

Global Equity Correlation in Carry and Momentum Trades

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Abstract

We provide a risk-based explanation for the excess returns of two widely-known currency speculation strategies: carry and momentum trades. We construct a global equity correlation factor and show that it explains the variation in average excess returns of both these strategies. The global correlation factor has a robust negative price of beta risk in the FX market. We also present a multi-currency model which illustrates why heterogeneous exposures to our correlation factor explain the excess returns of both portfolios.

JEL Classification: F31, G12, G15

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I Introduction

There is a great deal of evidence of significant excess return to foreign exchange (henceforth FX) carry and momentum strategies (see, e.g., Hansen and Hodrick (1980) and Okunev and White (2003)). Numerous studies provide different risk-based explanations for the forward premium puzzle.¹ However, it has proven rather challenging to explain carry and momentum strategies simultaneously using these risk factors (see, Burnside, Eichenbaum, and Rebelo (2011) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012b)).² This paper contributes to this literature by providing a risk-based explanation of FX excess returns across carry and momentum portfolios simultaneously. We construct a common factor that drives correlation across international equity markets and show that the cross-sectional variations in the average excess returns across carry and momentum sorted portfolios can be explained by different sensitivities to our correlation factor. We also present a multi-currency model which illustrates why heterogeneous exposures to our correlation factor explain the excess returns of both portfolios.

The correlation-based factor as a measure of the aggregate risk is motivated by the analysis in Pollet and Wilson (2010). They document that, since the aggregate wealth portfolio is a common component for all assets, the changes in the true aggregate risk reveal

¹The forward premium puzzle arises since FX changes do not compensate for the interest rate differentials. Under rational expectation assumption, exchange rates are expected to change in direction to eliminate gains from interest rate differentials. However, a number of empirical studies have found that the uncovered interest parity is violated. The extant literatures document various risk-based explanations for the forward premium puzzle. See, e.g., consumption growth risk (Lustig and Verdelhan (2007)), time-varying volatility of consumption (Bansal and Shaliastovich (2012)), exposure to the FX volatility (Bakshi and Panayotov (2013), Menkhoff, Sarno, Schmeling, and Schrimpf (2012a)), exposure to high-minus-low carry factor (Lustig, Roussanov, and Verdelhan (2011)), liquidity risk (Brunnermeier, Nagel, and Pedersen (2008), Mancini, Rinaldo, and Wrampelmeyer (2013)), disaster risk (Jurek (2008) and Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2009)) and peso problem (Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011)).

²While showing that the risk-based explanation for carry fails to explain momentum, Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) offered an alternative limits to arbitrage explanation by showing that the exposure to currency momentum strategies is subject to fundamental investment risk characterized by idiosyncratic components, such as idiosyncratic volatility or country risk, of the currencies involved. Similarly, Burnside, Eichenbaum, Kleshchelski, and Rebelo (2006) and Burnside, Eichenbaum, and Rebelo (2011) argue that the high excess returns should be understood, along with high bid-ask spread and price pressure, as an increasing function of net order flow.

themselves through changes in the correlation between observable stock returns. Therefore, an increase in the aggregate risk must be associated with increased tendency of co-movements across international equity indices. Since currency market risk premium should be driven by the same aggregate risk which governs international equity market premium, our correlation factor can explain the average excess returns across currency portfolios.

We construct two measures of correlations to quantify the evolution of co-movements in international equity market indices. First, we employ the dynamic equicorrelation (DECO) model of Engle and Kelly (2012) and apply it to monthly equity return series. Second, we measure the same correlation dynamics by taking a simple mean of bilateral intra-month correlations at each month's end using daily return series. The correlation innovation factors are constructed as the first difference in time series of the global correlation. Across portfolios, we run cross-sectional (CSR) asset pricing tests on *FX 10* portfolios which consist of two sets of five portfolios: the set of sorted carry and momentum portfolios.

We show that differences in exposures to our correlation factor can explain the systematic variation in average excess returns of portfolios sorted on interest rates and momentums. Our correlation factor has an explanatory power over the cross-section of carry and momentum portfolios with R^2 of 90 percent. The prices of beta risk for both measures of our correlation innovation factor are economically and statistically significant under Shanken's (1992) estimation error adjustment as well as misspecification error adjustment as in Kan, Robotti, and Shanken (2012). The negative price of beta suggests that investors demand low risk premium for the portfolios whose returns co-move with the global correlation innovation since they provides hedging opportunity against unexpected deteriorations of the investment opportunity set.

To explore the explanatory power of our correlation factor, we construct numerous risk factors discussed frequently in the currency literature. The list includes (i) a set of traded and non-traded factors constructed from FX data, (ii) a set of liquidity factors, and (iii) a set of US equity market risk factors. Consistent with the forward puzzle literature, we find that those factors have explanatory power over the cross-section of carry portfolios with

R^2 ranging from 58 percent for TED spread innovation to 92 percents for FX volatility factor. We show that the same set of factors fail to explain the cross-section of momentum portfolios which is consistent with the finding in Burnside, Eichenbaum, and Rebelo (2011) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012b). Furthermore, we demonstrate that our factor can explain the cross-section of momentum portfolios and significantly improve the explanatory power across carry portfolios, whereas the price of beta risk is not affected by the inclusion of those factors.

We also examine whether the statistical significance of the regression results is specifically driven by our choice of test assets. Lustig and Verdelhan (2007) add 5 bond portfolios and 6 Fama-French equity portfolios to their 8 FX portfolios. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) uses 25 Fama-French portfolios jointly with the equally-weighted carry trade portfolios. Following their methodologies, we augment our *FX 10* portfolios with Fama-French 25 portfolios formed on size and book-to-market and run cross-sectional regression on these expanded test assets. We find that the price of beta risk of our factor is still statistically and economically significant with these augmented test assets after controlling for market risk premium and Fama-French factors.

Since ours is a non-traded factor³, the variance of residuals generated from projecting the factor onto the returns could be very large, which leads to large misspecification errors (Kan, Robotti, and Shanken (2012)). Therefore, we convert our correlation factor into excess returns by projecting it onto the FX market space and test the significance of price of the factor-mimicking portfolio as in Lustig, Roussanov, and Verdelhan (2011) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012a). The cross-sectional regression result shows that a similar level of R^2 (about 90 percents) can be obtained whether the tests are performed on carry and momentum portfolios separately or jointly.

To investigate the robustness of our empirical findings, we perform the following series

³There have been recent developments to estimate the average correlation of US equity stocks that is implied in the option market. Correlation swap to hedge risks associated with the observed average correlation in stock, commodity and FX markets have also emerged from over-the-counter trades. See, Driessen, Maenhout, and Vilkov (2009) for details of the correlation swap trade.

of additional tests. First, we show that trading on portfolios sorted on the correlation innovation factor betas can yield a statistically significant monotonic relation in average returns (see, Wolak (1989) and Patton and Timmermann (2010) for the description of the monotonicity tests). The average excess returns of those portfolios are a decreasing function of the average beta exposure to our risk factor, confirming the idea of negative price of beta risk. Second, we investigate GLS cross-sectional regressions for different statistical implications of regression results. Third, we perform different regression tests excluding outliers, using different sampling periods (excluding the financial crisis period), forming alternative measures of innovation series (AR-1 or AR-2 model), and using different frequency of equity and FX data (weekly instead of monthly data). The results from these various specifications confirm that the correlation risk is an important driver of the risk premia in the FX market.

To deliver an economic intuition behind our empirical findings, we build a multi-currency model to analyze the sources of risk and the main drivers of the expected returns in currency portfolios. We follow the habit formation literature (see, Campbell and Cochrane (1999), Menzly, Santos, and Veronesi (2004) and Verdelhan (2010)) and present a multicurrency specification that captures heterogeneity and time variation in risk aversion across countries. Our model decomposition of the expected returns demonstrates that heterogeneity in risk aversion is able to explain the cross-section of average excess returns of carry portfolios. However, heterogeneity in risk aversion coefficient alone cannot explain carry and momentum simultaneously. We show instead that the cross-sectional differences in loading on the risk factor depend on two terms: the portfolio average risk aversion coefficient and the interaction between the risk aversion coefficient and country-specific consumption correlation.⁴ Carry portfolios are closely related to the former term, whereas momentum portfolios are closely related to the latter term. Thus, our decomposition explains why the payoffs from both long-short carry and momentum trades positively co-move with changes in global consumption

⁴Through simulation, we show that the model implied global equity correlation innovation is very similar to the consumption correlation.

level.

We also perform Monte-Carlo simulation experiments to elaborate further on the model implied risk-return relationship. Consistent with the mathematical decomposition, our simulation shows that portfolios of currencies with high interest rates (carry) have lower average risk-aversion coefficients but no significant pattern for the interaction between risk-aversion coefficient and country-specific correlation. On the other hand, portfolios of currencies with high momentum have a lower interaction term but no significant pattern for risk-aversion coefficient. Time-series decomposition of shocks from our simulation study also suggests that the payoffs from traditional long-short carry and momentum trades have negative loading on our correlation factor. These simulation results are strongly consistent with our empirical findings.

Finally, this paper also sheds light on the cross-market integration between the equity and the FX markets. Previous literature shows difficulties in finding a common risk factor that explains both equity and currency risk premia (see, for example, Burnside (2011)). If the financial markets are sufficiently integrated, the premiums in international equity and FX markets should be driven by the same aggregate risk. By using a factor constructed from the equity market to explain abnormal return in the FX market, we demonstrate the important linkage between the equity and FX market through equity correlations as a main instrument of the aggregate risk.

The rest of the paper is organized as follows: Section II presents data and Section III describes the portfolio construction method used in this paper. Section IV introduces the correlation innovation factor and provides the main empirical cross-sectional testing results. A number of alternative tests and robustness checks are performed in Section IV as well. Section V discuss theoretical model underlying the empirical findings and Section VI concludes.

II Data

This section describes the three sets of data used in the empirical analysis. Our database consist of spot and forward exchange rates as well as international equity market indices. In what follows, we describe each database separately and examine the currency strategies investigated in this paper.

II.1 Spot and Forward Rates

Following Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), we blend two datasets of spot and forward exchange rates to span a longer time period. Both datasets are obtained from Datastream. The datasets consist of daily observations for bid/ask/mid spot and one month forward exchange rates for 48 currencies. FX rates are quoted against the British Pound and US dollar for the first and second dataset, respectively. The first dataset spans the period between January 1976 and November 2013 and the second dataset spans the period between December 1996 and November 2013. To blend the two datasets, we convert pound quotes in the first dataset to dollar quotes by multiplying the GBP/Foreign currency units by the USD/GBP quotes for each of bid/ask/mid data. For the monthly data series, we sample the data on the last weekday of each month. For the weekly data series, which we use in section IV.H of this paper as a robustness check, we choose Wednesday, following the tradition of option literatures⁵.

Our full dataset consists of the currencies of 48 countries. In the empirical section, we carry out our analysis for the 48 countries as well as for a restricted database of only the 17 developed countries for which we have longer time series. Our choice of the currencies are reported in **Appendix**.

⁵See Bakshi, Cao, and Chen (1997) for the rationale for using Wednesday. Similar reasons can be applied to FX rates.

II.2 Equity Returns

We collect daily closing U.S. dollar MSCI indices from Datastream for all available countries in the FX data. The sample covers the period from January 1973 to November 2013. We note that the number of available international equity indices varies over time, as data for a number of emerging market countries only become available in the later period. Therefore, we create three separate datasets: The first dataset consists of 17 developed market indices available from January 1973 where the countries are selected to match with 17 developed market currencies. We use this dataset to create our main factor for the cross-sectional regression (henceforth, CSR) analysis. The second and third dataset consists of all the matching equity market indices available from January 1988 (31 indices) and 1995 (39 indices) respectively. The list of the equity market indices available for each of the datasets are also shown in **Appendix**. We find that, the innovation factors generated from the second and third datasets are very similar to the one from the first dataset. Thus, we rely on the correlation implied by 17 developed market indices for the analysis and use the second and third databases as a robustness check.

III Currency Portfolios

This section defines both spot and excess currency returns. It describes the portfolio construction methodologies for both carry and momentum and provides descriptive statistics of associated excess returns.

III.A Spot and Excess Returns for Currency

We use q and f to denote the log of the spot and forward nominal exchange rate measured in home currency per foreign currency, respectively. An increase in q^* means an appreciation of the foreign currency (*). Following Lustig and Verdelhan (2007), we define the log excess

return ($\Delta\pi_{t+1}^*$) of the currency (*) at time $t + 1$ as

$$\Delta\pi_{t+1}^* = \Delta q_{t+1}^* + i_t^* - i_t \approx q_{t+1}^* - f_t^* \quad (1)$$

where i_t^* and i_t denote the foreign and domestic nominal risk-free rates over a one-period horizon. This is the return on buying a foreign currency (f^*) in the forward market at time t and then selling it in the spot market at time $t + 1$. Since the forward rate satisfies the covered interest parity under normal conditions (see, Akram, Rime, and Sarno (2008)), it can be denoted as $f_t^* = \log(1+i_t) - \log(1+i_t^*) + q_t^*$. Therefore, the forward discount is simply the interest rate differential ($q_t^* - f_t^* \approx i_t^* - i_t$) which enables us to compute currency excess returns using forward contracts. Using forward contracts instead of treasury instruments has comparative advantages as they are easy to implement and the daily rates along with bid-ask spreads are readily available.

III.B Carry Portfolios

Carry portfolios are the portfolios where currencies are sorted on the basis of their interest rate differentials. As described in subsection III.A, they are equivalent to portfolios sorted on forward discounts due to the covered interest parity. Following Menkhoff, Sarno, Schmeling, and Schrimpf (2012a), portfolio 1 contains the 20 % of currencies with the lowest interest rate differentials against US counterparts, while portfolio 5 contains the 20 % of currencies with the highest interest rate differentials. The log currency excess return for portfolio i can be calculated by taking the equally-weighted average of the individual log currency excess returns (as described in Equation 1) in each portfolio i . The difference in returns between portfolio 5 and portfolio 1 is the average profit obtained by running a traditional long-short carry trade portfolio (HML_{Carry}) where investors borrow money from low interest rate countries and invest in high interest rate countries' money markets. Therefore, it is a strategy that exploits the broken uncovered interest rate parity in the cross-section. Previous research has found that the strategy is profitable, since interest rate differentials

are strongly autocorrelated and spot rate changes do not fully adjust to compensate for the differentials. Lustig, Roussanov, and Verdelhan (2011) construct risk factors from excess returns of portfolios sorted on interest rate differentials, level (DOL) and slope (HML_{Carry}) factors. They document that most of the cross-sectional variation in average excess returns among carry sorted portfolios can be mapped to differential exposure to the slope factor. Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) show that there is a strong relationship between the global FX volatility risk and the cross-section of excess returns in carry trades.

To take transaction costs into account, we split the way to calculate the net excess return of portfolio i at time $t+1$ into six different cases depending on the actions we take to rebalance the portfolio at the end of each month. For example, if a currency enters (In) a portfolio at the beginning of the time t and exits (Out) the portfolio at the end of the time t , we take into account two-way transaction costs ($\Delta\pi_{long,t+1}^{In-Out} = q_{t+1}^{bid} - f_t^{ask}$), whereas if it stays in the portfolio once it enters, then we take into account a one-way transaction cost only ($\Delta\pi_{long,t+1}^{In-Stay} = q_{t+1}^{mid} - f_t^{ask}$). A similar calculation is for a short position as well (with opposite signs while swapping bids and asks).

Descriptive statistics for our carry portfolios are shown in Panel 1 of **Table 1**. Panel 1 shows results for the sample of all 48 currencies (ALL) and the statistics for the sample of the 17 developed market currencies (DM) are shown on the right. Average excess returns and Sharpe ratios are monotonically increasing from portfolio 1 to portfolio 5 for both ALL and DM currencies. The unconditional average excess returns from holding a traditional long-short carry trade portfolio are about 5.8 % and 5.2 % per annum respectively after adjusting for transaction costs. These magnitudes are similar to the levels reported in the carry literature. Consistent with Brunnermeier, Nagel, and Pedersen (2008) and Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), we also observe decreasing a skewness pattern as we move from a low interest rate to a high interest rate currency portfolio.

