countries or developed countries only. *FIC* is the mimicking factor for global correlation innovations, DOL the average carry trade portfolio as in Lustig, Roussanov, and Verdelhan (2011). In Panel A, we report factor betas. Panel B reports the Fama and MacBeth (1973) factor prices on the carry return portfolios. Newey-West standard errors are reported in parentheses. Data runs from January 1999 to December 2010.

			DANIEI		DR BETAS			
			I ANEL A	A. FACIO	DR DEIAS			
		All Co	UNTRIES		DE	VELOPED	COUNTRI	IES
Pf	α	DOL	FIC	R^2	α	DOL	FIC	R^2
1	-0.01	0.94	0.60	0.93	-0.01	0.73	0.02	0.5
	(0.01)	(0.02)	(0.02)		(0.00)	(0.09)	(0.01)	
2	-0.01	1.08	-0.07	0.88	-0.01	1.00	0.00	0.8
	(0.01)	(0.03)	(0.03)		(0.00)	(0.05)	(0.00)	
3	0.00	1.03	-0.14	0.86	0.01	1.07	-0.01	0.8
	(0.00)	(0.04)	(0.04)		(0.00)	(0.07)	(0.00)	
4	0.01	0.94	-0.39	0.97	0.01	1.18	-0.02	0.8
	(0.01)	(0.02)	(0.02)		(0.00)	(0.06)	(0.01)	

PANEL B: FACTOR PRICES

	All Countries		1	Developed Co	UNTRIES
DOL	FIC	R^2	DOL	FIC	R^2
0.04	-0.08	0.87	0.01	-0.07	0.95
(0.01)	(0.01)		(0.00)	(0.01)	

Table 6Double Sorts and Fama and MacBeth Controlling for Volatility

Panel A reports the results of double sorts of currencies. We independently sort currencies into halves based on their exposure to volatility and correlation and then form portfolios on the intersection. For each of the four portfolios formed, we report the average return (annualized). Test assets are the four volatility sorted portfolios based on all countries. \widetilde{FIC} (\widetilde{FIV}) is the mimicking factor for global correlation (volatility) innovations. In Panel B, we report factor betas. Panel C reports the Fama and MacBeth (1973) monthly factor prices on the carry return portfolios. Newey-West standard errors are reported in parentheses. Data runs from January 1999 to December 2010.

	PANEL .	A: Dou	BLE SORT	
				T TT
1 371	Low		High Corr	LmH
low Vol	U	0.081	0.047	0.034
1.1.1.1.1	0	(4)	(6)	0.010
high Vol	. U	.064	0.047	0.018
LmH	0	(5) 0.017	$(6) \\ 0.001$	
LΠΠ	U	.017	0.001	
	D			
	PANEL I	3: FAC'I	OR BETAS	
Pf	α	\widetilde{FIC}	\widetilde{FIV}	R^2
1	0.00	0.42	2.32	0.94
	(0.00)	(0.03)	(0.08)	
2	0.00	0.32	1.85	0.50
	(0.00)	(0.10)	(0.19)	
3	0.00	0.02	1.71	0.36
	(0.00)	(0.10)	(0.16)	
4	0.00	0.05	2.18	0.60
	(0.00)	(0.08)	(0.20)	
]	Panel C	C: FACT	or Prices	
<u> </u>		•		
\widetilde{FIC}		\overline{FIV}	R^2	
0.11		0.08	0.98	
(0.00)	()	(00.00)		

Table 7 Choice of Parameter Values and Benchmark Values of State Variables

This table lists the parameter values used for all figures in the paper. All parameters are annualized. If not mentioned otherwise, we study a symmetric economy, where parameters for foreign countries are assumed to be the same.

