Global Equity Correlation in FX 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 propose a stylized multi-currency model which illustrates why heterogeneous exposures to our correlation factor explain the excess returns of both these strategies.

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1 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 (2011b) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012b)). 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 portfolios can be explained by different sensitivities to our correlation factor.

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 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.

For our main asset pricing test, 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 return series. Second, we measure the same correlation dynamics by taking a simple mean

[1] The extant literature documents 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, Ranaldo, and Wrampelmeyer (2013)), downside market risk (Lettau, Maggiori, and Weber (2014)), disaster risk (Jurek (2014) and Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2009)) and peso problem (Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011a)).

of bilateral intra-month correlations at each month's end using daily return series.[2] The correlation innovation factors are constructed as the first difference in time series of the global correlation. Across portfolios, we run cross-sectional asset pricing tests on *FX 10* portfolios which consist of two sets of five portfolios: the FX 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 past returns. 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 covariance 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 (2013). We also perform CSR-GLS, Fama-MacBeth and GMM methods, and find consistently across the models that one standard deviation of cross-sectional differences in beta to our factor explains more than 2% per annum in the cross-sectional differences in mean return of *FX 10* portfolios. The negative price of risk 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.

We construct various control 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 (2011b) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012b). We demonstrate that our factor not only improve the explanatory power across carry portfolios, but also can explain the cross-section of momentum portfolios.

[2] Given the U.S. plays dominant role in financial markets, it is prudent to emphasize the marginal effect of different weighting on our correlation measure. In Section 4.3, we construct two alternative measure of the aggregate intra-month correlation levels: GDP and Market-capitalization weighted average of all bilateral correlations. We show that different weightings do not have a large effect on the pricing power of our factor.

Since our equity correlation is a non-traded factor, 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 (2013)). 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). Since the converted factor is a traded asset, we can directly interpret the average excess returns of the traded portfolio as the price of our factor itself, and we find that they are economically large and negatively significant.[3] The cross-sectional regression result shows that about 90 percents of R^2 can be obtained, which is similar to what we can achieve using our non-traded equity correlation factor in the cross-section of carry and momentum portfolios.

Is our factor subject to the "useless" factor bias as defined in Kan and Zhang (1999)? To address this question, we follow three suggestions from their paper. We first show that both OLS R^2 and GLS R^2 are statistically different from zero. Second, we demonstrate that the betas to our factor between high and low portfolios are significantly different from each other. Lastly, we show that the statistical significance of the regression result is not driven by our choice of test assets. We find that the price of risk of our factor is significant whether the asset pricing tests are performed on carry and momentum portfolios separately or jointly. Similar conclusion can be reached when the tests are performed on an independent set of portfolios: the FX value portfolios.[4]

Beyond portfolios in the FX market, Lustig and Verdelhan (2007) add 5 bond portfolios and 6 Fama-French equity portfolios to their 8 FX portfolios. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011a) uses 25 Fama-French portfolios jointly with the equally-weighted carry trade portfolios. Following their methodologies, we augment our *FX 10* portfolios with the global/U.S. Fama-French 25 portfolios formed on size and book-to-market (or size and momentum) and run cross-sectional regression on these expanded test assets. We

[3]Specifically, the average excess returns of our factor mimicking portfolios varies from -3.9% to -7.2% per annum depending on our factor construction methods.

[4]The FX value portfolios are constructed by sorting currencies on their real effective exchange rate levels or 60-month changes. The detailed description of construction method and asset pricing test results are shown in Section 4.5.

find that the price of beta risk of our factor is still statistically and economically significant after controlling for the market risk premium and the global/U.S. Fama-French factors. These findings also shed light on the cross-market integration between the equity and the FX markets. 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 and international equity markets, we demonstrate the important linkage across the two markets through equity correlations as a main instrument of the aggregate risk.

To deliver an economic intuition behind our empirical findings, we propose a stylized 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)) for our model specification. The model decomposition of the expected returns shows that heterogeneity in risk aversion is able to explain the cross-section of average excess returns of carry portfolios. However, we find that heterogeneity in risk aversion coefficient alone cannot explain carry and momentum simultaneously. We suggest instead that the cross-sectional differences in beta loading on the risk factor depend on two parameters: the risk aversion coefficient and the country-specific consumption correlation coefficient which captures a proportion of country i in the world consumption shock. Carry portfolios are closely related to the former term, whereas momentum portfolios are closely related to the latter term. Thus, our decomposition explains why both carry and momentum portfolios can be simultaneously explained by the different loadings to our factor, while we observe low correlation between the two strategies in the empirics.

The rest of the paper is organized as follows: Section 2 presents data. Section 3 describes the portfolio construction method used in this paper. Section 4 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 4 as well. Section 5 discusses the theoretical model and Section 6 concludes.

2 Data

2.1 Spot and forward Rates

Following Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011a), 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 December 2014 and the second dataset spans the period between December 1996 and December 2014. The sample period varies by currency. 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 4.7 of this paper as a robustness check, we choose Wednesday, following the tradition of the option literature.

Our full dataset consists of the currencies of 48 countries. Out of the initial currency set, we drop four currencies: Bulgaria, Hong Kong, Kuwait and Saudi Arabia due to their effective currency pegging.[5] In the empirical section, we carry out our analysis for the 44 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 Table A1.

2.2 Equity returns

We collect daily closing MSCI international equity indices both in U.S. dollars and in local currencies from Datastream for all available countries in the FX data. We use returns in U.S. dollars as our base case.[6] The sample covers the period from January 1973 to December

[5]Following Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) and Lustig, Roussanov, and Verdelhan (2014), we also account for large deviations from the covered interest parity by deleting the following observations: Indonesia from January 2001 to May 2007, Malaysia from August 1998 to June 2005, and South Africa from July to August 1985.

[6]Our use of equity indices in U.S. dollars is to be consistent with our test assets, which are all paired against USD. We also construct our correlation innovation factor using MSCI international equity indices in local currencies in Section 4, and show that the equity correlation innovation is not largely affected by currency correlation.

2014. 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 Table A1. 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. We also collect MSCI indices in local currencies and use them to construct our correlation innovation factor.

2.3 Real effective exchange rate and 10-year interest rate

Real effective exchange rate is an index that measures relative strength of a currency relative to a basket of other currencies adjusted for the effects of inflation. This can be considered as a real value that a consumer will pay for an imported good at the consumer level. Monthly real effective exchange rate indices are obtained from the Bank For International Settlements (BIS) and Global Financial Data (GFD). The dataset spans the period January 1964 to December 2014. We collected the data for the same set of the developed market currencies described above. For these indices, the relative trade balances are used to determine the weights in the basket of currencies for normalization. We also collect monthly 10-year interest rates for the same set of countries from Global Financial Data (GFD).

3 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.

3.1 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 (USD) per foreign currency, respectively. An increase in q_i means an appreciation of the foreign currency i. Following Lustig and Verdelhan (2007), we define the log excess return ($\Delta\pi_{i,t+1}$) of the currency i at time $t+1$ as

$$\Delta\pi_{i,t+1} = \Delta q_{i,t+1} + i_{i,t} - i_{us,t} \approx q_{i,t+1} - f_{i,t} \tag{1}$$

where $i_{i,t}$ and $i_{us,t}$ denote the foreign and domestic nominal risk-free rates over a one-period horizon. This is the return on buying a foreign currency (f_i) 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 $f_{i,t} = log(1 + i_{us,t}) - log(1 + i_{i,t}) + q_{i,t}$. Therefore, the forward discount is simply the interest rate differential ($q_{i,t} - f_{i,t} \approx i_{i,t} - i_{us,t}$) 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.

3.2 Carry portfolios

Carry portfolios are the portfolios where currencies are sorted on the basis of their interest rate differentials. 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 a portfolio can be calculated by taking the equally-weighted average of the individual log currency excess returns (as described in Equation 1) in each portfolio.[7] 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})

[7] To take transaction costs into account, we split a 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 ($\Delta\pi^{In-Out}_{long,t+1} = q^{bid}_{t+1} - f^{ask}_{t}$). If it stays in the portfolio once it enters, then we take into account a one-way transaction cost only ($\Delta\pi^{In-Stay}_{long,t+1} = q^{mid}_{t+1} - f^{ask}_{t}$). A similar calculation is for a short position as well (with opposite signs while swapping bids and asks).

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.

Descriptive statistics for our carry portfolios are shown in Panel A of Table 1. Panel A shows results for the sample of all 44 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 6.8% and 5.4% per annum respectively after adjusting for transaction costs. Theses magnitudes are similar to the levels reported in the carry literature. Consistent with Brunnermeier, Nagel, and Pedersen (2008) and Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011a), we also observe decreasing a skewness pattern as we move from a low interest rate to a high interest rate currency portfolio.

3.3 Momentum portfolios

Momentum portfolios are the portfolios where currencies are sorted on the basis of past returns.[8] 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.

Panel B 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

[8]See, Asness, Moskowitz, and Pedersen (2013) and Moskowitz, Ooi, and Pedersen (2012) for the existence of ubiquitous evidence of cross-sectional momentum return premia across markets.

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 7.6% and 5.0% per annum after transaction costs for ALL and DM currencies respectively.

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 (2011b) similarly argue that it is difficult to explain carry and momentum strategies simultaneously, 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 carry and momentum portfolios. In addition, we provide a risk-based explanation for both these strategies.

4 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 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 the aggregate wealth portfolio as the conditional variance of the aggregate wealth portfolio increases. However, as noted in Roll (1977), the variance on the aggregate wealth portfolio is not directly observable and might be difficult to proxy for when conducting empirical tests. Indeed, Pollet and Wilson (2010) document that the stock market variance, as a proxy for the risk of the the aggregate wealth portfolio, has weak ability to forecast stock market expected returns. 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 capital markets. An 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. Specifically, 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.

4.1 Factor construction: Common equity correlation innovation

We construct two empirical measures of the international equity correlation factors 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.[9] 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, we consider both measures in our main empirical testing framework. We report the details of the DECO model in the Appendix (Section A.1).

For the empirical analysis, we construct a common factor in international equity correlation innovation ($\Delta Corr$) 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

[9]The 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.

equity market indices. $\Delta Corr_t = E_t[Corr_{t+1}] - E_{t-1}[Corr_t]$.[10] 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.[11]

Our hypothesis is that change in the global 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 should demand currencies that can hedge against the risk, hence they must pay a premium for those currencies. In other words, $\Delta Corr$ 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 1. 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 solid gray line depicts the time series of the global equity correlation without look ahead bias and we name this measure DECO OOS (out-of-sample). Out-of-sample correlation is estimated using the same DECO model, but the parameters 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. Based on the untabulated retults for an augmented Dicky-Fuller stationary test and Breusch-Godfrey serial dependence tests for

[10] Note that we use the first difference as our main approach to get innovation series simply because it is the most intuitive. 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 Section 4.7. Furthermore, given that we rely on the unconditional cross-sectional regression as our main test, the existence of autocorrelation should not affect the validity of our test.

[11] Campbell, Giglio, Polk, and Turley (2013) explores the ICAPM with stochastic volatility and indicates that the appropriate measure of variance risk is the innovation, not the level, of the discounted present value of future conditional variances.

the three innovation series, all of the innovation series are stationary which makes them statistically valid factors under an unconditional cross-sectional regression (CSR) framework.

4.2 Two-pass cross-sectional regression

4.2.1 Methods

To test whether our factor is a priced risk factor in the cross-section of currency portfolios, we utilize the two-pass cross-sectional regression (CSR-OLS) method. For statistical significance of beta, we report both the statistical measures of Shanken (1992) and Kan, Robotti, and Shanken (2013) throughout this paper.[12] We tests both the price of covariance risk and the price of beta risk in the empirical testing. To save space, we report the details of the estimation methodology of these statistics in the Appendix (Section A.2).

4.2.2 Results

In this section, we present empirical findings that show that the international equity correlation innovation factor ($\Delta Corr$) is a priced risk factor in the cross section of currency portfolios 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 3. We refer to all the carry and momentum portfolios as *FX 10* portfolios.

Table 2 presents the results of the second pass CSR using all *FX 10* portfolios. We use two

[12] 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 (2013) further investigate the asymptotic distribution of the price of beta risk under potentially misspecified models. 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. They also show how to use the asymptotic distribution of the sample R^2 in the second-pass CSR as the basis for a specification test.

factors, DOL and the global equity correlation innovation factor, where the correlation levels are measured by out-of-sample DECO model (OOS) for Panel A, and averaging intra-month bilateral correlations (henceforth, IM) for Panel B, respectively. We report the estimation results for all 44 currencies (ALL) on the left, and for 17 developed market (DM) currencies on the right. In each panel, the market price of covariance risk (λ) is presented first, followed by the price of beta risk (γ). The price of covariance (beta) risk normalized by standard deviation of the cross-sectional covariances (betas): λ_{norm} (γ_{norm}) are also reported.

In Panel A of Table 2, we find that our correlation innovation factor is negatively priced and the price of covariance risk is statistically significant under Shanken's (1992) estimation error adjustment as well as misspecification error adjustment, with t-ratio of -3.74 ($t\text{-}ratio_s$) and -2.95 ($t\text{-}ratio_{krs}$) respectively. The price of the covariance (beta) risk, λ_{norm} (γ_{norm}), is also economically significant, since one standard deviation of cross-sectional differences in covariance (beta) exposure can explain about 2.59 (2.56) % per annum in the cross-sectional differences in mean return for ALL currencies. We find that t-ratio for the price of beta risk with respect to our correlation innovation factor is generally higher (in absolute value) than t-ratio of the price of covariance risk. Kan, Robotti, and Shanken (2013) 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. It is thus important to note that our correlation factor, while not being traded, has a highly significant t-ratio.[13]

Overall, we have high explanatory power over the cross-section of the average returns across carry and momentum portfolios. We find the global correlation innovation factor could yield cross-sectional fit with R^2 of 89% and 77% for ALL and DM currencies respectively. While we cannot reject the null *H0:* $R^2 = 1$ under the assumption of the correctly specified model ($pval_1$), it is significant for the test that the model has any explanatory power for expected returns under the null of misspecified model *H0:* $R^2 = 0$ ($pval_2$). The p-value

[13] While there have been recent developments to estimate the average correlation of U.S. equity stocks that is implied in the option market (see, Driessen, Maenhout, and Vilkov (2009) for details of the correlation swap trade), we are not aware of any such swap trades in international equity market indices.

from the F-test, a generalized version of Shanken's CSRT statistic (χ^2) which allows for conditional heteroskedasticity and autocorrelated erros, shows that the null hypothesis that the pricing errors are zero cannot be rejected ($pval_4$).

The negative price of covariance risk suggests 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. Figure 2 illustrates that portfolios with low interest rate differential and low momentum have high betas with our global correlation factor, while high beta portfolios have low average excess returns. This strong pattern of decreasing beta across both sets of portfolios hint about our conclusion that investors indeed demand a low risk premium for the portfolios whose returns co-move with our correlation factor.

Are our asset pricing results driven by our choice of the dynamic correlation model? Panel B of Table 2 presents the results from the second pass CSR where our correlation factor is measured from the average of bilateral intra-month correlations (IM), instead of DECO correlations (OOS). Although the level of market price of covariance risk (λ) of IM is lower than the one using OOS, the economic magnitude of the covariance price (λ_{norm}) is about the same due to lower cross-sectional dispersions in the beta exposure to IM factor. For both measures of the global correlation innovation, one standard deviation of cross-sectional differences in covariance exposure can explain just about 2.5 % per annum in the cross-sectional differences in mean returns of the *FX 10* portfolios. Contrasting Panel A and Panel B of Table 2 shows that the two separate measures of our correlation factor also have similar γ_{norm} as well as t-ratios. Overall, these findings confirm that the global equity correlation factor is a priced risk factor in the cross-section of currency portfolios.