III.C Momentum Portfolios

Momentum portfolios are the portfolios where currencies are sorted on the basis of past returns.⁶ We form momentum portfolios sorted on the excess currency returns over a period of three months, as defined in Equation 1. Portfolio 1 contains the 20 % of currencies with the lowest excess returns, while portfolio 5 contains the 20 % of currencies with the highest excess returns over the last three months. As portfolios are rebalanced at the end of every month, formation and holding periods considered in this paper are three and one months, respectively. We consider three months for the formation period because we generally find highly significant excess returns from momentum strategies with a relatively short time horizon as documented in Menkhoff, Sarno, Schmeling, and Schrimpf (2012b). The significance, however, is not confined to this specific horizon and our empirical results are robust to other formation periods, such as a one or six month period, as well.⁷

We find that the returns from currency momentum trades are seemingly unrelated to the returns from carry trades since unconditional correlation between returns of the two trades is about 0.02. The weak relationship holds regardless of the choice of formation period for momentum strategy since momentum strategy is mainly driven by favorable spot rate changes, not by interest rate differentials. Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) also demonstrate that momentum returns in the FX market do not seem to be systematically related to standard factors such as business cycle risks, liquidity risks, the Fama-French factors, and the FX volatility risk. Burnside, Eichenbaum, and Rebelo (2011) similarly argue that it is difficult to explain carry and momentum strategies simultaneously,

⁶Compared to carry trades, relatively few studies have examined the momentum strategy in the cross-section of currencies. Among these papers, Asness, Moskowitz, and Pedersen (2013) have shown that there is consistent and ubiquitous evidence of cross-sectional momentum return premia across markets. The strong co-movement pattern across asset classes suggests that momentum profits could share a common root. Similar to their findings, Moskowitz, Ooi, and Pedersen (2012) document that there is also a common component affecting time-series momentum strategies across asset classes simultaneously which is not present in the underlying asset themselves. They document that time-series and cross-sectional momentum is different but significantly correlated, especially in the FX market.

⁷The cross-sectional regression results are available upon request.

hence they argue that the high excess returns should be understood with high bid-ask spread or price pressure associated with net order flow. In this paper, we also confirm that, using a different sample of countries and different time intervals, the factors that the later papers investigate are indeed unable to explain the carry and momentum portfolios. In addition, we provide a risk-based explanation for both these strategies.

Panel 2 of **Table 1** reports the descriptive statistics for momentum portfolios. There is a strong pattern of increasing average excess return from portfolio 1 to portfolio 5, whereas we do not find such a pattern in volatility. Unlike carry portfolios, we do not observe a decreasing skewness pattern from low to high momentum portfolios. A traditional momentum trade portfolio (HML_{MoM}) where investors borrow money from low momentum countries and invest in high momentum countries' money markets yields average excess return of 7.4 % and 3.6 % per annum after transaction costs for ALL and DM currencies respectively.

IV Asset Pricing Model and Empirical Testing

There is ample evidence that the world's capital markets are becoming increasingly integrated (see, Bekaert and Harvey (1995) and Bekaert, Harvey, Lundblad, and Siegel (2007)). Over the last three decades, we notice a high level of capital flows between countries through secularization, and liberalization. This high level of international capital flows leads to an equalization of the rates of return on financial assets with similar risk characteristics across countries (see, for example, Harvey and Siddique (2000)). Thus, order flow conveys important information about risk-sharing among international investors that currency markets need to aggregate. Indeed, Evans and Lyons (2002a) and Evans and Lyons (2002c) show that order flow from trading activities has a high correlation with contemporaneous exchange rate changes. Since equity trading explains a large proportion of capital flows, their empirical results document that there is a linkage between the dynamics of exchange rates and international equities. Motivated by their papers, Hau and Rey (2006) develop an equilibrium model in which exchange rates, stock prices, and capital flows are jointly determined. They

show that net equity flows are important determinants of foreign exchange rate dynamics. Differences in the performance of domestic and foreign equity markets change the FX risk exposure and induce portfolio rebalancing. Such rebalancing in equity portfolios initiates order flows, eventually affecting movements of exchange rates. Our paper builds on this intuition and demonstrates the important linkage between the equity and FX markets through equity correlations as a main driver to explain the cross-sectional differences in average return of currency portfolios.

If the premiums in international equity markets and FX markets are driven by the same aggregate risk, how should we measure it? CAPM indicates that investors require a greater compensation to hold an aggregate wealth portfolio as the conditional variance of the aggregate wealth portfolio increases. However, as noted in Roll (1977), the variance on an aggregate wealth portfolio is not directly observable and might be difficult to proxy for when conducting empirical asset pricing tests. Indeed, Pollet and Wilson (2010) document that the stock market variance, as a proxy to the risk on an aggregate wealth portfolio, has weak ability to forecast stock market expected returns in a domestic setting. They show that the changes in true aggregate risk may nevertheless reveal themselves through changes in the correlation between observable stock returns as the aggregate wealth portfolio is the common component for all assets.

The same logic can be applied to the international markets and international capital asset pricing models. Increase in the aggregate risk must be associated with an increased tendency of co-movements across international equity indices. Therefore, an increase in global equity correlation is due to an increase in aggregate risk. Risk-averse investors should demand a higher risk premium for portfolios whose payoffs are more negatively correlated to the changes in aggregate risk. The currency portfolios should not be an exception if the currency markets are sufficiently integrated into the international capital market. The FX market risk premium is driven by the same aggregate risk which governs international equity market premium. Thus, the cross-sectional variations in the average excess returns across currency portfolios must be explained by different sensitivity to the changes in global equity

correlation.

It is important to note that an increase in global correlation across bilateral currency returns may not be associated with increase in the aggregate risk. Therefore, currency correlation may not qualify as a proper risk factor. For example, a high level of correlation can arise when the variance of domestic stochastic discount factor is large. This high level of correlation is not due to the elevated aggregate risk, but due to single denomination for the bilateral currencies (the US domestic currency, for example). Therefore, the correlation of bilateral currency returns can be mainly driven by changes in local market conditions, while the correlation of international equity indices is related to the global aggregate risk.

The following section describes our main proxy for the global equity correlation innovation factor, cross-sectional asset pricing model, and empirical cross-sectional regression results.

IV.A Factor Construction: Common Equity Correlation Innovation

We construct two empirical measures of correlations to quantify the evolution of co-movements in international equity market indices. We rely on the dynamic equicorrelation (DECO) model of Engle and Kelly (2012) as our base case and apply the model to monthly equity return series.⁸ To mitigate model risk, we measure the same correlation dynamics by computing bilateral intra-month correlations at each month's end using daily return series. Then, we take an average of all the bilateral correlations to arrive a global correlation level of a particular month. Although the second approach has a comparative advantage due to its model-free feature, there is a potential benefit of relying on the first measure because of the bias in daily frequency returns from non-synchronous trading. Thus, for completeness,

⁸The DECO model assumes the correlations are equal across all pairs of countries but the common equicorrelation is changing over time. The model is closely related to the dynamic conditional correlation (DCC) of Engle (2002), but the two models are non-nested since DECO correlations between any pair of assets i and j depend on the return histories of all pairs, whereas DCC correlations depend only on the its own return history.

we consider both measures in our main empirical testing framework.

The following section illustrates the DECO model. To standardize the individual equity return series, we assume the return and the conditional variance dynamics of equity index i at time t are given by

$$r_{i,t} = \mu_i + \epsilon_{i,t} = \mu_i + \sigma_{i,t} z_{i,t} \quad (2)$$

$$\sigma_{i,t}^2 = \omega_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 \quad (3)$$

where μ_i denotes the unconditional mean, $\sigma_{i,t}^2$ the conditional variance, $z_{i,t}$ a standard normal random variable, ω_i the constant term, α_i the sensitivity to the squared innovation, and β_i the sensitivity to the previous conditional variance. Since the covariance is just the product of correlations and standard deviations, we can write the covariance matrix (Σ_t) of the returns at time t as

$$\Sigma_t = D_t R_t D_t \quad (4)$$

where D_t has the standard deviations ($\sigma_{i,t}$) on the diagonal and zero elsewhere, and R_t is an $n \times n$ conditional correlation matrix of standardized returns (z_t) at time t . Depending on the specification of the dynamics of the correlation matrix, DCC correlation (R_t^{DCC}) and DECO correlation (R_t^{DECO}) can be separated. Let Q_t denotes the conditional covariance matrix of z_t .

$$Q_t = (1 - \alpha_Q - \beta_Q) \bar{Q} + \alpha_Q \tilde{Q}_{t-1}^{\frac{1}{2}} z_{t-1} z_{t-1}' \tilde{Q}_{t-1}^{\frac{1}{2}} + \beta_Q Q_{t-1} \quad (5)$$

$$R_t^{DCC} = \tilde{Q}_t^{-\frac{1}{2}} Q_t \tilde{Q}_t^{-\frac{1}{2}} \quad (6)$$

$$\rho_t = \frac{1}{n(n-1)} (i' R_t^{DCC} i - n) \quad (7)$$

$$R_t^{DECO} = (1 - \rho_t) I_n + \rho_t J_{n \times n} \quad (8)$$

where α_Q is the sensitivity to the covariance innovation of z_t , β_Q is the sensitivity to the

previous conditional covariance of z_t , \tilde{Q}_t replaces the off-diagonal elements of Q_t with zeros but retains its main diagonal, \bar{Q} is the unconditional covariance matrix of z_t , ρ_t is the equicorrelation, $\mathbf{1}$ is an $n \times 1$ vector of ones, I_n is the n -dimensional identity matrix, and $J_{n \times n}$ is an $n \times n$ matrix of ones. To estimate our model, we follow the methodology in Engle and Kelly (2012). We refer the reader to the latter paper for an exhaustive description of the estimation methodology.

For the empirical analysis, we construct a common factor in international equity correlation innovation (ΔEQ_{corr}) as a risk factor. We simply take the first difference in time series of expected DECO correlation to quantify the evolution of co-movements in international equity market indices. $\Delta EQ_{corr,t} = E_t[EQ_{corr,t+1}] - E_{t-1}[EQ_{corr,t}]$.⁹ We rely on the shock to global equity correlation rather than the level as a factor for currency excess returns. This choice is motivated by the intertemporal capital asset pricing model (ICAPM) of Merton (1973). Under the ICAPM framework, investors consider the state variables that affect the changes in the investment opportunity sets.

Our hypothesis is that change in the global international equity correlation is a state variable that affects the changes in the international investment opportunity set. Therefore, the ICAPM predicts that investors who wish to hedge against unexpected changes (innovations) should demand currencies that can hedge against the risk, hence they must pay a premium for those currencies. In other words, ΔEQ_{corr} must be a priced risk factor in the cross-section of FX portfolios. The global equity correlation levels and innovations for both measures are plotted in **Figure 2**. We report two different versions of the DECO model implied correlation series. The solid black line, DECO IS (in-sample), is measured by the DECO model where parameters are estimated on the entire sample periods. The dotted blue

⁹Note that we use the first difference as our main approach to get the innovation series simply because it is the most intuitive way to do so. However, we also investigated alternative ways to measure innovations such as AR(1) or AR(2) shocks and find that the empirical testing results are quite robust to those variations. We report these findings in the robustness section. Furthermore, given that we rely on the unconditional cross-sectional regression as our test, the existence of autocorrelation should not affect the validity of our test.

line depicts the time series of the global equity correlation without look ahead bias and we name this measure DECO OOS (out-of-sample). In contrast to DECO IS, this correlation is estimated using the same DECO model, but the parameters in this case are measured on the data available only at that point in time and updated throughout as we observe more data. We also construct a non-parametric estimation of the correlation. The dotted red line, the intra-month correlation, is measured by computing bilateral intra-month correlations at each month end using daily return series of international equity indices and then taking the simple mean of those bilateral correlations.

Model-implied global correlation levels and innovations, whether parameters are updated or not, are very similar to those of the intra-month correlation. The descriptive statistics and p-values from an augmented Dicky-Fuller stationary test, Ljung-box and Breusch-Godfrey serial dependence tests for the three innovation series are shown in the upper right table. All of the innovation series are stationary which makes them statistically valid factors under an unconditional cross-sectional regression (CSR) framework. The lower right table shows the unconditional correlation between the model-implied DECO innovation series and the intra-month innovation series.

IV.B Cross-Sectional Regression

IV.B.1 Methods

To test whether our factor is a priced risk factor in the cross-section of currency portfolios, we utilize the popular two-pass cross-sectional regression (CSR) method. We first obtain estimates of betas by running a time-series regression of portfolio returns on our factors. In the second-pass, we regress the unconditional mean of excess return of portfolios on the estimated betas.

For statistical significance of beta, we report both the statistical measures of Shanken (1992) and Kan, Robotti, and Shanken (2012) throughout this paper. Shanken (1992) provides asymptotic distribution of the price of beta, adjusted for the errors-in-variables problem

to account for the estimation errors in beta. Kan, Robotti, and Shanken (2012) further investigate the asymptotic distribution of the price of beta risk under potentially misspecified models as well as under i.i.d multivariate elliptical distribution assumption (rather than i.i.d normal). They emphasized that statistical significance of the price of covariance risk is an important consideration if we want to answer the question of whether an extra factor improves the cross-sectional R^2 . Therefore, we apply both tests based on the price of covariance risk as well as the price of beta risk in the empirical testing. They also have shown how to use the asymptotic distribution of the sample R^2 in the second-pass CSR as the basis for a specification test. To save space, we report the details of the estimation methodology of these statistics to Section VII.

IV.B.2 Results

In this section, we present empirical findings that show that the international equity correlation innovation factor (ΔEQ_{corr}) is a priced risk factor in the cross section of currency portfolio and that it simultaneously explains the persistent significant excess returns in both carry and momentum strategies. We follow Lustig, Roussanov, and Verdelhan (2011) and account for the dollar risk factor (DOL) in all the main empirical asset pricing tests. DOL is the aggregate FX market return available to a U.S. investor and it is measured simply by averaging all excess returns available in the FX data at each point in time. Although DOL does not explain any of the cross-sectional variations in expected returns, it plays an important role in the variations in average returns over time since it captures the common fluctuations of the U.S. dollar against a broad basket of currencies. The test assets are the two sets of sorted currency portfolios described in Section III. We will refer to all the currency portfolios, the set of sorted carry (5) and momentum (5), as *FX 10* portfolios.

Table II presents the results of the asset pricing tests using all *FX 10* portfolios. The left side of Panel 1 reports estimation results with all 48 currencies (ALL) and the right side reports estimation results with 17 developed market (DM) currencies only. The market

price of beta risk (γ) is estimated to be about -8.75 % and -5.26 % per month for ALL and DM currencies, respectively. We find they are statistically significant under Shanken’s (1992) estimation error adjustment as well as misspecification error adjustment, with t-ratio of -3.83 and -3.37 respectively. The price of the beta risk is also economically significant, since one standard deviation of cross-sectional differences in beta exposure can explain about 2.5 % per annum in the cross-sectional differences in mean return for ALL currencies. Kan, Robotti, and Shanken (2012) show empirically that misspecification-robust standard errors are substantially higher when a factor is a non-traded factor. They document that this is because the effect of misspecification adjustment on the asymptotic variance of beta risk could potentially be very large due to the variance of residuals generated from projecting the non-traded factor on the returns. Therefore, it is surprising for us to see that a non-traded factor like our correlation factor has a highly significant t-ratio.

In each panel of **Table II**, we include the prices of covariance risk (λ) since the price of covariance risk allows us to identify factors that improve explanatory power (cross-sectional R^2) of the expected returns from a model. We find the global correlation innovation factor could yield cross-sectional fit with R^2 of 90% and 64% for ALL and DM currencies respectively. While we cannot reject the null $H0: R^2 = 1$ under the assumption of the correctly specified model, it is significance for the test that the model has any explanatory power for expected returns under the null of misspecified model $H0: R^2 = 0$.

The negative prices of beta and covariance risk suggest that investors would demand a low risk premium for portfolios whose returns co-move with the global correlation innovation, as they provide a hedging opportunity against unexpected deterioration of the investment opportunity set. To substantiate this finding, we investigate the negative price of beta risk for our global correlation factor. Panel 2 of **Table II** illustrates that portfolios with low forward discount (interest rate differential) and low momentum have high betas with our global correlation factor. Their average excess returns are relatively low compared to the average excess returns of high forward discount and high momentum portfolios. This strong pattern of decreasing beta across both sets of portfolios strengthens our conclusion that

investors indeed demand a low risk premium for the portfolios whose returns co-move with our correlation factor.

Similarly, Panel 1 of **Table III** presents the results from the second pass CSR where our correlation factor is now measured from the mean of bilateral intra-month correlations, instead of DECO correlations. Although the level of market price of beta risk (γ) is different from the one using DECO correlation, the economic magnitude of the beta price is about the same due to lower spreads in beta exposures across portfolios. In other words, one standard deviation of cross-sectional differences in beta exposure can explain just about 2.43 % per annum in the cross-sectional differences in mean return of the *FX 10* portfolios.

Contrasting Panel 1 of **Table III** and Panel 1 of **Table II** shows that the two separate measures of our correlation factor have similar beta coefficients as well as t-ratios. These findings confirm that the global equity correlation factor is a priced risk factor in the cross-section of currency portfolios. Overall, the results using the non-parametric intra-month correlation are similar to the DECO case presented above.

Finally, we present in **Figure 3** the pricing errors of the asset pricing model with our global equity correlation as a risk factor. The realized excess return is on the horizontal axis and the model-predicted average excess return is on the vertical axis. The fits for both of our models, using DECO OOS innovation on the left and intra-month correlation innovation on the right, suggest that our model can explain the cross-sectional differences in mean returns quite well.

