Global Equity Correlation in Carry and Momentum Trades

JOON WOO BAE and REDOUANE ELKAMHI*

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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 differences in exposure to our factor explain simultaneously the variation in average excess returns of these strategies. We find that the global correlation factor has a robust negative price of beta risk in the FX market. We also present a multi-currency model to explain why different exposures to the correlation factor drive the excess returns for these two currency strategies. We show that the cross-sectional differences in loading on the correlation factor depend on two terms, portfolio average risk aversion coefficient and the interaction between risk aversion coefficient and country-specific correlation. We demonstrate that carry portfolios are closely related to the former term, whereas momentum portfolios are closely related to the latter term. Taking both terms together, we show that the payoffs from both carry and momentum trades positively co-move with our global correlation innovation.

JEL Classification: F31, G12, G15

Keywords: Exchange Rates, Dynamic Conditional Correlation, Carry Trades, Momentum Trades, Predictability, Consumption Risk

* Joseph L. Rotman School of Management, University of Toronto, 105 St. George Street, Toronto, Ontario, M5S 3E6. *Email: Joon.Bae11@rotman.utoronto.ca (J.Bae), Redouane.Elkamhi@rotman.utoronto.ca (R.Elkamhi)*

I Introduction

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

The correlation-based factor as a measure of the aggregate risk is motivated by the analysis in Pollet and Wilson (2010). They document that the changes in true aggregate risk reveal themselves through changes in the correlation between observable stock returns as the aggregate wealth portfolio is common component for all assets. 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 must explain the average excess returns across currency portfolios.

[1]The forward premium puzzle arises since FX changes do not compensate for the interest rate differentials. Under rational expectation assumption, exchange rates are expected to change in direction to eliminate gains from interest rate differentials. However, a number of empirical studies have found that the uncovered interest parity is violated. The extant literatures document various risk-based explanation for the forward premium puzzle, from 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)), disaster risk (Jurek (2008) and Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2009)) and peso problem (Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011)).

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

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

We show that differences in exposure to the correlation factor can explain the systematic variation in average excess returns of portfolios sorted on interest rates and momentums. We present our correlation factor yields cross-sectional fit with R^2 of 90 percents on carry and momentum portfolios from the cross-section regression test. The prices of beta risk for both measures of our correlation innovation factor are economically and statistically significant under Shanken (1992) estimation error adjustment as well as misspcification error adjustment as in Kan, Robotti, and Shanken (2012). The negative price of beta suggests that investors demand low risk premium for the portfolios whose returns co-move with the common correlation innovation since they provide hedging opportunity against unexpected deterioration of investment opportunity set.

To explore the explanatory power of our correlation factor, we construct numerous risk factors discussed frequently in the currency literature. The list includes (i) a set of traded and non-traded factors constructed from FX data, (ii) a set of liquidity factors, and (iii) a set of US equity market risk factors. Consistent with the forward puzzle literature, we find that those factors have explanatory power over the cross-section of carry portfolios with R^2 raging from 58 percents 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 as documented in Burnside, Eichenbaum, and Rebelo (2011) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012b). Furthermore, we demonstrate that our factor can explain the cross-section of momentum portfolios and significantly improve the explanatory power across carry portfolios, whereas the price of beta risk is not affected by the inclusion of those factors.

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

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

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

To deliver an economic intuition behind our empirical findings, we build a multi-currency model to analyze the sources of risk and the main drivers of the expected returns in currency portfolios. We follow the habit formation literature (see, Campbell and Cochrane (1999), Menzly, Santos, and Veronesi (2004) and Verdelhan (2010)) and present a multicurrency specification that captures heterogeneity and time variation in risk aversion across countries. Our model decomposition of the expected returns demonstrates that heterogeneity in risk aversion is able to explain the cross-section of average excess returns of carry portfolios. However, heterogeneity in risk aversion coefficient alone cannot explain carry and momentum simultaneously. We show instead that the cross-sectional differences in loading on the risk factor depends on two terms, portfolio average risk aversion coefficient and the interaction between risk aversion coefficient and country-specific consumption correlation.[3] Carry portfolios are closely related to the former term, whereas momentum portfolios are closely related to the latter term. Payoffs from both traditional long-short carry and momentum trades positively co-move with changes in global consumption level because of the two terms. Therefore, the two trading strategies are considered risky.

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

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

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

[3]Through simulation, we show that the model implied common equity correlation innovation is very similar to the consumption correlation.

II Data

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

II..1 Spot and Forward Rates

Following Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), we blended two data sets of spot and forward rates to span longer time period. Both data sets are obtained from Datastream. The data sets 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 data set respectively. The first data set spans the period between January 1976 to November 2013 and the second set spans the period between December 1996 to November 2013. To obtain quotes measured in home currency per foreign currency, some of the original quotes were inverted while swapping the bid and ask prices. To blend the two data sets, we covert pound quotes in the first data set to dollar quotes by multiplying the GBP/Foreign currency units by the USD/GBP quotes for each of bid/ask/mid data set. For the monthly data series, we sample the data on the last weekday of each month.

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

II..2 Equity Returns

We collect daily closing U.S. dollar returns of MSCI indices for 39 markets from datastream. The sample covers the period between January 1973 to November 2013. We note that the number of available international equity indices varies over time as data for a number of emerging market countries become only 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 analysis. The second and third dataset consists 31 and 39 equity market indices available from January 1988 and 1995 respectively. The list of the equity market indices available for each of the datasets and the corresponding datastream mnemonics are shown in **Appendix II**. We find that, the innovation factors generated from the second and third datasets are very similar to the one from the first dataset (see, **Figure 2 in Appendix II**). Thus, we rely on correlation implied by 17 developed market indices for the analysis and use the second and third databse as a robustness.

III Currency Portfolios

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

III.A Spot and Excess Returns for Currency

We use q and f to denote the log of the spot and forward nominal exchange rate measured in home currency per foreign currency respectively. An increase in q^* means an appreciation of the foreign currency $(*)$. Following Lustig and Verdelhan (2007), we define the log excess return $(\Delta\pi^*_{t+1})$ of the currency $(*)$ at time $t+1$ as

$$\Delta\pi^*_{t+1} = \Delta q^*_{t+1} + i^*_t - i_t \approx q^*_{t+1} - f^*_t \tag{1}$$

where i^*_t and i_t denote the foreign and domestic nominal risk-free rates over one period horizon. This is the return on buying a foreign currency $(*)$ in the forward market at time t and then selling it in the spot market at time $t+1$. Since the forward rate satisfies the covered interest parity under normal conditions (see, Akram, Rime, and Sarno (2008)), it can be denoted as $f^*_t = log(1+i) - log(1+i^*) + q^*_t$. Therefore, the forward discount is simply the interest rate differential $(q^*_t - f^*_t \approx i^* - i)$ 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 be implemented and the daily rates along with bid-ask spreads are readily available.

III.B Carry Portfolios

Carry portfolios are the portfolios where currencies are sorted on the basis of their interest rate differentials. As described in the subsection III.A, they are equivalent to portfolios sorted on forward discounts due to the covered interest parity. Following Menkhoff, Sarno, Schmeling, and Schrimpf (2012a), the portfolio 1 contains the 20 % of currencies with the lowest interest rate differentials against US counterpart, whilst portfolio 5 contains the 20 % of currencies with the highest interest rate differentials. The log currency excess return for portfolio i can be calculated by taking equally weighted average of the individual log currency excess returns (as described in equation 1) in each portfolio i. The difference in returns between portfolio 5 and portfolio 1 is the average profit obtained by running a traditional long-short carry trade portfolio (HML_{Carry}) where investors borrows money from low interest rate countries and invests in high interest rate countries' money market. Therefore, it is a strategy that exploit the broken uncovered interest rate parity in the cross-section. Previous research have found that the strategy is profitable since interest rate differentials are strongly autocorrelated and spot rate changes do not fully adjust to compensate for the differentials. Lustig, Roussanov, and Verdelhan (2011) construct risk factors from excess returns of portfolios sorted on interest rate differentials, level (DOL) and slope (HML_{Carry}) factors. They document that most of the cross-sectional variation in average excess returns among carry sorted portfolios can be mapped to differential exposure to the slope factor. Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) show that there is a strong relationship between the global FX volatility risk and the cross-section of excess returns in carry trades.

To take transaction costs into account, we split the way to calculate the net excess return of portfolio i at time $t+1$ into six different cases depending on the actions we make to rebalance the portfolio at each month end. 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 should take into account two-way transaction costs ($\Delta\pi^{In-Out}_{long,t+1} = q^{bid}_{t+1} - f^{ask}_{t}$), whereas if it were to stay in the portfolio once it had entered, then we should take into account one-way transaction cost only ($\Delta\pi^{In-Stay}_{long,t+1} = q^{mid}_{t+1} - f^{ask}_{t}$). A similar calculation would be applied for a short position as well (with opposite signs while swapping bids and asks).

Descriptive statistics for our carry portfolios are shown in Panel 1 of **Table 1**. Panel 1 on the left of the table shows results for the sample of all 48 currencies (ALL), whilst the statistics for the sample of the 17 developed market currencies (DM) are shown on the right. Average excess returns and sharp ratios are monotonically increasing from portfolio 1 to portfolio 5 for both ALL and DM currencies. The unconditional average excess returns from holding traditional long-short carry trade portfolio are about 5.8 % and 5.2 % per annum respectively after adjusting for transaction costs. Theses magnitude are similar to the levels reported in the carry literature. Consistent with

Brunnermeier, Nagel, and Pedersen (2008) and Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), we also observe decreasing skewness pattern as we move from low interest rate to high interest rate currency portfolio.

III.C Momentum Portfolios

Momentum portfolios are the portfolios where currencies are sorted on the basis of past returns.[4] We form momentum portfolios sorted on the excess currency returns over a period of three months, as defined in the equation 1. The momentum portfolio formation follows the methodology used in Menkhoff, Sarno, Schmeling, and Schrimpf (2012b). The portfolio 1 contains the 20 % of currencies with the lowest excess returns, whilst portfolio 5 contains the 20 % of currencies with the highest excess returns over the last three month. As portfolios are rebalanced at the end of every month, formation and holding period considered here are three and one month respectively. We choose three month for formation period because we generally find highly significant excess returns from momentum strategies with relatively short time horizon and the profits slowly fade out with increasing formation periods. The significance, however, is not confined to this specific horizon and our empirical testing results are also robust to other formation periods as well.