Finally, we present the pricing errors of the asset pricing model with our global equity correlation as a risk factor in Figure 3. The realized excess return is on the horizontal axis and the model-predicted average excess return is on the vertical axis. The fit of our model, using OOS on the left and IM on the right, suggests that the cross-sectional dispersion across mean returns generated by our model fits the actual realization of mean excess returns well across carry and momentum portfolios.

4.3 Alternative asset pricing tests

We explore various measures of our correlation factor and alternative asset pricing tests in detail. In the previous section, we construct two correlation factors: OOS and IM. The implicit assumptions behind our methodology are that (i) there is a common component in the variation of co-movements across international equity indices, (ii) the common component can be represented by equally-weighted average of correlations, and (iii) this aggregate measure of correlation level and innovation are not subject to large variation from inclusion or exclusion of a particular country's stock index. Given the U.S. plays dominant role in financial markets, however, it is prudent to emphasize the marginal effect of different weighting on our correlation measure.

In this section, we construct two alternative measures of the aggregate intra-month correlation level: IM_{GDP} and IM_{MKT}. The correlation level for IM_{GDP} (IM_{MKT}) is estimated by computing GDP-weighted (Market-capitalization-weighted) average over all bilateral correlations at the end of each month using previous quarter's dollar values of GDP (Market-capitalization). The correlation levels and their respective innovations using different weightings, IM, IM_{GDP} and IM_{MKT}, are presented in Figure 4. From the visual inspection, different weightings only have marginal effect on the aggregate measure of correlation levels as well as the innovations. We also confirm this finding from the sample moments of the factors in Table 3. In this table, we include additional factor, the equally-weighted average of bilateral correlation using index returns in local currency units (IM_{LOC}). Motivation of adding IM_{LOC} is to clarify the following question: Is the aggregate correlation mainly driven by co-movements in equities, not by common currency denomination (USD)? We find that the mean of IM_{GDP} and IM_{MKT} correlation levels (0.27 for both series) are lower than our benchmark correlations (0.39 for both OOS and IM), whereas the mean of IM_{LOC} correlation level (0.33) is similar to our benchmark correlations. The averages of our correlation innovation factors are all close to zero and the volatilities of intra-month correlation innovations are generally higher than OOS. We also verify that the aggregate measures of the correlation is highly correlated to each other. This means that different weightings across countries do not have a large effect on the construction of our factor.

For the asset pricing tests, we first employ two-pass OLS regression (CSR-OLS) which is also our base case test used in Table 2. Given that our factor is non-traded factor, we use CSR-OLS as our main methodology since it has direct interpretation of the cross-sectional R^2, and it also allows us to make proper adjustments for beta estimation errors as well as misspecification errors. Second, we run two-pass CSR-GLS, a different way of measuring and aggregating sampling deviations.[14]

Third, we run the Fama-MacBeth (1973) regression both with and without time-varying beta assumptions. For the constant beta case, the first-pass time-series regression is identical to the two-pass CSR. Contrary to the two-pass CSR, however, we run T cross-sectional regressions (one for each time period) of excess returns of *FX 10* portfolios on the estimated unconditional factor loadings in the second-pass regression.[15] Since we restrict each portfolio's beta to be constant, each currency's excess return beta is only allowed to be time-varying through monthly portfolio rebalancing. For the time-varying beta case, we relax the condition so that each portfolio's beta can also be time-varying. Following the tradition in the literature, we use a rolling 60-month window for the estimation of time-varying portfolio beta. We correct for heteroskedasticity and autocorrelation in errors by using Newey and West (1987) standard errors computed with optimal number of lags according to Newey and West (1994) for both cases.

Lastly, we employ generalized method moments (GMM) methods of Hansen (1982) based on our assumption that a stochastic discount factor (SDF) is linear in our factors.

$$m_{t+1} = 1 - \lambda_{DOL}(DOL_{t+1} - \mu_{DOL}) - \lambda_{Corr}(\Delta Corr_{t+1} - \mu_{\Delta Corr})$$

Risk-adjusted currency excess returns ($\Delta\pi_{i,t+1}$) of currency i should have a price of zero, hence satisfy the Euler equation $\mathbb{E}[m_{t+1}\Delta\pi_{i,t+1}] = 0$. The unconditional factor means and elements of factor covariance matrix are estimated jointly with the price of covariance risk (λ). Therefore, it is closely related to the price of covariance risk from two-pass CSR.[16]

[14] Due to the well-known trade-off between statistical efficiency and robustness, the choice between OLS and GLS should be determined based on economic relevance rather than estimation efficiency.

[15] This method is essentially equivalent to the pooled time-series regression, and to CSR-OLS with standard errors corrected for cross-sectional correlation.

[16] We infer the price of covariance risk (λ) to the price of beta risk (γ) by pre-multiplying estimated factor covariance matrix (Σ_f) to λ.

Standard errors are also corrected for heteroskedasticity and autocorrelation with optimal number of lags using Newey and West (1994).

Table 4 presents results for these alternative cross-sectional asset pricing tests. In each panel, we perform one of the tests illustrated above and present the price of beta risk (γ), the price of beta risk normalized by standard deviation of the cross-sectional betas (γ_{norm}), and corresponding t-ratios in parentheses. In each column, we use one of the five different measures of our correlation innovation factor. Overall, our results show that we have similar estimates of the price of risk across different factor construction and asset pricing methodologies. On average, one standard deviation of cross-sectional differences in beta exposure to our factor can explain about 2% per annum in the cross-sectional differences in mean return of *FX 10* portfolios. The t-ratios are generally higher if we employ the Fama-MacBeth regression with constant beta assumption, ranging from -6.03 for IM_{LOC} to -7.84 for IM_{GDP}. When we allow portfolio betas to be also time-varying, however, we have lower pricing power due to weak forecastability of future betas from finite-sample estimation errors.

In the last column, we report results for IM_{LOC}, where we construct our correlation factor using equity index returns in local currency units. We find that the normalized price of beta risk (γ_{norm}) is about -1.7% per annum on average, and their t-ratios are highly significant raging from -2.20 (*CSR-GLS*) to -6.03 (*Fama-MacBeth Constant*). These results suggest that the aggregate correlation is mainly driven by co-movements in international equity returns, not by the implied correlation due to the common currency denomination (USD). More direct comparison in asset pricing test between international equity correlation and FX correlation factor, which is shown in the next section, also confirms our conclusion.

4.4 Cross-sectional regression with other factors

We explore the factors discussed in the FX literature and address the challenges in explaining 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 we consider 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, Ranaldo, 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.

Consistent with the empirical results from the FX literature, we find 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 with R^2 raging from 58 % for the TED spread innovation factor to 92 % for the FX volatility factor (untabulated). The factor prices are statistically significant under a misspecification robust cross-sectional regression, and have the expected signs, that is, negative for the illiquidity and the FX volatility factors and positive for the FX carry factor. Panel B to F in Figure 5 plot the pricing errors using selected factors from the list above and illustrate difficulties in pricing the joint cross-section of carry and momentum portfolios. This confirms the findings in Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) that the set of factors which have explanatory power over the cross-section of carry portfolios does not explain well momentum portfolios at the same time. In contrast, Panel A of the figure shows that our factor significantly improves the joint cross-section fits.

In Table 5, we include our correlation factor along with other factors described above to evaluate relative importance across those factors. The specification for the test is the same as in Table 2. In each panel of the table, the two-pass CSR test is performed on three factors jointly: DOL, one of the control variables from the list above, and OOS. The first column of Table 5 reports the name of variables to be controlled in each regression. We present the normalized prices of covariance risk (λ_{norm}) and associated t-ratios for DOL, each of the control factors, and OOS in the third, the fourth, and the fifth column, respectively.[17]

[17]The model in each panel of the table nests models which only use DOL and one of the control variables. The R^2s of the larger model should exceed that of the smaller model. When the models are potentially misspecified, R^2s 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 (H0: $\lambda_{\Delta EQ_{corr}} = 0$). Although we only show the case for the price of covariance risk, similar results can be obtained from the tests of the price of beta risk (untabulated).

We find that the prices of the covariance risk for our correlation factor are statistically significantly different from zero in all cases. Comparing the results for the fourth and the fifth column of the table, our correlation innovation factor dominates each of the control variables in terms of economic magnitude of pricing power. The normalized price of covariance risk (λ_{norm}) is ranging from -2.13 to -3.03 after controlling MOM_{HML} and ΔLIQ_{PS}, respectively. These estimates are similar to the estimates from Table 2, therefore, the pricing power of our factor is not affected by the inclusion of other factors in the previous literature.[18] However, none of the control variables in the fourth column has statistically significant the price of risk, where the highest absolute level of t-ratio is 1.27 for EQ_{HML} factor.

R^2s are also economically and statistically different from the nested models with control variables only.[19] The economically significant results for the cross-sectional fit as well as the price of covariance risk of our correlation factor confirm that our correlation factor improves the explanatory power across the average excess returns of carry and momentum (*FX 10*) portfolios over the risk factors discussed frequently in the FX literature.

4.5 Factor-mimicking portfolio

In this subsection, we project the global equity correlation innovation factor onto FX market space. This exercise converts the non-traded factor to a traded risk factor. We first regress our correlation innovation series (OOS and IM) on *FX 10* portfolios and then retrieve the fitted return series. The fitted excess return series is in fact the factor-mimicking portfolio's excess return. Figure 6 shows a time-series plot of the factor-mimicking portfolio returns. Since the converted factor is a traded asset, we can directly interpret the mean return of the traded portfolio as the price of our factor itself, and we find that they are large and negatively significant. The average excess returns of our factor-mimicking portfolios are

[18] Regarding to alternative downside market risk explanations, Jurek (2014) demonstrates that crash risk premia account for less than 10% of the excess returns of the carry trade. We also control for downside beta with respect to the world equity market risk factor as in Lettau, Maggiori, and Weber (2014), and find our results are robust (untabulated). There could be other explanations such as different exposure to shocks to the common factor in idiosyncratic volatility (Herskovic, Kelly, Lustig, and Nieuwerburgh (2014)) in the global equity market, but we leave those to future research to examine them.

[19] Alternatively, 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^2s. The results are available upon request.

-3.87 and -7.20 % per annum for *OOS* and *IM*, respectively.

We test the pricing ability of the factor-mimicking portfolio. The results from the cross-sectional asset pricing test applied to different sets of test assets using our correlation innovation factors and the corresponding factor-mimicking portfolios' excess returns are reported in Table 6. For each set of test assets, the pricing errors from the model using factor-mimicking portfolio are plotted in Figure 7. We examine carry and momentum portfolios separately to understand whether explanatory power of the cross-sectional differences in mean return is mainly driven by one particular type of strategy. In Table 6, we have our carry and momentum portfolios in Panel A, and we use alternative carry and momentum portfolios in Panel B. To construct the alternative sets of portfolios, we sort currencies based on their 10-year interest rate differentials instead of 1-month forward discount for carry, and on their excess returns over the last 6-months instead of 3-months for momentum. For each set of the portfolios, we report annualized average return differentials between high and low portfolios (*HML Spread*) and associated *p-values* under the null hypothesis that *HML Spread* are not statistically different from zero (*HML Spreal p-val*). Lastly, we perform Patton and Timmermann (2010)'s test whether average portfolio returns are monotonically increasing with underlying characteristics (*Monotonicity p-val*). We find that all the FX strategies are able to generate economically and statistically significant *HML Spread*. The average excess returns also rise monotonically along with their underlying characteristics.

With respect to *Carry 5* and *Momentum 5* portfolios in the table, the price of beta risk is statistically significant with a similar level of R^2 regardless of (i) whether the cross-sectional regression is performed on carry and momentum portfolios separately or jointly, or (ii) whether we use our non-traded factors or the factor-mimicking portfolios (R^2 of about 90% in all cases). Generally, the price of beta risk for the original non-traded factor is much larger than the price of the traded risk factor (γ: untabulated) because differences in beta exposure to the traded factor across *FX 10* portfolios are larger than those to the non-traded factor. However, the traded and non-traded factors have economically similar explanatory power over the cross-section of carry and momentum strategies since the normalized prices of beta risk (γ_{norm} in Table 6) are about the same. In other words, one standard deviation of cross-sectional differences in beta exposure to our factor can explain about -2.5 % per annum in the cross-sectional differences in mean returns across those portfolios.

Regarding the concern related to a useless factor bias as in Kan and Zhang (1999), we follow three suggestions from their paper. We first check that OLS R^2 and GLS R^2 are statistically different from zero. Second, we check that the betas to our factor between high and low portfolios are significantly different from each other (*Beta Spread* in Table 6). The p-values for the test of the null hypothesis $H0 : R^2 = 0$ from Kan, Robotti, and Shanken (2013) and $H0 : |\beta_5 - \beta_1| = 0$ from Patton and Timmermann (2010) are reported in square bracket under R^2 and *Beta Spread* estimates, respectively. We find that beta spreads using the factor mimicking portfolios are greater than those using our non-traded factors due to lower volatility of the factor mimicking portfolio's return. However, all of the beta spreads, including those using our non-traded factors, are statistically different from zero at 5% rejection level for carry and momentum portfolios, except one case for 10-year interest sorted portfolios with $\Delta Corr_{IM}$ factor. Similarly to the findings in Figure 2, we also confirm that not only the high-minus-low beta spreads are statistically different from zero, but there are monotonic patterns in the expected returns and the estimated betas. Furthermore, we find that OLS R^2 (R^2 in Table 6) and GLS R^2 (untabulated) are also statistically significant at 5% rejection level in all cases. These results from the two tests suggest that the significance of our factor risk premium is unlikely due to the useless factor bias.

The third suggestion is to use independent test assets to examine the significance of the risk premium associated with our correlation factor, hence we generate *Value 5* portfolios in this section and we augment equity portfolios in the following section. The FX value portfolios are constructed by sorting currencies on their real effective exchange rate (inverted) levels and 60-months negative changes in Panel A and B, respectively. It is interesting to find that our factor also has explanatory power over the value premium in FX market. We have relatively high R^2s above 80% and economically large price of risk. At the same time, however, the pricing errors are relatively large compared to carry and momentum portfolios in Figure 7. We also have mixed results in terms of statistical significance of the price of risk. Out of 8 cases for the two sets of Value 5 portfolios, we have statistically significance at 5% rejection level in about half of the cases. There is also a potential that the pricing power is subject to the useless factor bias, given that beta spreads are not always statistically different from zero. Therefore, it is premature to conclude that our factor also has strong explanatory power across value portfolios simply because of high R^2s, and further research to enhance the explanatory power across the value portfolios is warranted.[20]

4.6 Why equity correlation innovation, not volatility innovation?

An increase in aggregate risk is associated with the variance of the market portfolio return which is unobservable in practice. However, when the international stock market portfolio is a relatively large component of aggregate wealth, there must be positive relationship between an increase in aggregate risk and observed aggregate stock market variance. The changes in aggregate stock market variance can be sourced from two components: innovations in average volatility and innovations in average correlation. The two components tend to be correlated,[21] hence it is important to analyze the source of pricing power in the cross-section.

To investigate this, we construct the global equity volatility innovation factor by taking first difference of the aggregate level of volatility. The aggregate volatility is measured by averaging individual volatility estimates from GARCH(1,1) model for all MSCI international equity market indices. The global correlation innovation factor is constructed from DECO OOS model as described in Section 4.1.[22] We design two empirical tests to identify the source of explanatory power. In the first test, we orthogonalize our correlation innovation factor ($\Delta Corr$) against the global equity volatility innovation factor (ΔVol). We then perform all five forms of cross-sectional asset pricing tests as in Table 4 using the correlation residual factor ($\Delta Corr_{resid}$) after controlling DOL and ΔVol. In the second test, we do the opposite, meaning that ΔVol is orthogonalized against $\Delta Corr$ and the volatility residual factor (ΔVol_{resid}) is used jointly with DOL and $\Delta Corr$. The results from the formal test is shown in Panel A and those from the latter test is shown in Panel B of Table 7, respectively. The first set of columns (*1.Correlation Residual*) shows that the price of risk to our correlation

[20] Regarding to the concern related to independent test assets, we also perform Fama-Macbeth test on individual currencies. We find that our factor is significantly priced in the cross-section of individual currencies with the normalized price of beta risk (γ_{norm}) of -1.6 and t-statistic of -2.6.