IV.C Cross-sectional regression with other factors

In this subsection, we confirm that the factors discussed in the FX literature fail to explain the cross-sectional differences in mean returns across the extended test assets (*FX 10*). We also test whether the inclusion of our correlation factor improves the explanation of carry and momentum portfolios above these existing factors.

The factors in this empirical exercise are i) FX volatility innovations from Menkhoff,

Sarno, Schmeling, and Schrimpf (2012a), ii) FX correlation innovation, iii) the TED spread, iv) the global average bid-ask spread from Mancini, Rinaldo, and Wrampelmeyer (2013), v) the Pastor and Stambaugh (2003) liquidity measure, vi) US equity market premiums, vii) US small-minus-big size factor, viii) US high-minus-low value factor, ix) US equity momentum factor, and high-minus-low risk factors from excess returns of portfolios sorted on interest differentials, x) the FX carry factor from Lustig, Roussanov, and Verdelhan (2011), and sorted on past returns, xi) the FX momentum factor. We verified that the FX volatility factor, a set of illiquidity innovation factors and the FX carry factor can explain the spreads in mean returns of carry portfolios very well with R^2 ranging from 58 % for the TED spread innovation factor to 92 % for the FX volatility factor. The factor prices are statistically significant under a misspecification robust cross-sectional regression, and have the expected signs, that is, negative for illiquidity and FX volatility factors and positive for the FX carry factor. However, the same set of factors which have great explanatory power over the cross-section of carry portfolios does not explain well momentum portfolios at the same time.

In **Table IV**, we add our correlation factor along with other factors described above to evaluate the relative importance of the factors. The specification for the test is exactly the same as in **Table II**. In each panel of the table, a CSR test is performed on three factors, the dollar factor, the control variable X, and the global equity correlation innovation factor from the DECO model for Panel 1 and intra-month correlation for Panel 2. In this way, the model in each panel of **Table IV** nests the model in Panel 1 of **Table II** and **Table III**. It is straightforward to see that the explanatory power of the larger model exceeds that of the smaller model. **Table IV** also reports that the pricing power for our factor is not much affected by the inclusion of other factors in the previous literature.

Although we only show the case for the price of beta risk, the same conclusion can be drawn from the price of covariance risk. When the models are potentially misspecified, Kan, Robotti, and Shanken (2012) document that R^2 s of two (nested) models are statically different from each other if and only if the covariance risk (λ) of the additional factor is statistically different from zero with misspecification robust errors. Therefore, we perform a statistical

test on the price of covariance risk of our correlation factor under the null hypothesis of zero price ($H_0: \lambda_{\Delta EQ_{corr}} = 0$). The nested models are CSR using only two factors, the dollar factor and each of the control variables. We find that the prices of the covariance risk are statistically significantly different from zero in all cases. R^2 s are also economically and statistically different from the nested models with control variables only.¹⁰ The significant price of covariance risk of our correlation factor confirms that our correlation factor improves the explanatory power across the mean returns of carry and momentum portfolios. Overall, we find that the inclusion of our correlation factor enhances the explanation of cross-sectional differences in mean returns of carry and momentum portfolios over the risk factors discussed frequently in the FX literature.

IV.D Factor-mimicking portfolio

In this subsection we convert the global equity correlation innovation factor into excess returns by projecting the factor onto the FX market space. This exercise converts the non-traded macro factor to a traded risk factor within the FX market. We first regress our correlation innovation series on *FX 10* portfolios and then retrieve fitted return series. The fitted excess return series is in fact the factor-mimicking portfolio's excess return. **Table V** reports the cross-sectional asset pricing test applied to different sets of test assets with the correlation innovation factors used in previous tables and the corresponding factor-mimicking portfolio's excess returns. We also report cross-sectional regression tests for carry and momentum portfolios separately to examine whether the explanatory power for cross-sectional differences in mean return is mainly driven by one particular type of strategy. We find that the price of beta risk is statistically significant with a similar level of R^2 whether the cross-sectional regression is performed on the two strategies separately or jointly. The price of the traded risk factor is much smaller than the price of the original non-traded factor. The

¹⁰Alternatively, we use the orthogonalized component of each factor with respect to the correlation innovation factor by taking the residuals from regressions. We still find similar level of R^2 s. The results are available upon request.

reason is that differences in beta exposure to the traded factor across *FX 10* portfolios are much larger in absolute terms than those to the non-traded factor. Therefore, the factor-mimicking portfolio can explain about the same level of cross-sectional differences in mean returns among *FX 10* portfolios as the non-traded factor (R^2 of about 90% in both cases).

IV.E Alternative test assets

In this section, we follow Lustig and Verdelhan (2007) and Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) and examine whether the statistical significance of the regression results are specifically driven by our choice of test assets. Lustig and Verdelhan (2007) used the 6 Fama-French portfolios sorted on size and book-to-market to test whether compensation for the consumption growth risk in currency markets differs from that in domestic equity markets from the perspective of a US investor. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) also use the 25 Fama-French portfolios together with the equally weighted carry trade portfolio to see whether the carry payoffs are correlated with traditional risk factors. We augment the *FX 10* portfolios with the 25 Fama-French portfolios formed on size and book-to-market. We test whether the entire cross-section of average returns of the 35 equity and currency portfolios can be priced by the same stochastic discount factor that prices currency market risks. This test also serves as a test for market integration across the international currency market and the domestic equity market.

Table VI reports the cross-sectional pricing test results. In Panel 1 of **Table VI**, we report the results where the dollar risk factor and our global equity correlation factor are used to price the extended portfolios. In Panel 2 of **Table VI**, we report the results where the US market risk premium (MRP), US equity size (SMB) and value (HML) factors are added as additional control variables. We find that both coefficients on beta and covariance risks of our correlation factor are negatively significant, which is consistent with our previous findings. The negatively significant price of the risk across the *FX* and domestic equity market also supports the conjecture of market integration. This exercise confirms that the

statistical significance of the regression results is not specifically driven by our choice of test assets.

IV.F Trading on Betas with Common Equity Correlation

This section presents the results for trading on portfolios sorted on our correlation factor betas. Building portfolios based on each currency’s exposure to the risk factor provides a direct alternative test of whether the correlation factor is a priced-risk factor. If our correlation factor is a risk factor with negative price of risk, we should expect currencies that provide hedging opportunity against the correlation risk (high beta currencies) to yield low average excess returns. The average portfolio returns in **Figure 4** show that the empirical results are consistent with this intuition.

In this exercise, we assume that portfolios are rebalanced at the end of each month t by sorting currencies into five groups based on the slope coefficients (betas) available at time t . Each beta is obtained by regressing currency i ’s excess return on the global equity correlation innovation factor on a 24-period moving window (left) or on a 36-period moving window (right). Portfolio 1 contains currencies with the lowest betas, while portfolio 5 contains currencies with the highest betas. Both figures illustrate that the average excess returns of portfolios are a decreasing function of average beta exposure to the risk factor, confirming the idea of negative price of the risk. We also perform a formal monotonicity test and we fail to reject the null hypothesis of weak monotonicity in average excess returns from the multivariate inequality test of Wolak (1989), with p-value of 0.95 for 24 months and 0.96 for 36 months. Under the monotonic relation (MR) test of Patton and Timmermann (2010), we can only reject the null of a non-monotonic relationship at the 5% level for 24 months with p-value of 0.04, while it is 0.11 for 36 months. On the other hand, both sets of portfolios show statistical significance in favor of a monotonically increasing pattern in post-ranked betas with p-value close to zero. The results suggest that past beta estimates are stable and have predictive power over future betas.

IV.G GLS Cross-sectional Regression

OLS and GLS represent different ways of measuring and aggregating the sample deviations. Since we want to allow for the model misspecification, the choice between OLS and GLS should be determined based on economic relevance rather than estimation efficiency. We argue that in our setting OLS is more relevant if the focus is on the expected returns for a particular set of test portfolios, but GLS may be of greater interest from an investment perspective. Therefore, we also run GLS cross-sectional regression tests and report the results in **Table VII**. As expected from the choice of the weighting matrix on sample deviations, we find lower R^2 s for GLS cross-section regression (42% and 51% for DECO OOS and Intra-month correlation respectively). Those R^2 s are still economically large in GLS regression. We also find that both our global equity correlation factor measures remain statistically significant. The high absolute magnitudes of t-ratios, -2.74 and -3.04 for DECO OOS and Intra-month correlation respectively, confirm that our cross-sectional regression results are robust to econometric modification.

IV.H Other Robustness Checks

In this subsection we perform a number of other robustness checks associated with outliers, different sampling periods, an alternative measure of innovations, and different frequency of data. First we winsorize the correlation innovation series at the 90% level, which means we exclude the 10% of sample periods. Secondly, we set different time horizons for the testing period. In particular, we pick a time period before the financial crisis, from March 1976 to December 2006, since the large positive innovations during the crisis period can potentially drive the CSR testing results. The testing results for 10% winsorization and the different time period are shown in Panel 1 and Panel 2 of **Table VIII**. We still find strong significance for the price of the risk in both cases. For the alternative specification of innovation, we choose an AR(2) shock for the robustness check to see if the different definition of the shock changes the empirical testing results. Panel 3 reports the estimation

results with an AR(2) shock and we generally find that the results are extremely robust to the other specifications as well. Last, we construct both of our factors (the dollar and DECO equity correlation innovation factors) and test assets (FX 10 portfolios) from weekly data series. For forward exchange rates, we use forward contract with a maturity of one week to properly account for the interest rate differentials in the holding period. The weekly sample covers the period from October 1997 to November 2013. In Panel 4, we confirm that the correlation innovation factor is a priced-risk factor in the FX market.

V Theoretical Model

So far, we have shown that our international global equity correlation factor is a priced risk factor in the cross-section of currency portfolios. For the economic intuition behind our empirical findings, we present a model that allows us to decompose the sources of risk for the currency risk premiums. Specifically, we build a multi-currency model with global shock to analyze sources of risk following the habit-based specification (see, Campbell and Cochrane (1999), Menzly, Santos, and Veronesi (2004) and Verdelhan (2010)). Under complete market assumption, the real exchange rate is simply the ratio of foreign to domestic pricing kernels (see, Lustig, Roussanov, and Verdelhan (2011)). Therefore, the bilateral exchange rate depends on country specific (both domestic and foreign) and global consumption shocks. In our modeling framework, we assume global shock affects all countries simultaneously whereas country specific shock is partially correlated with the global shock.

Backus, Foresi, and Thelmer (2001) show that any currency risk premia can be measured as the difference between the higher moments of domestic and foreign stochastic discount factor (SDF). Since we use log-normal specification in our model, presenting difference in conditional variance of SDF should be sufficient to measure currency risk premia. A foreign currency from a country with smaller conditional variance of SDF is expected to appreciate more.

Our model decomposition of the expected returns in this section demonstrates that het-

erogeneity in the risk aversion is able to explain the cross-section of average excess returns of carry portfolios. However, heterogeneity in the risk aversion coefficient alone cannot explain carry and momentum simultaneously. We show instead that the cross-sectional differences in loading on the risk factor depends on two terms, the portfolio average risk aversion coefficient and the interaction between the risk aversion coefficient and the country-specific consumption correlation. We demonstrate that carry portfolios are closely related to the former term, whereas momentum portfolios are closely related to the latter term. Payoffs from both traditional long-short carry and momentum trades positively co-move with changes in the global consumption level because of the two terms. Therefore, the two trading strategies are considered risky.

Last, a large negative global consumption shock is associated with a large positive innovation to the global correlation due to the model-implied response of correlation to consumption shock (see, for example, Ang and Chen (2002); Hong, Tu, and Zhou (2007)).¹¹ Hence, unexpected increases in the global correlation level would imply an adverse price effect for carry and momentum trades. This relation is consistent with our empirical cross-sectional regression results, where we find a negatively significant price of beta risk to the equity correlation innovation factor. More detailed specification of the model is described in this section.

¹¹In our model, we show that the model-implied equity correlation across countries inherits the same properties of the global consumption correlation specified in our framework. By incorporating time varying and asymmetric correlation dynamics in our specification of the dynamic consumption process, we are able to relate the source of currency market premium to aggregate consumption risk through equity market correlation.

V.A Preferences and Consumption Growth Dynamics

Under Habit-based preferences¹², the agents of country i maximizes

$$E \left[\sum_{t=0}^{\infty} \beta^t U(C_t, H_t) \right]$$

$$U(C_t, H_t) = \ln(C_t - H_t)$$

where U denotes Habit utility function, H_t the external habit level, and C_t consumption level at time t .

Log consumption growth dynamics is given by

$$\begin{aligned} \Delta c_{t+1} &= g + \underbrace{\sigma * (\rho_{t+1} \epsilon_{w,t+1} + \sqrt{1 - \rho_{t+1}^2} \epsilon_{t+1})}_{\text{Country-specific shock}} + \underbrace{\sigma_{w,t+1} * \epsilon_{w,t+1}}_{\text{Global shock}} \\ &= g + \sigma \sqrt{1 - \rho_{t+1}^2} * \epsilon_{t+1} + (\sigma \rho_{t+1} + \sigma_{w,t+1}) * \epsilon_{w,t+1} \end{aligned} \quad (9)$$

where σ denotes the volatility for country-specific consumption shock, σ_w is the volatility for global consumption shock, ϵ_{t+1} and $\epsilon_{w,t+1}$ are the standardized idiosyncratic and global shock, respectively. We assume that both ϵ_{t+1} and $\epsilon_{w,t+1}$ are independent and normally distributed with mean of zero and standard deviation of one (ϵ_{t+1} and $\epsilon_{w,t+1} \sim \mathbf{N}(0, 1)$). ρ_{t+1} is the correlation parameter between the country-specific and the global consumption shock. We extend the habit model in Campbell and Cochrane (1999) and Verdelhan (2010) and assume that the consumption growth innovations have two components, the country-specific and global shocks. Our specification allows the variance of country-specific shock to be constant but the variance of global shock is time-varying. This setup allows us to

¹²We have also explored the model under a CRRA framework. The most important assumption we have to make under a CRRA framework is the existence of heterogeneity in risk aversion coefficients across the countries. Habit preference relaxes this assumption by delivering conditional heterogeneity in risk aversion coefficients even with similar long-term average risk aversion across countries. In other words, given that investors rebalance the portfolios every month, the conditional heterogeneity in risk aversion coefficients should be a sufficient condition.

distinguish between global and country-specific factors and to capture the dynamics of the global consumption correlation among N different countries.

We assume that the volatility of the global consumption shock follows asymmetric GARCH form. Its dynamics are given by

$$\sigma_{w,t+1}^2 = \omega + \alpha_{garch} * \sigma_{w,t}^2 (\epsilon_{w,t} - \theta_{garch})^2 + \beta_{garch} * \sigma_{w,t}^2$$

where ω , α_{garch} , θ_{garch} , and β_{garch} are the GARCH parameters. The dynamics of the correlation between the country specific shock and the global shock are given by

$$\rho_{t+1} = \tanh[\kappa_\rho(\bar{\rho} - \rho_t) + \alpha_\rho(\Delta c_t - E[\Delta c_t])]$$

where \tanh denotes the hyperbolic tangent function, which guarantees the correlation to be between -1 and 1, κ_ρ is the speed of mean reversion, and α_ρ is the sensitivity to the consumption shock. For simplicity of the exposition, we assume g , σ , ω , α_{garch} , θ_{garch} , β_{garch} , κ_ρ , α_ρ are the same across all countries.