We find that the returns from currency momentum trade are seemingly unrelated with the returns from carry trade. The week relationship holds regardless of the choice of formation period for momentum strategy since momentum strategy is mainly driven by favorable spot rate changes, not by interest rate differentials. Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) also demonstrate that momentum returns in the FX market do not seem to be systematically related to standard factors such as business cycle risks, liquidity risks, the Fama-French factors, and the FX volatility risk. Burnside, Eichenbaum, and Rebelo (2011) similarly argue that it is difficult to explain carry and momentum strategies simultaneously, hence the high excess returns should be understood with high bid-ask spread or price pressure associated with net order flow. In this article, we also confirm that, using a different sample of countries and different time interval, the factors that the later papers investigate are indeed unable to explain the carry and momentum portfolios. In addition,

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

our aim is to deliver a risk based explanation for both these strategies.

Panel 2 of **Table 1** reports the descriptive statistics for momentum portfolios. There is strong pattern of increasing average excess return from portfolio 1 to portfolio 5, whereas we do not find such a pattern in volatility. Contrary to 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 invests in high momentum countries' money markets yields average excess return of 7.4 % and 3.6 % per annum after transaction costs for ALL and DM currencies respectively.

IV Asset Pricing Model and Empirical Testing

There are ample evidence that 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 noticed high level of capital flows between countries through securitisation, and liberalisation. This high level of international capital flows leads to an equalisation 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. Evans and Lyons (2002a) and Evans and Lyons (2002c) show that order flow from trading activities has high correlation with contemporaneous exchange rate changes. Since equity trading explains a large proportion of the capital flows, their empirical results document that there is an 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 market change the FX risk exposure and induce portfolio rebalancing. Such rebalancing in equity portfolio initiates order flow eventually affects movements of exchange rates. Our paper builds on this intuition and demonstrates the important linkage between the equity and FX market 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 aggregate wealth portfolio as the conditional variance of the aggregate wealth portfolio increases. However, as noted in Roll (1977), the variance on aggregate wealth portfolio is not directly observable and might be difficult to proxy for conducting empirical asset pricing tests. Indeed, Pollet and Wilson (2010) document that the stock market variance, as a proxy to the risk on aggregate wealth portfolio, has weak ability to forecast stock market expected returns in domestic setting. They show that the changes in true aggregate risk may nevertheless reveal themselves through changes in the correlation between observable stock returns as the aggregate wealth portfolio is common component for all assets.

The same logic can be applied to the international markets and international capital asset pricing models. Increase in the aggregate risk must be associated with increased tendency of co-movements across international equity indices. Therefore, an increase in common equity correlation is due to an increase in aggregate risk. Risk-averse investors should demand 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 to the international capital market. Currency market risk premium is also 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 common equity correlation.

It is important to note that an increase in common correlation across bilateral currency returns may not be associated with increase in the aggregate risk. Therefore, currency correlation is not qualified as a proper risk factor. For example, high level of correlation can arise when 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 the changes in local market condition, while the correlation of international equity indices is related to the global aggregate risk.

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

IV.A Factor Construction: Common Equiy Correlation Innovation

We construct two empirical measures of correlations to quantify the evolution of co-movements in international equity market indices. We employ the dynamic equicorrelation (DECO) model of

Engle and Kelly (2012) as our base case and apply the model to monthly equity return series.[5] To mitigate model risk, we also measure the same correlation dynamics by computing bilateral intra-month correlations at each month end using daily return series. Then, we take an average of all the bilateral correlations to arrive a common correlation level of a particular month. Although the second approach has comparative advantage due to its model-free feature, there is potential for us to have biased conditional correlation levels owing to non-synchronous trading with daily return series. Thus, it is important to consider both measures in our main empirical testing framework and see whether the choice of measurement leads to different results.

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

$$
\begin{aligned}
r_{i,t} &= \mu_i + \epsilon_{i,t} = \mu_i + \sigma_{i,t} z_{i,t} && (2) \\
\sigma_{i,t}^2 &= \omega_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 && (3)
\end{aligned}
$$

where μ_i denotes unconditional mean, $\sigma_{i,t}^2$ the conditional variance, $z_{i,t}$ 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

$$\Sigma_t = D_t R_t D_t \tag{4}$$

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

[5]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.

can be separated. Let Q_t denotes the conditional covariance matrix of z_t.

$$\begin{aligned} Q_t &= (1-\alpha_Q-\beta_Q)\overline{Q}+\alpha_Q\tilde{Q}_{t-1}^{\frac{1}{2}}z_{t-1}z_{t-1}^{'}\tilde{Q}_{t-1}^{\frac{1}{2}}+\beta_Q Q_{t-1} && (5)\\ R_t^{DCC} &= \tilde{Q}_t^{-\frac{1}{2}}Q_t\tilde{Q}_t^{-\frac{1}{2}} && (6)\\ \rho_t &= \frac{1}{n(n-1)}(\imath' R_t^{DCC}\imath-n) && (7)\\ R_t^{DECO} &= (1-\rho_t)I_n+\rho_t J_{n\times n} && (8) \end{aligned}$$

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.

For the empirical analysis, we construct a factor based on the common factor in international equity correlation innovation (ΔEQ_{corr}) as non-traded risk factor. We simply take the first difference in time series of expected DECO correlation to quantify the evolution of co-movements in international equity market indices. $\Delta EQ_{corr,t}=E_t[EQ_{corr,t+1}]-E_{t-1}[EQ_{corr,t}]$.[6] 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 more the state variables that affect the changes in the investment opportunity sets.

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

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

sample periods. The dotted blue line depicts the time series of the global equity correlation without look ahead bias (we name this measure DECO OOS). In contrast to DECO IS, this correlation is estimated using the same DECO model, but the parameters in this case are measured on the data available only at the 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 in each month end using daily return series of international equity indices and then taking simple mean of those bilateral correlations.

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

IV.B Cross-Sectional Regression

IV.B.1 Methods

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

For statistical significance of beta, we report both the statistical measures of Shanken (1992) and Kan, Robotti, and Shanken (2012) throughout all this article. Shanken (1992) provides asymptotic distribution of price of beta adjusted for the errors-in-variables problem to account for the estimation errors in beta. Kan, Robotti, and Shanken (2012) further investigate the asymptotic distribution of price of beta risk under potentially misspecified models as well as under i.i.d multivariate elliptically distribution assumption (rather than i.i.d normal). They emphasized that statistical significance of the price of covariance risk is important consideration if we want to answer the question whether a extra factor improves the cross-sectional R^2. Therefore, we apply both tests based on the price of covariance risk as well as the price of beta risk in the empirical testing.

They also have shown how to use the asymptotic distribution of the sample R^2 in the second-pass CSR as the basis for a specification test. To save space, we report the details of the estimation methodology of these statistics to Section VII of the Appendix.

IV.B.2 Results

In this section, we present empirical findings that show the international equity correlation innovation factor (ΔEQ_{corr}) is a priced risk factor in the cross section of currency portfolio and 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 for 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 the section III. We will refer to the all currency portfolios, the set of sorted carry (5) and momentum (5), as *FX 10* portfolios.

Table II presents the results from the asset pricing tests using all *FX 10* portfolios. Panel 1 on the left of the table reports estimation results with all 48 currencies (ALL) and the panel on the right reports estimation results with 17 developed market (DM) currencies only. The market price of beta risk (γ) is estimated to be about -8.75 % and -5.26 % per month for ALL and DM currencies respectively. We find they are statistically significant under Shanken (1992) estimation error adjustment as well as misspecification error adjustment with t-ratio of -3.83 and -3.37 respectively. The price of the beta risk is also economically significant since one standard deviation of cross-sectional differences in beta exposure can explain about 2.5 % per annum in the cross-sectional differences in mean return for ALL currencies. Kan, Robotti, and Shanken (2012) show empirically that misspecification-robust standard errors are substantially higher when a factor is a non-traded factor. They document that it is because the effect of misspecification adjustment on the asymptotic variance of beta risk could potentially be very large due to the variance of residuals generated from projecting the non-traded factor on the returns. Therefore, it is surprising for us to see that a non-traded factor like our correlation factor has significant t-ratio.

In each panel of **Table II**, we include the prices of covariance risk (λ) since the price of covariance risk allows us to identify factors that improve explanatory power (cross-sectional R^2)

of the expected returns from a model. We find the common correlation innovation factor could yield cross-sectional fit with R^2 of 90% and 64% for ALL and DM currencies respectively. While we cannot reject the null *H0:* R^2 *= 1* under the assumption of correctly specified model, we does have significance for the test that the model has any explanatory power for expected returns under the null of misspecified model *H0:* R^2 *= 0.*

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

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

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

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

IV.C Cross-sectional regression with other factors

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

The factors in this empirical exercise are i) FX volatility innovations from Menkhoff, Sarno, Schmeling, and Schrimpf (2012a), ii) FX correlation innovation, iii) the TED spread, iv) the global average percentage bid-ask spread from Mancini, Ranaldo, and Wrampelmeyer (2013), v) 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) FX carry factor from Lustig, Roussanov, and Verdelhan (2011), and sorted on past returns, xi) FX momentum factor. We verified that FX volatility factor, a set of illiquidity innovation factors and FX carry factor can explain the spreads in mean returns of carry portfolios very well with R^2 raging from 58 % for TED spread innovation factor to 92 % for FX volatility factor. The factor prices are statistically significant under misspecification robust CSR, and have the expected signs, that is, negative for illiquidities and FX volatility, positive for the FX carry factor as in their papers. However, the same set of factors which have great explanatory power over the cross-section of carry portfolios does not explain well momentum portfolios at the same time.

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

Although we only show the case for the price of beta risk, the same conclusion can be drawn from the price of covariance risk. When the models are potentially misspecified, Kan, Robotti, and Shanken (2012) documents that, 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 significance test on the price of covariance risk of our correlation factor under the null hypothesis of zero price (H0: $\lambda_{\Delta EQ_{corr}} = 0$). The nested models are CSR using only two factors, the dollar factor and each of the control variable. We find that the prices of the covariance risk are statistically significantly different from zero in all cases. R^2s are also economically and statistically different from the nested models with control variables only.[7] The significant price of covariance risk of our correlation factor confirms that our correlation factor improves the explanatory power across the mean returns of carry and momentum portfolios.