[21] The estimated correlation coefficient between the aggregate volatility innovation and correlation innovation is 0.49 from March 1976 to December 2014.

[22] Our method of using DECO model also generate outputs for GARCH volatility levels. Therefore, the two different estimates, volatilities and correlations, are in fact sourced from one model.

factor is still economically and statistically significant after orthogonalizing the volatility components. However, the opposite it not true: the global equity volatility innovation does not have pricing power after removing the correlation component (*2. Volatility Residual*). The t-ratios are ranging from -2.51 (-2.98) to -6.88 (-7.83) for the formal (latter) case. Even for the formal case, where our correlation factor is orthogonalized against the volatility innovation factor, the normalized prices of risk for $\Delta Corr_{resid}$ are much greater than those for ΔVol, about -2.0 versus -1.1 on average. Therefore, we conclude that innovations in the average correlation rather than volatility reveal changes in true aggregate risk more clearly.

As described in Section 4.5, we further extend our analysis to the cross-section of equity markets. More specifically, we augment *FX 10* portfolios with the global (or U.S.) 25 Fama-French portfolios formed on size and book-to-market (or size and momentum) following Lustig and Verdelhan (2007) and Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011a).[23] 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 risk. This test also shed light on the degree of the market integration across the international currency market and the international or U.S. equity market.

Table 8 reports the cross-sectional test results. We use the global size and book-to-market (or momentum) portfolios and the global Fama-French-Carhart 4 factors in Panel A (or B) and the U.S. size and book-to-market (or momentum) portfolios and U.S. Fama-French-Carhart 4 factors in Panel C (or D) of Table 8, respectively. On left hand side, we report cross-sectional pricing results where only *DOL* and the factor-mimicking portfolio of our correlation factor are used to price the extended set of test assets. On the right hand, we perform CSR tests jointly with Fama-French-Carhart 4 factors and the factor-mimicking portfolio of equity volatility innovation factor. This setup allows us to find out a marginal contribution of our factor since our factor is directly competing against the volatility innovation factor as well as other traditional equity risk factors.

[23] Lustig and Verdelhan (2007) use 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 U.S. investor. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011a) 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 find that coefficients on covariance risk of our correlation factor are negatively significant across all sets of the test assets. The economic magnitude of the normalized price of covariance risk (λ_{norm}) is also very close to our previous findings in Table 2 and Table 7, ranging from -2.24 to -2.59. Other than our correlation innovation factor, the market (MRP), value (HML), and momentum (MOM) factors are found to have significant pricing power. Interestingly, the aggregate equity volatility innovation factor does not improve the cross-section fit after controlling our correlation factor. Moreover, the signs of price of volatility risk are all positive in these models, which are different from what we find in Table 7. These results show evidence that the source of pricing power in the cross-section is derived from the innovations in the aggregate correlation. The negatively significant price of the risk across the FX, international and domestic equity markets also supports the conjecture of market integration. This exercise also confirms that the statistical significance of the regression results is not specifically driven by our choice of test assets.

4.7 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 A and Panel B of Table 9. 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 C 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 *DOL* and *OOS* factors and *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 December 2014. In Panel D, we confirm that the correlation innovation factor is a priced-risk factor in the FX market.

5 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 propose a stylized 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)). In our model, the bilateral exchange rate depends on country specific (both domestic and foreign) and global consumption shocks. We assume the global shock affect all countries simultaneously whereas the country specific shock is partially correlated with the global shock.

Our model can generate both carry and momentum expected returns. The decomposition of the FX returns demonstrates why both carry and momentum portfolios can be simultaneously explained by the different loadings to our factor, while we observe low correlation between the two strategies in the empirics. We show in this section that the cross-sectional dispersion of beta loadings to our factor depends on two parameters, the risk aversion coefficient and the country-specific consumption correlation which captures a proportion of country i in the world consumption shock. 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 long-short carry and momentum trades positively co-move with changes in the global consumption shock because of the two terms, hence the two trading strategies are considered risky.

Lastly, a negative global consumption shock is associated with a positive innovation to the global correlation due to the asymmetric response of correlation to the global consumption shock (see, Ang and Chen (2002); Hong, Tu, and Zhou (2007)). In Section 5.5, we show that the model-implied equity correlation across countries inherits the same properties of the global consumption correlation specified in our framework. Hence, unexpected increases in the global equity correlation level 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.

5.1 The purpose of our model

Through our model, we are interested to know whether the excess return of any carry and momentum portfolios can be specified as follows.

$$\Delta\pi_{p,t+1} - E_t[\Delta\pi_{p,t+1}] = \alpha_p + \beta_{DOL,p} DOL_{t+1} + \beta_{\Delta Corr,p}\Delta Corr_{t+1} + \epsilon_{p,t+1} \tag{2}$$

$\Delta\pi_{p,t+1}$ is the excess return of portfolio p, where $p = 1, ..., 10$ is a portfolio sorted on interest rates or past returns. First, we investigate whether there can be any cross-sectional dispersion in $\beta_{\Delta Corr}$ across the FX portfolios, while there is no dispersion in β_{DOL}. Second, we check that both high (low) interest and high (low) momentum portfolios have negative (positive) beta loadings to our correlation innovation factor. Third, we explore to understand the source of dispersion in $\beta_{\Delta Corr}$ for carry and momentum trades. Fourth, we verify that the expected return of high interest (momentum) portfolio is higher than that of low interest (momentum) portfolio, hence the price of beta risk to our correlation innovation factor is negative, as shown in our empirical section.

5.2 Preferences and Consumption Growth Dynamics

Following Campbell and Cochrane (1999) and Menzly, Santos, and Veronesi (2004), we assume that the representative agent in country i maximizes expected utility of the form: $E\left[\sum_{t=0}^{\infty} \delta^t U(C_{i,t}, H_{i,t})\right]$,where U denotes Habit utility function: $U(C_{i,t}, H_{i,t}) = ln(C_{i,t} - H_{i,t})$, $H_{i,t}$ the external habit level, and $C_{i,t}$ aggregate consumption level of country i at time t.[24]
Log consumption growth dynamics is given by

$$\begin{aligned}
\Delta c_{i,t+1} &= g + \underbrace{\sigma \cdot (\rho_{i,t+1}\epsilon_{w,t+1} + \sqrt{1-\rho^2_{i,t+1}}\epsilon_{i,t+1})}_{\text{Country-specific shock}} + \underbrace{\sigma_{w,t+1} \cdot \epsilon_{w,t+1}}_{\text{Global shock}} \\
&= g + \sigma\sqrt{1-\rho^2_{i,t+1}} \cdot \epsilon_{i,t+1} + (\sigma\rho_{i,t+1} + \sigma_{w,t+1}) \cdot \epsilon_{w,t+1}
\end{aligned} \tag{3}$$

[24] We 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.

where σ denotes the volatility for a country-specific consumption shock, and $\sigma_{w,t+1}$ is the expected volatility for a global consumption shock, which is known at time t ($\sigma_{w,t+1} = E_t[\sigma_{w,t+1}]$). $\epsilon_{i,t+1}$ and $\epsilon_{w,t+1}$ are the standardized idiosyncratic and global shocks respectively. We assume that both $\epsilon_{i,t+1}$ and $\epsilon_{w,t+1}$ are independent and normally distributed with mean of zero and standard deviation of one ($\epsilon_{i,t+1}$ and $\epsilon_{w,t+1} \sim \mathsf{N}(0,1)$). $\rho_{i,t+1}$ is the correlation parameter between the country-specific and the global consumption shock, which is known at time t. The greater $\rho_{i,t+1}$ is, the more the total consumption shock of country i is connected to the global consumption shock.

We extend the habit model in Campbell and Cochrane (1999) and Verdelhan (2010) and assume that the total consumption growth innovation has 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 distinguish between global and country-specific factors and to capture the dynamics of the global correlation among N different countries.
We assume that the volatility of the global consumption shock follows asymmetric GARCH,

$$\sigma^2_{w,t+1} = E_t[\sigma^2_{w,t+1}] = \omega + \alpha_w \sigma^2_{w,t}(\epsilon_{w,t} - \theta_w)^2 + \beta_w \sigma^2_{w,t}$$

where ω, α_w, θ_w, and β_w are the asymmetric GARCH parameters. The dynamics of the correlation between the country specific shock and the global shock is given by

$$\rho_{i,t+1} = E_t[\rho_{i,t+1}] = tanh[\kappa_\rho(\bar{\rho} - \rho_{i,t+1}) + \alpha_\rho(\Delta c_{i,t} - E\left[\Delta c_{i,t}\right])]$$

where κ_ρ is the speed of mean reversion and $tanh$ denotes the hyperbolic tangent function, which guarantees the correlation to be between -1 and 1. α_ρ is the sensitivity of $\rho_{i,t+1}$ to the total consumption shock of country i and has positive value since country i becomes more connected to the world as its consumption grows. We assume g, σ, ω, α_w, θ_w, β_w, κ_ρ, α_ρ are the same across all countries for simplicity. Nevertheless, there is dispersion in $\rho_{i,t+1}$ across countries due to different realization path of consumption innovation for each country i.

The local curvature ($\Gamma_{i,t}$) and their log dynamics ($\Delta\gamma_{i,t}$) follow,[25]

$$\begin{aligned} log\ \Gamma_{i,t} &= log(-C_{i,t}\frac{U_{cc}}{U_c}) = log(\frac{C_{i,t}}{C_{i,t} - H_{i,t}}) \equiv \gamma_{i,t} \\ \Delta\gamma_{i,t+1} &= \kappa_\gamma(\bar{\gamma} - \gamma_{i,t+1}) - \alpha_\gamma(\gamma_{i,t+1} - \theta_\gamma)(\Delta c_{i,t+1} - E\left[\Delta c_{i,t+1}\right]) \end{aligned}$$

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

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

5.3 Risk-Free Rates

Given the log-normal assumption of the pricing kernel, the risk free rates can be written as

$$\begin{aligned} i_{i,t} &= -logE_t(M_{i,t+1}) = -[E_t(m_{i,t+1}) + \frac{1}{2}\sigma_t^2(m_{i,t+1})] \\ &= -\log\ \delta + g - \kappa_\gamma(\bar{\gamma} - \gamma_{i,t}) - \frac{1}{2}\ \hat{\gamma_{i,t}}^2\ [\sigma^2 + \sigma_{w,t+1}^2 + 2\ \sigma\ \sigma_{w,t+1}\ \rho_{i,t+1}] \end{aligned} \tag{4}$$

Denoting U.S. as a domestic country, the interest differentials between foreign country i and domestic rates boil down to

$$i_{i,t} - i_{us,t} = -\kappa_\gamma(\hat{\gamma}_{us,t} - \hat{\gamma}_{i,t}) + \frac{1}{2}(\hat{\gamma}_{us,t}^2 - \hat{\gamma}_{i,t}^2)[\sigma^2 + \sigma_{w,t+1}^2] + (\rho_{us,t+1}\hat{\gamma}_{us,t}^2 - \rho_{i,t+1}\hat{\gamma}_{i,t}^2)\ \sigma\ \sigma_{w,t+1}$$

[25] See Menzly, Santos, and Veronesi (2004) and Christoffersen, Du, and Elkamhi (2015) for the dynamics of the risk aversion coefficient

5.4 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: $E_t(M^i_{t+1}R^i_{t+1}) = 1$ and $E_t(M^{us}_{t+1}R^i_{t+1}\frac{Q^i_{t+1}}{Q^i_t}) = 1$ where Q is the real exchange rates measured in home country goods per foreign country i's good. The change in log real exchange rate is given by

$$\begin{aligned}
\Delta q_{i,t+1} &= m_{i,t+1} - m_{us,t+1} \\
&= \kappa_\gamma(\hat{\gamma}_{us,t} - \hat{\gamma}_{i,t}) - \ \hat{\gamma}_{i,t}\,[\sigma\sqrt{1-\rho^2_{i,t+1}}\epsilon_{i,t+1} + (\sigma\rho_{i,t+1} + \sigma_{w,t+1})\,\epsilon_{w,t+1}] \\
&\quad + \hat{\gamma}_{us,t}\ [\sigma\sqrt{1-\rho^2_{us,t+1}}\epsilon_{us,t+1} + (\sigma\rho_{us,t+1} + \sigma_{w,t+1})\,\epsilon_{w,t+1}] \qquad (5)
\end{aligned}$$

The exchange rate premium, or excess return of the currency ($\Delta\pi_{i,t+1}$), 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.

$$\begin{aligned}
\Delta\pi_{i,t+1} &= \Delta q_{i,t+1} + i_{i,t} - i_{us,t} \\
&= \frac{1}{2}(\hat{\gamma}^2_{us,t} - \hat{\gamma}^2_{i,t})[\sigma^2 + \sigma^2_{w,t+1}] + \ (\rho_{us,t+1}\hat{\gamma}^2_{us,t} - \rho_{i,t+1}\hat{\gamma}^2_{i,t})\,\sigma\,\sigma_{w,t+1} \\
&\quad - \hat{\gamma}_{i,t}\,[\sigma\sqrt{1-\rho^2_{i,t+1}}\epsilon_{i,t+1} + (\sigma\rho_{i,t+1} + \sigma_{w,t+1})\,\epsilon_{w,t+1}] \\
&\quad + \hat{\gamma}_{us,t}\ [\sigma\sqrt{1-\rho^2_{us,t+1}}\epsilon_{us,t+1} + (\sigma\rho_{us,t+1} + \sigma_{w,t+1})\,\epsilon_{w,t+1}] \qquad (6)
\end{aligned}$$

5.5 The Model Implied Consumption Correlation

Under the specification of the model in Equation 3, a consumption correlation between two countries (i and j) is defined as

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

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

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

The currency risk premium required by investors for holding currency i 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 (2014) and Verdelhan (2010). Cross-sectionally, investors demand high compensation holding a currency of a country with a low risk aversion coefficient (low $\gamma_{i,t}$) and low idiosyncratic consumption correlation (low $\rho_{i,t+1}$). Then, why do investors require higher premium for those currencies? To answer this, we investigate whether there is a factor structure in the excess return of any FX portfolio.

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

$$\begin{aligned} \overline{\Delta\pi_{i,t+1}} - E_t[\overline{\Delta\pi_{i,t+1}}] &= \hat{\gamma}_{us,t}\,\sigma\sqrt{1-\rho^2_{us,t+1}}\epsilon_{us,t+1} - \overline{\hat{\gamma}_{i,t}\,\sigma\sqrt{1-\rho^2_{i,t+1}}\epsilon_{i,t+1}} \\ &\quad + \underbrace{[(\hat{\gamma}_{us,t} - \overline{\hat{\gamma}_{i,t}})\,\sigma_{w,t+1} \;+\; (\rho_{us,t+1}\hat{\gamma}_{us,t} - \overline{\rho_{i,t+1}\hat{\gamma}_{i,t}})\,\sigma]}_{Loading}\;\underbrace{\epsilon_{w,t+1}}_{Factor} \end{aligned} \tag{7}$$

We let $\overline{\Delta\pi_{i,t+1}}$ denote the average of $\Delta\pi_{i,t+1}$ across currencies in a portfolio. The first term on the right side of Equation 8 is closely related to the dollar factor (DOL) in our empirical setup, since it drives a common variation of currencies across all countries. Excess returns of any currency portfolio are positively correlated with domestic (U.S.) consumption shock, and more importantly, the degree of sensitivity to the shock is countercyclical and depends only on domestic condition. Therefore, this term captures the domestic country's countercyclical risk premia. The second term represents the idiosyncratic foreign consumption shock, which is independent of shocks from other currency portfolios.