PARAMETERS FOR ENDOWMENT		
Endowment expected growth rate	μ	0.03
Endowment volatility parameter	σ	0.04
Endowment correlation parameter	$ ilde{ ho}$	0.10
PREFERENCE PARAMETERS		
Subjective rate of time preference	ρ	0.04
Speed of G mean reversion	φ	0.03
G sensitivity to consumption growth shocks	δ	120
Lower bound of G	l	20
Steady-state value of G	\bar{G}	34

Table 8 Summary Statistics Simulated Conditional Risk Aversion Sorted

This table reports summary statistics for portfolios sorted on global risk aversion betas using 500 simulations of 144 months for 22 countries (21 foreign and one domestic). We also report annualized Sharpe Ratios (SR) and the first order autocorrelation coefficient (AC(1)). Portfolio 1 contains 25% of all the currencies with the lowest global risk aversion beta whereas Portfolio 4 contains currencies with the highest global risk aversion beta. HmL denotes a long-short strategy that is long in Pf1 and short in Pf4.

	Pf1	Pf2	Pf3	Pf4	HmL
Mean	0.058	0.009	-0.022	-0.043	0.101
StDev	0.036	0.032	0.035	0.036	0.023
Skewness	-0.657	-0.106	-0.225	-0.162	-0.487
Kurtosis	11.383	7.053	10.968	10.801	6.746
SR	1.676	0.291	-0.661	-1.255	4.383
AC(1)	-0.02	-0.01	-0.01	0.01	0.10

Table 9 Summary Statistics Simulated Carry Trade Portfolios

This table reports summary statistics for simulated portfolios sorted on time t-1 forward discounts. We also report annualized Sharpe Ratios (SR) and the first order autocorrelation coefficient (AC(1)). Portfolio 1 contains 25% of all the currencies with the lowest forward discounts whereas Portfolio 4 contains currencies with the highest forward discounts. All returns are excess returns in USD. DOL denotes the average return of the four currency portfolios, HmL denotes a long-short strategy that is long in Pf1 and short in Pf4.

	Pf1	Pf2	Pf3	Pf4	DOL	HmL
Mean	-0.010	-0.001	0.010	0.024	0.003	0.034
StDev	0.061	0.056	0.057	0.061	0.056	0.030
Skewness	0.304	0.051	-0.009	-0.051	-0.010	-0.024
Kurtosis	4.547	4.780	4.858	4.790	4.618	3.478
SR	-0.165	-0.164	0.204	0.426	0.083	1.141
AC(1)	0.01	0.01	0.01	0.01	-0.01	0.42

Appendix C Figures

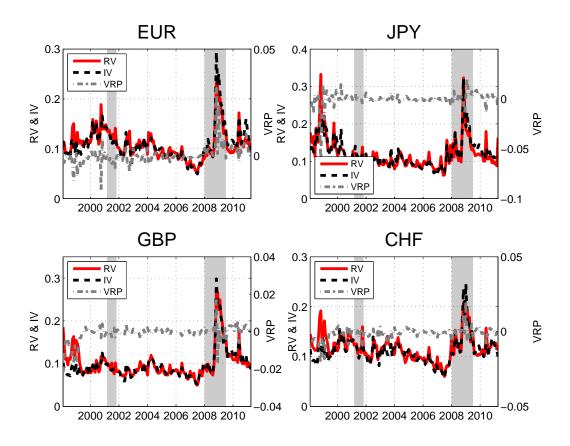


Figure 1. Implied and Realized Volatility and Variance Risk Premium

This figure plots the monthly time series of realized and implied volatility (left axis) and variance risk premia (right axis) for four currency pairs. Realized and implied volatility are calculated from five minute tick data and daily option prices. All currencies are with respected to the USD. Gray shaded areas are recessions as defined by the NBER. Data runs from January 1999 to December 2010.