The local curvature (Γ_t) of the utility function is inversely related to the surplus consumption ratio (S_t) and the dynamics of log local curvature, risk aversion coefficient (γ_t), follow the equation below,¹³

$$\begin{aligned}\Gamma_t &= -C_t \frac{U_{cc}}{U_c} = \frac{C_t}{C_t - H_t} \equiv \frac{1}{S_t} \\ \log \Gamma_t &= \log \frac{1}{S_t} = -s_t = \gamma_t \\ \Delta \gamma_{t+1} &= \kappa_\gamma(\bar{\gamma} - \gamma_t) - \alpha_\gamma(\gamma_t - \theta_\gamma)(\Delta c_{t+1} - E[\Delta c_{t+1}])\end{aligned}$$

where U_c and U_{cc} are the first and second derivatives of the utility function with respect to consumption, κ_γ denotes the speed of mean reversion, $\alpha_\gamma > 0$ is the sensitivity of γ_t to the

¹³See Menzly, Santos, and Veronesi (2004) and Christoffersen, Du, and Elkamhi (2013) for the dynamics of the risk aversion coefficient

consumption shock, and $\theta_\gamma \geq 1$ is the lower bound for γ_t . Note that the total sensitivity of γ_t to the consumption shock is also a function of the level of γ_t . The higher the level of risk aversion, the more sensitive to the consumption shock, hence countercyclical variation in volatility of γ_t . The log of pricing kernel m_t can be derived as follows

$$\begin{aligned}
m_{t+1} &\equiv \log(M_{t+1}) = \log \beta \frac{U_c(C_{t+1}, H_{t+1})}{U_c(C_t, H_t)} = \log \beta \left(\frac{S_{t+1}}{S_t} \frac{C_{t+1}}{C_t} \right)^{-1} \\
&= \log \beta + \Delta \gamma_{t+1} - \Delta c_{t+1} \\
&= \log \beta + \kappa_\gamma(\bar{\gamma} - \gamma_t) - g - \underbrace{[1 + \alpha_\gamma(\gamma_t - \theta_\gamma)]}_{\hat{\gamma}_t} [\sigma(\rho_{t+1}\epsilon_{w,t+1} + \sqrt{1 - \rho_{t+1}^2}\epsilon_{t+1}) + \sigma_{w,t+1}\epsilon_{w,t+1}]
\end{aligned}$$

V.B Risk-Free Rates

Given the log-normal assumption of the pricing kernel, the time-varying risk free rates can be simplified to

$$\begin{aligned}
i_t &= -\log E_t(M_{t+1}) = -[E_t(m_{t+1}) + \frac{1}{2}\sigma_t^2(m_{t+1})] \\
&= -\log \beta + g - \underbrace{\kappa_\gamma(\bar{\gamma} - \gamma_t)}_{\text{intertemporal substitution}} - \underbrace{\frac{1}{2}\hat{\gamma}_t^2[\sigma^2 + \sigma_{w,t+1}^2 + 2\sigma\sigma_{w,t+1}\rho_{t+1}]}_{\text{precautionary saving}} \quad (10)
\end{aligned}$$

When the precautionary saving term dominates intertemporal substitution effect, interest rates become procyclical, which we will assume in this paper. We define (*) as a foreign country. The interest differentials between foreign (*) and domestic rates boil down to

$$i_t^* - i_t = -\kappa_\gamma(\hat{\gamma}_t - \hat{\gamma}_t^*) + \frac{1}{2}(\hat{\gamma}_t^2 - \hat{\gamma}_t^{*2})[\sigma^2 + \sigma_{w,t+1}^2] + (\rho_{t+1}\hat{\gamma}_t^2 - \rho_{t+1}^*\hat{\gamma}_t^{*2})\sigma\sigma_{w,t+1}$$

V.C Real Exchange Rates

With a complete financial market assumption, there is a unique stochastic discount factor (SDF) that satisfies the following N systems of equations simultaneously: $E_t(M_{t+1}^i R_{t+1}^i) = 1$ and $E_t(M_{t+1} R_{t+1}^i \frac{Q_{t+1}^i}{Q_t^i}) = 1$ where Q is the real exchange rates measured in home country goods per foreign country i 's good. As a result, the change in log real exchange rate (Δq_{t+1}^*) is given by

$$\begin{aligned}
\Delta q_{t+1}^* &= m_{t+1}^* - m_{t+1} \\
&= \kappa_\gamma (\hat{\gamma}_t - \hat{\gamma}_t^*) \\
&\quad - \hat{\gamma}_t^* [\sigma \sqrt{1 - \rho_{t+1}^{*2}} \epsilon_{t+1}^* + (\sigma \rho_{t+1}^* + \sigma_{w,t+1}) \epsilon_{w,t+1}] \\
&\quad + \hat{\gamma}_t [\sigma \sqrt{1 - \rho_{t+1}^2} \epsilon_{t+1} + (\sigma \rho_{t+1} + \sigma_{w,t+1}) \epsilon_{w,t+1}]
\end{aligned} \tag{11}$$

The exchange rate premium, or excess return of the currency ($\Delta \pi_{t+1}^*$), is defined as the return for an investor who borrows funds at a domestic risk-free rate, converts them to foreign currency, lends them at foreign risk free rate at time t , and converts the money back to domestic currency at time $t+1$ once she collects the money from a foreign borrower.

$$\begin{aligned}
\Delta \pi_{t+1}^* &= \Delta q_{t+1}^* + i_t^* - i_t \\
&= \frac{1}{2} (\hat{\gamma}_t^2 - \hat{\gamma}_t^{*2}) [\sigma^2 + \sigma_{w,t+1}^2] + (\rho_{t+1} \hat{\gamma}_t^2 - \rho_{t+1}^* \hat{\gamma}_t^{*2}) \sigma \sigma_{w,t+1} \\
&\quad - \hat{\gamma}_t^* [\sigma \sqrt{1 - \rho_{t+1}^{*2}} \epsilon_{t+1}^* + (\sigma \rho_{t+1}^* + \sigma_{w,t+1}) \epsilon_{w,t+1}] \\
&\quad + \hat{\gamma}_t [\sigma \sqrt{1 - \rho_{t+1}^2} \epsilon_{t+1} + (\sigma \rho_{t+1} + \sigma_{w,t+1}) \epsilon_{w,t+1}]
\end{aligned} \tag{12}$$

V.D The Model Implied Consumption Correlation

Under the specification of the model in Equation 9, consumption correlation between two countries (i and j) is defined as

$$\begin{aligned}
corr_{t+1}^{i,j} &= corr(\Delta c_{t+1}^i - E_t[\Delta c_{t+1}^i], \Delta c_{t+1}^j - E_t[\Delta c_{t+1}^j]) \\
&= \frac{cov(\Delta c_{t+1}^i - E_t[\Delta c_{t+1}^i], \Delta c_{t+1}^j - E_t[\Delta c_{t+1}^j])}{\sqrt{var(\Delta c_{t+1}^i - E_t[\Delta c_{t+1}^i]) * var(\Delta c_{t+1}^j - E_t[\Delta c_{t+1}^j])}} \\
&= \underbrace{\frac{\sigma_{w,t+1}^2}{\sigma^2 + \sigma_{w,t+1}^2}}_{\Psi_{t+1}} * \frac{1 + (\frac{\sigma}{\sigma_{w,t+1}})(\rho_{t+1}^i + \rho_{t+1}^j) + (\frac{\sigma}{\sigma_{w,t+1}})^2 \rho_{t+1}^i \rho_{t+1}^j}{\sqrt{1 + 2(\frac{\sigma \sigma_{w,t+1}}{\sigma^2 + \sigma_{w,t+1}^2})(\rho_{t+1}^i + \rho_{t+1}^j) + 4(\frac{\sigma \sigma_{w,t+1}}{\sigma^2 + \sigma_{w,t+1}^2})^2 \rho_{t+1}^i \rho_{t+1}^j}}
\end{aligned}$$

Note that Ψ_{t+1} does not depend on any particular selection of countries and thus can be considered a common driver of the global consumption correlation across countries. The global correlation level is high when the conditional volatility of global shock is elevated relative to the volatility of a country-specific shock. In other words, it is high when the consumption shock is expected to be more likely driven by global shock. Since we have $E_t[\Psi_{t+1}] = \Psi_{t+1}$ due to GARCH specification for conditional volatility, the expected excess return of any currency or currency portfolio can be written as

$$\begin{aligned}
E_t[\Delta \pi_{t+1}^*] &= \frac{1}{2}(\hat{\gamma}_t^2 - \hat{\gamma}_t^{*2})\sigma^2 \\
&+ \frac{1}{2}(\hat{\gamma}_t^2 - \hat{\gamma}_t^{*2})[\sigma^2 + \sigma_{w,t+1}^2]\Psi_{t+1} \\
&+ (\rho_{t+1}\hat{\gamma}_t^2 - \rho_{t+1}^*\hat{\gamma}_t^{*2})\sigma\sqrt{\sigma^2 + \sigma_{w,t+1}^2}\sqrt{\Psi_{t+1}}
\end{aligned}$$

The currency risk premium required by investors for holding currency (*) depends on both domestic and foreign risk aversion coefficients. Across time, for a given level of consumption volatility and correlation, domestic investors require greater currency excess return when they are more risk averse (high γ_t). This countercyclical risk premium shares the

same intuition with Lustig, Roussanov, and Verdelhan (Forthcoming) and Verdelhan (2010). Cross-sectionally, investors demand high compensation for bearing global correlation risk because of holding a currency of a country with a low risk aversion coefficient (low γ_t^*) and low interaction between idiosyncratic correlation and the risk aversion coefficient (low $\rho_{t+1}^* \hat{\gamma}_t^{*2}$).

The ex-post unexpected excess return of holding a portfolio of currency set (*) is given by

$$\begin{aligned} \Delta \overline{\pi_{t+1}^*} - E_t[\Delta \overline{\pi_{t+1}^*}] &= \hat{\gamma}_t \sigma \sqrt{1 - \rho_{t+1}^2} \epsilon_{t+1} - \hat{\gamma}_t^* \sigma \sqrt{1 - \rho_{t+1}^{*2}} \epsilon_{t+1}^* \\ &\quad + [(\hat{\gamma}_t - \overline{\hat{\gamma}_t^*}) \sigma_{w,t+1} + (\rho_{t+1} \hat{\gamma}_t - \overline{\rho_{t+1}^* \hat{\gamma}_t^*}) \sigma] \epsilon_{w,t+1} \end{aligned} \quad (13)$$

The first term on the right side of Equation 13 is about countercyclical risk premia as it carries greater domestic consumption risk when γ_t is high. If the number of currencies in portfolio (*) is large enough, the idiosyncratic foreign consumption shocks cancel each other out. Thus, the second term would have a marginal effect on risk premia. The last term shows that the payoffs from a portfolio of currencies that have a relatively low level of risk aversion rate or low level of interaction term positively co-move with global consumption shocks. Equation 13 also illustrates that the cross-sectional differences in loading on the global consumption risk only depend on two terms, portfolio $\overline{\hat{\gamma}_t^*}$ and $\overline{\rho_{t+1}^* \hat{\gamma}_t^*}$. The lower the two terms, the more positively related the payoffs from portfolios to the global consumption shock. Therefore, those portfolios that have relatively low $\overline{\hat{\gamma}_t^*}$ or low $\overline{\rho_{t+1}^* \hat{\gamma}_t^*}$ are considered more risky and investors will require a greater rate of return as compensation.

We show that, on one hand, portfolios of currencies with high interest rates have lower $\overline{\hat{\gamma}_t^*}$ but no significant pattern for $\overline{\rho_{t+1}^* \hat{\gamma}_t^*}$. On the other hand, portfolios of currencies with high momentum have lower $\overline{\rho_{t+1}^* \hat{\gamma}_t^*}$ but no significant pattern for $\overline{\hat{\gamma}_t^*}$. In other words, sorting currencies by interest rate differentials is nothing more than sorting by average risk aversion rates of countries, and sorting currencies by momentum is essentially sorting by the interaction term, idiosyncratic consumption correlations and risk aversion rates.

To illustrate this relation, we perform a Monte-Carlo simulation. We first simulate the

consumption dynamics of 48 countries, and drive the changes in spot rates and excess returns of the corresponding currencies through Equation 11 and 12. To be consistent with our empirical analysis, we create five carry portfolios sorted on interest differentials and five momentum portfolios sorted on the past three month excess returns. On the left panel of **Figure 5**, we plot time-series of the average $\hat{\gamma}_t^*$ of the highest and the lowest interest portfolios from the simulation. The average $\hat{\gamma}_t^*$ of the portfolio with low interest rate currencies is persistently higher than the average $\hat{\gamma}_t^*$ of the portfolio with high interest rate currencies. We do not find this persistent gap in the average $\hat{\gamma}_t^*$ in the cross-section of momentum portfolios. The right side of **Figure 5** shows the average $\rho_{t+1}^* \hat{\gamma}_t^*$ of the highest and the lowest momentum portfolios. The average $\rho_{t+1}^* \hat{\gamma}_t^*$ of the portfolio with low momentum currencies is persistently higher than the average $\rho_{t+1}^* \hat{\gamma}_t^*$ of the portfolio with high momentum currencies. We do not find this persistent gap in the average $\rho_{t+1}^* \hat{\gamma}_t^*$ in the cross-section of carry portfolios. Thus, this simulation exercise confirms the idea that carry portfolios are closely related to the risk aversion coefficient, whereas momentum portfolios are closely related to the interaction between the risk aversion coefficient and country-specific correlation.

We now turn our attention to the ex-post unexpected excess return on the long (L) - short (S) portfolios. Doing so gives us a better representation of the sources of risk driving the excess returns in the long and short portfolios. Using equation 13 and taking first difference of the ex-post unexpected excess return of long and short portfolios gives

$$\begin{aligned} \Delta \pi_{t+1}^{L-S} - E_t[\Delta \pi_{t+1}^{L-S}] &\approx [(\hat{\gamma}_t^S - \hat{\gamma}_t^L) \sigma_{w,t+1} + (\rho_{t+1}^S \hat{\gamma}_t^S - \rho_{t+1}^L \hat{\gamma}_t^L) \sigma] \epsilon_{w,t+1} \\ &\approx \underbrace{-[(\hat{\gamma}_t^S - \hat{\gamma}_t^L) \sigma_{w,t+1}]}_{(1)} + \underbrace{(\rho_{t+1}^S \hat{\gamma}_t^S - \rho_{t+1}^L \hat{\gamma}_t^L) \sigma}_{(2)} \Delta \Psi_{t+1} \end{aligned}$$

The payoff from any currency long-short portfolio is no longer exposed to a domestic consumption shock but only exposed to a global consumption shock. Second, the degree of exposure to global shock depends on the gap between (1) the risk aversion coefficient and (2) interaction between the idiosyncratic correlation and risk aversion coefficient of the long

and short portfolios. Last, a large negative consumption shock is closely related to a large positive innovation to the global correlation level due to asymmetric response.

We also perform Monte-Carlo simulation experiments to elaborate further on the model implied risk-return relationship. **Figure 6** plots the time-series decomposition of shocks from the traditional long-short carry trades and the long-short momentum trades. The carry trade on the left panel shows a persistently positive pattern for the first component but no systematic pattern for the second component. For momentum trades, on the other hand, there is a persistent positive pattern for the second component and it dominates the first component. Therefore, when the terms are combined, the payoffs from traditional carry and momentum trades would have negative loading on innovations to the global consumption correlation. This finding explains our results in the empirical section where we find negatively significant price of beta risk for our correlation factor.

Throughout the theoretical section, we have relied on countries' consumption correlation as a source of risk while it is the global equity correlation that is of interest to us in the empirical section. It is straightforward to show that in our theoretical setting global equity correlation innovation is actually capturing the same information as the global consumption correlation innovation. To show the relation between our model global equity correlation as a function of consumption correlation, we first simulate the consumption dynamics of 48 countries, and drive equity returns using numerical integration. A time-series of the global consumption correlation level is given by the equation for Ψ_{t+1} and that of the global equity correlation level is estimated by running the DECO model on the simulated equity return series. **Figure 7** plots the time-series of the global consumption levels and innovations (solid blue line) and the equity correlation levels and innovations (dotted red lines) in the upper and lower panel, respectively. The figure shows that they are essentially measuring the same thing, hence using equity correlation in the empirical setting is motivated by our model.

VI Conclusion

Carry and momentum trades are a widely known speculative strategies in the FX markets. As the strategies draw more attention from global investors, there have been recent developments to create benchmark indices and ETFs reflecting this popularity in FX carry and momentum. These strategies have also received a great deal of attention in the academic literature to explain their abnormal profitability. Despite this popularity, the risk based explanations in the literature have not been very successful in simultaneously explaining their returns. In this paper, we build a factor which governs the evolution of co-movements in the international equity markets and show that it explains the cross-sectional differences in the excess return of carry and momentum portfolios. We find that FX portfolios which deliver high average excess returns are negatively related to innovations in the global equity correlation. The differences in exposure to our correlation factor can explain the systematic variation in average excess returns of portfolios sorted on interest rates and momentums simultaneously. Furthermore, we derive the condition under which investors should demand high compensation for bearing the global correlation risk. From the decomposition of FX risk premia, we show that the cross-sectional differences in loading on the correlation factor depend on two terms, the portfolio average risk aversion coefficient and the interaction between the risk aversion coefficient and country-specific correlation. We demonstrate that carry portfolios are closely related to the former term, whereas momentum portfolios are closely related to the latter term. Taking both terms together, we show that the payoffs from both carry and momentum trades positively co-move with our global correlation innovation.

While a large body of the FX literature explores the linkages between economic fundamentals and carry and momentum strategies, our global equity correlation factor bridges both the FX and international equity markets. By showing that a factor constructed from the international equity market can explain abnormal returns in the FX market, we shed light on the cross-market integration where premiums in two different markets are driven by

the same aggregate risk. A useful extension of this study would be to investigate the role of currency risk in equity market contagion. Identifying crisis and non-crisis periods through our global correlation factor may help to link a contagion indicator in one market to the other market. We leave this cross-market contagion for future research.