Similarly to the first term, the last term of the equation also drives a common variation in excess returns of a currency portfolio. However, this term represents the exposure to the global consumption shock and the sensitivity to the shock varies by country. The cross-sectional differences in exposure to the global consumption risk depend on two terms, portfolio $\overline{\hat{\gamma}_{i,t}}$ and $\overline{\rho_{i,t+1}\hat{\gamma}_{i,t}}$. 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 $\overline{\hat{\gamma}_{i,t}}$ or low $\overline{\rho_{i,t+1}\hat{\gamma}_{i,t}}$ are considered more risky and investors require a greater rate of return as compensation. Since we empirically measure negative global consumption shocks through global correlation innovations, Equation 8 can be denoted as,

$$\Delta\pi_{p,t+1} - E_t[\Delta\pi_{p,t+1}] = DOL_{t+1} + \beta_{\Delta Corr,p}\Delta\Psi_{t+1} + \epsilon_{p,t+1} \tag{8}$$

Relating to Equation 2, we have $\alpha_p = 0$, $\beta_{DOL,p} = 1$ and $\beta_{\Delta Corr,p} = (\hat{\gamma}_{us,t} - \hat{\gamma}_{p,t})\,\sigma_{w,t+1} + (\rho_{us,t+1}\hat{\gamma}_{us,t} - \rho_{p,t+1}\hat{\gamma}_{p,t})\,\sigma$ for all currency portfolio p in Equation 8.[26] Therefore, there are two distinct sources of dispersion in $\beta_{\Delta Corr,p}$ across currency portfolios: $\hat{\gamma}_{p,t}$ and $\rho_{p,t+1}$.

We show below that, on one hand, portfolios of currencies with high interest rates have low $\hat{\gamma}_{p,t}$, but no significant pattern for $\rho_{p,t+1}\hat{\gamma}_{p,t}$. On the other hand, portfolios of currencies with high momentum have low $\rho_{p,t+1}\hat{\gamma}_{p,t}$, but no significant pattern for $\hat{\gamma}_{p,t}$. Given the independent variations of $\hat{\gamma}_{p,t}$ and $\rho_{p,t+1}$, sorting currencies by interest rate differentials is closely related to sorting currencies by the risk aversion rate of individual country ($\hat{\gamma}_{i,t}$), and sorting currencies by momentum is related to sorting by level of closeness of the country specific shock to the world consumption shock ($\rho_{i,t+1}$). Moreover, we also verify that both high (low) interest and high (low) momentum portfolios have negative (positive) beta loadings to our correlation innovation factor because of low (high) $\hat{\gamma}_{p,t}$ and $\rho_{p,t+1}$, respectively.

In what follows, we perform a Monte-Carlo simulation to generate carry and momentum returns. We first simulate the consumption dynamics of 200 countries, and drive the changes in spot rates and excess returns of the corresponding currencies through Equation 5 and 6. We choose our parameters following Menzly, Santos, and Veronesi (2004) and Christoffersen, Du, and Elkamhi (2015), who calibrate their models to fit U.S. equity premiums and con-

[26] $\hat{\gamma}_{p,t}$ and $\rho_{p,t+1}\hat{\gamma}_{p,t}$ are $\overline{\hat{\gamma}_{i,t}}$ and $\overline{\rho_{i,t+1}\hat{\gamma}_{i,t}}$ respectively, which are the average levels across countries in a portfolio p at time t.

sumption dynamics. Our choice of parameters are presented in Panel A of Table 10. 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. Our simulation results show that we are able to generate 4.3% and 2.1% spreads in annualized average excess returns for high-minus-low carry and momentum portfolios respectively. We also have monotonically increasing pattern of average excess returns across carry and momentum portfolios, although the spreads are lower than the actual spreads which we observe in our empirics. The moments of excess returns of simulated carry and momentum portfolios are presented in Panel B of Table 10.

On the top panels of Figure 8, we plot time-series of the $\hat{\gamma}_{p,t}$ of the highest and the lowest interest portfolios from the simulation. The $\hat{\gamma}_{p,t}$ of the portfolio with low interest rate currencies is persistently higher than the $\hat{\gamma}_{p,t}$ of the portfolio with high interest rate currencies. We do not find this persistent gap in the $\hat{\gamma}_{p,t}$ in the cross-section of momentum portfolios. the bottom panels of Figure 8 shows the $\rho_{p,t+1}\hat{\gamma}_{p,t}$ of the highest and the lowest momentum portfolios. The $\rho_{p,t+1}\hat{\gamma}_{p,t}$ of the portfolio with low momentum currencies is persistently higher than the $\rho_{p,t+1}\hat{\gamma}_{p,t}$ of the portfolio with high momentum currencies. We do not find this persistent gap in the $\rho_{p,t+1}\hat{\gamma}_{p,t}$ in the cross-section of carry portfolios. The independent variations of $\hat{\gamma}_{p,t}$ and $\rho_{p,t+1}$, therefore, imply that carry portfolios are closely related to the risk aversion coefficient, whereas momentum portfolios are closely related to the level of the country-specific correlation to the world consumption shock ($\rho_{p,t+1}$).

In our model, intuitively, sorting by interest differentials (carry) boils down to sorting by risk aversion coefficients.[27] As a result, our model generates low excess returns for the currencies from low interest rates countries since they provide hedge against negative world consumption shocks. Momentums, on the other hand, are about the past realizations of the pricing kernel (see, Equation 5) since momentum returns are driven by changes in exchange rates, not interest rate differentials as described in Menkhoff, Sarno, Schmeling, and Schrimpf (2012b). The realization of the pricing kernel and consumption is negatively related as

[27] We point out that there exists heterogeneity in the risk aversion across countries even with similar long-term average risk aversion due to different realizations of consumption path in each country (slow-moving habit formation).

described in Hau and Rey (2006). Thus, as a country i experiences relatively high level of consumption growth, the proportion of country i in the world consumption shock grows, which implies an increase in the level of country-specific correlation defined as ρ in our model. Consistent with the intuition from Hassan (2013), the currencies of high level of country-specific correlation demand low average excess returns because they insure against shocks that affect a larger fraction of the world economy.

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 8 and taking first difference of the ex-post unexpected excess return of long and short portfolios gives

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

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 our correlation innovation factor depends on (1) the risk aversion coefficient and (2) the idiosyncratic correlation coefficient between the long and short portfolios. Combining the two sources of dispersion, Figure 9 plots the aggregate beta loadings to the correlation innovation factor. The figure shows that both of high-minus-low return spreads in traditional carry and momentum trades would have negative beta 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 for the same number of countries in our empirical analysis, and drive equity returns using numerical integration.[28] 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 10 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.

6 Conclusion

Carry and momentum trades are a widely known 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 past returns 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 conditions, the risk aversion coefficient and the 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.

[28]See, Watcher (2005) for details of the numerical integration methodology.

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.

A Appendices

A.1 DECO model

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

$$\begin{aligned} r_{i,t} &= \mu_i + \epsilon_{i,t} = \mu_i + \sigma_{i,t} z_{i,t} \qquad (9) \\ \sigma^2_{i,t} &= \omega_i + \alpha_i \epsilon^2_{i,t-1} + \beta_i \sigma^2_{i,t-1} \qquad (10) \end{aligned}$$

where μ_i denotes the unconditional mean, $\sigma^2_{i,t}$ 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 $\Sigma_t = D_t R_t D_t$ 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.

$$\begin{aligned} Q_t &= (1 - \alpha_Q - \beta_Q)\overline{Q} + \alpha_Q \tilde{Q}^{\frac{1}{2}}_{t-1} z_{t-1} z'_{t-1} \tilde{Q}^{\frac{1}{2}}_{t-1} + \beta_Q Q_{t-1} \qquad (11) \\ R_t^{DCC} &= \tilde{Q}_t^{-\frac{1}{2}} Q_t \tilde{Q}_t^{-\frac{1}{2}} \qquad (12) \\ \rho_t &= \frac{1}{n(n-1)}(\imath' R_t^{DCC} \imath - n) \qquad (13) \\ R_t^{DECO} &= (1 - \rho_t) I_n + \rho_t J_{n \times n} \qquad (14) \end{aligned}$$

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, $\overline{Q}$ is the unconditional covariance matrix of z_t, ρ_t is the equicorrelation, $\imath$ 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.

A.2 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

$$\begin{aligned} \mu = E[Y_t] &= \begin{bmatrix} \mu_f \\ \mu_R \end{bmatrix} \\ V = Var[Y_t] &= \begin{bmatrix} V_f & V_{fR} \\ V_{Rf} & V_R \end{bmatrix} \end{aligned}$$

If the K factor asset pricing model holds, the expected returns of the N assets are given by $\mu_R = X\gamma$, 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 two-pass cross-sectional regression (CSR) method first obtains estimates $\hat{\beta}$ by running the following multivariate regression:

$$\begin{aligned} R_t &= \alpha + \beta f_t + \epsilon_t, \quad t = 1, \cdots, T \\ \hat{\beta} &= \hat{V}_{Rf}\hat{V}_f^{-1} \\ \gamma_W &= argmin_\gamma(\mu_R - X\gamma)'W(\mu_R - X\gamma) = (X'WX)^{-1}X'W\mu_R \\ \hat{\gamma} &= (\hat{X}'W\hat{X})^{-1}\hat{X}'W\hat{\mu}_R \end{aligned}$$

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 $\rho_W^2 = 1 - \frac{Q}{Q_0}$, where $Q = e'_W W e_W$, $Q_0 = e'_0 W e_0$, $e_W = [I_N - X(X'WX)^{-1}X'W]\mu_R$, and $e_0 = [I_N - 1_N(1_N'W1_N)^{-1}1_N'W]\mu_R$.

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

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

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

Kan, Robotti, and Shanken (2013) 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. The distribution is given by

$$\begin{aligned} \sqrt{T}(\check{\gamma}-\gamma) &\overset{A}{\sim} N(0_{K+1}, V(\hat{\gamma})) \\ V(\hat{\gamma}) &= \sum_{j=-\infty}^{\infty} E[h_t h_{t+j}'] \\ h_t &= (\gamma_t - \gamma) - (\theta_t - \theta)w_t + Hz_t \end{aligned}$$

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 (2013) 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.

$$\mu_R = X\gamma = C\lambda \tag{15}$$

$$\hat{\lambda} = (\hat{C}'W\hat{C})^{-1}\hat{C}'W\hat{\mu}_R \tag{16}$$

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 matter 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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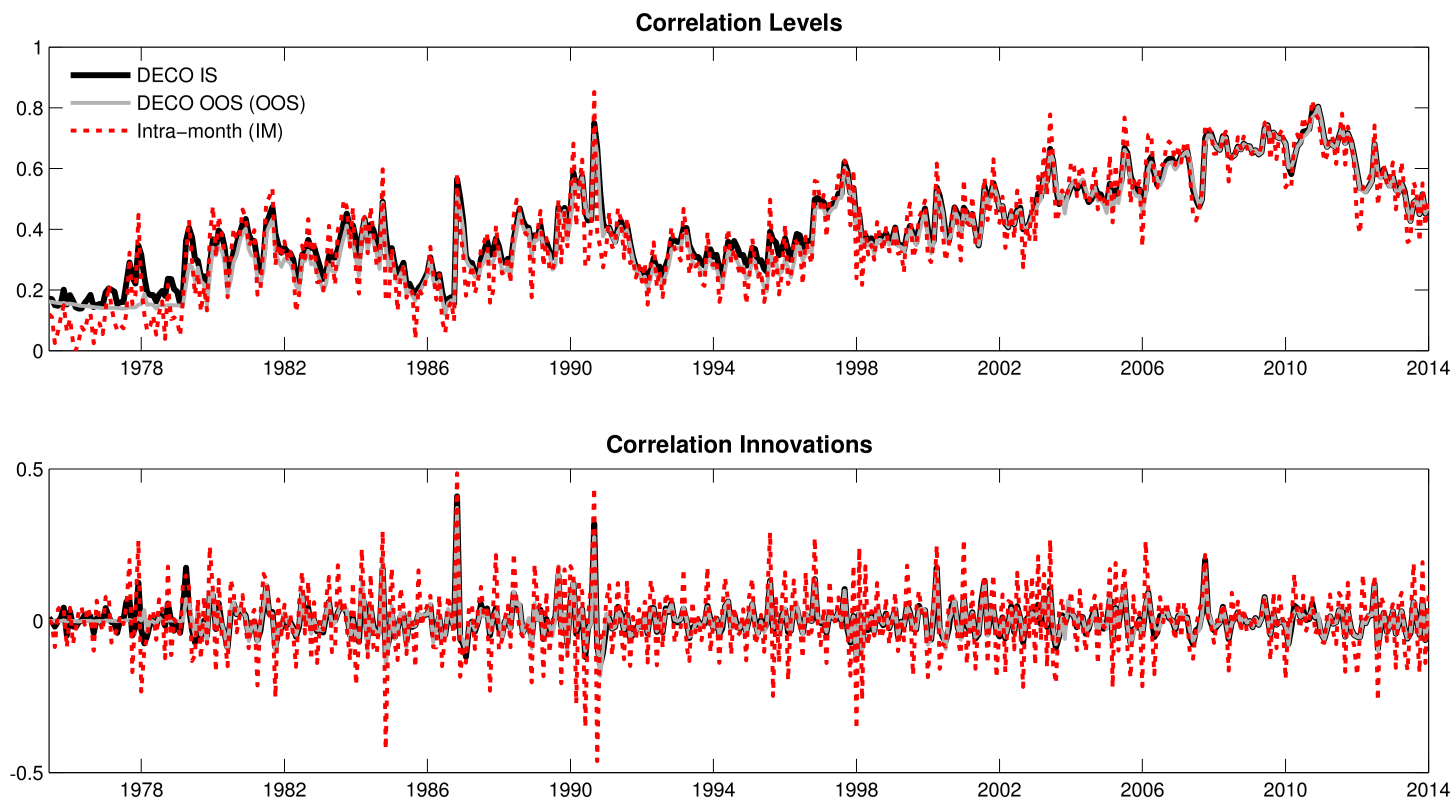


Figure 1: **Correlation Innovation Factors**

The upper panel of the figure shows a time-series plot of the global equity correlation levels. The solid black line, DECO *IS*, is measured by DECO model (Engle and Kelly, 2012) where parameters are estimated on the entire monthly return series of international indices. The solid gray 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 (IM) 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. 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 levels. The sample covers the period March 1976 to December 2014.