IV.D Factor mimicking portfolio

In this subsection, we convert the common equity correlation innovation factor into excess returns by projecting the factor onto the FX market space. This exercise converts the non-traded macro factor to a traded risk factor within the FX market. We first regress our correlation innovation series on *FX 10* portfolios and then retrieve fitted return series. The fitted excess return series is in fact the factor-mimicking portfolio's excess return. **Table V** reports the cross-sectional asset pricing test applied to different sets of test assets with the correlation innovation factors used in previous tables and the corresponding factor mimicking portfolio's excess returns. We also report cross-sectional regression tests for carry and momentum portfolios separately to examine whether the explanatory power for cross-sectional differences in mean return is mainly driven by one particular type of strategy. We find that the price of beta risk is statistically significant with a similar level of R^2 whether the cross-sectional regression is performed on the two strategies separately or jointly. The price of the traded risk factor is much smaller than the price of the original non-traded factor. The reason is that differences in beta exposure to the traded factor across *FX 10* portfolios are much larger in absolute term than those to the non-traded factor. Therefore, the factor mimicking portfolio could explain just about the same level of cross-sectional differences in mean returns among *FX 10* portfolios as the non-traded factor does with R^2 about 90% in both cases.

IV.E Alternative test assets

In this section, we follow Lustig and Verdelhan (2007) and Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) and examine whether the statistical significance of the regression results are

[7] 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 results as in Table IV. The results are available upon request.

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

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

IV.F Trading on Betas with Common Equity Correlation

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

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

IV.G GLS Cross-sectional Regression

OLS and GLS represent different ways of measuring and aggregating the sample deviations. Since we want to allow for the model misspecification, the choice between OLS and GLS should be determined based on economic relevance rather than estimation efficiency. We argue that in our setting OLS is more relevant if the focus is on the expected returns for a particular set of test portfolios, but GLS may be of greater interest from an investment perspective. Therefore, we also run GLS cross-sectional regression tests and reports the results in **Table VII**. We find that both our global equity correlation factor measures remain statistically significant. As expected from the choice of the weighting matrix on sample deviations, we find lower R^2s for GLS cross-section regression.

IV.H Other Robustness Checks

In this subsection, we perform a number of other robustness checks associated with outliers, different sampling periods, an alternative measure of innovations, and different frequency of data. First of all, we winzorize the correlation innovation series at the 90% level, which means we exclude the 10% of sample periods where the most extreme correlation innovation is realized. Secondly, we set different time horizons for 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 may potentially drive the CSR testing results. The testing results for 10% winsorization and the different time period are shown on Panel 1 and Panel 2 of **Table VIII** respectively, and we still find strong significances for the price of the risk in both cases. For the alternative specification of innovation, we choose AR(2) shock for the robustness check to see if the different definition of the shock would change the empirical testing results. Panel 3 reports the estimation results with AR(2) shock and we generally found that the results are extremely robust to the other specifications as well. Lastly, we construct both of our factors (the dollar and DECO equity correlation innovation factors) and test assets (FX 10 portfolios) from weekly data series. For forward exchange rates, we use forward contract with maturity of one week to properly accounts for the interest rate differencials in the holding period. The weekly sample covers the period October 1997 to November 2013. In Panel 4, we confirm that the correlation innovation factor is priced risk in the FX market with weekly holding period as well.

V Theoretical Model

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

Backus, Foresi, and Thelmer (2001) show that any currency risk premia can be measured as the difference between the higher moments of domestic and foreign stochastic discount factor (SDF). Since we use log-normal specification in our model, presenting difference in conditional variance of SDF should be sufficient to currency risk premia. A foreign currency from a country with smaller conditional variance of SDF is expected to appreciate more. Our model shows that, in conjunction with countercyclical risk aversion and procyclical interest rate, heterogeneity in risk aversion is able to explain the cross-section of average excess returns of carry portfolios.

As we show in this section, however, heterogeneity in risk aversion coefficient alone cannot explain carry and momentum simultaneously. Investors are no longer exposed to any country-specific risk, but they are still exposed to the global consumption shocks when they form a traditional long-short portfolio of currencies. Therefore, the cross-sectional variation in excess returns of portfolios should be explained with heterogeneity in exposure to the global consumption innovations. In our model, we show that the cross-sectional differences in loading on the global consumption risk depends on two terms, portfolio average risk aversion coefficient and the interaction between risk aversion coefficient and country-specific consumption correlation. Carry portfolios are closely related to the former term, whereas momentum portfolios are closely related to the latter term. Payoffs from both traditional carry and momentum trades positively co-move with global consumption innovation because of the two terms. Lastly, a large negative global consumption shock is associated with a large positive innovation to the common correlation due to asymmetric reponse of correlation to consumption shock (see, for example Ang and Chen (2002); Hong, Tu, and Zhou (2007)).[8] Hence, unexpected increases in the common correlation level would have adverse price effect for carry and momentum trades. This conclusion is consistent with our empirical cross-sectional regression results where we find negatively significant price of beta risk to the equity correlation innovation factor. More detailed specification of the model is described in this section.

V.A Preferences and Consumption Growth Dynamics

Under Habit-based preferences[9], the agents of country i maximizes

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

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

[8] In our model, we show that common equity correlaiton is the same as common consumption correlation across countries. Therefore, the significant excess returns in FX markets are systematically related to business cycle risk to the extent that the variations in common consumption correlation level is related to cyclical global economic condition. Then, is the change is international equity correlation a function of business cycle conditions or stock market performance? Christoffersen, Errunza, Jacobs, and Langlois (2012) document international equity markets are characterized by nonlinear dependence and asymmetries. Longin and Solnik (2001) uses extreme value theory and document that international equity market correlation increases in bear markets, but not in bull market. Similarly, Ang and Belaert (2002) develop regime-switching model and show that high correlation in bear market regime limit the benefits of international diversification. These papers show that international equity market correlation do have close relationship with the cyclical global economic condition. By incorporating these characteristics in our specification of dynamic consumption process, we are able to relate the source of currency market premium to aggregate consumption risk through equity market correlation.

[9] We have also explored the model under CRRA framework. The most important assumption we have to make under CRRA framework is the existence of permanent heterogeneity in risk aversion coefficients across the countries. Habit preference can weaken this assumption by delivering conditional heterogeneity in risk aversion coefficients even with the same permanent or long-term average rate assumption across countries. In fact, since we are allowed to rebalance our currency portfolios every month, the conditional heterogeneity in risk aversion coefficients should be sufficient condition.

where γ denotes the risk-aversion coefficients, H_t the external habit level, and C_t consumption level at time t.

Log consumption growth dynamics is,

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

where σ denotes the volatility for country specific consumption shock, σ_w the volatility for common consumption shock, $\epsilon_{t+1}/\epsilon_{w,t+1}$ the standardized idiosyncratic/common consumption shock with $\epsilon_{t+1}/\epsilon_{w,t+1} \sim \mathsf{N}(0,1)$ and they are independent to each other, ρ_{t+1} the correlation between the country specific and the common consumption shock. Unlike the original model developed by Campbell and Cochrane (1999) or the one proposed by Verdelhan (2010), we assume the consumption growth innovations have two components, the country-specific and common (global) shocks. Note also that the variance of country-specific shock is constant but the variance of common shock is time-varying. This setup allows us to distinguish between common and country-specific factors and to capture dynamics of common consumption correlation among N different countries eventually.

Dynamics of the volatility of common consumption shock follows asymmetric GARCH form,

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

Dynamics of the correlation between the country specific shock and the common shock,

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

where tanh denotes hyperbolic tangent function, κ_ρ the speed of mean reversion, α_ρ the sensitivity to the consumption shock. For simplicity, we assume g, σ, ω, α_{garch}, θ_{garch}, β_{garch}, κ_ρ, α_ρ are the same across all countries.

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

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

where κ_γ denotes the speed of mean reversion, $\alpha_\gamma > 0$ the sensitivity of γ_t to the consumption shock, and $\theta_\gamma \geq 1$ the lower bound for γ_t. Note the total sensitivity of γ_t to the consumption shock is also function of the level of γ_t. Higher the level of risk aversion, more sensitive to the consumption shock, hence, countercyclical variation in volatility of γ_t. Log of pricing kernel of country i, or SDF, can be derived as the following,

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

V.B Risk-Free Rates

Due to log-normal assumption of SDF, the time-varying risk free rates can be simplified to,

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

Note when precautionary saving term dominates intertemporal substitution effect, interest rates become procyclical which we will assume in this paper. Furthermore, an interest rate differential between foreign (*) and domestic rate would be,

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

V.C Real Exchange Rates

Following Verdelhan (2010), there should be no arbitrage opportunities under complete financial market assumption. In other words, there is an unique SDF which satisfies the following N systems of equations simultaneously: $E_t(M^i_{t+1}R^i_{t+1}) = 1$ and $E_t(M_{t+1}R^i_{t+1}\frac{Q^i_{t+1}}{Q^i_t}) = 1$ where Q is the real exchange rates measured in home country goods per foreign country i good. As a result, in logs, the change in real exchange rate (Δq^*_{t+1}) is

$$\begin{aligned}
\Delta q^*_{t+1} &= m^*_{t+1} - m_{t+1} \\
&= \kappa_\gamma(\hat{\gamma}_t - \hat{\gamma}^*_t) \\
&\quad - \hat{\gamma}^*_t \; [\sigma\sqrt{1-\rho^{*2}_{t+1}}\epsilon^*_{t+1} + (\sigma\rho^*_{t+1} + \sigma_{w,t+1})\,\epsilon_{w,t+1}] \\
&\quad + \hat{\gamma}_t \; [\sigma\sqrt{1-\rho^{2}_{t+1}}\epsilon_{t+1} + (\sigma\rho_{t+1} + \sigma_{w,t+1})\,\epsilon_{w,t+1}]
\end{aligned}$$

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

$$\begin{aligned}
\Delta\pi^*_{t+1} &= \Delta q^*_{t+1} + i^*_t - i_t \\
&= \frac{1}{2}(\hat{\gamma}^2_t - \hat{\gamma}^{*2}_t)[\sigma^2 + \sigma^2_{w,t+1}] + \; (\rho_{t+1}\hat{\gamma_t}^2 - \rho^*_{t+1}\hat{\gamma_t}^{*2})\,\sigma\,\sigma_{w,t+1} \\
&\quad - \hat{\gamma}^*_t \; [\sigma\sqrt{1-\rho^{*2}_{t+1}}\epsilon^*_{t+1} + (\sigma\rho^*_{t+1} + \sigma_{w,t+1})\,\epsilon_{w,t+1}] \\
&\quad + \hat{\gamma}_t \; [\sigma\sqrt{1-\rho^{2}_{t+1}}\epsilon_{t+1} + (\sigma\rho_{t+1} + \sigma_{w,t+1})\,\epsilon_{w,t+1}]
\end{aligned}$$

V.D The Model Implied Consumption Correlation

Under the specification of the model above, consumption correlation between two countries (i and j) is the following,

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

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

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

The currency risk premium required by investors for holding currency $(*)$ depends both on domestic and foreign risk aversion coefficients. Across time, for a given level of consumption volatility and correlation, the domestic investors require greater currency excess return when they are more risk averse (high γ_t). This countercyclical risk premia shares the same intuition with Lustig, Roussanov, and Verdelhan (Forthcoming) and Verdelhan (2010). Cross-sectionally, investors demand high compensation for bearing global correlation risk from holding a currency of country with low risk aversion coefficient (low γ^*_t) and low interaction between idiosyncratic correlation and risk aversion coeffcient (low $\rho^*_{t+1}\hat{\gamma_t}^{*2}$).