VII Appendix: Cross-Sectional Asset Pricing Model

Let f be a K -vector of factors, R be a vector of returns on N test assets with mean μ_R and covariance matrix V_R , and β be the $N \times K$ matrix of multiple regression betas of the N assets with respect to the K factors. Let $Y_t = [f'_t, R'_t]'$ be an $N + K$ vector. Denote the mean and variance of Y_t as

$$\mu = E[Y_t] = \begin{bmatrix} \mu_f \\ \mu_R \end{bmatrix} \quad (14)$$

$$V = Var[Y_t] = \begin{bmatrix} V_f & V_{fR} \\ V_{Rf} & V_R \end{bmatrix} \quad (15)$$

If the K factor asset pricing model holds, the expected returns of the N assets are given by

$$\mu_R = X\gamma \quad (16)$$

where $X = [1_N, \beta]$ and $\gamma = [\gamma_0, \gamma'_1]'$ is a vector consisting of the zero-beta rate and risk premia on the K factors. In a constant beta case, the popular two-pass cross-sectional regression

(CSR) method first obtains estimates $\hat{\beta}$ by running the following multivariate regression:

$$R_t = \alpha + \beta f_t + \epsilon_t, \quad t = 1, \dots, T \quad (17)$$

$$\hat{\beta} = \hat{V}_{Rf} \hat{V}_f^{-1} \quad (18)$$

$$\gamma_W = \operatorname{argmin}_{\gamma} (\mu_R - X\gamma)' W (\mu_R - X\gamma) = (X' W X)^{-1} X' W \mu_R \quad (19)$$

$$\hat{\gamma} = (\hat{X}' W \hat{X})^{-1} \hat{X}' W \hat{\mu}_R \quad (20)$$

where $W = I_N$ under OLS CSR and $W = \Sigma^{-1} = (V_R - V_{Rf} V_f^{-1} V_{fR})^{-1}$ under GLS CSR (or equivalently use $W = V_R^{-1}$).

A normalized goodness-of-fit measure of the model (cross-sectional R^2) can be defined as

$$\rho_W^2 = 1 - \frac{Q}{Q_0} \quad (21)$$

where $Q = e'_W W e_W$, $Q_0 = e'_0 W e_0$,

and $e_W = [I_N - X(X' W X)^{-1} X' W] \mu_R$, $e_0 = [I_N - 1_N(1'_N W 1_N)^{-1} 1'_N W] \mu_R$

Shanken (1992) provides asymptotic distribution of γ adjusted for the errors-in-variables problem when we need to account for the estimation errors in β . For OLS CSR, and GLS CSR,

$$\begin{aligned} \sqrt{T}(\tilde{\gamma} - \gamma) &\stackrel{A}{\sim} N(0_{K+1}, (1 + \gamma' V_f^{-1} \gamma)(X' X)^{-1} (X' \Sigma X)(X' X)^{-1} + \begin{bmatrix} 0 & 0'_K \\ 0_K & V_f \end{bmatrix}) \\ \sqrt{T}(\tilde{\gamma} - \gamma) &\stackrel{A}{\sim} N(0_{K+1}, (1 + \gamma' V_f^{-1} \gamma)(X' \Sigma X)^{-1} + \begin{bmatrix} 0 & 0'_K \\ 0_K & V_f \end{bmatrix}) \end{aligned} \quad (22)$$

Kan, Robotti, and Shanken (2012) further investigate the asymptotic distribution of $\hat{\gamma}$ under potentially misspecified models as well as under the case when the factors and returns are i.i.d. multivariate elliptically distribution (rather than i.i.d normal). The distribution is

given by

$$\sqrt{T}(\check{\gamma} - \gamma) \overset{A}{\rightsquigarrow} N(0_{K+1}, V(\hat{\gamma})) \quad (23)$$

$$V(\hat{\gamma}) = \sum_{j=-\infty}^{\infty} E[h_t h'_{t+j}] \quad (24)$$

$$h_t = (\gamma_t - \gamma) - (\theta_t - \theta)w_t + Hz_t \quad (25)$$

where $\theta_t = [\gamma_{0t}, (\gamma_{1t} - f_t)']'$, $\theta = [\gamma_0, (\gamma_1 - \mu_f)']'$, $u_t = e'W(R_t - \mu_R)$, $w_t = \gamma_1' V_f^{-1}(f_t - \mu_f)$, and $z_t = [0, u_t(f_t - \mu_f)' V_f^{-1}]'$. Note that the term h_t is now specified with three terms which are the asymptotic variance of γ when the true β is used, the errors-in-variables (EIV) adjustment term, and the misspecification adjustment term. Please see Kan, Robotti, and Shanken (2012) for details of the estimation.

An alternative specification will be in terms of the $N \times K$ matrix V_{Rf} of covariances between returns and the factors.

$$\mu_R = X\gamma = C\lambda \quad (26)$$

$$\hat{\lambda} = (\hat{C}'W\hat{C})^{-1}\hat{C}'W\hat{\mu}_R \quad (27)$$

where $C = [1_N, V_{RF}]$ and $\lambda_W = [\lambda_{W,0}, \lambda'_{W,1}]'$.

Although the pricing errors from this alternative CSR are the same as those in the one using β above (thus the cross-sectional R^2 will also be the same), they emphasize the differences in the economic interpretation of the pricing coefficients. In fact, according to the paper, what matters is whether the price of covariance risk associated additional factors is nonzero if we want to answer whether the extra factors improve the cross-sectional R^2 . Therefore, we apply both tests based on λ as well as β in the empirical testing. They also have shown how to use the asymptotic distribution of the sample $R^2(\hat{\rho})$ in the second-pass CSR as the basis for a specification test. Testing $\hat{\rho}$ also crucially depends on the value of ρ .

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Table I
Descriptive Statistics

The table reports statistics for the annualized excess currency returns of currency portfolios sorted by the following procedures. 1. (Carry) portfolios are sorted on time t-1 forward discounts, 2. (MoM) portfolios on their excess return over the last 3 month. All portfolios are rebalanced at the end of each month and the excess returns are adjusted for transaction costs (bid-ask spread). The portfolio 1 contains the 20% of currencies with the lowest measures, whilst portfolio 5 contains currencies with highest measures. HML denotes the difference in returns between portfolio 5 and 1, and HAC standard error of Newey West (1987) is used for t-test. The excess returns cover the period March 1976 to November 2013.

All Currencies (48)

1. (Carry) Portfolios Sorted on Forward Discount

Portfolio	1	2	3	4	5	HML*(5-1)
Mean	-1.60	-0.13	1.76	2.85	4.21	5.80
Median	-1.20	1.28	2.49	4.06	8.95	9.85
Std. Dev	9.21	9.25	8.54	8.98	10.38	8.37
Skewness	-0.12	-0.45	-0.01	-0.43	-1.11	-1.92
Kurtosis	4.37	4.60	4.07	4.63	6.79	13.51
Sharpe Ratio	-0.17	-0.01	0.21	0.32	0.41	0.69

* t-stats (HML) = 4.78

2. (MoM) Portfolios Sorted on Past Excess Return

Portfolio	1	2	3	4	5	HML*(5-1)
Mean	-1.79	-1.13	0.64	1.89	5.60	7.39
Median	-0.30	0.75	1.33	1.81	6.30	7.31
Std. Dev	9.69	9.40	9.27	9.11	9.15	8.33
Skewness	-0.24	-0.42	-0.22	-0.30	-0.32	-0.11
Kurtosis	4.69	4.52	4.54	4.14	4.60	3.86
Sharpe Ratio	-0.19	-0.12	0.07	0.21	0.61	0.89

* t-stats (HML) = 5.44

Developed Market Currencies (17)

1. (Carry) Portfolios Sorted on Forward Discount

Portfolio	1	2	3	4	5	HML*(5-1)
Mean	-0.86	-0.70	1.65	2.59	4.31	5.17
Median	-0.26	0.71	3.28	3.98	5.26	9.53
Std. Dev	10.02	9.92	9.23	9.90	11.37	9.65
Skewness	0.01	-0.25	-0.16	-0.42	-0.60	-0.96
Kurtosis	3.72	4.01	4.28	4.93	5.14	6.18
Sharpe Ratio	-0.09	-0.07	0.18	0.26	0.38	0.54

* t-stats (HML) = 2.88

2. (MoM) Portfolios Sorted on Past Excess Return

Portfolio	1	2	3	4	5	HML*(5-1)
Mean	-1.75	1.41	0.75	1.71	3.61	5.37
Median	-0.64	2.14	2.18	2.94	4.36	7.08
Std. Dev	10.18	10.20	10.40	9.82	9.96	9.66
Skewness	-0.12	-0.22	-0.42	-0.16	-0.20	-0.06
Kurtosis	4.91	4.18	4.21	3.91	4.17	3.72
Sharpe Ratio	-0.17	0.14	0.07	0.17	0.36	0.56

* t-stats (HML) = 4.44

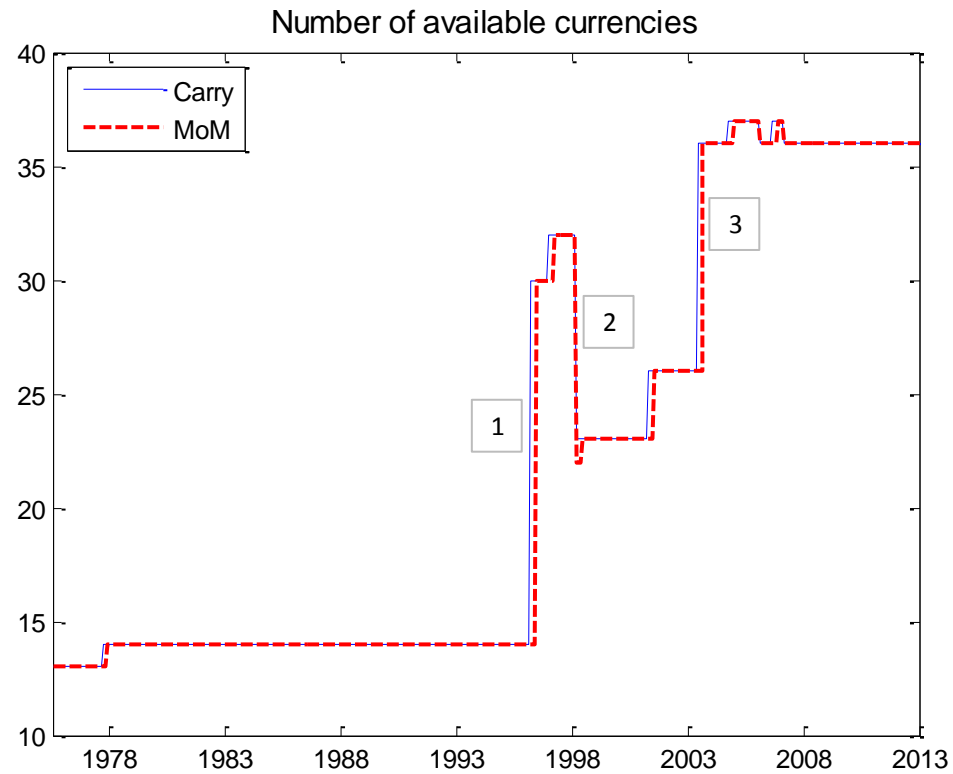


Figure 1. The figure shows a time-series plot of number of available currencies to construct carry portfolios (blue line) and momentum portfolios (dotted red line).

1. December 1996: The increase in the number of currencies is due to merger of two separate dataset (one denominated in GBP, the other denominated in USD).
2. January 1999: The decrease is due to introduction of EURO.
3. March 2004: The increase is due to inclusion of many emerging market currencies

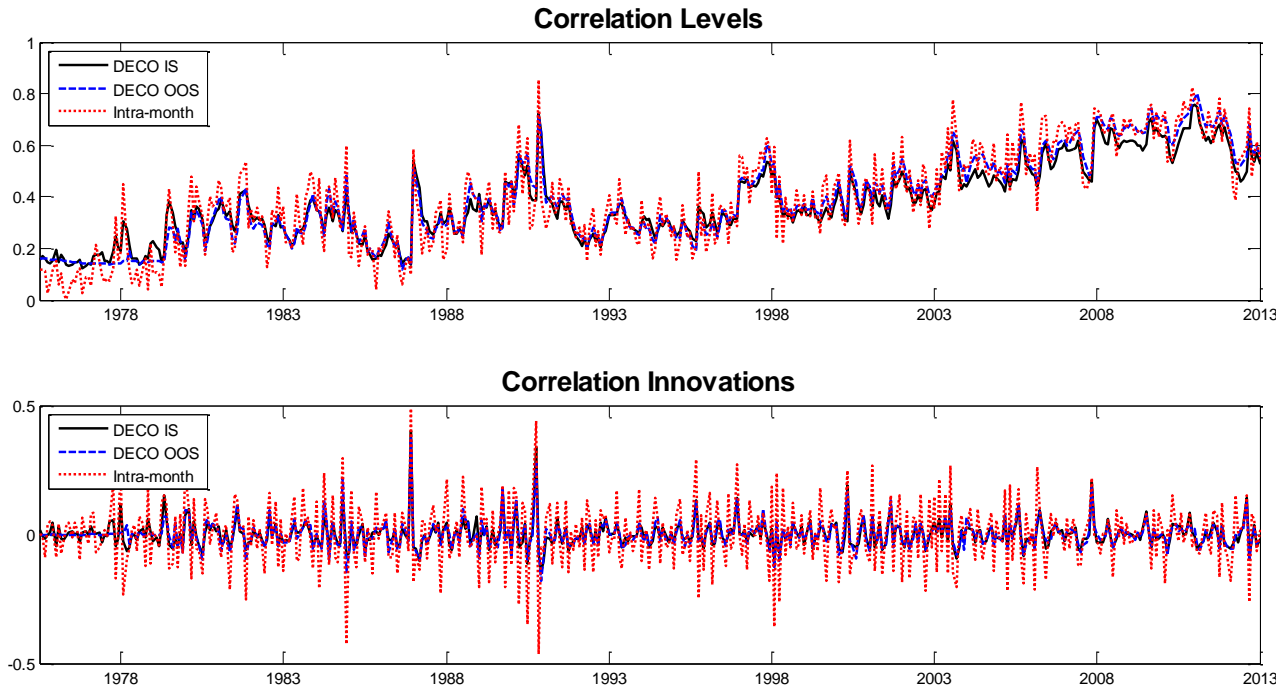


Figure 2. The upper panel of the figure shows a time-series plot of the global equity correlation levels. The solid black line, DECO IS (in-sample), is measured by DECO model (Engle and Kelly, 2012) where parameters are estimated on the entire monthly return series of international indices. The dotted blue line, DECO OOS (out-of-sample), is measured by the same model where parameters are estimated on the data available only at the point in time and updated with expanding window as we collect more data. The dotted red line, correlation level is measured by computing bilateral intra-month correlations at each month end using daily return series of international indices and then average over all bilateral correlations of the particular month. The lower panel shows a time-series plot of the global equity correlation innovations. The correlation innovations are measured by taking first difference of each of the correlation level series respectively. The sample covers the period March 1976 to November 2013.

Statistics for Factors	1. DECO IS Innovation	2. DECO OOS Innovation	3. Intra-Month Innovation
Mean (Monthly)	0.001	0.001	0.001
Volatility (Monthly)	0.051	0.051	0.119
Augmented Dicky-Fuller test (p-val)	0.001	0.001	0.001
AR(1) coefficient	-0.015	-0.037	-0.364
Ljung-Box Test (p-val)	0.744	0.432	0.000
Breusch-Godfrey Test (p-val)	0.740	0.491	0.000

* Augmented Dicky-Fuller test is a test for a unit root (H_0 = Unit root is present), Ljung-box test and Breusch-Godfrey test are tests for serial dependence (H_0 = No serial correlation is present)

Correlation across the factors			
Correlation Level	DECO IS	DECO OOS	Intra-month
DECO IS	1.00	0.99	0.94
DECO OOS	0.99	1.00	0.94
Intra-month	0.94	0.94	1.00

Correlation Innovation	DECO IS	DECO OOS	Intra-month
DECO IS	1.00	0.92	0.76
DECO OOS	0.92	1.00	0.76
Intra-month	0.76	0.76	1.00

**Table II. Cross-Sectional Regression (CSR) Asset Pricing Tests
: Equity Correlation Innovation (DECO OOS) on FX 10 Portfolios**

The table reports cross-sectional pricing results for the factor model based on the dollar risk factor (DOL) and Global Equity Correlation Innovation where the correlation levels are measured by DECO model (ΔEQ_corr). The test assets are the set of sorted carry portfolios (1-5), and the set of sorted momentum portfolios (1-5). Panel 1. on the left reports estimation results for test assets constructed using currencies from all 48 countries and the panel on the right reports estimation results for test assets constructed using currencies from 17 developed market countries only. Market price of beta risk Υ (multiplied by 100), market price of covariance risk λ , the Shanken (1992) and the Jagannathan and Wang (1998) t-ratios under correctly specified models and account for the EIV problem: [$t-ratio(s)$ and $t-ratio(jw)$] and the Kan, Robotti, and Shanken (2012) misspecification-robust t-ratios: [$t-ratio(krs)$] are reported. $pval-1$ is the p-value for the test of $H_0: R^2 = 1$. $pval-2$ is the p-value for the test of $H_0: R^2 = 0$, $pval-3a$ and $pval-3b$ are the p-value for Wald test of $H_0: \Upsilon = 0$ with and without imposing price of beta is zero under the null respectively. Panel 2 shows beta estimation results for time-series regressions of excess returns on a constant, the dollar risk factor (DOL) and Global Equity Correlation Innovation (ΔEQ_corr). HAC standard errors are reported in parentheses. Data are monthly and the sample covers the period March 1976 to November 2013.