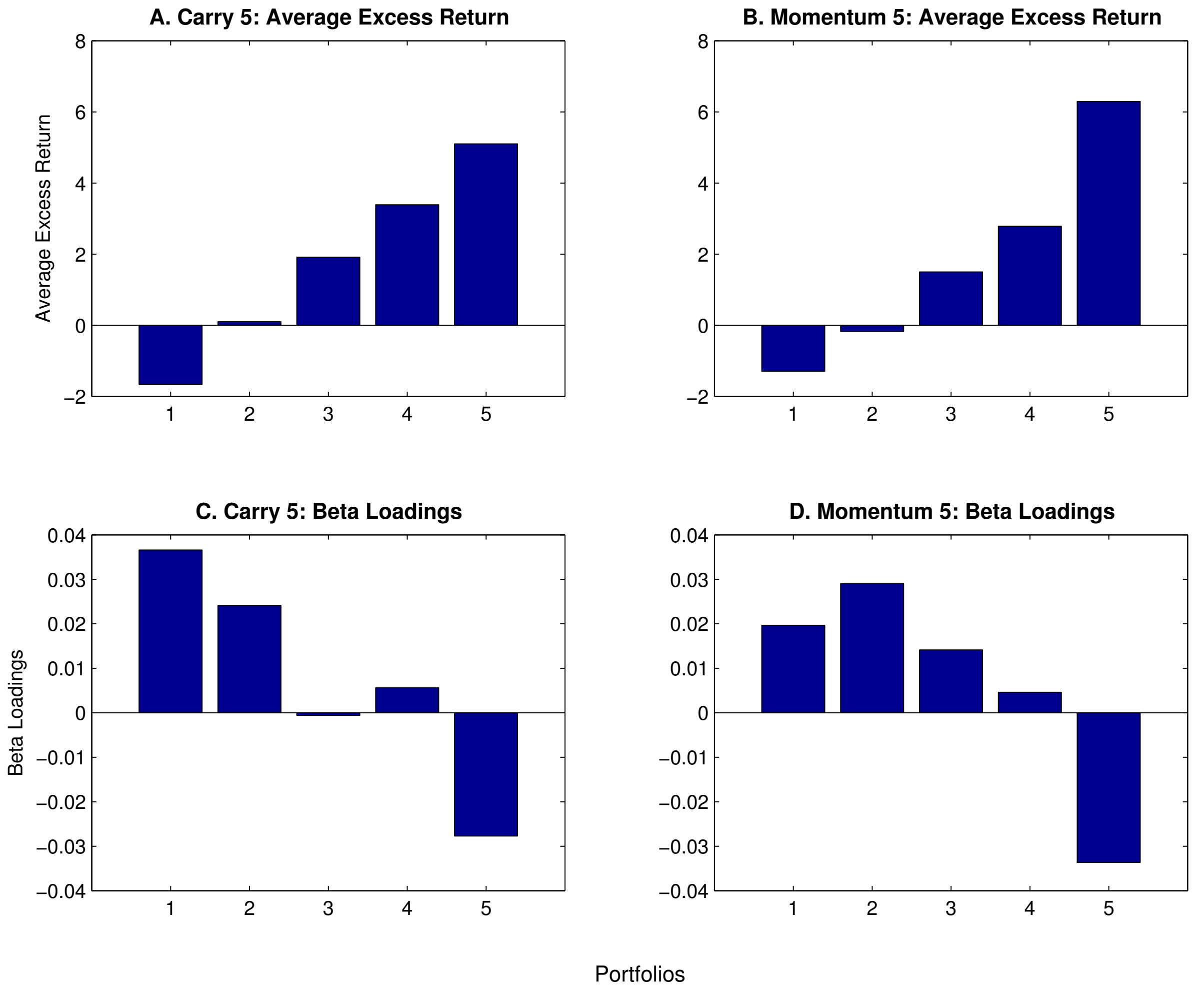


Figure 2: **Average Excess Returns and Beta Loadings**
This figure plots the average excess returns of carry and momentum portfolios in Panel A and B, and each portfolio's beta loading with respect to our global equity correlation innovation factor in Panel C and D. The aggregate correlation levels are measured by out-of-sample DECO model (OOS) as described in Section 4.1. The sample covers the period May 1976 to December 2014.

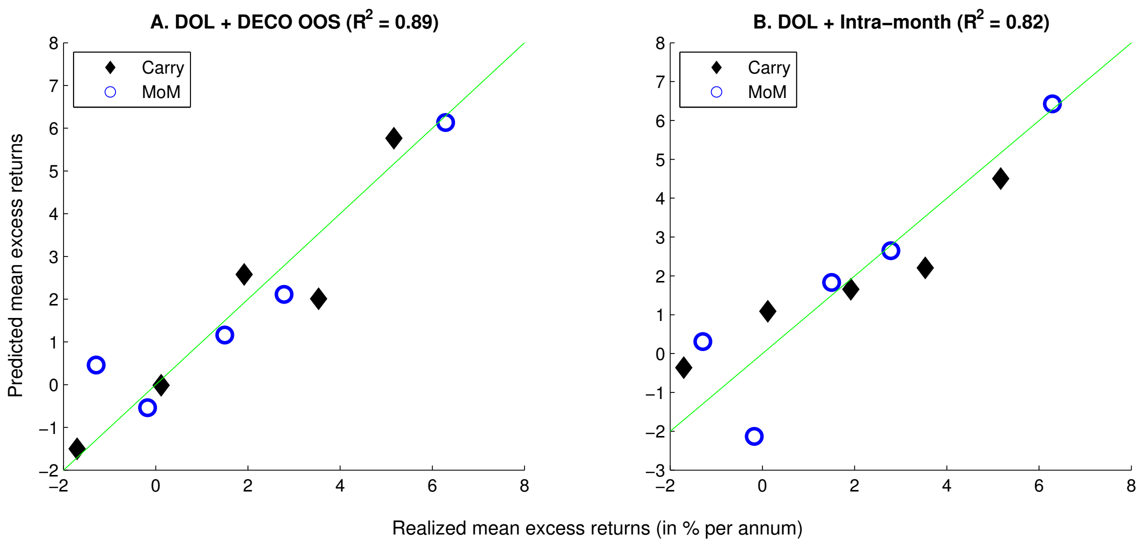


Figure 3: **Pricing Error Plot: Correlation Innovation Factors on *FX 10***
This figure presents the pricing errors of the asset pricing models with our global equity correlation as a risk factor. The global equity correlation levels are measured by DECO model (OOS) for Panel A and by averaging intra-month bilateral correlations (IM) for Panel B. The realized actual excess returns are on the horizontal axis and the model predicted average excess returns are on the vertical axis. The test assets are *FX 10* portfolios: the set of carry portfolios (5) and momentum portfolios (5). The estimation results are based on OLS CSR test while imposing the same price of risk for the test assets within each plot. The sample covers the period March 1976 to December 2014.

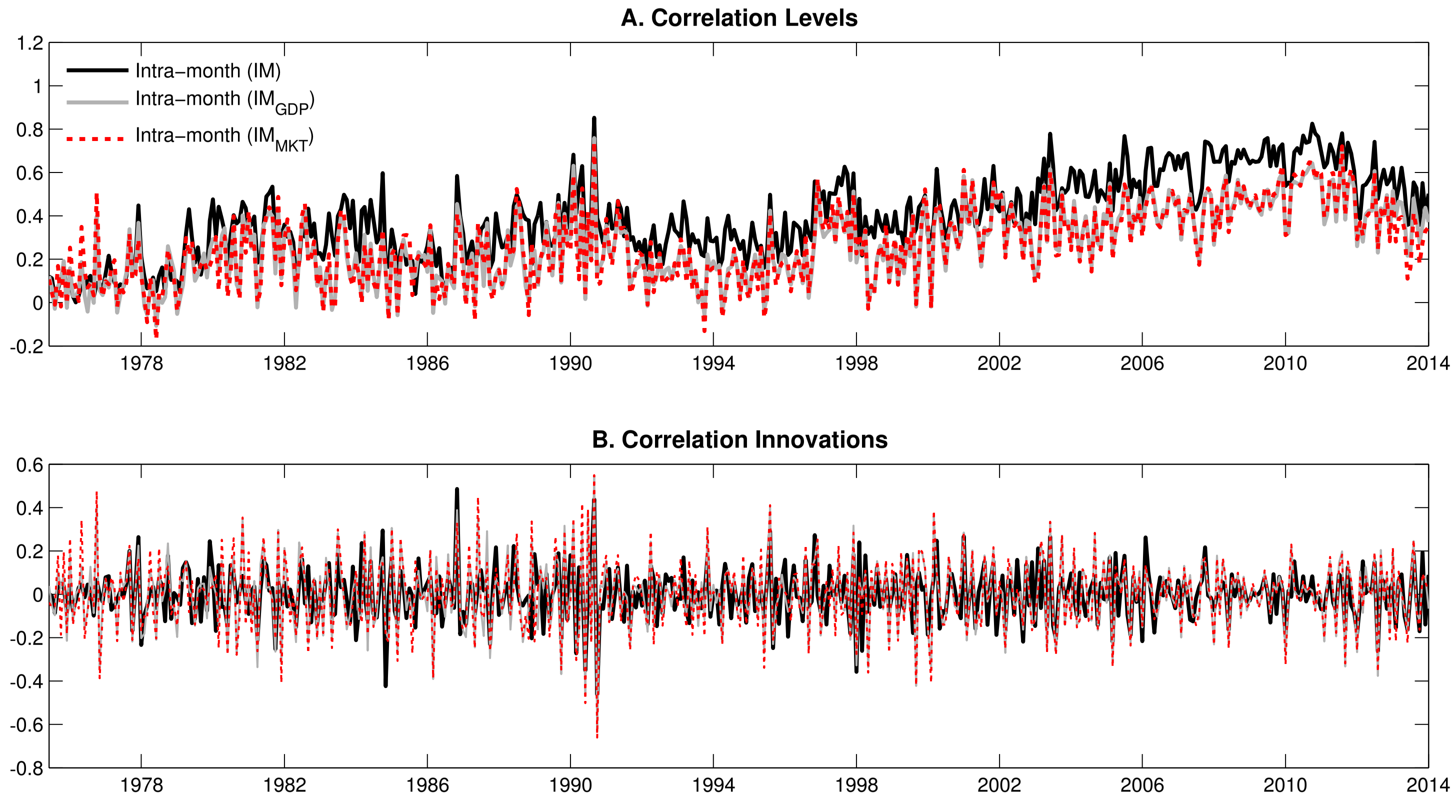


Figure 4: **Different Weightings for the Global Correlation Innovation Factor**

The upper panel of the figure shows a time-series plot of the global equity correlation levels. In each month end, correlation levels are measured by computing bilateral intra-month correlations at each month end using daily return series of international MSCI equity indices. The solid black line, IM, the aggregate correlation level is estimated by computing equally-weighted average over all bilateral correlations at the end of each month. The gray (dotted red) line, IM_{GDP} (IM_{MKT}), correlation levels are estimated by computing GDP-weighted (Market-capitalization-weighted) average over all bilateral correlations. 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 levels. The sample covers the period March 1976 to December 2014.

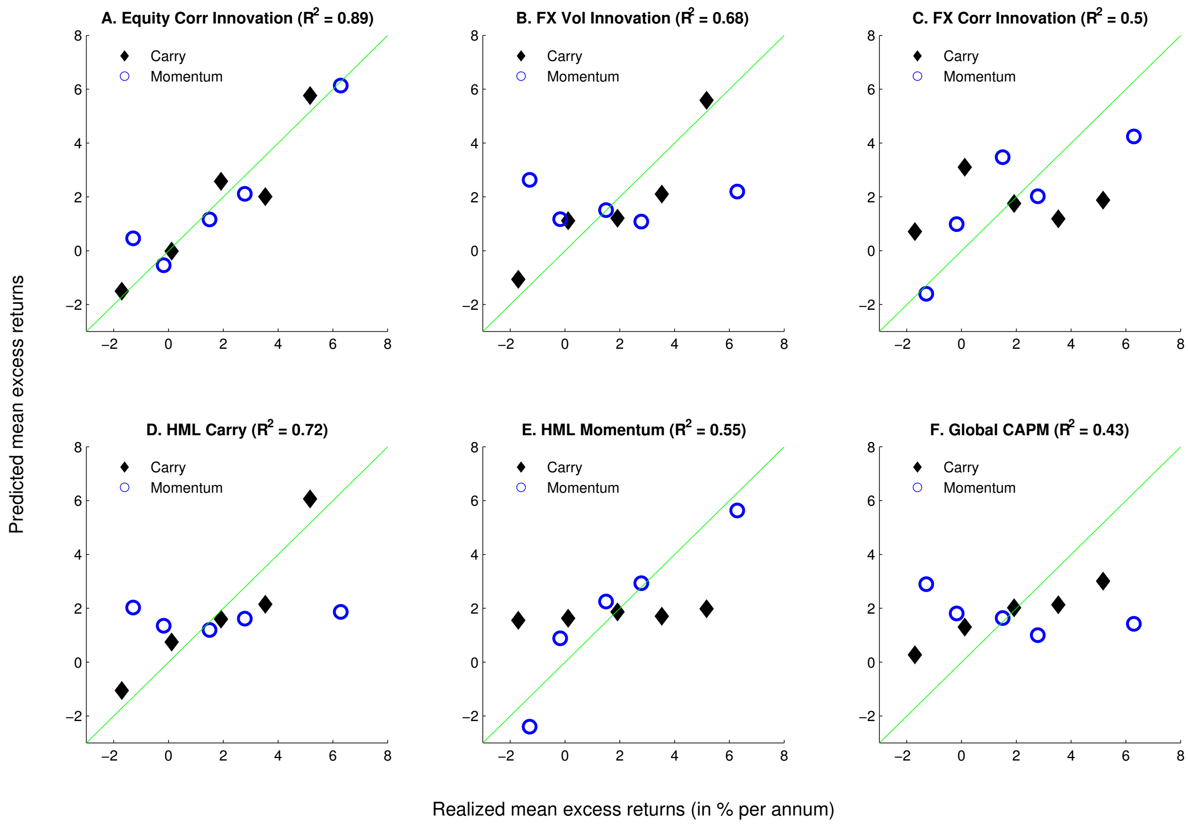
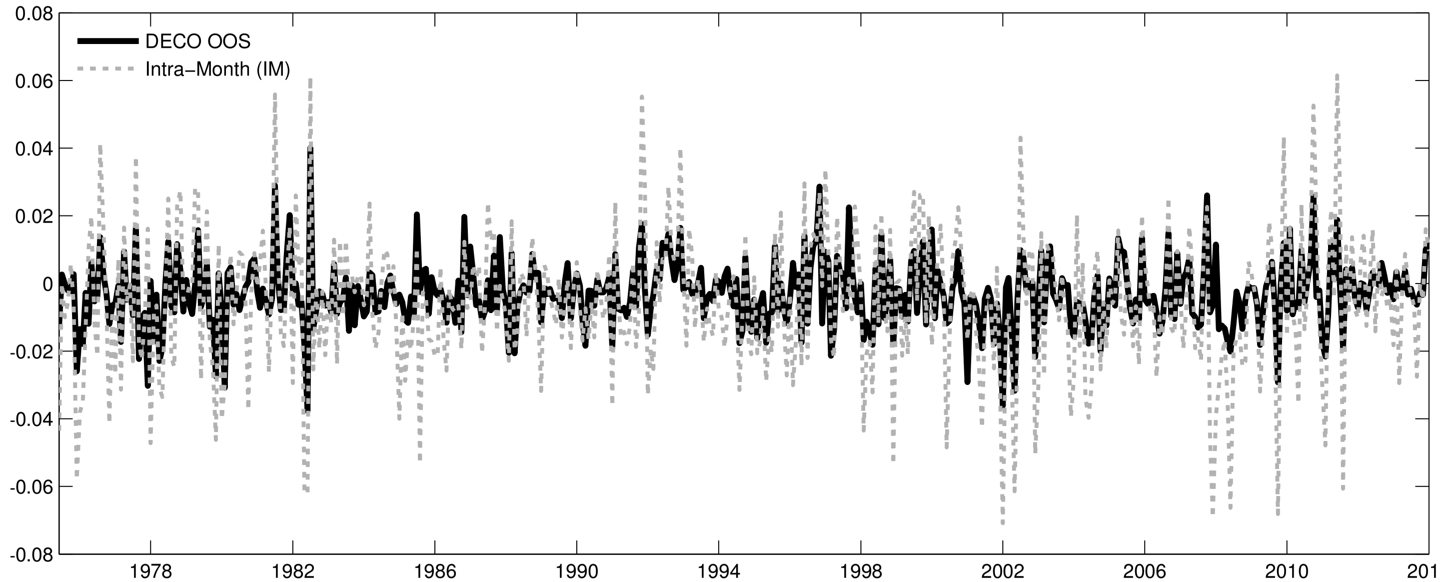


Figure 5: **Pricing Error Plot: Other Factors**

The figure presents the pricing errors of the asset pricing models with the selected risk factors from the list described in Section 4.4. The realized actual excess returns are on the horizontal axis and the model predicted average excess returns are on the vertical axis. The test assets are *FX 10* portfolios: the set of carry portfolios (5) and momentum portfolios (5). We use our global equity correlation innovation factor (*OOS*) in Panel A, the FX volatility innovation factor in Panel B, the FX correlation innovation factor in Panel C, the high-minus-low carry factor in Panel D, the high-minus-low momentum factor in Panel E, and the global equity market factor in Panel F. The estimation results are based on OLS CSR test. The sample covers the period March 1976 to December 2014.