The ex-post unexpected excess return of holding portfolio of currency set $(*)$ is,

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

The first term on the right hand side of the equation is about countercyclical risk premia as it carries greater domestic consumption risk when γ_t is high. If the number of currencies in portfolio $(*)$ is large enough, the second term would have marginal effect on risk premia by the law of large numbers. Lastly, when we bundle together the currencies which have relatively low risk aversion or low interaction term, the currency portfolio not only bears domestic consumption growth risk, but also bears global consumption risk. Note that the cross-sectional differences in loading on the global consumption risk only depend on the two terms, portfolio $\overline{\hat{\gamma}^*_t}$ and $\overline{\rho^*_{t+1}\hat{\gamma_t}^*}$. The lower the two terms, the more positively related the payoffs from portfolios to the global consumption shock. Thus, those portfolios are considered more risky and investors will require greater rate of returns as compensation. Here we will show that portfolios of currencies with high interest rates have lower $\overline{\hat{\gamma}^*_t}$ but no significant pattern for $\overline{\rho^*_{t+1}\hat{\gamma_t}^*}$. On the other hands, portfolios of currencies with high momentum have lower $\overline{\rho^*_{t+1}\hat{\gamma_t}^*}$ but no significant pattern for $\overline{\hat{\gamma}^*_t}$. In other words, sorting currencies by interest rate differentials is nothing more than sorting by average risk aversion rates of countries, and sorting currencies by momentum is essentially sorting by the interaction term, idiosyncratic consumption correlations and risk aversion rates. **Figure 5** on the left shows time-series plot of $\overline{\hat{\gamma}^*_t}$ of high and low interest portfolios from simulation. The figure on the right shows $\overline{\rho^*_{t+1}\hat{\gamma_t}^*}$ of high and low momentum portfolios.

Now, let's turn to the ex-post unexpected excess return on the any long (L) - short (S) portfolios to grasp the source of risk more clearly,

$$\begin{aligned} \Delta\pi^{L-S}_{t+1} - E_t[\Delta\pi^{L-S}_{t+1}] &\approx [(\hat{\gamma}^S_t - \hat{\gamma}^L_t)\,\sigma_{w,t+1} \;+\; (\rho^S_{t+1}\hat{\gamma_t}^S - \rho^L_{t+1}\hat{\gamma_t}^L)\,\sigma]\,\epsilon_{w,t+1} \\ &\approx -[\underbrace{(\hat{\gamma}^S_t - \hat{\gamma}^L_t)\,\sigma_{w,t+1}}_{(1)} + \underbrace{(\rho^S_{t+1}\hat{\gamma_t}^S - \rho^L_{t+1}\hat{\gamma_t}^L)\,\sigma}_{(2)}]\,\Delta\Psi_{t+1} \end{aligned}$$

First of all, note that the payoffs from any currency long-short portfolio is no longer exposed to domestic consumption shock but only exposed to common (global) consumption shock. Secondly, the degree of exposure to common shock depends on the gap between (1) risk aversion coefficient and (2) interaction between idiosyncratic correlation and risk aversion coefficient of the long and short portfolios. Lastly, a large negative consumption shock is closely related to a large positive innovation to the common correlation level due to asymmetric response. On **Figure 6**, we show time-series decomposition of shocks from the traditional long-short carry trades and the long-short momentum trades. The carry trade on the left panel shows persistently positive pattern for the first component whereas no systematic pattern for the second component. For momentum trades, on the other hand, there is persistently positive pattern for the second component and it is dominating the first component. Therefore, when both terms are combined, the payoffs from traditional carry and momentum trades would have negative loading on innovations to the common consumption correlation. This is consistent with our empirical cross-sectional regression results where we find negatively significant price of beta risk for our correlation factor.

Finally, to close the loop between empirical setup and theoretical foundation, we need to show that the common equity correlation innovation is actually capturing the same information as the common consumption correlation innovation. To show this, we first simulated consumption dynamics of 48 countries based on the model discussed above, and then drive equity returns using numerical integration through simulations. A time-series of the common consumption correlation level is given by the equation for Ψ_{t+1} and that of the common equity correlation level is estimated by running DECO model on the simulated equity return series. **Figure 7** shows a time-series plot of the common consumption levels and innovations (solid blue line) and the equity correlation levels and innovations (dotted red lines) in the upper and lower panel respectively. As we can see from the figure, they are essentially measuring the same thing, hence it verifies the validity of our empirical setup.

VI Conclusion

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 in the FX market. We found that FX portfolios which deliver high average excess returns are negatively related to innovations in the common equity correlation. The differences in exposure to the correlation factor can explain the systematic variation in average excess returns of portfolios sorted on interest rates and momentums much better than existing risk factors in the FX literatures. Furthermore, we derive the condition under which investors should demand high compensation for bearing the global correlation risk. Theoretically, from the decomposition of FX risk premia, we show that the cross-sectional variations in average excess returns should be explained by heterogeneity in the beta loadings on the global consumption innovation. We find that a large negative global consumption shock is associated with a large positive innovation to the common equity correlation, hence unexpected increases in the common correlation level would have adverse price effect for carry and momentum trades. The conclusion is consistent with negatively significant price of beta risk from our empirical exercises.

While the active body of the FX literatures try to link economic fundamentals to carry and momentum strategies, our international equity correlation innovation can be used as an instrument to explore global market integration both in equity and FX markets. Some useful extension of our article is to investigate the cross-sectional pricing power of excess returns across FX value portfolios or across individual firms in the international stock markets using our correlation factor. Furthermore, we could also direct our focus on the role of currency risk in equity market contagion and vice versa. By identifying crises and non-crises periods through the common international equity market correlation, we would be able to link a contagion indicator in one market to the one in the other market. Lastly, we could also extend our asset-pricing model to investigate FX risk implied in investing in international equity markets.

VII Appendix: Cross-Sectional Asset Pricing Model

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

$$\mu = E[Y_t] = \begin{bmatrix} \mu_f \\ \mu_R \end{bmatrix} \tag{9}$$

$$V = Var[Y_t] = \begin{bmatrix} V_f & V_{fR} \\ V_{Rf} & V_R \end{bmatrix} \tag{10}$$

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

$$\mu_R = X\gamma \tag{11}$$

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 constant beta case, the popular two-pass cross-sectional regression (CSR) method first obtains estimates $\hat{\beta}$ by running the following multivariate regression,

$$\begin{aligned} R_t &= \alpha + \beta f_t + \epsilon_t, \quad t = 1, \cdots, T & (12) \\ \hat{\beta} &= \hat{V}_{Rf}\hat{V}_f^{-1} & (13) \\ \gamma_W &= argmin_\gamma(\mu_R - X\gamma)^{'}W(\mu_R - X\gamma) = (X^{'}WX)^{-1}X^{'}W\mu_R & (14) \\ \hat{\gamma} &= (\hat{X}^{'}W\hat{X})^{-1}\hat{X}^{'}W\hat{\mu}_R & (15) \end{aligned}$$

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 definde as,

$$\rho_W^2 = 1 - \frac{Q}{Q_0} \tag{16}$$

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

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

$$\begin{aligned} \sqrt{T}(\check{\gamma} - \gamma) &\overset{A}{\sim} N(0_{K+1}, (1 + \gamma^{'}V_f^{-1}\gamma)(X^{'}X)^{-1}(X^{'}\Sigma X)(X^{'}X)^{-1} + \begin{bmatrix} 0 & 0_K^{'} \\ 0_K & V_f \end{bmatrix} \\ \sqrt{T}(\check{\gamma} - \gamma) &\overset{A}{\sim} N(0_{K+1}, (1 + \gamma^{'}V_f^{-1}\gamma)(X^{'}\Sigma X)^{-1} + \begin{bmatrix} 0 & 0_K^{'} \\ 0_K & V_f \end{bmatrix} & (17) \end{aligned}$$

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

multivariate elliptically distribution (rather than i.i.d normal). The distribution is given by,

$$\sqrt{T}(\check{\gamma} - \gamma) \stackrel{A}{\sim} N(0_{K+1}, V(\hat{\gamma})) \tag{18}$$

$$V(\hat{\gamma}) = \sum_{j=-\infty}^{\infty} E[h_t h'_{t+j}] \tag{19}$$

$$h_t = (\gamma_t - \gamma) - (\theta_t - \theta)w_t + Hz_t \tag{20}$$

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, errors-in-variables (EIV) adjustment term, and the misspecification adjustment term. Please see Kan, Robotti, and Shanken (2012) for details of the estimation.

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

$$\mu_R = X\gamma = C\lambda \tag{21}$$

$$\hat{\lambda} = (\hat{C}' W \hat{C})^{-1} \hat{C}' W \hat{\mu}_R \tag{22}$$

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

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Table I
Descriptive Statistics

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

All Currencies (48)

1. (Carry) Portfolios Sorted on Forward Discount

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

* t-stats (HML) = 4.78

2. (MoM) Portfolios Sorted on Past Excess Return

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

* t-stats (HML) = 5.44

Developed Market Currencies (17)