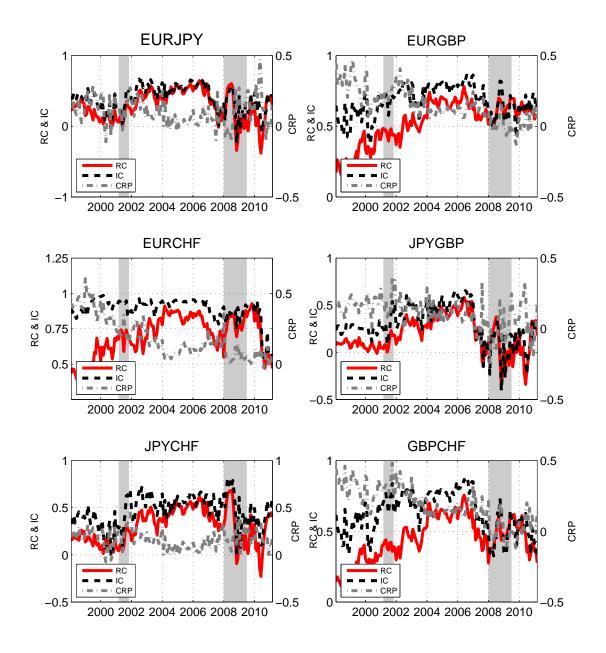


Figure 2. Implied and Realized Correlation and Correlation Risk Premium

This figure plots the monthly time series of realized and implied correlation (left axis) and correlation risk premium (right axis) for six currency pairs. Realized and implied correlation are calculated from five minute tick data and daily option prices. All currencies are with respected to the USD. Gray shaded areas are recessions as defined by the NBER. Data runs from January 1999 to December 2010.

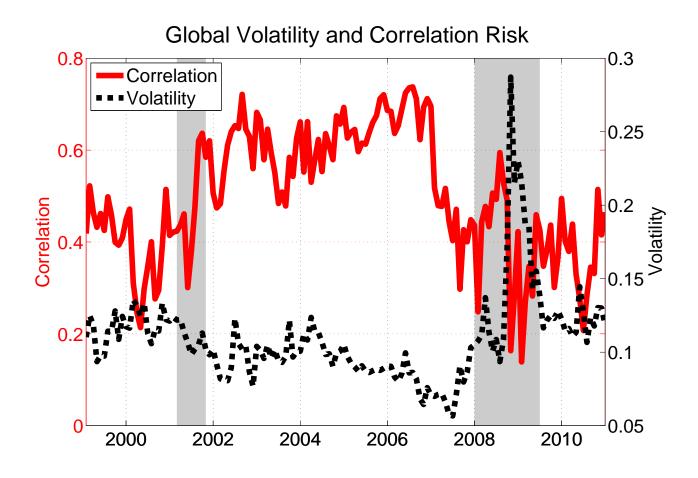


Figure 3. Global Volatility and Correlation Risk

This figure plots the global volatility and correlation risk factor defined as an equal weighted average of individual implied volatility and correlation measures. Implied volatilities and correlations are calculated using daily options on different currency pairs. Gray shaded areas are recessions as defined by the NBER. Data is monthly and runs from January 1999 to December 2010.

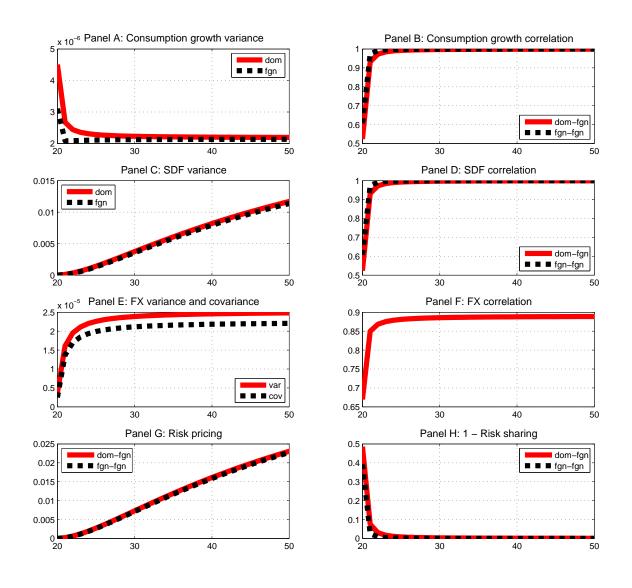


Figure 4. Conditional Global Risk Aversion on Conditional Moments

Plots of conditional second moments of consumption growth (Panels A and B), SDF (Panels C and D) and the real exchange rate (Panels E and F). Panels G and H plot the risk pricing (RP) and risk sharing (1-RS) components of real exchange rate conditional variance, as defined in the main text. The horizontal axis measures global conditional risk aversion, assuming conditional risk aversion is equal in all countries, while the vertical axis measures the moment of interest. The global economy comprises 22 countries, the domestic country and 21 foreign countries. The calibrated values for the parameters of the model are given in Table 7.