Panel 1. Factor Prices									
All Countries (48)					Developed Countries (17)				
Factor:	DOL	ΔEQ_corr	R^2	0.907	Factor:	DOL	ΔEQ_corr	R^2	0.643
Υ	0.107	-8.745	$pval-1$	0.612	Υ	0.091	-5.263	$pval-1$	0.102
$t-ratio(s)$	0.929	-3.829	$pval-2$	0.001	$t-ratio(s)$	0.727	-3.099	$pval-2$	0.017
$t-ratio(jw)$	0.932	-3.488	$pval-3a$	0.000	$t-ratio(jw)$	0.726	-2.906	$pval-3a$	0.001
$t-ratio(krs)$	0.932	-3.366	$pval-3b$	0.002	$t-ratio(krs)$	0.724	-2.315	$pval-3b$	0.002
λ	1.354	-33.20			λ	0.843	-19.98		
$t-ratio(s)$	0.355	-3.710			$t-ratio(s)$	0.330	-3.034		
$t-ratio(jw)$	0.296	-3.022			$t-ratio(jw)$	0.284	-2.659		
$t-ratio(krs)$	0.296	-2.935			$t-ratio(krs)$	0.286	-2.205		

Descriptions

Υ : Coefficients on beta risk

λ : Coefficients on covariance risk

$t-ratio(s)$: Shanken Error-in-Variables adjusted t-ratio

$t-ratio(jw)$: EIV t-ratio under general distribution assumption

$t-ratio(krs)$: Misspecification robust t-ratio

$pval-1$: p-value of testing $R^2 = 1$

$pval-2$: p-value of testing $R^2 = 0$ (without imposing $H_0: \Upsilon = 0_N$)

$pval-3a$: p-value of Wald $\Upsilon = 0_k$ ($H_0: \Upsilon = 0_N$)

$pval-3b$: p-value of Wald $\Upsilon = 0_k$ (without imposing $H_0: \Upsilon = 0_N$)

Panel 2. Factor Betas									
Carry					Momentum				
Portfolio	α	$\beta(DOL)$	$\beta(\Delta EQ_Corr)$	R^2	Portfolio	α	$\beta(DOL)$	$\beta(\Delta EQ_Corr)$	R^2
1	-0.003 (0.001)	0.993 (0.044)	0.031 (0.009)	0.832	6	-0.003 (0.001)	1.005 (0.040)	0.013 (0.011)	0.774
2	-0.002 (0.000)	1.034 (0.025)	0.018 (0.009)	0.893	7	-0.003 (0.001)	1.035 (0.026)	0.023 (0.008)	0.873
3	0.000 (0.000)	0.954 (0.025)	-0.007 (0.006)	0.892	8	-0.001 (0.000)	1.045 (0.017)	0.006 (0.007)	0.913
4	0.001 (0.000)	0.999 (0.029)	-0.004 (0.007)	0.891	9	0.000 (0.000)	1.001 (0.024)	-0.003 (0.008)	0.867
5	0.002 (0.001)	1.005 (0.034)	-0.037 (0.016)	0.702	10	0.003 (0.001)	0.893 (0.043)	-0.041 (0.014)	0.692

**Table III. Cross-Sectional Regression (CSR) Asset Pricing Tests
: Equity Correlation Innovation (Intra-month) on FX 10 Portfolios**

The table reports cross-sectional pricing results for the factor model based on the dollar risk factor (DOL) and Global Equity Correlation Innovation where the correlation levels are measured by intra-month realized correlation (ΔEQ_corr). The test assets are the set of sorted carry portfolios (1-5), and the set of sorted momentum portfolios (1-5). Panel 1. on the left reports estimation results for test assets constructed using currencies from all 48 countries and the panel on the right reports estimation results for test assets constructed using currencies from 17 developed market countries only. Market price of beta risk Υ (multiplied by 100), market price of covariance risk λ , the Shanken (1992) and the Jagannathan and Wang (1998) t-ratios under correctly specified models and account for the EIV problem: [$t\text{-ratio}(s)$ and $t\text{-ratio}(jw)$] and the Kan, Robotti, and Shanken (2012) misspecification-robust t-ratios: [$t\text{-ratio}(krs)$] are reported. $pval-1$ is the p-value for the test of $H_0: R^2 = 1$. $pval-2$ is the p-value for the test of $H_0: R^2 = 0$, $pval-3a$ and $pval-3b$ are the p-value for Wald test of $H_0: \Upsilon = 0$ with and without imposing price of beta is zero under the null respectively. Panel 2 shows beta estimation results for time-series regressions of excess returns on a constant, the dollar risk factor (DOL) and Global Equity Correlation Innovation (ΔEQ_corr). HAC standard errors are reported in parentheses. Data are monthly and the sample covers the period March 1976 to November 2013.

Panel 1. Factor Prices									
All Countries (48)					Developed Countries (17)				
Factor:	DOL	ΔEQ_corr	R^2	0.841	Factor:	DOL	ΔEQ_corr	R^2	0.373
Υ	0.146	-24.075	$pval-1$	0.569	Υ	0.093	-11.974	$pval-1$	0.004
$t\text{-ratio}(s)$	1.081	-3.362	$pval-2$	0.001	$t\text{-ratio}(s)$	0.742	-2.616	$pval-2$	0.088
$t\text{-ratio}(jw)$	1.046	-3.464	$pval-3a$	0.000	$t\text{-ratio}(jw)$	0.741	-2.548	$pval-3a$	0.043
$t\text{-ratio}(krs)$	1.047	-3.723	$pval-3b$	0.002	$t\text{-ratio}(krs)$	0.739	-1.986	$pval-3b$	0.016
λ	-2.107	-17.14			λ	-0.756	-8.52		
$t\text{-ratio}(s)$	-0.498	-3.278			$t\text{-ratio}(s)$	-0.286	-2.573		
$t\text{-ratio}(jw)$	-0.444	-3.396			$t\text{-ratio}(jw)$	-0.266	-2.545		
$t\text{-ratio}(krs)$	-0.450	-3.669			$t\text{-ratio}(krs)$	-0.272	-1.996		
Descriptions Υ : Coefficients on beta risk λ : Coefficients on covariance risk $t\text{-ratio}(s)$: Shanken Error-in-Variables adjusted t-ratio $t\text{-ratio}(jw)$: EIV t-ratio under general distribution assumption $t\text{-ratio}(krs)$: Misspecification robust t-ratio <p style="margin-left: 400px;"> $pval-1$: p-value of testing $R^2 = 1$ $pval-2$: p-value of testing $R^2 = 0$ (without imposing $H_0: \Upsilon = 0_N$) $pval-3a$: p-value of Wald $\Upsilon = 0_k$ ($H_0: \Upsilon = 0_N$) $pval-3b$: p-value of Wald $\Upsilon = 0_k$ (without imposing $H_0: \Upsilon = 0_N$) </p>									
Panel 2. Factor Betas									
Portfolio	Carry				Portfolio	Momentum			
	α	$\beta(DOL)$	$\beta(\Delta EQ_Corr)$	R^2		α	$\beta(DOL)$	$\beta(\Delta EQ_Corr)$	R^2
1	-0.003 (0.001)	0.994 (0.044)	0.008 (0.005)	0.830	6	-0.003 (0.001)	1.007 (0.040)	0.006 (0.005)	0.774
2	-0.002 (0.000)	1.034 (0.025)	0.003 (0.003)	0.892	7	-0.003 (0.001)	1.038 (0.026)	0.015 (0.004)	0.875
3	0.000 (0.000)	0.954 (0.025)	0.001 (0.004)	0.892	8	-0.001 (0.000)	1.045 (0.017)	0.000 (0.003)	0.913
4	0.001 (0.000)	0.999 (0.029)	-0.003 (0.003)	0.891	9	0.000 (0.000)	1.001 (0.024)	-0.002 (0.004)	0.867
5	0.002 (0.001)	1.004 (0.035)	-0.008 (0.006)	0.698	10	0.003 (0.001)	0.890 (0.043)	-0.015 (0.005)	0.691

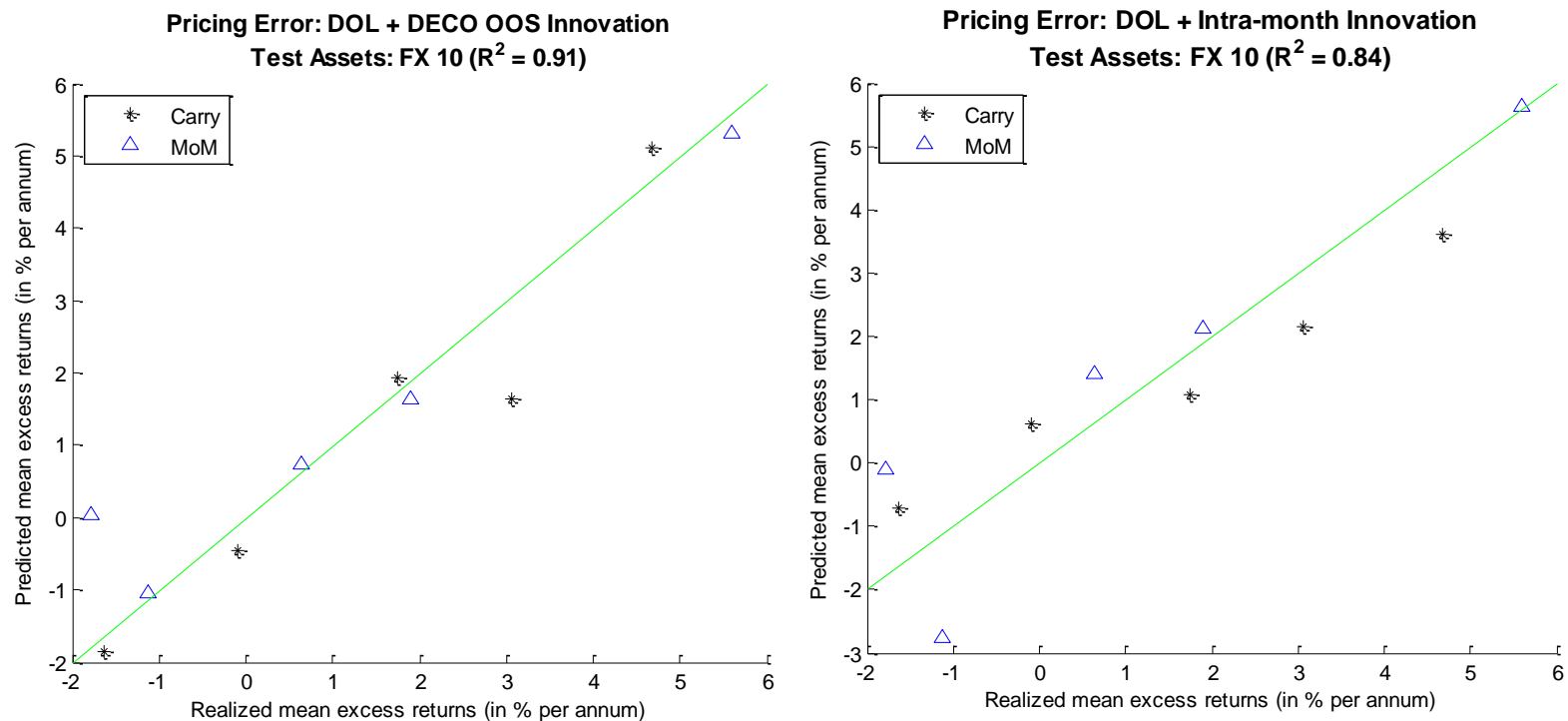


Figure 3. The figure shows pricing errors for asset pricing models with global equity correlation as the risk factor. The realized actual excess return is on the horizontal axis and the model predicted average excess return is on the vertical axis. The test assets are the set of sorted carry portfolios (5) and momentum portfolios (5), "FX 10". The estimation results are based on OLS CSR test while imposing the same price of beta/covariance risk for the test assets within each plot. The sample data are available on monthly frequency and cover the period March 1976 to November 2013.

Table IV. Cross-Sectional Regression (CSR) Asset Pricing Tests: All 10 Portfolios

The test assets are the set of sorted carry portfolios (1-5), and the set of sorted momentum portfolios (1-5).

Panel 1 and 2 reports cross-sectional pricing results for the factor model based on the dollar risk factor (DOL), a control factor X, and Global Equity Correlation Innovation factors: DECO OOS innovation (ΔEQ_corr_OOS) and Intra-month innovation (ΔEQ_corr_IM) respectively. Kan, Robotti, and Shanken (2012) misspecification-robust t-ratio: [t-ratio(krs)] is reported in parentheses under beta coefficient. The p-values for the test of $H_0: R^2 = 0$ is reported in parentheses under coefficient of determination.

Factor Description

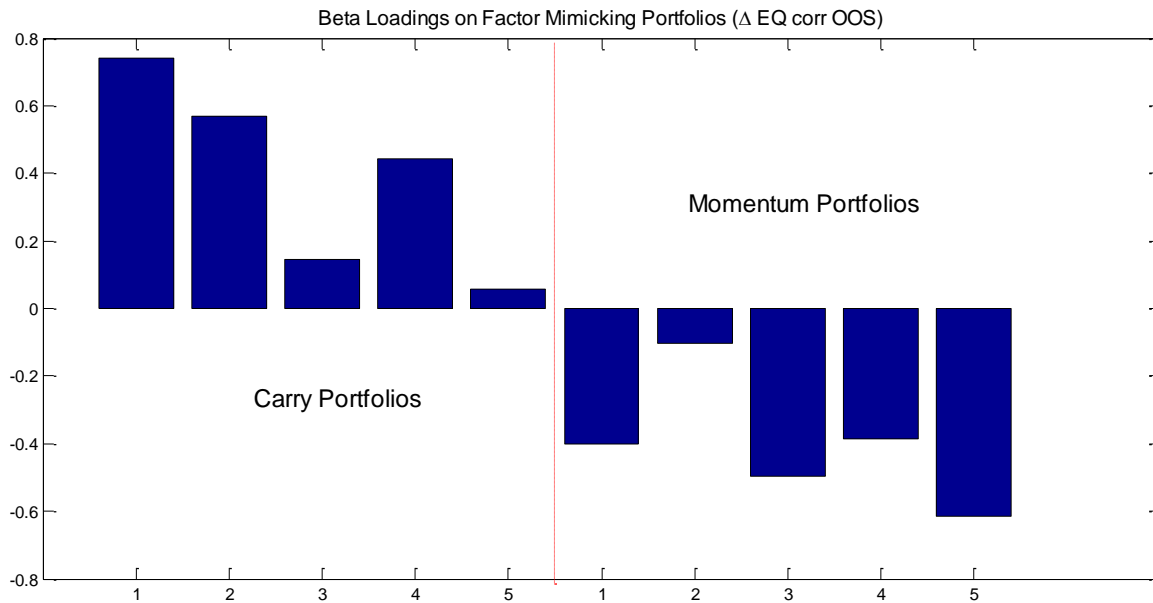
ΔFX_vol = global FX volatility innovationas (*Menkhoff, Sarno, Schmeling and Schrimpf, 2012 JF*), ΔFX_corr = global FX correlation innovations, ΔTED = TED spread innovation, ΔFX_BAS = Innovations to aggregate FX bid-ask spreads (*Mancini, Renaldo and Wrampelmeyer, 2013 JF*), ΔLIQ_PS = Pastor-Stambaugh liquidity innovation, EQ_MRP = Market risk premium, EQ_SMB = US equity sizefactor, EQ_HML = US equity value factor, EQ_MoM = US equity momentum factor, $Carry_HML$ = High-minus-low FX carry factor (*Lustig, Roussanov, and Verdelhan, 2011 RFS*), MoM_HML = High-minus-low FX momentum factor.