1. (Carry) Portfolios Sorted on Forward Discount

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

* t-stats (HML) = 2.88

2. (MoM) Portfolios Sorted on Past Excess Return

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

* t-stats (HML) = 4.44

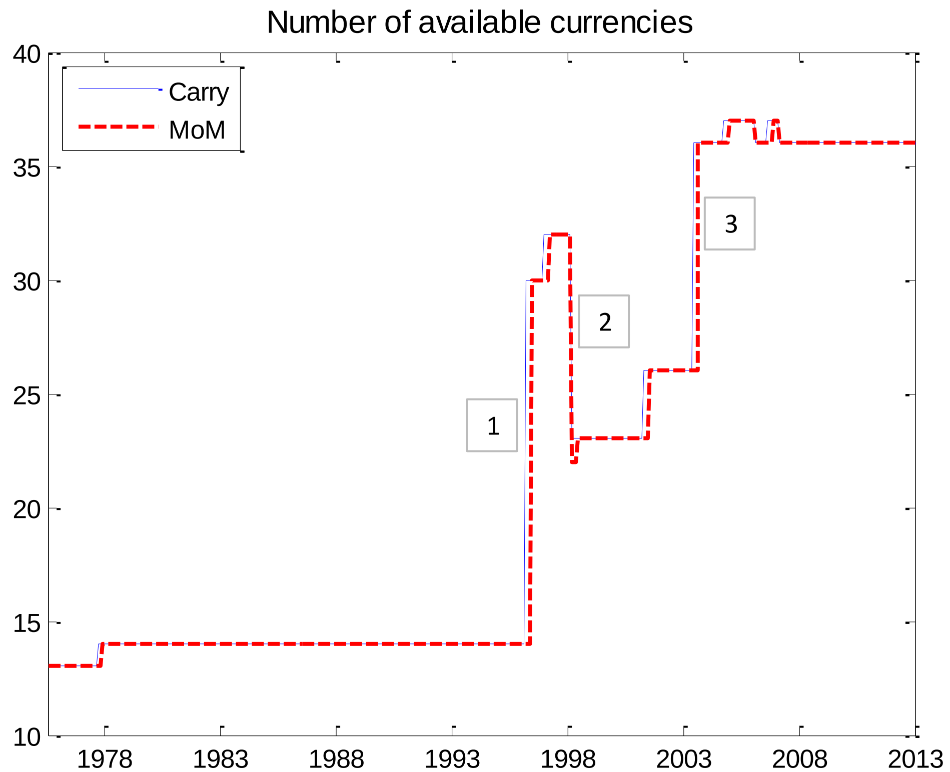
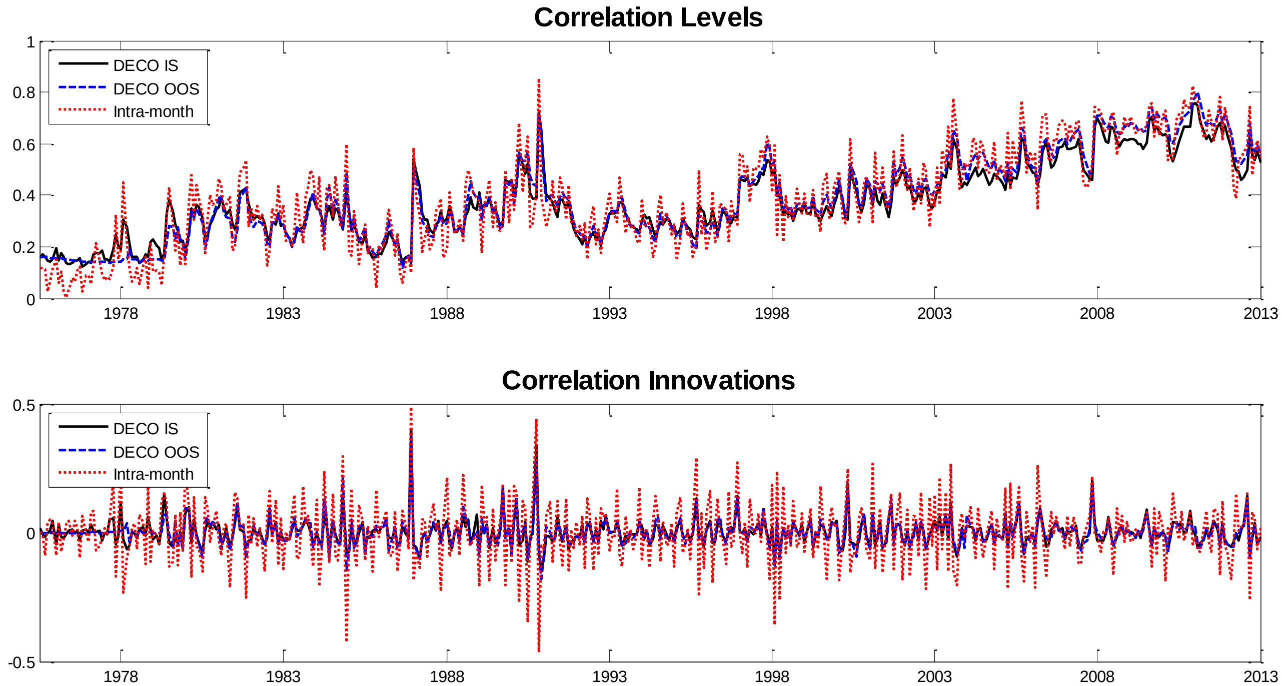


Figure 1. The figure shows a time-series plot of number of available currencies to construct carry portfolios (blue line) and momentum portfolios (dotted red line).
1. December 1996: The increase in the number of currencies is due to merger of two separate dataset (one denominated in GBP, the other denominated in USD).
2. January 1999: The decrease is due to introduction of EURO.
3. March 2004: The increase is due to inclusion of many emerging market currencies



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

* Augmented Dicky-Fuller test is a test for a unit root (H0 = Unit root is present), Ljung-box test and Breusch-Godfrey test are tests for serial dependence (H0 = No serial correlation is present)

Correlation across the factors

Correlation Level	DECO IS	DECO OOS	Intra-month
DECO IS	1.00	0.99	0.94
DECO OOS	0.99	1.00	0.94
Intra-month	0.94	0.94	1.00

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

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

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

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

Panel 1. Factor Prices

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

Descriptions

ϒ: Coefficients on beta risk
λ: Coefficients on covariance risk
t-ratio (s): Shanken Error-in-Variables adjusted t-ratio
t-ratio (jw): EIV t-ratio under general distribution assumption
t-ratio (krs): Misspecification robust t-ratio

pval-1: p-value of testing $R^2 = 1$
pval-2: p-value of testing $R^2 = 0$ (without imposing H_O: $\Upsilon = 0_N$)
pval-3a: p-value of Wald $\Upsilon = 0_k$ (H_O: $\Upsilon = 0_N$)
pval-3b: p-value of Wald $\Upsilon = 0_k$ (without imposing H_O: $\Upsilon = 0_N$)

Panel 2. Factor Betas

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

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

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

Panel 1. Factor Prices

All Countries (48)

Factor:	DOL	ΔEQ_corr	R^2	0.841
Υ	**0.146**	**-24.075**	*pval-1*	0.569
t-ratio (s)	1.081	-3.362	*pval-2*	0.001
t-ratio (jw)	1.046	-3.464	*pval-3a*	0.000
t-ratio (krs)	1.047	-3.723	*pval-3b*	0.002
λ	**-2.107**	**-17.14**		
t-ratio (s)	-0.498	-3.278		
t-ratio (jw)	-0.444	-3.396		
t-ratio (krs)	-0.450	-3.669		

Developed Countries (17)

Factor:	DOL	ΔEQ_corr	R^2	0.373
Υ	**0.093**	**-11.974**	*pval-1*	0.004
t-ratio (s)	0.742	-2.616	*pval-2*	0.088
t-ratio (jw)	0.741	-2.548	*pval-3a*	0.043
t-ratio (krs)	0.739	-1.986	*pval-3b*	0.016
λ	**-0.756**	**-8.52**		
t-ratio (s)	-0.286	-2.573		
t-ratio (jw)	-0.266	-2.545		
t-ratio (krs)	-0.272	-1.996		

Descriptions

Υ: Coefficients on beta risk

λ: Coefficients on covariance risk

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

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

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

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

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

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

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

Panel 2. Factor Betas

	Carry					Momentum			
Portfolio	α	β(DOL)	β(ΔEQ_Corr)	R^2	**Portfolio**	α	β(DOL)	β(ΔEQ_Corr)	R^2
1	-0.003	0.994	0.008	0.830	**6**	-0.003	1.007	0.006	0.774
	(0.001)	(0.044)	(0.005)			(0.001)	(0.040)	(0.005)	
2	-0.002	1.034	0.003	0.892	**7**	-0.003	1.038	0.015	0.875
	(0.000)	(0.025)	(0.003)			(0.001)	(0.026)	(0.004)	
3	0.000	0.954	0.001	0.892	**8**	-0.001	1.045	0.000	0.913
	(0.000)	(0.025)	(0.004)			(0.000)	(0.017)	(0.003)	
4	0.001	0.999	-0.003	0.891	**9**	0.000	1.001	-0.002	0.867
	(0.000)	(0.029)	(0.003)			(0.000)	(0.024)	(0.004)	
5	0.002	1.004	-0.008	0.698	**10**	0.003	0.890	-0.015	0.691
	(0.001)	(0.035)	(0.006)			(0.001)	(0.043)	(0.005)	

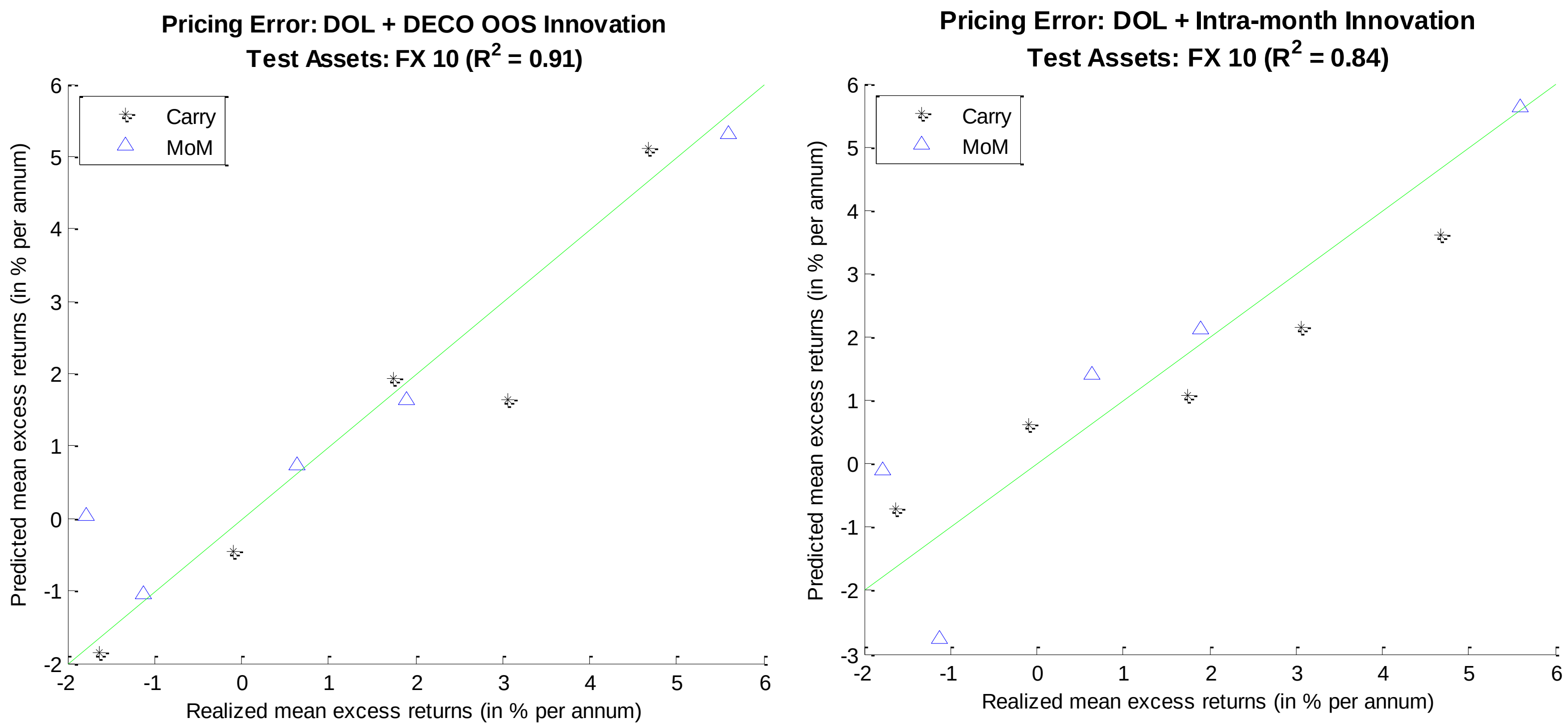


Figure 3. The figure shows pricing errors for asset pricing models with global equity correlation as the risk factor. The realized actual excess return is on the horizontal axis and the model predicted average excess return is on the vertical axis. The test assets are the set of sorted carry portfolios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