Online Appendix to "International Correlation Risk"

High Frequency Data

The exchange rate series consist of the last available mid-quote in each five-minute interval, resulting in 288 observations a day, as trading on the FX markets takes places 24h a day due to the fact that market opening hours rotate around the globe, from Asia to Europe to America to Asia and so on. Our choice of these specific series has the following reasons:

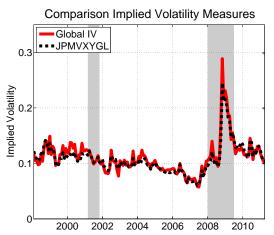
- 1. Equally spaced intervals of five minutes: constructing an artificial time series of equally spaced observations, called "sampling in calender time", is the only time scale lending itself to multivariate applications. Choosing five-minute intervals is standard in empirical studies (see Andersen and Bollerslev, 1998). Although the theory of quadratic variation asks for the highest possible sampling frequency to yield the most accurate volatility measurement, returns measured at intervals shorter than five minutes heavily suffer from spurious serial correlation due to market-microstructure effects. These effects, as well as the optimal sampling frequency will be addressed below.
- 2. Last quote in every interval: in constructing the equally spaced time series, this so-called "previous-tick interpolation" only uses data available at this very point in time and hence respects causality. The increase in the number of quotes collected in the O&A database diminishes the average time interval between two consecutive quotes from 10-20 seconds in 1997 to less than a second in 2010. This gives a hint at how liquid the FX market is and how close to the five-minute time-stamps the last quotes in every interval are. Hence, problems arising from non-synchronous quotations or stale quotes are insignificant.
- 3. Mid-quotes (instead of transaction prices): as currency trading is mainly OTC, it is hard to get records of true transaction prices. However, Goodhart, Itô, and Payne (1995) and Danielsson and Payne (2001) verify by means of a short data sample from the Reuters 2000-2 electronic FX trading platform that the characteristics of the merely indicative quotes of the O&A data closely match the ones of the true transaction prices. In addition, using mid-quotes avoids contamination of the data series with market-microstructure noise arising from transactions being executed at either the quoted bid or ask price (bid-ask bounces), see e.g. Roll (1984).

To determine periods of inactive trading and hence possible problems with missing data, we find that a quote is recorded for each of the $7 \times 24 \times 12 = 2016$ five-minute intervals of a week. In the calculation of volatilities and correlations, the days are set to end at 16:00 GMT to match the time of the daily option quotes (all times in this study refer to Greenwich Mean Time). Monday to Friday is treated as business days, while the reduced market activity on Saturdays and Sundays calls for a special treatment of the weekend period, which is defined as usual to last from Friday 21:00 to Sunday 21:00, see Andersen and Bollerslev (1998). Hence, "Mondays" consist of the remaining five hours on Friday from 16:00 to 21:00 and the 19 hours from Sunday 21:00 to Monday 16:00. In the 3% of cases that a quote is not available on a business day, the missing value is filled with the previous quote, which induces a slight bias towards zero in the realized (co-)volatility measures.

Implied Volatility Comparison

Subset of Currencies Chosen

To calculate our implied volatility and correlation measures, we rely on the four exchange rates between the EUR, JPY, GBP and CHF vis-à-vis the USD. Even though these five currencies make 65% of the total global turnover in the currency market (see BIS, 2010), the question remains how much these currencies truly capture a global risk. In the following we compare our series with the global implied volatility series introduced by JP Morgan. Their global volatility index consists of 22 different currencies: Australian Dollar, Brazilian Real, Canadian Dollar, Swiss Franc, Chinese Yuan, Euro, British Pound, Hungarian Forint, Indian Rupee, Japanese Yen, South Korean Won, Mexican Peso, Norwegian Krona, New Zealand Dollar, Philippine Peso, Polish Zloty, Russian Rouble, Swedish Krona, Singapore Dollar, Turkish Lira, Taiwan Dollar and the South African Rand. We plot our global implied volatility index (Global IV) together with the JP Morgan IV index (JPMVXYGL) in Figure 1 and report summary statistics in Table 1.