	Mean	Median	Volatility	Skewness	Kurtosis
OOS	-3.87	-4.02	3.40	0.20	4.64
IM	-7.20	-7.00	6.99	-0.10	4.10

Figure 6: **Time-series Plot of Factor-Mimicking Portfolio**

This figure shows a time-series of the factor-mimicking portfolio of our global equity correlation innovation factors. To obtain the return series, we first regress our correlation innovation series (*OOS* or *IM*) on carry and momentum portfolios (*FX 10* portfolios) and then retrieve the fitted returns. *OOS* is measured by DECO model (Engle and Kelly, 2012) where parameters are estimated on the data available at the point in time and updated with expanding window as we collect more data. For *IM*, the aggregate correlation level is estimated by computing equally-weighted average of all daily bilateral correlations at the end of each month. The sample covers the period March 1976 to December 2014.

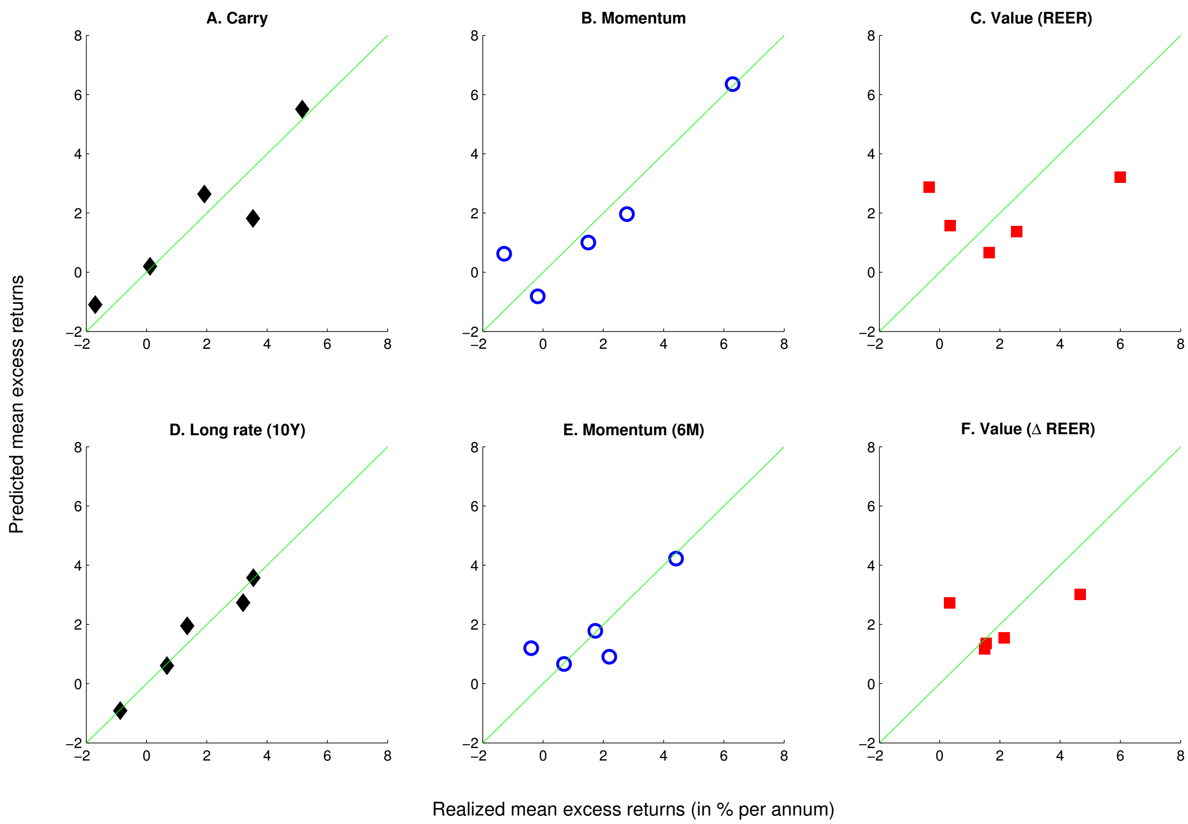


Figure 7: **Pricing Error Plot: Factor-Mimicking Portfolio**
The figure shows the pricing errors of the asset pricing models with a factor-mimicking portfolio of our correlation innovation (OOS) as a risk factor. The realized actual excess returns are on the horizontal axis and the model predicted average excess returns are on the vertical axis. The test assets are five portfolios sorted on A. Carry: short-term (1M) interest rate differentials, B. Momentum: past three-months excess returns, C. Value (REER): the level of real effective exchange rates, D. Long rate: long-term (10Y) interest rate differentials, E. Momentum (6M): past 6-month excess returns, and F. Value (ΔREER): past 60-month changes of real effective exchange rates. The estimation results are based on OLS CSR test. The sample covers the period March 1976 to December 2014.

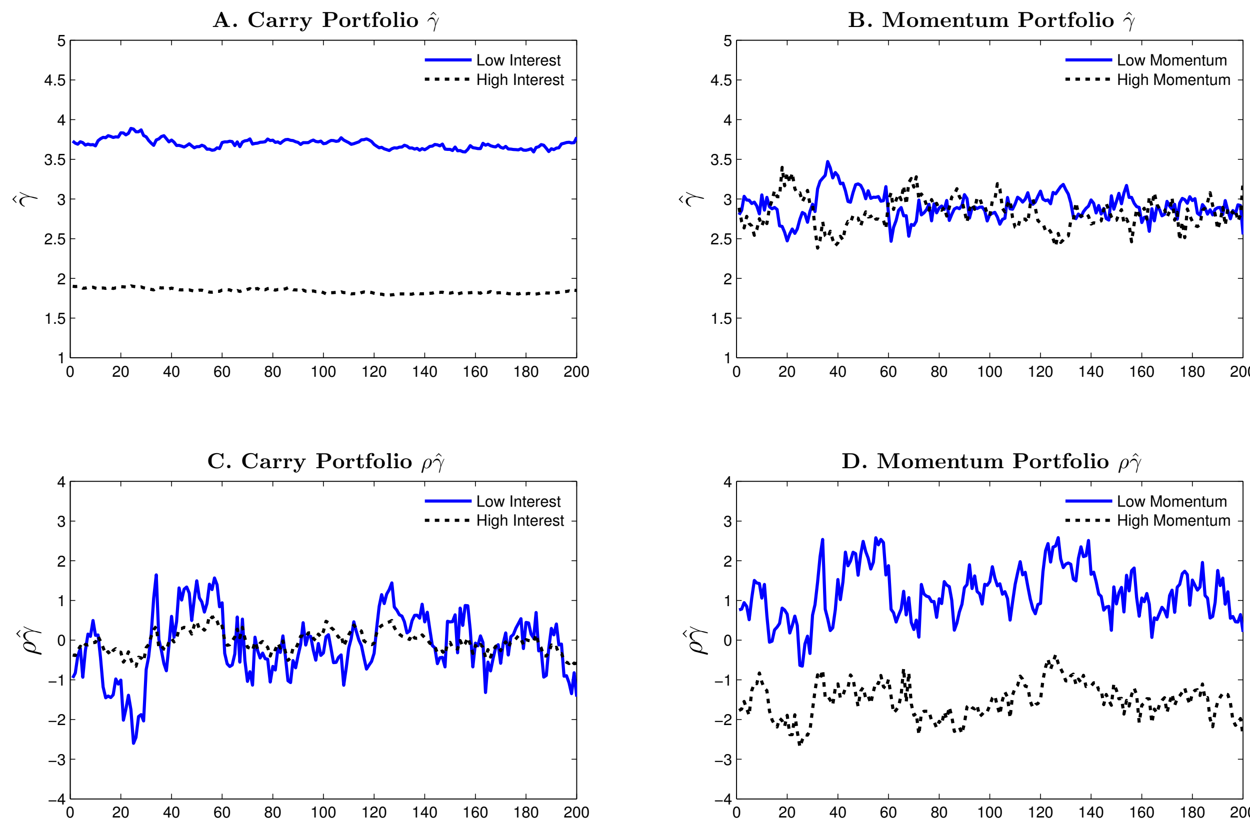


Figure 8: **Simulated Parameters for Carry and Momentum Portfolios**
This figure shows the simulated parameters for carry and momentum portfolios. Panel A and C (B and D) show the average values of the parameters for carry (momentum) portfolios. We show a time-series plot of $\hat{\gamma}$ in the upper panels (Panel A and B), and a time-series plot of $\rho\hat{\gamma}$ in the lower panels (Panel C and D) respectively. In each panel, the solid blue line is a time-series plot of the parameter values for a low interest (momentum) portfolio, and the dotted black line is for a high interest (momentum) portfolio.

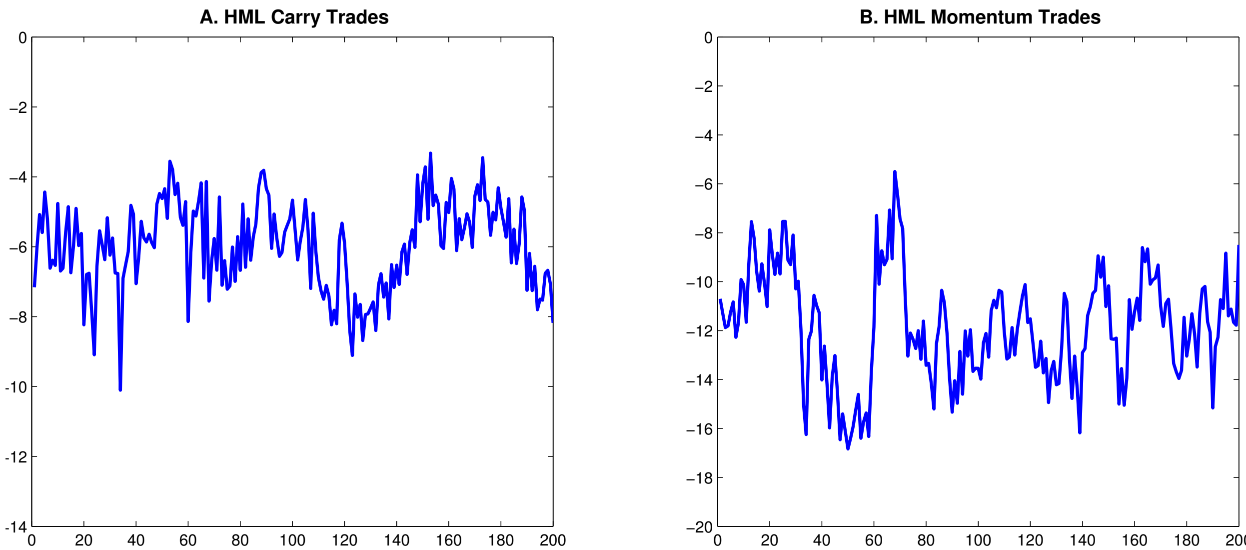


Figure 9: **Beta Loadings to the Correlation Innovation Factor**

The figure on the left shows a time-series of beta loadings to the correlation innovation factor of HML carry trades: long high interest rate currencies and short low interest rate currencies, using simulated rates and returns. The figure on the right shows those of HML momentum trades: long high excess return currencies and short excess return currencies over the last three month, using simulated returns. In other words, the solid blue line plots $\beta_{\Delta Corr,L-S}$ of the equation below for the long-short carry trades (Panel A) and for the long-short momentum trades (Panel B).

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

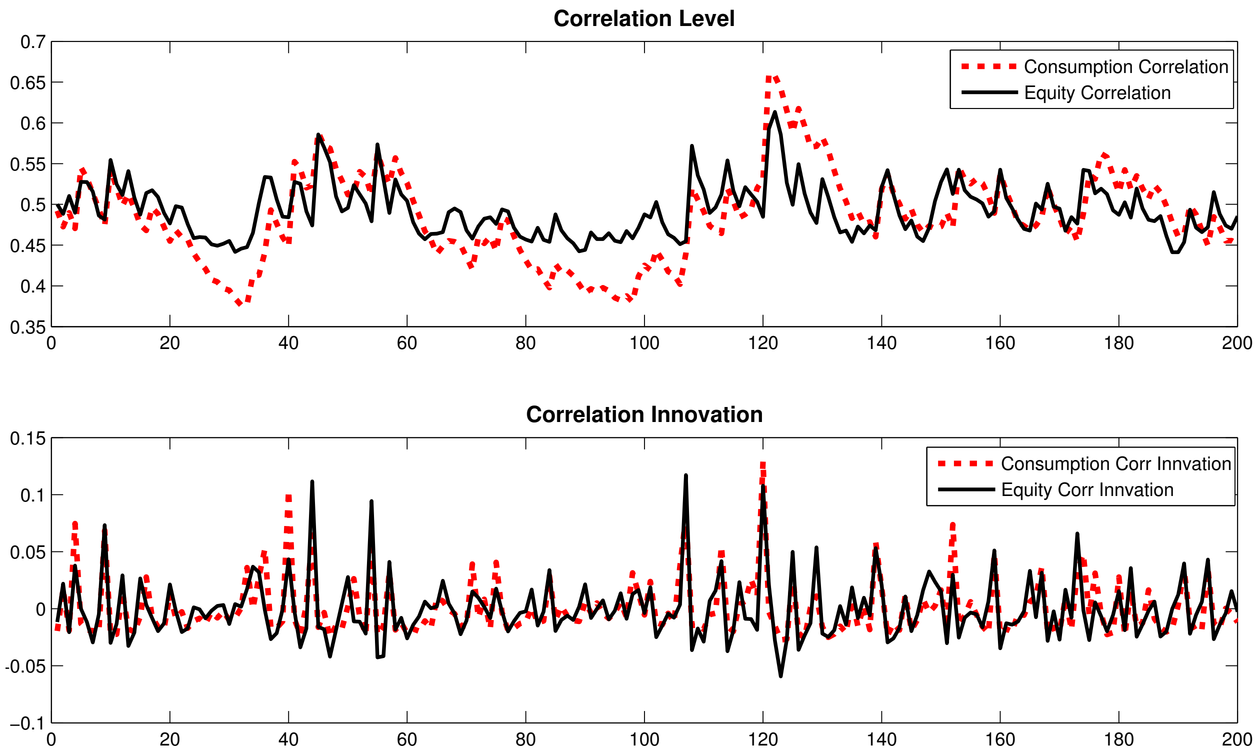


Figure 10: **Simulated Consumption and Equity Correlation Innovation**
This figure compares consumption correlations and equity correlations where both series are simulated from our model. The upper panel of the figure shows a time-series plot of the common consumption correlation levels (solid blue line) and the equity correlation levels estimated by running DECO model on the simulated equity returns (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 levels. The correlations between two series are 0.76 and 0.80 for the level and the innovation respectively.

Table 1: Moments of Carry and Momentum Portfolios

The table reports statatistics for the annualized excess currency returns of currency portfolios sorted as follows. A. Carry portfolios are sorted on last month's forward discounts with one-month maturity, B. Momentum 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 the lowest interest differentials (or past returns), while portfolio 5 contains currencies with the highest interest differentials (or past returns). HML denotes differences in returns between portfolio 5 and 1. The excess returns cover the period March 1976 to December 2014.