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

The test assets are the set of sorted carry portfolios (1-5), and the set of sorted momentum portfolios (1-5).
Panel 1 and 2 reports cross-sectional pricing results for the factor model based on the dollar risk factor (DOL), a factor X, and Global Equity Correlation Innovation factors: DECO OOS innovation (ΔEQ_corr_OOS) and Intra-month innovation(ΔEQ_corr_IM) respectively. Kan, Robotti, and Shanken (2012) misspecification-robust t-ratio: [t-ratio(krs)] is reported in prentheses under beta coefficient. The p-values for the test of H0: R squared = 0 is reported in prentheses under coefficient of determination.

Factor Description

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

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

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

The table reports cross-sectional pricing results for the factor model based on the dollar risk factor (DOL) and Global Equity Correlation Innovation factors: DECO OOS innovation (ΔEQ_corr_OOS) and Intra-month innovation(ΔEQ_corr_IM) respectively. The factor mimicking portfolios are obtained by projecting the factor into FX 10 portfolio space. The test assets are the set of portfolios are sorted on time t-1 forward discounts for (Carry 5), the set of portfolios are sorted on their excess return over the last 3 month for (Momentum 5), the set of sorted Carry 5 and Momentum 5 portfolios for (FX10). Developed market currencies are used to construct the test assets for (DM FX 10). Kan, Robotti, and Shanken (2012) misspecification-robust t-ratio: [t-ratio(krs)] is reported in prentheses under beta coefficient. The p-values for the test of H0: R squared = 0 is reported in prentheses under coefficient of determination.

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

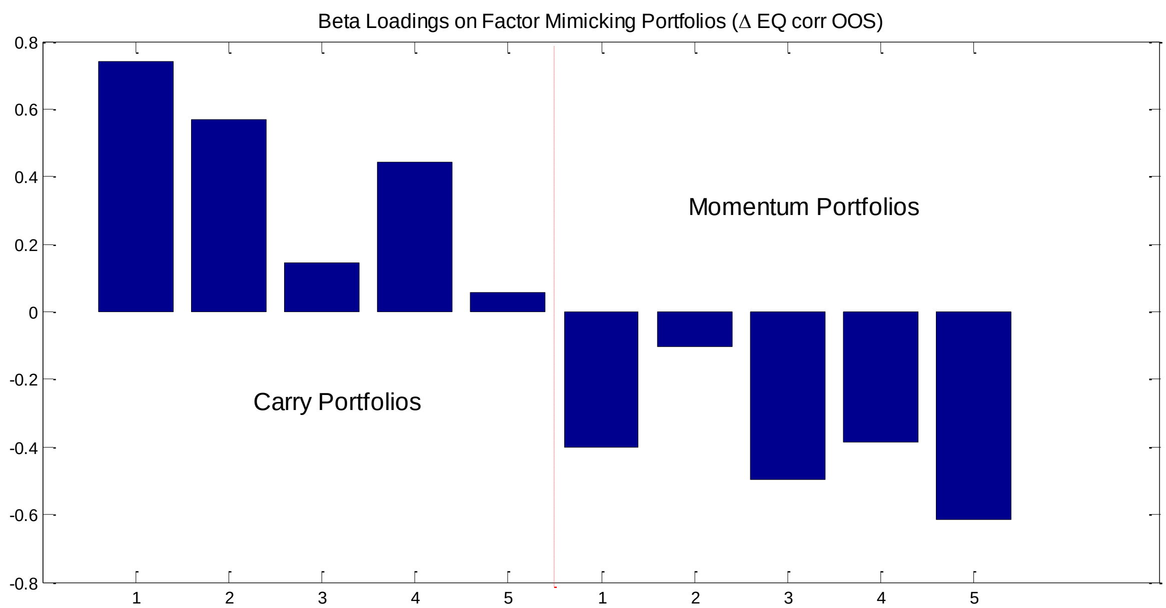


Table VI. Cross-Sectional Regression (CSR) Asset Pricing Tests
: FX 10 Portfolios + 25 Size and Book-to-Market sorted portfolios

The table reports cross-sectional pricing results for the factor model based on Fama/French factors. The test assets are the set of sorted carry (5), momentum (5) and Fama/French 25 portfolios (portfolios formed on Size and Book-to-Market ratio). MRP is the market risk premium, SMB is the small-minus-big size factor, HML is the high-minus-low value factor, DOL is the dollar factor, and ΔEQ_corr is the global equity correlation innovation where the correlation levels are measured by DECO model. Market price of beta risk ϒ (multiplied by 100), market price of covariance risk λ, the Shanken (1992) and the Jagannathan and Wang (1998) t-ratios under correctly specified models and account for the EIV problem: [t-ratio(s) and t-ratio(jw)] and the Kan, Robotti, and Shanken (2012) misspecification-robust t-ratios: [t-ratio(krs)] are reported. pval-1 is the p-value for the test of H0: R squared = 1. pval-2 is the p-value for the test of H0: R squared = 0, pval-3a and pval-3b are the p-value for Wald test of H0: ϒ = 0 with and without imposing price of beta is zero under the null respectively. Panel 2 shows beta estimation results for time-series regressions of excess returns on a constant, the dollar risk factor (DOL) and common equity correlation innovation (ΔEQ_corr). HAC standard errors are reported in parentheses. Data are monthly and the sample covers the period March 1976 to November 2013.

Panel 1

Factor:	**MRP**	**SMB**	**HML**	**DOL**	**ΔEQ_corr**	**R^2**	**0.619**
ϒ				**0.111**	**-2.808**	*pval-1*	0.000
t-ratio (s)				0.962	-2.974	*pval-2*	0.330
t-ratio (jw)				0.966	-2.172	*pval-3a*	0.002
t-ratio (krs)				0.970	-2.186	*pval-3b*	0.060
λ				**1.724**	**-10.66**		
t-ratio (s)				0.780	-2.916		
t-ratio (jw)				0.697	-1.837		
t-ratio (krs)				0.705	-1.849		

Panel 2

Factor:	**MRP**	**SMB**	**HML**	**DOL**	**ΔEQ_corr**	**R^2**	**0.848**
ϒ	**0.545**	**0.262**	**0.395**	**0.105**	**-4.592**	*pval-1*	0.001
t-ratio (s)	2.529	1.774	2.703	0.906	-3.488	*pval-2*	0.091
t-ratio (jw)	2.537	1.774	2.692	0.909	-3.456	*pval-3a*	0.000
t-ratio (krs)	2.521	1.768	2.701	0.911	-2.253	*pval-3b*	0.000
λ	**-1.721**	**0.673**	**6.434**	**2.224**	**-18.07**		
t-ratio (s)	-0.788	0.264	2.626	0.827	-3.245		
t-ratio (jw)	-0.648	0.257	2.522	0.682	-3.067		
t-ratio (krs)	-0.457	0.231	2.419	0.653	-2.198		

Descriptions

ϒ: Coefficients on beta risk

λ: Coefficients on covariance risk

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

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

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

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

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

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

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

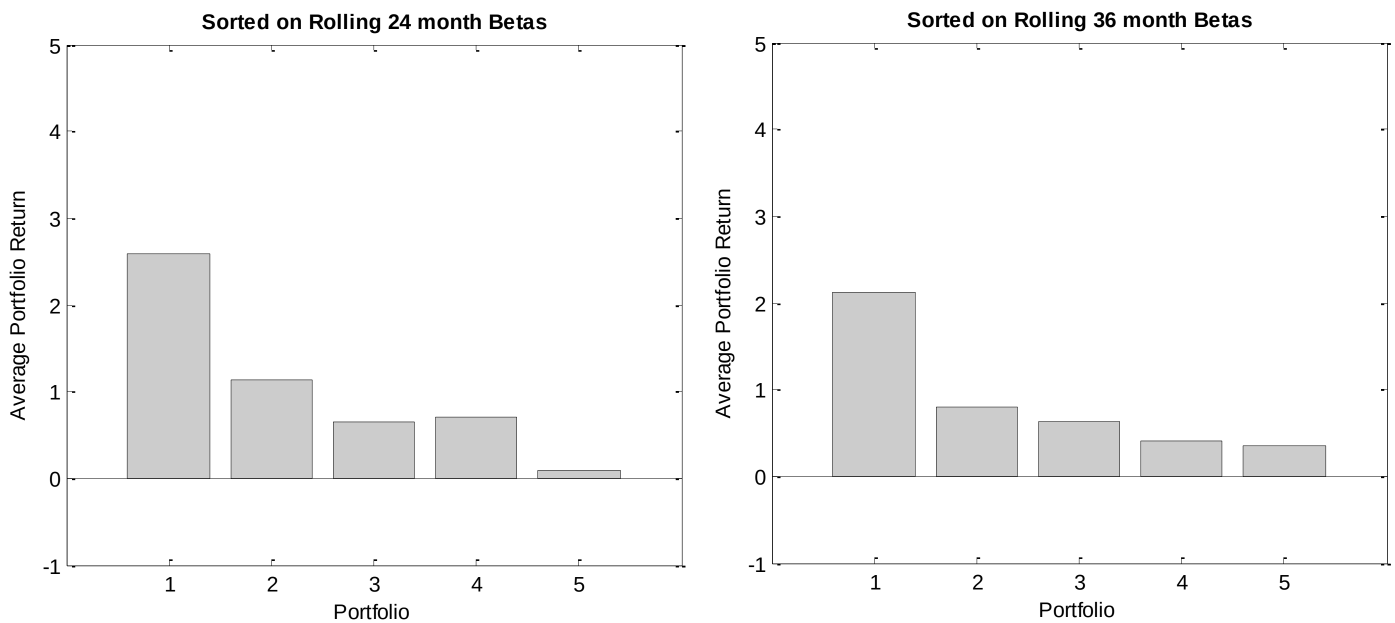


Figure 4. The figure reports average returns for the portfolios sorted on the correlation betas. Currencies are sorted according to their beta in a rolling time-series regression of individual currencies's excess returns on Global Equity Correlation Innovations. Portfolios are rebalanced at the end of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