Descriptions	Controls	Panel 1				Panel 2			
		Beta			R ²	Beta			R ²
	X	DOL	X	ΔEQ_corr_OOS		DOL	X	ΔEQ_corr_IM	
FX moments	ΔFX_vol	0.11 (0.48)	-0.23 (0.50)	-9.38 (-2.76)	0.92 (0.09)	0.12 (-0.61)	-0.57 (-0.64)	-22.74 (-2.92)	0.87 (0.10)
	ΔFX_corr	0.11 (0.08)	-10.13 (-0.89)	-8.40 (-2.54)	0.95 (0.09)	0.12 (-0.48)	-7.67 (-0.26)	-23.49 (-3.03)	0.85 (0.11)
Liquidity	ΔTED	0.11 (0.58)	10.47 (0.75)	-9.43 (-2.94)	0.93 (0.09)	0.12 (-0.33)	0.38 (0.27)	-24.80 (-3.19)	0.85 (0.11)
	ΔFX_BAS	0.11 (0.24)	0.01 (0.60)	-8.79 (-2.99)	0.93 (0.09)	0.12 (-0.40)	-0.01 (-0.40)	-24.69 (-3.52)	0.86 (0.11)
	ΔLIQ_PS	0.12 (0.28)	-2.21 (-0.91)	-10.86 (-2.50)	0.93 (0.09)	0.12 (-0.28)	2.98 (0.34)	-21.93 (-2.32)	0.83 (0.12)
FF factors	EQ_MRP	0.11 (0.65)	0.92 (-0.77)	-9.21 (-3.02)	0.94 (0.09)	0.12 (-0.56)	2.18 (0.39)	-23.76 (-3.53)	0.85 (0.11)
	EQ_SMB	0.11 (0.19)	-1.15 (-0.68)	-9.23 (-2.77)	0.93 (0.09)	0.12 (-0.35)	1.77 (0.37)	-23.23 (-3.28)	0.85 (0.11)
	EQ_HML	0.10 (0.52)	2.65 (1.05)	-7.78 (-2.68)	0.95 (0.09)	0.11 (-0.15)	3.13 (0.81)	-22.41 (-3.08)	0.88 (0.10)
	EQ_MoM	0.11 (0.56)	3.71 (0.84)	-9.43 (-2.84)	0.95 (0.09)	0.12 (-0.37)	0.55 (0.20)	-24.26 (-3.55)	0.84 (0.11)
HML factors	$Carry_HML$	0.11 (0.27)	0.52 (-0.54)	-10.06 (-2.71)	0.92 (0.09)	0.11 (-0.40)	0.55 (0.78)	-20.97 (-3.26)	0.88 (0.10)
	MoM_HML	0.11 (0.47)	0.63 (0.96)	-7.40 (-2.38)	0.95 (0.09)	0.12 (-0.31)	0.61 (0.54)	-21.03 (-2.99)	0.85 (0.11)

Table V. Cross-Sectional Regression (CSR) Asset Pricing Tests: Factor Mimicking Portfolios

The table reports cross-sectional pricing results for the factor model based on the dollar risk factor (DOL) and Global Equity Correlation Innovation factors: DECO OOS innovation (ΔEQ_corr_OOS) and Intra-month innovation (ΔEQ_corr_IM) respectively. The factor mimicking portfolios are obtained by projecting the factor into FX 10 portfolio space. The test assets are the set of portfolios are sorted on time t-1 forward discounts for (Carry 5), the set of portfolios are sorted on their excess return over the last 3 month for (Momentum 5), the set of sorted Carry 5 and Momentum 5 portfolios for (FX10). Developed market currencies are used to construct the test assets for (DM FX 10). Kan, Robotti, and Shanken (2012) misspecification-robust t-ratio: $[t\text{-ratio}(krs)]$ is reported in parentheses under beta coefficient. The p-values for the test of $H_0: R^2 = 0$ is reported in parentheses under coefficient of determination.

		Carry 5		Momentum 5		FX 10		DM FX 10	
		Beta	R ²	Beta	R ²	Beta	R ²	Beta	R ²
Original	ΔEQ_corr_OOS	-7.77	0.93	-9.80	0.93	-8.74	0.91	-5.26	0.64
		(-2.54)	(0.13)	(-2.83)	(0.07)	(-2.94)	(0.00)	(-2.21)	(0.00)
	ΔEQ_corr_IM	-35.38	0.97	-20.79	0.85	-24.05	0.84	-11.97	0.37
		(-1.72)	(0.12)	(-3.42)	(0.09)	(-3.68)	(0.00)	(-2.00)	(0.04)
Mimicking	ΔEQ_corr_OOS	-0.34	0.92	-0.45	0.91	-0.39	0.88	-0.32	0.76
	(mimicking)	(-4.08)	(0.13)	(-4.96)	(0.07)	(-5.22)	(0.10)	(-3.97)	(0.25)
	ΔEQ_corr_IM	-1.37	0.95	-0.73	0.81	-0.85	0.79	-0.72	0.66
	(mimicking)	(-3.49)	(0.12)	(-5.69)	(0.09)	(-6.49)	(0.12)	(-4.36)	(0.28)



**Table VI. Cross-Sectional Regression (CSR) Asset Pricing Tests
: FX 10 Portfolios + 25 Size and Book-to-Market sorted portfolios**

The table reports cross-sectional pricing results for the factor model based on Fama/French factors. The test assets are the set of sorted carry (5), momentum (5) and Fama/French 25 portfolios (portfolios formed on Size and Book-to-Market ratio). MRP is the market risk premium, SMB is the small-minus-big size factor, HML is the high-minus-low value factor, DOL is the dollar factor, and ΔEQ_corr is the global equity correlation innovation where the correlation levels are measured by DECO model. Market price of beta risk Υ (multiplied by 100), market price of covariance risk λ , the Shanken (1992) and the Jagannathan and Wang (1998) t-ratios under correctly specified models and account for the EIV problem: [t-ratio(s) and t-ratio(jw)] and the Kan, Robotti, and Shanken (2012) misspecification-robust t-ratios: [t-ratio(krs)] are reported. pval-1 is the p-value for the test of $H_0: R^2 = 1$. pval-2 is the p-value for the test of $H_0: R^2 = 0$, pval-3a and pval-3b are the p-value for Wald test of $H_0: \Upsilon = 0$ with and without imposing price of beta is zero under the null respectively. HAC standard errors are reported in parentheses. Data are monthly and the sample covers the period March 1976 to November 2013.

Panel 1							
Factor:	MRP	SMB	HML	DOL	ΔEQ_corr	R^2	0.619
Υ				0.111	-2.808	<i>pval-1</i>	0.000
<i>t-ratio (s)</i>				0.962	-2.974	<i>pval-2</i>	0.330
<i>t-ratio (jw)</i>				0.966	-2.172	<i>pval-3a</i>	0.002
<i>t-ratio (krs)</i>				0.970	-2.186	<i>pval-3b</i>	0.060
λ				1.724	-10.66		
<i>t-ratio (s)</i>				0.780	-2.916		
<i>t-ratio (jw)</i>				0.697	-1.837		
<i>t-ratio (krs)</i>				0.705	-1.849		
Panel 2							
Factor:	MRP	SMB	HML	DOL	ΔEQ_corr	R^2	0.848
Υ	0.545	0.262	0.395	0.105	-4.592	<i>pval-1</i>	0.001
<i>t-ratio (s)</i>	2.529	1.774	2.703	0.906	-3.488	<i>pval-2</i>	0.091
<i>t-ratio (jw)</i>	2.537	1.774	2.692	0.909	-3.456	<i>pval-3a</i>	0.000
<i>t-ratio (krs)</i>	2.521	1.768	2.701	0.911	-2.253	<i>pval-3b</i>	0.000
λ	-1.721	0.673	6.434	2.224	-18.07		
<i>t-ratio (s)</i>	-0.788	0.264	2.626	0.827	-3.245		
<i>t-ratio (jw)</i>	-0.648	0.257	2.522	0.682	-3.067		
<i>t-ratio (krs)</i>	-0.457	0.231	2.419	0.653	-2.198		
Descriptions							
Υ : Coefficients on beta risk					pval-1: p-value of testing $R^2 = 1$		
λ : Coefficients on covariance risk					pval-2: p-value of testing $R^2 = 0$ (without imposing $H_0: \Upsilon = 0_N$)		
t-ratio (s): Shanken Error-in-Variables adjusted t-ratio					pval-3a: p-value of Wald $\Upsilon = 0_k$ ($H_0: \Upsilon = 0_N$)		
t-ratio (jw): EIV t-ratio under general distribution assumption					pval-3b: p-value of Wald $\Upsilon = 0_k$ (without imposing $H_0: \Upsilon = 0_N$)		
t-ratio (krs): Misspecification robust t-ratio							

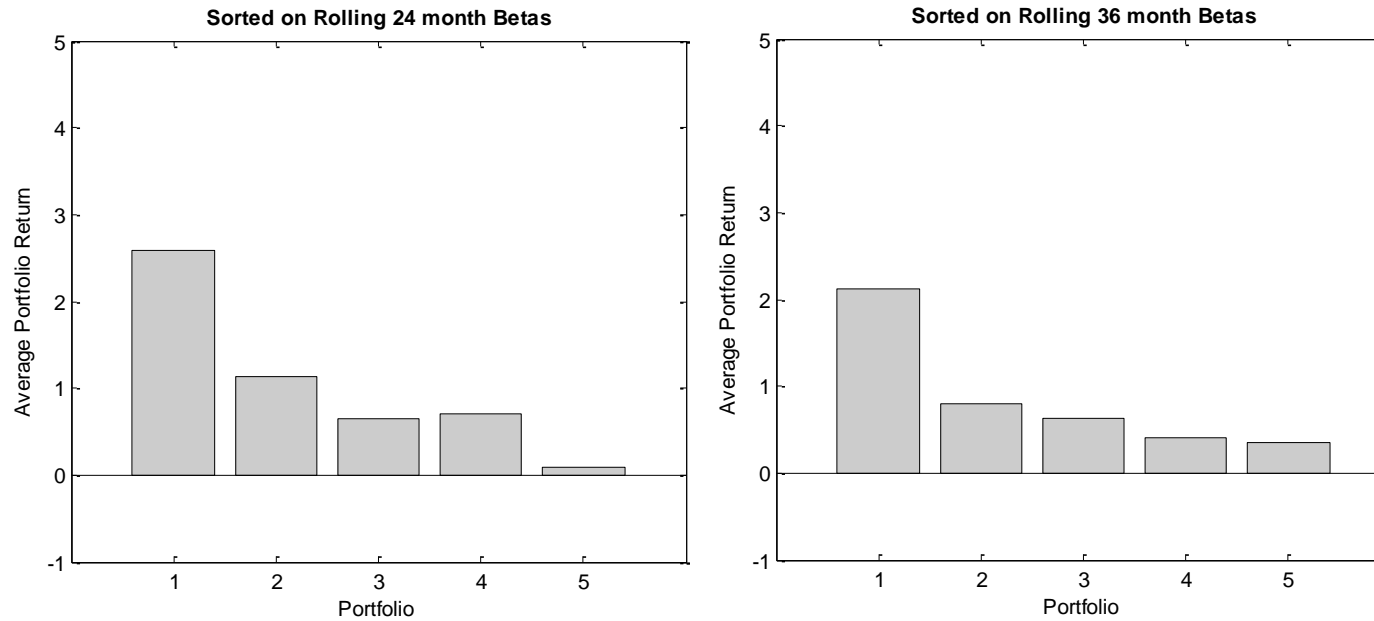


Figure 4. The figure reports average returns for the portfolios sorted on the correlation betas. Currencies are sorted according to their beta in a rolling time-series regression of individual currencies's excess returns on Global Equity Correlation Innovations. Portfolios are rebalanced at the end of each month t by sorting currencies into five groups based on beta coefficients available at time t . Each beta is obtained by regressing currency i 's excess return on the correlation innovation (ΔEQ_corr) on a 24-period moving window (left) or on a 36-period moving window (right). Portfolio 1 contains currencies with the lowest betas, whilst portfolio 5 contains currencies with highest betas. All moments are annualized and the excess returns are adjusted for transaction costs (bid-ask spread). The excess returns cover the period March 1976 to November 2013.

Table VII. GLS Cross-Sectional Regression (CSR) Asset Pricing Tests: All 10 Portfolios

The table reports cross-sectional pricing results for the factor model based on the dollar risk factor (DOL) and Global Equity Correlation Innovation where the correlation levels are measured by DECO model (ΔEQ_corr). The test assets are the set of sorted carry portfolios (1-5), and the set of sorted momentum portfolios (1-5). Panel 1. on the left reports estimation results for test assets constructed using currencies from all 48 countries and the panel on the right reports estimation results for test assets constructed using currencies from 17 developed market countries only. Market price of beta risk Υ (multiplied by 100), market price of covariance risk λ , the Shanken (1992) and the Jagannathan and Wang (1998) t-ratios under correctly specified models and account for the EIV problem: [t-ratio(s) and t-ratio(jw)] and the Kan, Robotti, and Shanken (2012) misspecification-robust t-ratios: [t-ratio(krs)] are reported. pval-1 is the p-value for the test of $H_0: R^2 = 1$. pval-2 is the p-value for the test of $H_0: R^2 = 0$, pval-3a and pval-3b are the p-value for Wald test of $H_0: \Upsilon = 0$ with and without imposing price of beta is zero under the null respectively. HAC standard errors are reported in parentheses. Data are monthly and the sample covers the period March 1976 to November 2013.

1. DECO OOS Correlation Innovation					2. Intra-Month Correlation Innovation				
Factor:	DOL	ΔEQ_corr	R^2	0.419	Factor:	DOL	ΔEQ_corr	R^2	0.514
Υ	0.111	-6.870	<i>pval-1</i>	0.011	Υ	0.115	-20.200	<i>pval-1</i>	0.185
<i>t-ratio (s)</i>	0.964	-3.904	<i>pval-2</i>	0.010	<i>t-ratio (s)</i>	0.996	-3.652	<i>pval-2</i>	0.004
<i>t-ratio (jw)</i>	0.965	-3.495	<i>pval-3a</i>	0.000	<i>t-ratio (jw)</i>	1.003	-4.109	<i>pval-3a</i>	0.000
<i>t-ratio (krs)</i>	0.966	-2.744	<i>pval-3b</i>	0.002	<i>t-ratio (krs)</i>	1.002	-3.035	<i>pval-3b</i>	0.000
λ	1.753	-26.75			λ	-1.628	-14.38		
<i>t-ratio (s)</i>	0.539	-3.778			<i>t-ratio (s)</i>	-0.416	-3.545		
<i>t-ratio (jw)</i>	0.453	-3.001			<i>t-ratio (jw)</i>	-0.375	-4.043		
<i>t-ratio (krs)</i>	0.453	-2.357			<i>t-ratio (krs)</i>	-0.372	-3.015		
Descriptions									
Υ : Coefficients on beta risk					pval-1: p-value of testing $R^2 = 1$				
λ : Coefficients on covariance risk					pval-2: p-value of testing $R^2 = 0$ (without imposing $H_0: \Upsilon = 0_N$)				
t-ratio (s): Shanken Error-in-Variables adjusted t-ratio					pval-3a: p-value of Wald $\Upsilon = 0_k$ ($H_0: \Upsilon = 0_N$)				
t-ratio (jw): EIV t-ratio under general distribution assumption					pval-3b: p-value of Wald $\Upsilon = 0_k$ (without imposing $H_0: \Upsilon = 0_N$)				
t-ratio (krs): Misspecification robust t-ratio									

Table VIII. Cross-Sectional Regression (CSR) Asset Pricing Tests: All 10 Portfolios

The table reports cross-sectional pricing results for the factor model based on the dollar risk factor (DOL) and Global Equity Correlation Innovation where the correlation levels are measured by DECO model (ΔEQ_corr). The test assets are the set of all FX 10 portfolios (Carry 5 and Momentum 5). The winsorized correlation innovation series (at the 10% level) is used for Panel 1, pre-financial crisis period (from March 1976 to December 2006) is chosen for Panel 2. For Panel 3, AR(2) shock instead of the first difference is used to measure the correlation innovations. Data are monthly and the sample covers the period March 1976 to November 2013. For Panel 4, both factors (DOL and ΔEQ_corr) and test assets (FX 10 portfolios) are constructed from weekly data series. Weekly sample cover the period October 1997 to November 2013.