Panel A. Carry: Portfolios Sorted on Forward Discounts

	All Countries (44)						**Developed Countries (17)**					
	Low	2	3	4	High	HML	Low	2	3	4	High	HML
Mean	-1.67	0.10	1.91	3.39	5.10	6.77	-0.88	-0.77	1.25	2.58	4.48	5.37
Median	-1.49	1.40	2.35	4.75	9.21	9.90	-0.52	1.54	2.41	3.92	5.24	9.39
Std. Dev	9.14	9.13	8.45	8.92	10.07	7.95	10.02	9.79	9.08	9.56	10.73	9.33
Skewness	-0.10	-0.43	0.00	-0.44	-1.05	-1.84	0.05	-0.16	-0.16	-0.42	-0.40	-0.58
Kurtosis	4.41	4.66	4.12	4.65	6.99	6.25	3.77	3.90	4.08	5.05	5.00	4.91
Sharpe Ratio	-0.18	0.01	0.23	0.38	0.51	0.85	-0.09	-0.08	0.14	0.27	0.42	0.58
AR(1)	0.03	0.01	0.04	0.07	0.13	0.14	0.00	0.06	0.05	0.03	0.08	0.03

Panel B. Momentum: Portfolios Sorted on Past Excess Returns

	All Countries (44)						**Developed Countries (17)**					
	Low	2	3	4	High	HML	Low	2	3	4	High	HML
Mean	-1.29	-0.18	1.50	2.79	6.29	7.58	-1.32	1.58	1.24	1.84	3.69	5.01
Median	-0.27	1.27	2.21	3.19	6.46	7.34	-0.49	2.45	2.55	3.21	4.96	6.38
Std. Dev	9.63	9.29	9.21	9.00	9.01	8.23	9.90	10.04	10.32	9.85	9.47	9.37
Skewness	-0.20	-0.40	-0.20	-0.27	-0.26	-0.14	-0.12	-0.18	-0.34	-0.13	-0.14	-0.03
Kurtosis	4.67	4.63	4.50	4.16	4.55	3.84	5.18	4.27	4.02	3.90	4.11	4.03
Sharpe Ratio	-0.13	-0.02	0.16	0.31	0.70	0.92	-0.13	0.16	0.12	0.19	0.39	0.53
AR(1)	0.04	0.06	0.01	0.05	0.06	-0.08	0.04	0.04	0.06	0.00	0.02	-0.06

Table 2: Cross-Sectional Regression (CSR) Tests

The table reports cross-sectional pricing results for the factor model based on the dollar risk factor (DOL) and Global Equity Correlation Innovation ($\Delta Corr$) where the correlation levels are measured by DECO (OOS) model for Panel A and by averaging intra-month bilateral correlations (IM) for Panel B, respectively. The test assets are the set of carry portfolios (1-5), and the set of momentum portfolios (1-5). Table on the left (right) reports the estimation results for the test assets using currencies from all 44 countries (17 developed market countries only). The market price of covariance risk λ, the market price of beta risk γ (multiplied by 100), and the price of covariance (beta) risk normalized by standard deviation of the cross-sectional covariances (betas): λ_{norm} (γ_{norm}) are reported. Shanken (1992)'s t-ratios under correctly specified models accounting for the EIV problem: ($t\text{-}ratio_s$) and the Kan, Robotti, and Shanken (2012) misspecification-robust t-ratios: ($t\text{-}ratio_{krs}$) are reported in the parentheses. $pval_1$ is the p-value for the test of H0: $R^2 = 1$. $pval_2$ is the p-value for the test of H0: $R^2 = 0$. $pval_3$ is the p-value for Wald test of H0: $\gamma = 0_K$ without imposing price of beta is zero under the null. $pval_4$ is the p-value for approximate finite sample p-value of Shanken's CSRT statistic (a generalized χ^2-test). Data are monthly and the sample covers the period May 1976 to December 2014.

	All Countries (44)					**Developed Countries (17)**			

Panel A. DECO (OOS)

Factor:	DOL	$\Delta Corr_{OOS}$			Factor:	DOL	$\Delta Corr_{OOS}$		
λ	**2.28**	**-35.85**	R^2	**0.89**	λ	**1.52**	**-19.00**	R^2	**0.77**
λ_{norm}	**0.07**	**-2.56**	$pval_1$	[0.55]	λ_{norm}	**0.08**	**-1.65**	$pval_1$	[0.36]
$t\text{-}ratio_{fm}$	(1.16)	(-7.94)	$pval_2$	[0.00]	$t\text{-}ratio_{fm}$	(0.76)	(-4.57)	$pval_2$	[0.02]
$t\text{-}ratio_s$	(0.56)	(-3.74)	$pval_3$	[0.00]	$t\text{-}ratio_s$	(0.55)	(-3.24)	$pval_3$	[0.02]
$t\text{-}ratio_{krs}$	(0.46)	(-2.95)	$pval_4$	[0.71]	$t\text{-}ratio_{krs}$	(0.49)	(-2.53)	$pval_4$	[0.28]
γ	**0.22**	**-9.37**			γ	**0.13**	**-4.97**		
γ_{norm}	**0.12**	**-2.59**			γ_{norm}	**0.12**	**-1.66**		
$t\text{-}ratio_{krs}$	(1.81)	(-3.39)			$t\text{-}ratio_{krs}$	(1.15)	(-2.99)		

Panel B. Intra-month (IM)

Factor:	DOL	$\Delta Corr_{IM}$			Factor:	DOL	$\Delta Corr_{IM}$		
λ	**-1.50**	**-18.70**	R^2	**0.82**	λ	**-0.29**	**-8.83**	R^2	**0.67**
λ_{norm}	**-0.05**	**-2.39**	$pval_1$	[0.55]	λ_{norm}	**-0.01**	**-1.40**	$pval_1$	[0.34]
$t\text{-}ratio_{fm}$	(-0.74)	(-7.89)	$pval_2$	[0.00]	$t\text{-}ratio_{fm}$	(-0.14)	(-4.15)	$pval_2$	[0.02]
$t\text{-}ratio_s$	(-0.30)	(-3.20)	$pval_3$	[0.01]	$t\text{-}ratio_s$	(-0.10)	(-2.84)	$pval_3$	[0.05]
$t\text{-}ratio_{krs}$	(-0.27)	(-3.48)	$pval_4$	[0.72]	$t\text{-}ratio_{krs}$	(-0.09)	(-2.74)	$pval_4$	[0.18]
γ	**0.21**	**-26.38**			γ	**0.12**	**-12.47**		
γ_{norm}	**0.12**	**-2.49**			γ_{norm}	**0.11**	**-1.45**		
$t\text{-}ratio_{krs}$	(1.77)	(-3.54)			$t\text{-}ratio_{krs}$	(1.07)	(-2.78)		

Description

λ : The price of covariance risk
γ : The price of beta risk
$t\text{-}ratio_{fm}$: Fama-MacBeth t-ratio
$t\text{-}ratio_s$: Shanken error-in-variables adjusted t-ratio
$t\text{-}ratio_{krs}$: Misspecification robust t-ratio

R^2 : Sample CSR R-squared
$pval_1$: p-value of testing $R^2 = 1$
$pval_2$: p-value of testing $R^2 = 0$
$pval_3$: p-value of Wald test $\gamma = 0_K$
$pval_4$: p-value of Shanken's CSRT statistic

Table 3: Moments of Correlation Innovation Factors

This table reports statistics for the global equity correlation innovation factors. OOS is measured by DECO model (Engle and Kelly, 2012) where parameters are estimated on the data available at the point in time and updated with expanding window as we collect more data. From the second to the third column, the correlation level is measured by computing bilateral intra-month correlations at each month end using daily return series of international MSCI equity indices in U.S. dollars. For IM, the aggregate correlation level is estimated by computing equally-weighted average of all daily bilateral correlations at the end of each month. For IM_{GDP} (IM_{MKT}), the correlation level is estimated by computing GDP-weighted (Market-capitalization-weighted) average over all bilateral correlations. For IM_{LOC}, daily return series of international MSCI equity indices in local currency units are used to compute bilateral intra-month correlations, and we take equally-weighted averages for the aggregation at each month end. The correlation innovations are measured by taking first difference of each of the correlation levels. The sample covers the period March 1976 to December 2014.

A. Correlation Level

	OOS	IM	IM_{GDP}	IM_{MKT}	IM_{LOC}
Mean	0.39	0.39	0.27	0.27	0.33
Volatility	0.17	0.19	0.17	0.17	0.21
Correlation					
IM	0.94				
IM_{GDP}	0.79	0.84			
IM_{MKT}	0.75	0.79	0.97		
IM_{LOC}	0.83	0.81	0.71	0.67	

B. Correlation Innovation

	OOS	IM	IM_{GDP}	IM_{MKT}	IM_{LOC}
Mean	0.00	0.00	0.00	0.00	0.00
Volatility	0.05	0.12	0.16	0.17	0.13
Correlation					
IM	0.77				
IM_{GDP}	0.50	0.61			
IM_{MKT}	0.45	0.55	0.96		
IM_{LOC}	0.51	0.63	0.48	0.45	

Table 4: Alternative Cross-Sectional Asset Pricing Tests

This table reports the price of beta risk (γ) for the global equity correlation innovation factors from the various forms of asset pricing models. The test assets are *FX 10* portfolios: the set of carry and momentum portfolios. *CSR-OLS* (*CSR-GLS*) is the two-pass cross-sectional *OLS* (*GLS*) regression. In the first pass, we run time-series regressions to estimate each asset's beta to the risk factors. In the second pass, we run cross-sectional regression where all assets' average returns are regressed against the estimated betas to determine the risk premium of each factor. For *Fama-MacBeth Constant*, the first pass regression is the same as *CSR-OLS*. However, in the second pass, we run cross-sectional regressions at each time period. The risk premium of each factor is determined to be the average price of risk across time. For *Fama-MacBeth Rolling 60M*, the second pass regression is the same as *Fama-MacBeth Constant*. However, in the first pass, we run time-series regressions with rolling 60 months window to estimate each asset's time-varying beta to the risk factors. For *GMM*, we measure the price of risk by specifying the pricing kernel to be linear function of the risk factors (see, Section 4.3). The misspecification robust t-ratios from Kan, Robotti, and Shanken (2013, JF) are reported in the parentheses for *CSR-OLS* and *CSR-GLS*. The heteroskedasticity and autocorrelation adjusted t-ratio with automatic lag selection from Newey-West (1994, RES) are reported in the parentheses for *Fama-MacBeth* and *GMM*. The description of the factors is the same as Table 3. The sample covers the period March 1976 to December 2014.

	1. OOS		**2. IM**		**3. GDP**		**4. MKT**		**5. LOC**	
	DOL	*OOS*	*DOL*	*IM*	*DOL*	IM_{GDP}	*DOL*	IM_{MKT}	*DOL*	IM_{LOC}
A. CSR - OLS										
γ	0.22	-9.37	0.21	-26.38	0.19	-63.03	0.17	-60.49	0.19	-19.92
γ_{norm}	0.12	-2.59	0.12	-2.49	0.10	-2.47	0.09	-2.39	0.10	-1.89
$t\text{-}ratio_{krs}$	(1.81)	(-3.39)	(1.77)	(-3.54)	(1.53)	(-1.95)	(1.39)	(-2.01)	(1.66)	(-2.93)
B. CSR - GLS										
γ	0.20	-8.22	0.19	-20.68	0.17	-42.66	0.15	-43.51	0.16	-12.83
γ_{norm}	0.11	-2.27	0.10	-1.96	0.09	-1.67	0.08	-1.72	0.09	-1.22
$t\text{-}ratio_{krs}$	(1.72)	(-3.08)	(1.62)	(-2.92)	(1.45)	(-1.85)	(1.34)	(-1.79)	(1.44)	(-2.20)
C. Fama-MacBeth Constant										
γ	0.22	-9.37	0.21	-26.38	0.19	-63.03	0.17	-60.49	0.19	-19.92
γ_{norm}	0.12	-2.59	0.12	-2.49	0.10	-2.47	0.09	-2.39	0.10	-1.89
$t\text{-}ratio_{nw}$	(1.87)	(-7.71)	(1.80)	(-7.80)	(1.64)	(-7.84)	(1.45)	(-7.67)	(1.68)	(-6.03)
D. Fama-MacBeth Rolling 60M										
γ	0.17	-3.64	0.17	-7.51	0.19	-5.19	0.19	-6.57	0.21	-8.63
γ_{norm}	0.21	-1.61	0.21	-1.45	0.20	-0.61	0.21	-0.71	0.24	-1.45
$t\text{-}ratio_{nw}$	(1.27)	(-3.68)	(1.23)	(-3.42)	(1.38)	(-1.46)	(1.39)	(-1.64)	(1.56)	(-2.71)
E. GMM										
γ	0.22	-9.26	0.21	-26.11	0.19	-62.66	0.17	-60.18	0.19	-19.77
γ_{norm}	0.07	-2.53	-0.04	-2.36	0.06	-2.45	-0.06	-2.26	0.09	-1.84
$t\text{-}ratio_{nw}$	(0.48)	(-3.27)	(-0.31)	(-3.84)	(0.24)	(-2.10)	(-0.28)	(-2.14)	(0.77)	(-3.64)

Table 5: CSR Tests: Other Factors

This table reports the price of covariance risk (λ) from *CSR-OLS* from factor models based on the dollar risk factor (DOL), a control factor, and our global equity correlation innovation factors (OOS). The test assets are *FX 10* portfolios: the set of carry and momentum portfolios. The price of covariance risks normalized by standard deviation of the cross-sectional covariances (λ_{norm}) are reported. The misspecification-robust t-ratio ($t - ratio_{krs}$) from Kan, Robotti, and Shanken (2013, JF) and the p-values for the test of $H0 : R^2 = 0$ are reported in parentheses and in square bracket, respectively. The control factors are described as follows. ΔFX_{VOL}: the aggregate FX volatility innovationas (Menkhoff, Sarno, Schmeling and Schrimpf, 2012 JF), ΔFX_{CORR}: the aggregate FX correlation innovationas, ΔTED: TED spread innovation, ΔFX_{BAS}: innovations to the aggregate FX bid-ask spreads (Mancini, Renaldo and Wrampelmeyer, 2013 JF), ΔLIQ_{PS}: Pastor-Stambaugh liquidity innovation, EQ_{MRP}: the market risk premium, EQ_{SMB}: U.S. equity size factor, EQ_{HML}: U.S. equity value factor, EQ_{MOM}: U.S. equity momentum factor, $Carry_{HML}$: the high-minus-low FX carry factor (Lustig, Roussanov, and Verdelhan, 2011 RFS), MOM_{HML}: the high-minus-low FX momentum factor.

		Factors			
Control Factor	*Statistics*	*DOL*	*Control Factor*	*OOS*	R^2
A. FX volatility & correlation factors					
ΔFX_{VOL}	λ_{norm}	0.09	0.45	-2.90	0.94
	$t\text{-}ratio_{krs}$	(0.59)	(0.49)	(-2.74)	[0.00]
ΔFX_{CORR}	λ_{norm}	0.04	-0.53	-2.30	0.92
	$t\text{-}ratio_{krs}$	(0.27)	(-0.78)	(-2.54)	[0.00]
B. Liquidity factors					
ΔTED	λ_{norm}	0.12	0.55	-2.83	0.93
	$t\text{-}ratio_{krs}$	(0.78)	(0.86)	(-2.91)	[0.00]
ΔFX_{BAS}	λ_{norm}	0.07	0.31	-2.65	0.94
	$t\text{-}ratio_{krs}$	(0.47)	(0.48)	(-3.09)	[0.00]
ΔLIQ_{PS}	λ_{norm}	0.07	-0.59	-3.03	0.92
	$t\text{-}ratio_{krs}$	(0.46)	(-0.67)	(-2.72)	[0.00]
C. Equity factors					
EQ_{MRP}	λ_{norm}	0.12	-0.48	-2.78	0.93
	$t\text{-}ratio_{krs}$	(0.76)	(-0.67)	(-3.00)	[0.00]
EQ_{SMB}	λ_{norm}	0.06	-0.49	-2.88	0.91
	$t\text{-}ratio_{krs}$	(0.37)	(-0.69)	(-2.73)	[0.00]
EQ_{HML}	λ_{norm}	0.10	0.68	-2.33	0.95
	$t\text{-}ratio_{krs}$	(0.66)	(1.27)	(-2.64)	[0.00]
EQ_{MOM}	λ_{norm}	0.11	0.63	-2.82	0.94
	$t\text{-}ratio_{krs}$	(0.72)	(0.83)	(-2.82)	[0.00]
D. FX carry & momentum factors					
$Carry_{HML}$	λ_{norm}	0.07	-0.34	-2.81	0.92
	$t\text{-}ratio_{krs}$	(0.41)	(-0.36)	(-2.69)	[0.00]
MOM_{HML}	λ_{norm}	0.08	0.73	-2.13	0.95
	$t\text{-}ratio_{krs}$	(0.61)	(1.04)	(-2.39)	[0.00]

Table 6: CSR Tests: Factor-mimicking Portfolios

The table reports the cross-sectional pricing results for the factor model based on the dollar risk factor (*DOL*) and our global equity correlation innovation factors: DECO *OOS* ($\Delta Corr_{OOS}$) and intra-month innovation ($\Delta Corr_{IM}$) respectively. The factor mimicking portfolios are obtained by projecting the factors into FX 10 portfolio space. For Panel A, the test assets are the set of portfolios sorted on last month's forward discounts (*Carry 5*), their excess returns over the last 3 months (*Momentum 5*), and real effective exchange rates (*Value 5*). For Panel B, the test assets are similarly defined as Panel A, but we use 10-year interest rate differentials for *Carry 5*, 6-month excess returns for *Momentum 5*, and 60-month changes in real effective exchange rates for *Value 5*. We report the average annualized returns for HML portfolios (*HML Spread*), p-values for the test of H0: HML Spread = 0 (*HML Spread p-val*), and p-values for the monotonic relationship test from Patton and Timmermann, 2010 (*Monotonicity p-val*). We present the price of beta risks normalized by standard deviation of the cross-sectional betas (γ_{norm}). The misspecification-robust t-ratios are reported in parentheses (Kan, Robotti, and Shanken, 2012). The p-values for the test of $H0 : R^2 = 0$ and $H0 : |\beta_5 - \beta_1| = 0$ (Patton and Timmermann, 2010) are reported in square bracket.