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

The table reports cross-sectional pricing results for the factor model based on the dollar risk factor (DOL) and Global Equity Correlation Innovation where the correlation levels are measured by DECO model (ΔEQ_corr). The test assets are the set of sorted carry portfolios (1-5), and the set of sorted momentum portfolios (1-5). Panel 1. on the left reports estimation results for test assets contructed using currencies from all 48 countries and the panel on the right reports estimation results for test assets constructed using currencies from 17 developed market countries only. Market price of beta risk ϒ (multiplied by 100), market price of covariance risk λ, the Shanken (1992) and the Jagannathan and Wang (1998) t-ratios under correctly specified models and account for the EIV problem: [t-ratio(s) and t-ratio(jw)] and the Kan, Robotti, and Shanken (2012) misspecification-robust t-ratios: [t-ratio(krs)] are reported. pval-1 is the p-value for the test of H0: R squared = 1. pval-2 is the p-value for the test of H0: R squared = 0, pval-3a and pval-3b are the p-value for Wald test of H0: ϒ = 0 with and without imposing price of beta is zero under the null respectively. HAC standard errors are reported in parentheses. Data are monthly and the sample covers the period March 1976 to November 2013.

1. DECO OOS Correlation Innovation					2. Intra-Month Correlation Innovation				
Factor:	**DOL**	**ΔEQ_corr**	**R^2**	**0.419**	**Factor:**	**DOL**	**ΔEQ_corr**	**R^2**	**0.514**
ϒ	**0.111**	**-6.870**	*pval-1*	0.011	**ϒ**	**0.115**	**-20.200**	*pval-1*	0.185
t-ratio (s)	0.964	-3.904	*pval-2*	0.010	***t-ratio (s)***	0.996	-3.652	*pval-2*	0.004
t-ratio (jw)	0.965	-3.495	*pval-3a*	0.000	***t-ratio (jw)***	1.003	-4.109	*pval-3a*	0.000
t-ratio (krs)	0.966	-2.744	*pval-3b*	0.002	***t-ratio (krs)***	1.002	-3.035	*pval-3b*	0.000
λ	**1.753**	**-26.75**			**λ**	**-1.628**	**-14.38**		
t-ratio (s)	0.539	-3.778			***t-ratio (s)***	-0.416	-3.545		
t-ratio (jw)	0.453	-3.001			***t-ratio (jw)***	-0.375	-4.043		
t-ratio (krs)	0.453	-2.357			***t-ratio (krs)***	-0.372	-3.015		

Descriptions

ϒ: Coefficients on beta risk

λ: Coefficients on covariance risk

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

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

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

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

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

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

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

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

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

Panel 1. 10% Winsorization

Factor:	DOL	ΔEQ_corr	R^2	0.61
ϒ	**0.15**	**-10.94**	*pval-1*	0.43
t-ratio (s)	1.27	-2.35	*pval-2*	0.16
t-ratio (jw)	1.29	-2.43	*pval-3a*	0.00
t-ratio (krs)	1.29	-2.69	*pval-3b*	0.02
λ	**5.24**	**-88.26**		
t-ratio (s)	0.75	-2.32		
t-ratio (jw)	0.75	-2.51		
t-ratio (krs)	0.75	-2.77		

Panel 2. Before Financial Crisis (to Dec 2006)

Factor:	DOL	ΔEQ_corr	R^2	0.84
ϒ	**0.10**	**-9.89**	*pval-1*	0.50
t-ratio (s)	0.78	-3.40	*pval-2*	0.13
t-ratio (jw)	0.78	-3.19	*pval-3a*	0.00
t-ratio (krs)	0.78	-3.24	*pval-3b*	0.01
λ	**4.79**	**-34.79**		
t-ratio (s)	1.03	-3.30		
t-ratio (jw)	0.90	-2.79		
t-ratio (krs)	0.90	-2.80		

Panel 3. AR(2) Shock

Factor:	DOL	ΔEQ_corr	R^2	0.93
ϒ	**0.11**	**-8.47**	*pval-1*	0.78
t-ratio (s)	0.95	-3.94	*pval-2*	0.00
t-ratio (jw)	0.96	-3.65	*pval-3a*	0.00
t-ratio (krs)	0.96	-3.52	*pval-3b*	0.00
λ	**1.71**	**-33**		
t-ratio (s)	0.46	-3.81		
t-ratio (jw)	0.38	-3.17		
t-ratio (krs)	0.38	-3.07		

Panel 4. Weekly Data

Factor:	DOL	ΔEQ_corr	R^2	0.65
ϒ	**0.03**	**-1.67**	*pval-1*	0.31
t-ratio (s)	0.83	-3.04	*pval-2*	0.08
t-ratio (jw)	0.83	-2.29	*pval-3a*	0.00
t-ratio (krs)	0.83	-2.22	*pval-3b*	0.07
λ	**-11.31**	**-40.15**		
t-ratio (s)	-1.61	-2.99		
t-ratio (jw)	-1.15	-2.04		
t-ratio (krs)	-1.13	-1.95		

Descriptions

ϒ: Coefficients on beta risk

λ: Coefficients on covariance risk

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

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

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

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

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

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

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

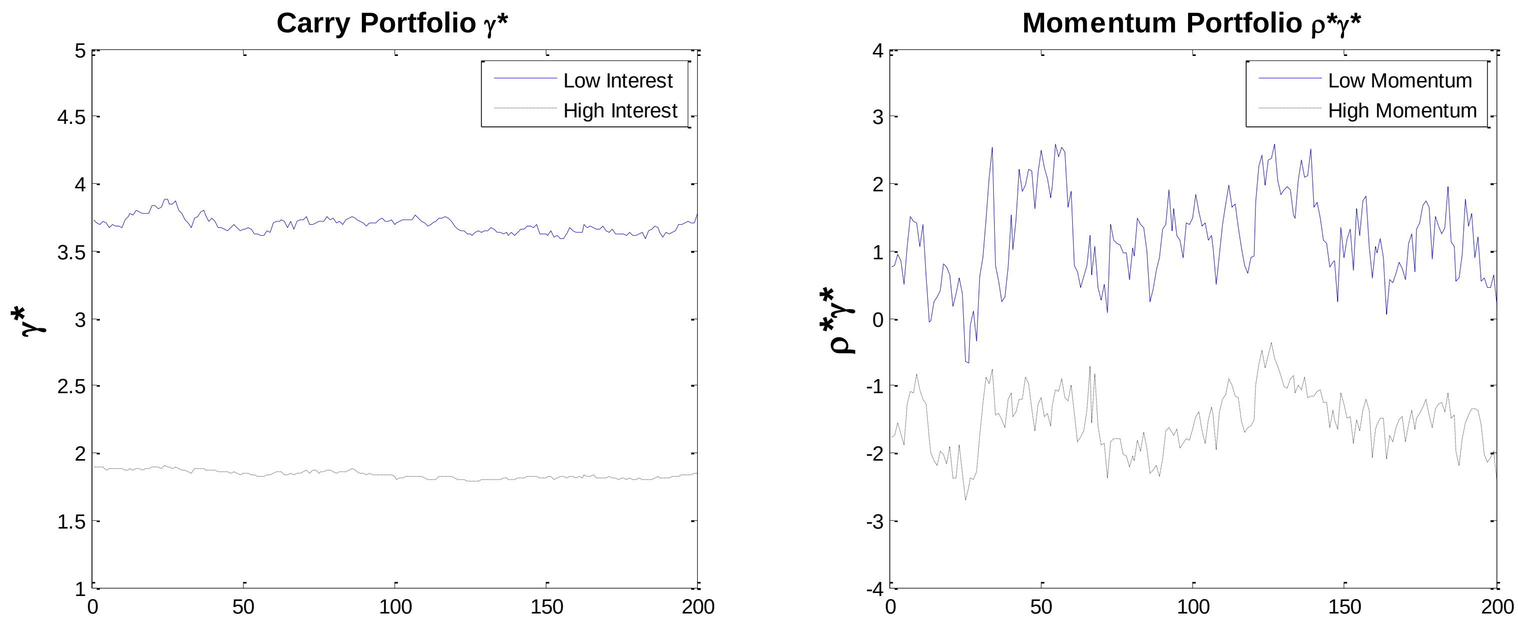


Figure 5. The figure on the left shows average ϒ for the portfolios sorted on simulated time t-1 forward discouts. The solid blue line is a time-series plot of ϒ for low interest rate portfolio, and the dotted blue line is for high interest rate portfolio. The figure on the right shows average ρϒ for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