Panel 1. 10% Winsorization					Panel 2. Before Financial Crisis (to Dec 2006)				
Factor:	DOL	ΔEQ_corr	R^2	0.61	Factor:	DOL	ΔEQ_corr	R^2	0.84
Υ	0.15	-10.94	<i>pval-1</i>	0.43	Υ	0.10	-9.89	<i>pval-1</i>	0.50
<i>t-ratio (s)</i>	1.27	-2.35	<i>pval-2</i>	0.16	<i>t-ratio (s)</i>	0.78	-3.40	<i>pval-2</i>	0.13
<i>t-ratio (jw)</i>	1.29	-2.43	<i>pval-3a</i>	0.00	<i>t-ratio (jw)</i>	0.78	-3.19	<i>pval-3a</i>	0.00
<i>t-ratio (krs)</i>	1.29	-2.69	<i>pval-3b</i>	0.02	<i>t-ratio (krs)</i>	0.78	-3.24	<i>pval-3b</i>	0.01
λ	5.24	-88.26			λ	4.79	-34.79		
<i>t-ratio (s)</i>	0.75	-2.32			<i>t-ratio (s)</i>	1.03	-3.30		
<i>t-ratio (jw)</i>	0.75	-2.51			<i>t-ratio (jw)</i>	0.90	-2.79		
<i>t-ratio (krs)</i>	0.75	-2.77			<i>t-ratio (krs)</i>	0.90	-2.80		
Panel 3. AR(2) Shock					Panel 4. Weekly Data				
Factor:	DOL	ΔEQ_corr	R^2	0.93	Factor:	DOL	ΔEQ_corr	R^2	0.65
Υ	0.11	-8.47	<i>pval-1</i>	0.78	Υ	0.03	-1.67	<i>pval-1</i>	0.31
<i>t-ratio (s)</i>	0.95	-3.94	<i>pval-2</i>	0.00	<i>t-ratio (s)</i>	0.83	-3.04	<i>pval-2</i>	0.08
<i>t-ratio (jw)</i>	0.96	-3.65	<i>pval-3a</i>	0.00	<i>t-ratio (jw)</i>	0.83	-2.29	<i>pval-3a</i>	0.00
<i>t-ratio (krs)</i>	0.96	-3.52	<i>pval-3b</i>	0.00	<i>t-ratio (krs)</i>	0.83	-2.22	<i>pval-3b</i>	0.07
λ	1.71	-33			λ	-11.31	-40.15		
<i>t-ratio (s)</i>	0.46	-3.81			<i>t-ratio (s)</i>	-1.61	-2.99		
<i>t-ratio (jw)</i>	0.38	-3.17			<i>t-ratio (jw)</i>	-1.15	-2.04		
<i>t-ratio (krs)</i>	0.38	-3.07			<i>t-ratio (krs)</i>	-1.13	-1.95		
Descriptions									
Υ : Coefficients on beta risk					<i>pval-1</i> : p-value of testing $R^2 = 1$				
λ : Coefficients on covariance risk					<i>pval-2</i> : p-value of testing $R^2 = 0$ (without imposing $H_0: \Upsilon = 0_N$)				
<i>t-ratio (s)</i> : Shanken Error-in-Variables adjusted t-ratio					<i>pval-3a</i> : p-value of Wald $\Upsilon = 0_k$ ($H_0: \Upsilon = 0_N$)				
<i>t-ratio (jw)</i> : EIV t-ratio under general distribution assumption					<i>pval-3b</i> : p-value of Wald $\Upsilon = 0_k$ (without imposing $H_0: \Upsilon = 0_N$)				
<i>t-ratio (krs)</i> : Misspecification robust t-ratio									

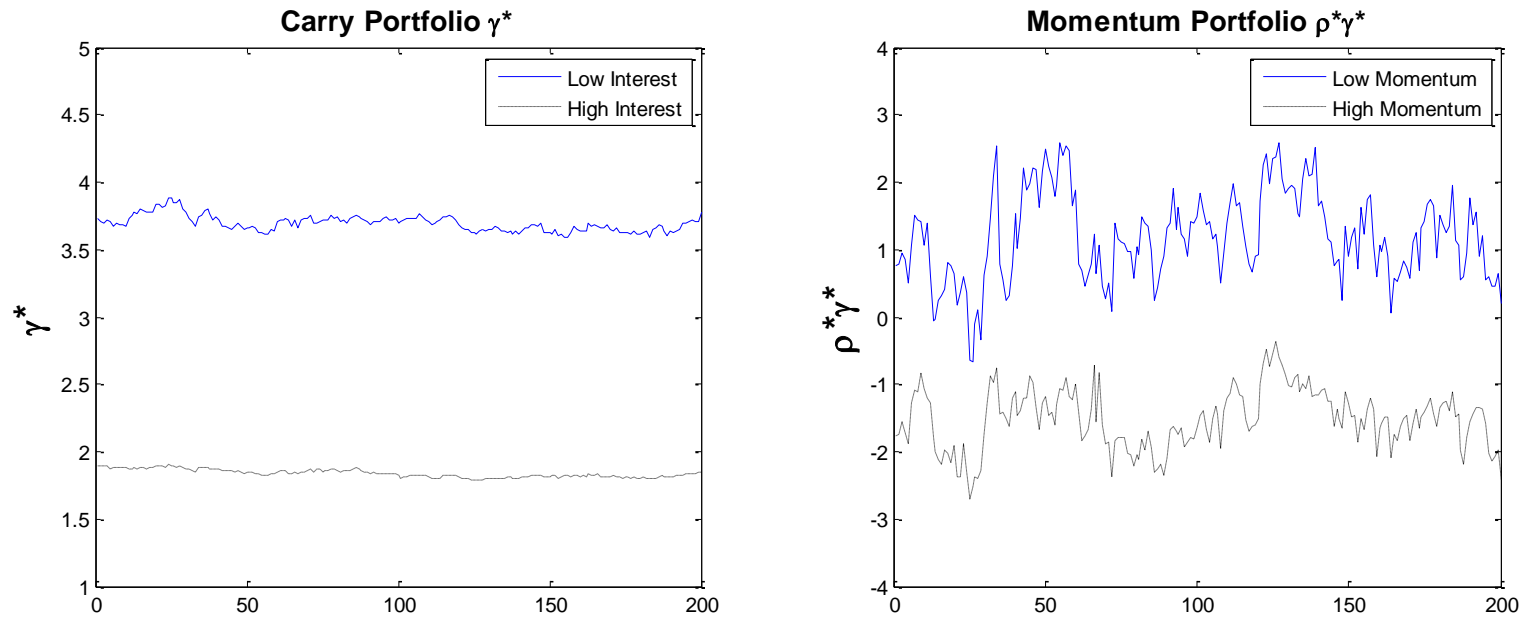


Figure 5. The figure on the left shows average Υ for the portfolios sorted on simulated time $t-1$ forward discounts. The solid blue line is a time-series plot of Υ for low interest rate portfolio, and the dotted blue line is for high interest rate portfolio. The figure on the right shows average $\rho\Upsilon$ for the portfolios sorted on simulated excess returns over the last 3 month. The solid blue line is a time-series plot of $\rho\Upsilon$ for low momentum portfolio, and the dotted blue line is for high momentum portfolio.

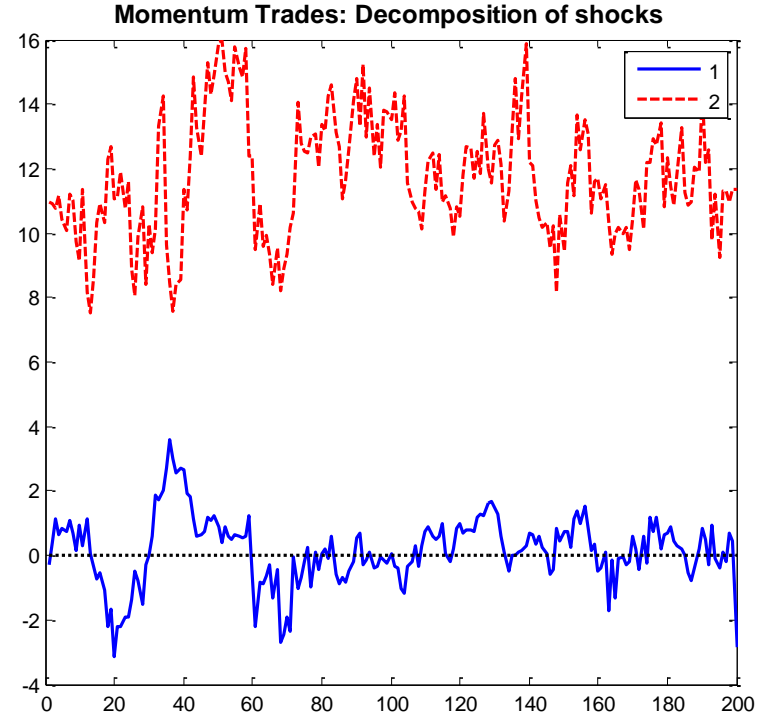
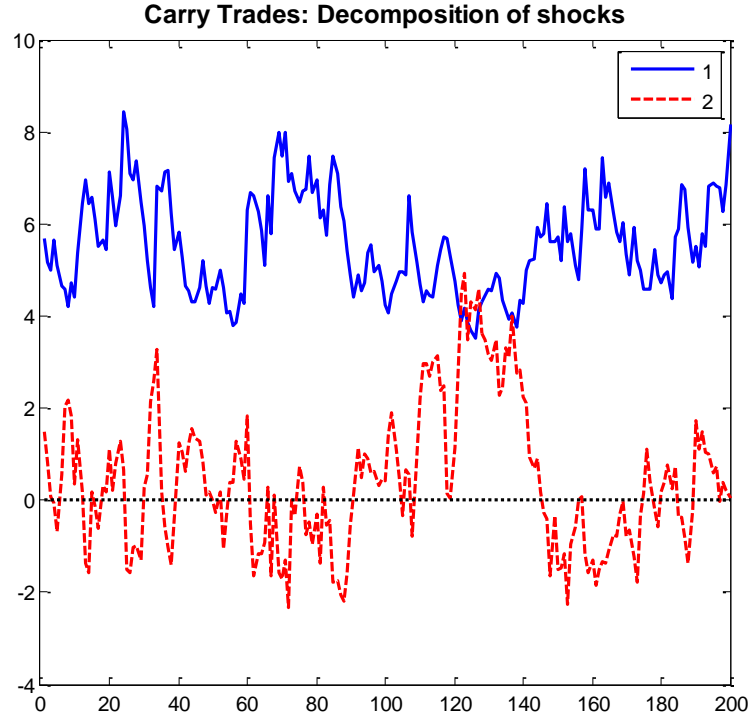


Figure 6. The left chart of the figure shows time-series decomposition of shocks for carry trades, long high interest rate currencies and short low interest rate currencies using simulated rates and returns. The right chart of the figure shows time-series decomposition of shocks for momentum trades, long high excess return currencies and short excess return currencies over the last 3 month using simulated returns. The solid blue line and the dotted red line shows the first and the second part of the equation above respectively.

$$\begin{aligned}
 \Delta \pi_{t+1}^{L-S} - E_t[\Delta \pi_{t+1}^{L-S}] &= [(\hat{\gamma}_t^S - \hat{\gamma}_t^L) \sigma_{w,t+1} + (\rho_{t+1}^S \hat{\gamma}_t^S - \rho_{t+1}^L \hat{\gamma}_t^L) \sigma] \epsilon_{w,t+1} \\
 &\approx -\underbrace{[(\hat{\gamma}_t^S - \hat{\gamma}_t^L) \sigma_{w,t+1}]}_{\textcircled{1}} + \underbrace{(\rho_{t+1}^S \hat{\gamma}_t^S - \rho_{t+1}^L \hat{\gamma}_t^L) \sigma}_{\textcircled{2}} \Delta \Psi_{t+1}
 \end{aligned}$$

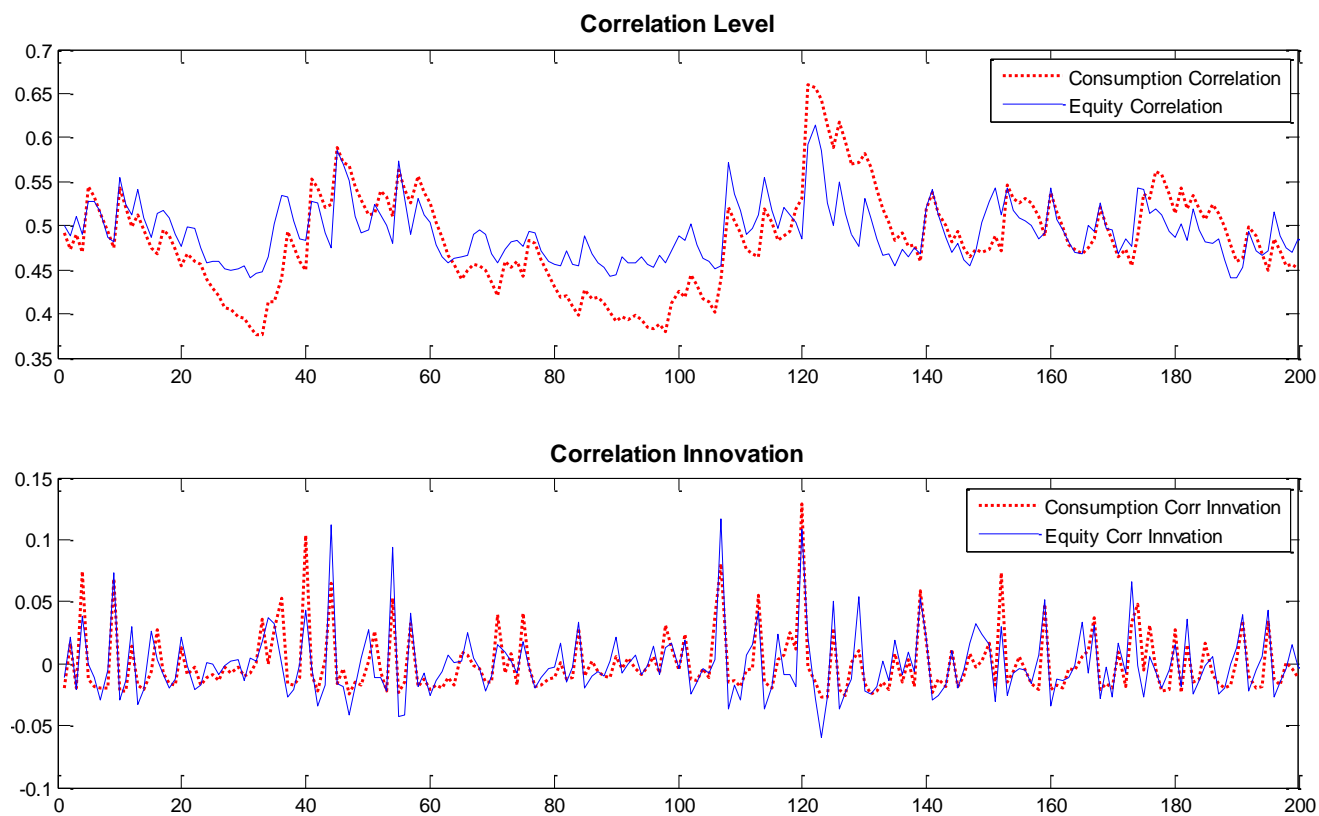


Figure 7. This figure compares consumption correlation and equity correlation where both series are simulated from our model. The upper panel of the figure shows a time-series plot of the common consumption correlation levels (solid blue line) and the equity correlation levels estimated by running DECO model on the simulated equity return series (dotted red line). The lower panel shows a time-series plot of the correlation innovations. The correlation innovations are measured by taking first difference of each of the correlation level series. The correlations between two series are 0.76 and 0.80 for the level and the innovation respectively.

Appendix: Country Selection

Country	FX		Equity		
	FX All	FX DM	Equity DM (1973 ~)	Equity (1988 ~)	Equity (1995 ~)
Number of country	48	17	17	31	39
1.Australia	V	V	V	V	V
2.Austria	V	V	V	V	V
3.Belgium	V	V	V	V	V
4.Brazil	V			V	V
5.Bulgaria	V				
6.Canada	V	V	V	V	V
7.Croatia	V				
8.Cyprus	V				
9.Czech Repulbic	V				V
10.Denmark	V	V	V	V	V
11.Egypt	V				V
12.Euro area	V	V			
13.Finland	V			V	V
14.France	V	V	V	V	V
15.Germany	V	V	V	V	V
16.Greece	V			V	V
17.Hong Kong	V			V	V
18.Hungary	V				V
19.Iceland	V				
20.India	V				V
21.Indonesia	V			V	V
22.Ireland	V			V	V
23.Israel	V				V
24.Italy	V	V	V	V	V
25.Japan	V	V	V	V	V
26.Kuwait	V				
27.Malaysia	V			V	V
28.Mexico	V			V	V
29.Netherlands	V	V	V	V	V
30.New Zealand	V	V	V	V	V
31.Norway	V	V	V	V	V
32.Philippines	V			V	V
33.Poland	V				V
34.Portugal	V			V	V
35.Russia	V				V
36.Saudi Arabia	V				
37.Singapore	V			V	V
38.Slovakia	V				
39.Slovenia	V				
40.South Africa	V				V
41.South Korea	V			V	V
42.Spain	V	V	V	V	V
43.Sweden	V	V	V	V	V
44.Switzerland	V	V	V	V	V
45.Taiwan	V			V	V
46.Thailand	V			V	V
47.Ukraine	V				
48.UK	V	V	V	V	V
49.US			V	V	V