	JPM	Our
Mean	10.91	11.04
StDev	2.73	3.01
Max	24.70	28.88
Min	6.10	5.72
Skewness	1.90	2.33
Kurtosis	9.40	12.53

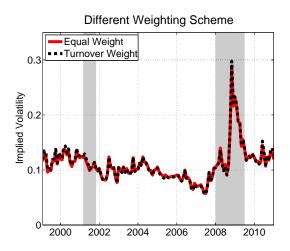
Table 1: Summary Statistics

Figure 1: Global Implied Volatility

As one can see immediately, the co-movement of the two time series is very high: The unconditional correlation between the levels is 98% and between the changes it is 90%. This indicates that our measure of global implied volatility based on five currencies captures well global risk.

Weighting Scheme to Construct Global Measures

We use an equal weighted average to calculate our global volatility and correlation measures. To check the robustness of this assumption, we apply a turnover weighted average and construct the global volatility proxy using equal and turnover weights as the JP Morgan currency volatility index. The turnover weights are based on the Bank of International Settlement (BIS) Triennial Central Bank Survey of foreign exchange downloadable on the BIS webpage. Since turnover data is only published on a 3 year frequency, we keep the weights constant for 3 years and then update the following year when the new data is published. Turnover weights are chosen over trade weights, as they capture demand for the currencies as a function of both commercial and financial demand. Figure 2 plots the two time series and Table 2 reports the summary statistics.



	Equal	Turnover
Mean	11.04	11.05
StDev	3.01	3.28
Max	28.88	29.78
Min	5.72	5.61
Skewness	2.33	2.26
Kurtosis	12.53	11.74

Table 2: Summary Statistics

Figure 2: Weighting Schemes

The two time series are extremely highly correlated with an unconditional correlation of 99.8% (levels) and 99.7% (changes). The summary statistics are also almost identical. We therefore conclude that the assumption of an equal weighted average is not driving our results. We also note that we cannot perform the same kind of robustness check for the correlation, as the BIS only provides data on currencies either vis-à-vis the U.S. Dollar or the Euro.

Realized Correlation Sorting

In this section, we check whether our sorting procedure is also robust to realized measures of correlation. We apply the same procedure as in Section II.B. of the main paper. Realized global correlation risk is defined as the realized counterpart to equation (4).

The results are reported in Table 3. We note that the results remain qualitatively unchanged. Low exposure currencies yield higher returns than high exposure currencies. The HmL portfolios are slightly higher for the realized correlation portfolios and the Sharpe ratios are also slightly higher with an annualized Sharpe ratio of 0.65 for the realized correlation sorted currencies.

Volatility Sorting

We check whether our sorting procedure is robust to volatility sorting, we sort currencies according to their implied and realized volatility exposure. Summary statistics are reported in Tables 4 and 5. The results are in line with the correlation sorted portfolios: Sharpe ratios are quite attractive, ranging between 0.5 for the implied volatility sorted LmH portfolio and almost 0.7 for the realized volatility sorted LmH portfolio. Low exposure currencies have higher expected returns than high exposure currencies.

Table 3Portfolios Sorted on Betas with Realized Correlation Risk

This table reports summary statistics for portfolios sorted on correlation risk betas, i.e. currencies are sorted according to their betas in a rolling time-series regression of individual currencies' daily excess returns on daily innovations in the realized correlation risk. Correlation risk is defined as the residual from an AR(1) process of realized correlation. Portfolio 1 contains currencies with the lowest betas whereas portfolio 4 contains currencies with the highest betas. LmH is long Portfolio 1 and short Portfolio 4. The mean, standard deviation, and Sharpe Ratios are annualized, the rest is per month. We also report pre-formation betas, Pre β . Data is monthly and runs from January 1999 to December 2010.