Panel A	**Carry 5**			**Momentum 5**			**Value 5 (REER)**		
HML Spread		6.87			7.58			6.34	
HML Spread p-val		[0.00]			[0.00]			[0.00]	
Monotonicity p-val		[0.00]			[0.00]			[0.00]	
	γ_{norm}	R^2	*Beta Spread*	γ_{norm}	R^2	*Beta Spread*	γ_{norm}	R^2	*Beta Spread*
$\Delta Corr_{OOS}$	-2.58	0.91	0.06	-2.94	0.91	0.05	-2.00	0.81	0.02
	(-2.57)	[0.00]	[0.01]	(-3.00)	[0.00]	[0.01]	(-2.37)	[0.03]	[0.15]
$\Delta Corr_{IM}$	-2.61	0.93	0.02	-2.83	0.86	0.02	-1.78	0.81	0.01
	(-1.64)	[0.00]	[0.04]	(-3.36)	[0.00]	[0.02]	(-1.37)	[0.04]	[0.23]
$\Delta Corr_{OOS}$	-2.52	0.88	1.54	-2.82	0.87	1.24	-1.16	0.86	0.25
(mimicking)	(-4.53)	[0.00]	[0.00]	(-5.92)	[0.01]	[0.00]	(-1.60)	[0.00]	[0.04]
$\Delta Corr_{IM}$	-2.61	0.90	0.50	-2.83	0.83	0.66	-2.00	0.81	0.19
(mimicking)	(-3.44)	[0.00]	[0.00]	(-6.38)	[0.00]	[0.00]	(-2.60)	[0.00]	[0.00]

Panel B	**Carry 5 (10Y)**			**Momentum 5 (6M)**			**Value 5 (ΔREER)**		
HML Spread		4.42			4.81			4.34	
HML Spread p-val		[0.00]			[0.00]			[0.00]	
Monotonicity p-val		[0.00]			[0.10]			[0.32]	
	γ_{norm}	R^2	*Beta Spread*	γ_{norm}	R^2	*Beta Spread*	γ_{norm}	R^2	*Beta Spread*
$\Delta Corr_{OOS}$	-1.67	0.98	0.05	-1.38	0.60	0.05	-1.57	0.80	0.04
	(-2.62)	[0.00]	[0.01]	(-2.21)	[0.16]	[0.01]	(-2.63)	[0.01]	[0.01]
$\Delta Corr_{IM}$	-1.55	0.96	0.01	-1.44	0.88	0.02	-1.46	0.83	0.01
	(-1.82)	[0.00]	[0.14]	(-2.18)	[0.01]	[0.02]	(-2.21)	[0.17]	[0.07]
$\Delta Corr_{OOS}$	-1.78	0.98	1.02	-1.54	0.88	0.90	-1.01	0.89	0.20
(mimicking)	(-4.05)	[0.00]	[0.00]	(-2.85)	[0.01]	[0.00]	(-1.17)	[0.00]	[0.11]
$\Delta Corr_{IM}$	-1.83	0.99	0.28	-1.79	0.98	0.51	-0.62	0.90	0.05
(mimicking)	(-3.60)	[0.00]	[0.00]	(-3.03)	[0.00]	[0.00]	(-0.51)	[0.00]	[0.27]

Table 7: Cross-Sectional Asset Pricing Tests with Volatility Innovation Factor

This table reports the price of beta risk (γ) for the global equity volatility (ΔVol) and the global correlation innovation ($\Delta Corr$) factors from the various forms of asset pricing models. The test assets are *FX 10* portfolios: the set of carry and momentum portfolios. The global equity volatility innovation factor is constructed by taking first difference of the aggregate levels of volatility. The aggregate volatility is measured by taking average of the individual volatility estimates from GARCH(1,1) model for all MSCI international equity indices. The global correlation innovation factor is constructed from *DECO OOS* model as described in Section 4.1. In Panel A, we orthogonalize our correlation innovation factor against the global volatility innovation factor. In Panel B, the global volatility innovation factor is orgonalized against our correlation innovation factor. The cross-sectional asset pricing tests are the same as Table 4. The price of beta risks normalized by standard deviation of the cross-sectional betas (γ_{norm}) and the misspecification robust t-ratios from Kan, Robotti, and Shanken (2013, JF) are reported in the parentheses. The sample covers the period March 1976 to December 2014.

	1. Correlation Residual			**2. Volatility Residual**		
	DOL	ΔVol	$\Delta Corr_{resid}$	DOL	ΔVol_{resid}	$\Delta Corr$
A. CSR - OLS						
γ	0.21	-1.33	-7.34	0.21	0.34	-9.59
γ_{norm}	0.11	-1.17	-2.17	0.11	0.32	-2.66
$t\text{-}ratio_{krs}$	(1.77)	(-1.79)	(-2.93)	(1.77)	(0.51)	(-3.36)
B. CSR - GLS						
γ	0.20	-1.24	-6.59	0.20	0.28	-8.68
γ_{norm}	0.10	-1.09	-1.94	0.10	0.26	-2.40
$t\text{-}ratio_{krs}$	(1.71)	(-2.37)	(-2.58)	(1.71)	(0.55)	(-2.98)
C. Fama-MacBeth Constant						
γ	0.21	-1.33	-7.34	0.21	0.34	-9.59
γ_{norm}	0.11	-1.17	-2.17	0.11	0.32	-2.66
$t\text{-}ratio_{nw}$	(1.83)	(-3.78)	(-6.88)	(1.83)	(1.11)	(-7.83)
D. Fama-MacBeth Rolling 60M						
γ	0.18	-1.00	-1.89	0.18	-0.38	-3.58
γ_{norm}	0.21	-1.24	-1.22	0.21	-0.25	-1.73
$t\text{-}ratio_{nw}$	(1.31)	(-2.62)	(-2.51)	(1.31)	(-1.32)	(-3.41)
E. GMM						
γ	0.21	-1.29	-7.31	0.21	0.37	-9.49
γ_{norm}	0.15	-1.05	-2.34	0.15	0.39	-2.59
$t\text{-}ratio_{nw}$	(0.83)	(-1.49)	(-3.29)	(0.83)	(0.63)	(-3.30)

Table 8: CSR Tests: FX 10 + FF 25 Portfolios

The table reports cross-sectional pricing results with Fama-French factors. The test assets are the set of *Carry 5*, *Momentum 5* and *Fama-French 25* portfolios. For *Fama-French 25* portfolios, the global (US) size and value sorted portfolios are used in Panel A (C) and the global (US) size and momentum sorted portfolios are used in Panel B (D), respectively. MRP, SMB, HML and MOM are *Fama-French-Carhart* four factors, DOL is the dollar factor, ΔVol is the factor-mimicking portfolio of our global equity volatility innovation where the volatility levels are measured by GARCH(1,1) model. $\Delta Corr$ is the factor-mimicking portfolio of the global equity correlation innovation where the correlation levels are measured by DECO model. The specification of test is the same as Table 2. The p-values for the test of $H0 : R^2 = 0$ are reported in square bracket.

	1.Two Factors		**2. Seven Factors**						
Panel A. FX 10 + Global Size & Value 25									
Factor	DOL	$\Delta Corr$	MRP	SMB	HML	MOM	DOL	ΔVol	$\Delta Corr$
λ	0.35	-43.47	6.89	-1.56	17.52	17.73	-2.09	16.01	-40.56
λ_{norm}	0.01	-2.40	5.33	-0.37	4.39	3.68	-0.08	0.57	-2.24
$t\text{-}ratio_{krs}$	(0.10)	(-1.91)	(2.29)	(-0.37)	(3.40)	(2.35)	(-0.38)	(0.65)	(-3.67)
R^2	0.508		0.867						
pval	[0.044]		[0.021]						
Panel B. FX 10 + Global Size & Momentum 25									
Factor	DOL	$\Delta Corr$	MRP	SMB	HML	MOM	DOL	ΔVol	$\Delta Corr$
λ	-0.61	-51.68	3.80	4.91	14.05	6.59	-0.61	22.63	-45.53
λ_{norm}	-0.04	-2.94	3.06	1.02	2.19	4.38	-0.04	0.90	-2.59
$t\text{-}ratio_{krs}$	(-0.15)	(-2.20)	(1.59)	(1.32)	(2.86)	(2.99)	(-0.11)	(0.80)	(-4.10)
R^2	0.550		0.837						
pval	[0.007]		[0.004]						
Panel C. FX 10 + U.S. Size & Value 25									
Factor	DOL	$\Delta Corr$	MRP	SMB	HML	MOM	DOL	ΔVol	$\Delta Corr$
λ	3.60	-76.64	7.15	-0.38	13.87	22.42	3.43	6.09	-36.46
λ_{norm}	0.80	-4.74	7.75	-0.24	6.05	3.75	0.76	0.11	-2.26
$t\text{-}ratio_{krs}$	(1.24)	(-2.45)	(2.45)	(-0.12)	(3.34)	(2.03)	(0.75)	(0.20)	(-3.47)
R^2	0.743		0.894						
pval	[0.004]		[0.003]						
Panel D. FX 10 + U.S. Size & Momentum 25									
Factor	DOL	$\Delta Corr$	MRP	SMB	HML	MOM	DOL	ΔVol	$\Delta Corr$
λ	3.33	-64.33	5.26	1.63	12.57	6.07	4.01	16.96	-36.61
λ_{norm}	0.71	-4.34	5.96	0.92	3.53	5.05	0.85	0.39	-2.47
$t\text{-}ratio_{krs}$	(1.20)	(-2.45)	(2.45)	(0.71)	(2.98)	(3.33)	(1.01)	(0.60)	(-3.79)
R^2	0.577		0.894						
pval	[0.005]		[0.001]						

Table 9: Cross-Sectional Regression (CSR) Tests: Robustness

This table reports the cross-sectional pricing results based on the dollar risk factor (*DOL*) and the global equity correlation innovation factor where the correlation levels are measured by DECO model (*OOS*). The test assets are the set of Carry 5 and Momentum 5 (*FX 10*) portfolios. The winsorized correlation innovation series (at the 10% level) is used for Panel A, and the pre-financial crisis period (from March 1976 to December 2006) is chosen for Panel B. For Panel C, AR(2) instead of the first difference is used to measure the correlation innovations. Data are monthly and the sample covers the period March 1976 to December 2014. For Panel D, both factors (*DOL* and *OOS*) and test assets (*FX 10* portfolios) are constructed from weekly data series. The price of covariance risks normalized by standard deviation of the cross-sectional covariances (λ_{norm}) are reported. The misspecification robust t-ratios from Kan, Robotti, and Shanken (2013) and the p-value for the test of the null hypothesis H0: $R^2 = 0$ are reported in the parentheses and square bracket, respectively. Weekly sample covers the period October 1997 to December 2014.

Panel A. 10% Winsorization

Factor:	*DOL*	*OOS*		
λ	0.16	-22.59	R^2	0.54
λ_{norm}	0.01	-1.98	*pval*	[0.01]
$t\text{-}ratio_{krs}$	(0.03)	(-2.16)		

Panel B. Before Financial Crisis (to Dec 2006)

Factor:	*DOL*	*OOS*		
λ	1.91	-16.53	R^2	0.81
λ_{norm}	0.08	-2.56	*pval*	[0.00]
$t\text{-}ratio_{krs}$	(0.33)	(-3.46)		

Panel C. AR(2) Shock

Factor:	*DOL*	*OOS*		
λ	-1.50	-18.70	R^2	0.82
λ_{norm}	-0.05	-2.39	*pval*	[0.00]
$t\text{-}ratio_{krs}$	(-0.27)	(-3.48)		

Panel D. Weekly Data

Factor:	*DOL*	*OOS*		
λ	-11.31	-40.15	R^2	0.65
λ_{norm}	-0.40	-2.05	*pval*	[0.01]
$t\text{-}ratio_{krs}$	(-1.13)	(-1.95)		

Table 10: Parameter Choices and Moments of Simulated Carry and Momentum Portfolios

We simulate the consumption dynamics of 200 countries, and drive the changes in spot rates and excess returns of the corresponding currencies through Equation 5 and 6. We choose our parameters following Menzly, Santos, and Veronesi (2004) and Christoffersen, Du, and Elkamhi (2015), and our choice of parameters are presented in Panel A. 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. Moments of excess returns of the simulated carry and momentum portfolios are presented in Panel B.

Panel A

A.1. Consumption Dynamics

g	σ
0.02	0.015

A.2. Volatility Dynamics

α_w	θ_w	β_w	$\sigma_{w,t=0}$
0.07	1.30	0.80	0.01

A.3. Correlation Dynamics

κ_ρ	$\bar{\rho}$	α_ρ	$\rho_{i,t=0}$
0.01	0.30	180	0.30

A.4. Risk Aversion and SDF

κ_γ	$\bar{\gamma}$	α_γ	$\gamma_{i,t=0}$	
0.16	33.9	39.4	20	0.90

Panel B

	B.1 Carry Portfolios						B.2 Momentum Portfolios					
	Low	2	3	4	High	HML	Low	2	3	4	High	HML
Mean	-2.01	0.50	1.35	1.62	2.27	4.27	-0.90	1.06	1.19	1.68	1.17	2.06
Median	0.97	2.23	1.97	1.21	1.78	5.64	-0.31	1.25	0.83	2.74	3.04	2.45
Std. Dev	18.47	12.54	11.24	10.64	10.70	16.58	15.29	11.56	11.17	11.15	12.52	10.88
Skewness	-0.08	-0.02	-0.02	0.07	0.11	0.10	-0.01	0.02	0.02	0.06	-0.09	-0.30
Kurtosis	3.90	3.71	4.01	4.23	4.92	5.11	3.44	3.97	4.02	3.97	4.62	5.59
Sharpe Ratio	-0.11	0.04	0.12	0.15	0.21	0.26	-0.06	0.09	0.11	0.15	0.09	0.18
AR(1)	-0.06	0.00	-0.02	0.01	-0.03	-0.03	-0.08	-0.04	0.02	0.03	0.03	-0.08

Table A1: Country Selection

Country	FX All	FX DM	Equity DM (1973 ~)	Equity (1988 ~)	Equity (1995 ~)
	FX		Equity		
Number of country	44	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					
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*
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					
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					
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*