	Pf1	Pf2	Pf3	Pf4	LmH		
PANEL A: ALL COUNTRIES							
Mean	0.084	0.054	0.020	0.023	0.061		
StDev	0.080	0.088	0.095	0.100	0.081		
Skewness	0.348	-0.287	-0.466	-0.346	0.423		
Kurtosis	3.601	6.767	5.223	3.422	3.446		
SR	1.057	0.609	0.208	0.231	0.757		
AC(1)	0.19	0.11	0.16	0.10	0.05		
Pre β	-100.315	-11.005	48.272	141.281			
Mean	Panel 0.065	B: Develo	ped Count 0.026	RIES 0.014	0.051		
StDev	0.005 0.097	0.039	0.020	0.014 0.099	0.031		
Skewness	-0.030	-0.200	-0.174	-0.476	0.812		
Kurtosis	4.003	3.982	3.986	4.280	6.664		
SR	0.671	0.388	0.237	0.141	0.557		
AC(1)	-0.01	0.13	0.12	0.20	0.16		
Pre β	-89.464	-3.663	41.651	114.288			

Table 4Portfolios Sorted on Betas with Volatility Risk

This table reports summary statistics for portfolios sorted on volatility risk betas, i.e. currencies are sorted according to their betas in a rolling time-series regression of individual currencies' daily excess returns on daily innovations in the global implied volatility risk. Volatility risk is defined as the residual from an AR(1) process of implied volatility. Portfolio 1 contains currencies with the lowest betas whereas portfolio 4 contains currencies with the highest betas. LmH is long Portfolio 1 and short Portfolio 4. The mean, standard deviation, and Sharpe Ratios are annualized, the rest is per month. We also report pre-formation betas, Pre β . Data is monthly and runs from January 1999 to December 2010.

	Pf1	Pf2	Pf3	Pf4	LmH		
PANEL A: ALL COUNTRIES							
Mean	0.101	0.059	0.037	0.033	0.068		
StDev	0.109	0.093	0.092	0.076	0.032		
Skewness	-1.011	-0.700	-0.167	-0.393	-0.618		
Kurtosis	6.113	4.879	4.952	3.379	2.735		
SR	0.924	0.638	0.403	0.430	0.494		
AC(1)	0.212	0.175	0.049	0.165	0.047		
Pre β	-28.540	-24.438	-6.141	5.638			
	PANEL	B: DEVELO	ped Countr	IES			
Mean	0.132	0.066	0.063	0.023	0.066		
StDev	0.124	0.109	0.110	0.098	0.015		
Skewness	-0.856	-0.111	-0.332	0.006	-0.745		
Kurtosis	5.650	3.515	3.966	3.667	2.135		
SR	1.064	0.605	0.571	0.235	0.460		
AC(1)	0.194	0.108	0.068	0.123	0.086		
	-32.015	-27.422	-12.070	3.405			

Table 5Portfolios Sorted on Betas with Realized Volatility Risk

This table reports summary statistics for portfolios sorted on realized volatility risk betas, i.e. currencies are sorted according to their betas in a rolling time-series regression of individual currencies' daily excess returns on daily innovations in the global realized volatility risk. Volatility risk is defined as the residual from an AR(1) process of realized volatility. Portfolio 1 contains currencies with the lowest betas whereas portfolio 4 contains currencies with the highest betas. LmH is long Portfolio 1 and short Portfolio 4. The mean, standard deviation, and Sharpe Ratios are annualized, the rest is per month. We also report pre-formation betas, Pre β . Data is monthly and runs from January 1999 to December 2010.

	Pf1	Pf2	Pf3	Pf4	LmH
	PA	ANEL A: ALL	Countries		
Mean	0.085	0.048	0.054	0.045	0.040
StDev	0.098	0.102	0.089	0.082	0.076
Skewness	-0.098	-0.889	-0.484	-0.184	0.280
Kurtosis	4.635	6.065	5.267	3.775	3.345
SR	0.864	0.477	0.609	0.547	0.525
AC(1)	0.140	0.222	0.051	0.146	0.131
$\operatorname{Pre}\beta$	-41.908	-26.673	-13.646	9.453	

PANEL B: DEVELOPED COUNTRIES

Mean	0.123	0.092	0.023	0.055	0.068
StDev	0.101	0.131	0.108	0.115	0.099
Skewness	0.235	-0.498	-0.867	-0.133	0.133
Kurtosis	2.983	6.709	4.931	3.961	3.533
\mathbf{SR}	1.222	0.697	0.214	0.478	0.688
AC(1)	0.146	0.312	0.167	0.035	0.173
Pre β	-41.606	-28.761	-18.907	6.225	