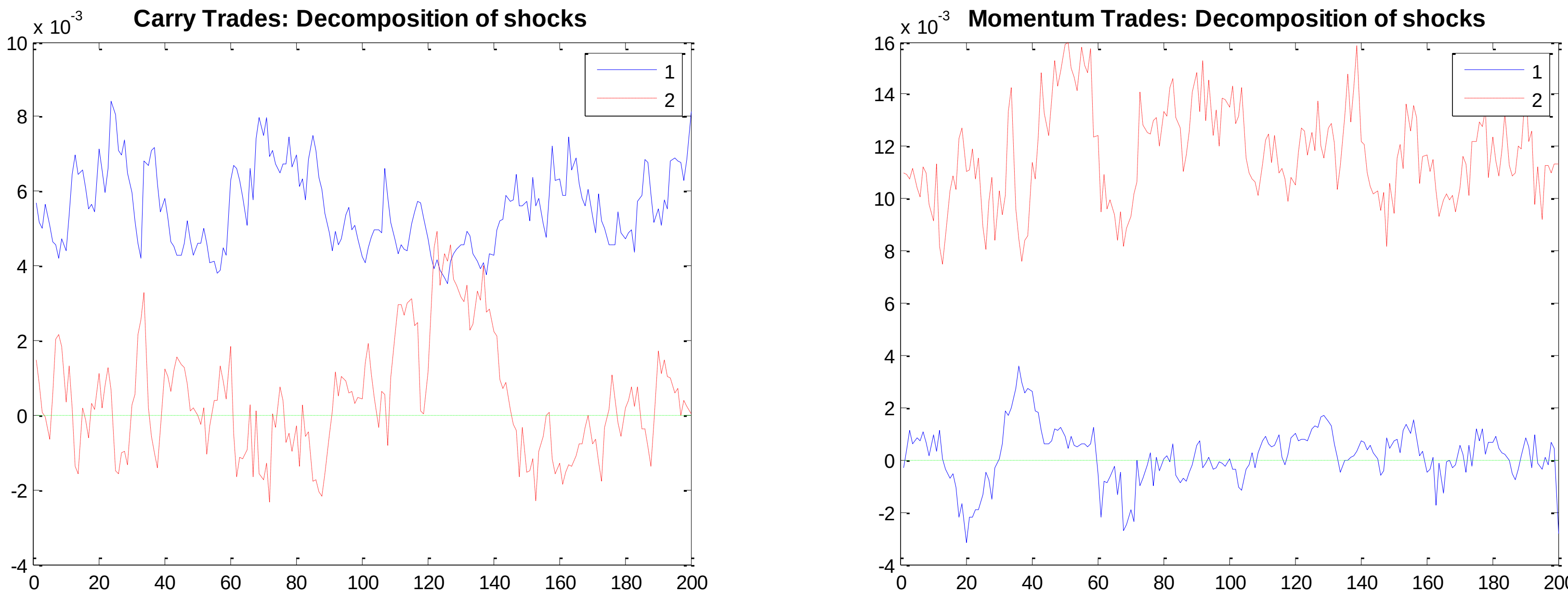


Figure 6. The left chart of the figure shows time-series decomposition of shocks for carry trades, long high interest rate currencies and short low interest rate currencies using simulated rates and returns. The right chart of the figure shows time-series decomposition of shocks for momentum trades,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

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

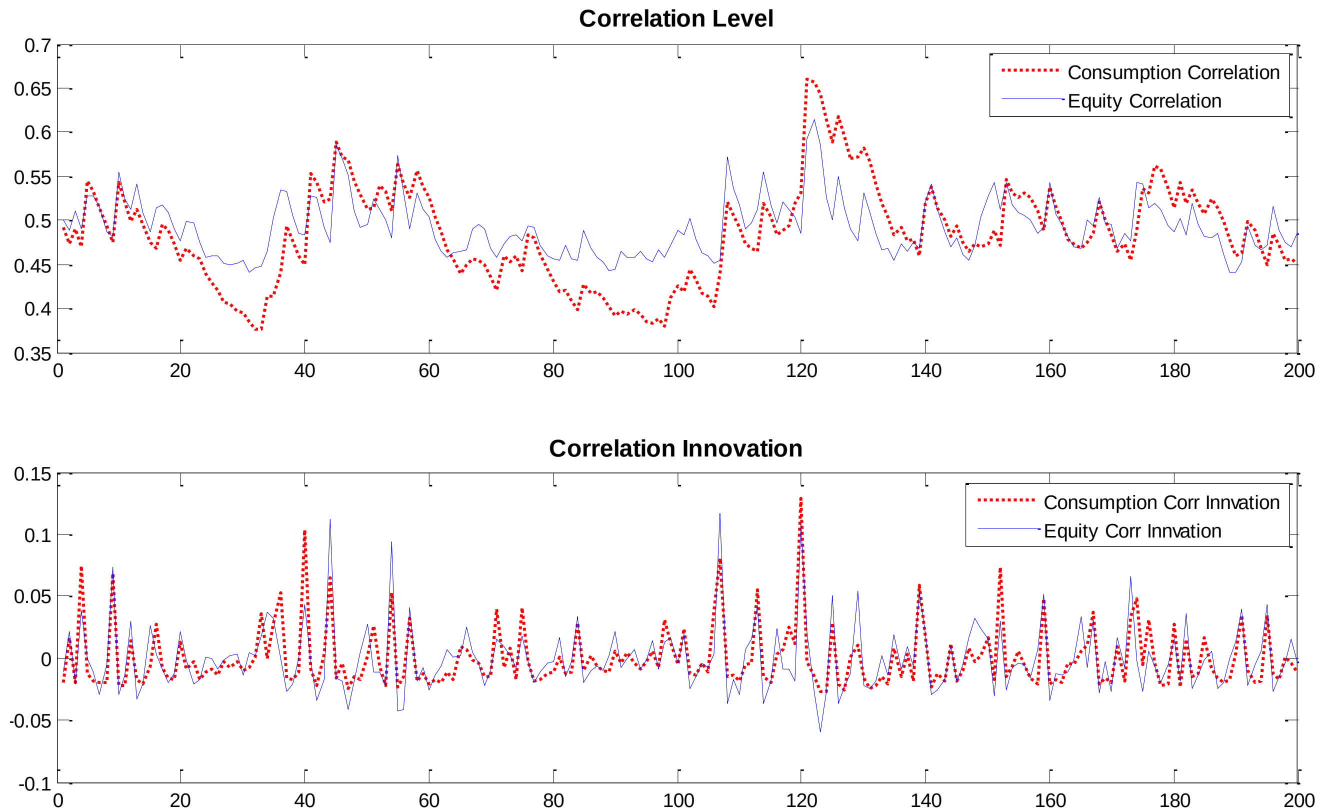


Figure 7. This figure compares consumption correlation and equity correlation where both series are simulated from our model. The upper panel of the figure shows a time-series plot of the common consumption correlation levels (solid blue line) and the equity correlation levels estimated by running DECO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

Appendix I: Country Selection with Datastream Mnemonics

	Spot Rates		1M Forward Rates		Equity Indices	
Country	**Pound**	**Dollar**	**Pound**	**Dollar**	**Local**	**USD**
1.Australia	AUSTDOL	AUSTDO$	UKAUD1F	USAUD1F	MSAUSTL	MSAUST$
2.Austria	AUSTSCH	AUSTSC$	AUSTS1F	USATS1F	MSASTRL	MSASTR$
3.Belgium	BELGLUX	BELGLU$	BELXF1F	USBEF1F	MSBELGL	MSBELG$
4.Brazil	BRACRUZ	BRACRU$	UKBRL1F	USBRL1F	MSBRAZL	MSBRAZ$
5.Bulgaria	BULGLEV	BULGLV$	UKBGN1F	USBGN1F	MSBLGNL	MSBLGN$
6.Canada	CNDOLLR	CNDOLL$	CNDOL1F	USCAD1F	MSCNDAL	MSCNDA$
7.Croatia	CROATKN	CROATK$	UKHRK1F	USHRK1F	MSCROAL	MSCROA$
8.Cyprus	CYPRUSP	CYPRUS$	UKCYP1F	USCYP1F		
9.Czech Repulbic	CZECHCM	CZECHC$	UKCZK1F	USCZK1F	MSCZCHL	MSCZCH$
10.Denmark	DANISHK	DANISH$	DANIS1F	USDKK1F	MSDNMKL	MSDNMK$
11.Egypt	EGYPTNP	EGYPTN$	UKEGP1F	USEGP1F	MSEGYTL	MSEGYT$
12.Euro erea	EURSTER	EUDOLLR	UKXEU1F	EUDOL1F		
13.Finland	FINMARK	FINMAR$	UKFIM1F	USFIM1F	MSFINDL	MSFIND$
14.France	FRENFRA	FRENFR$	FRENF1F	USFRF1F	MSFRNCL	MSFRNC$
15.Germany	DMARKER	DMARKE$	DMARK1F	USDEM1F	MSGERML	MSGERM$
16.Greece	GREDRAC	GREDRA$	UKGRD1F	USGRD1F	MSGDEEL	MSGDEE$
17.Hong Kong	HKDOLLR	HKDOLL$	UKHKD1F	USHKD1F	MSHGKGL	MSHGKG$
18.Hungary	HUNFORT	HUNFOR$	UKHUF1F	USHUF1F	MSHUNGL	MSHUNG$
19.Iceland	ICEKRON	ICEKRO$	UKISK1F	USISK1F		
20.India	INDRUPE	INDRUP$	UKINR1F	USINR1F	MSINDIL	MSINDI$
21.Indonesia	INDORUP	INDORU$	UKIDR1F	USIDR1F	MSINDFL	MSINDF$
22.Ireland	IPUNTER	IPUNTE$	UKIEP1F	USIEP1F	MSARGTL	MSARGT$
23.Israel	ISRSHEK	ISRSHE$	UKILS1F	USILS1F	MSISRLL	MSISRL$
24.Italy	ITALIRE	ITALIR$	ITALY1F	USITL1F	MSITALL	MSITAL$
25.Japan	JAPAYEN	JAPAYE$	JAPYN1F	USJPY1F	MSJPANL	MSJPAN$
26.Kuwait	KUWADIN	KUWADI$	UKKWD1F	USKWD1F	MSKUWAL	MSKUWA$
27.Malaysia	MALADLR	MALADL$	UKMYR1F	USMYR1F	MSMALFL	MSMALF$
28.Mexico	MEXPESO	MEXPES$	UKMXN1F	USMXN1F	MSMEXFL	MSMEXF$
29.Netherlands	GUILDER	GUILDE$	UKNLG1F	USNLG1F	MSNETHL	MSNETH$
30.New Zealand	NZDOLLR	NZDOLL$	UKNZD1F	USNZD1F	MSNZEAL	MSNZEA$
31.Norway	NORKRON	NORKRO$	NORKN1F	USNOK1F	MSNWAYL	MSNWAY$
32.Philippines	PHILPES	PHILPE$	UKPHP1F	USPHP1F	MSPHLFL	MSPHLF$
33.Poland	POLZLOT	POLZLO$	UKPLN1F	USPLN1F	MSPLNDL	MSPLND$
34.Portugal	PORTESC	PORTES$	PORTS1F	USPTE1F	MSPORDL	MSPORD$
35.Russia	CISRUBM	CISRUB$	UKRUB1F	USRUB1F	MSRUSSL	MSRUSS$
36.Saudi Arabia	SAUDRIY	SAUDRI$	UKSAR1F	USSAR1F	MSSARDL	MSSARD$
37.Singapore	SINGDOL	SINGDO$	UKSGD1F	USSGD1F	MSSINGL	MSSING$
38.Slovakia	SLOVKOR	SLOVKO$	UKSKK1F	USSKK1F		
39.Slovenia	SLOVTOL	SLOVTO$	UKSIT1F	USSIT1F	MSSLVNL	MSSLVN$
40.South Africa	COMRAND	COMRAN$	UKZAR1F	USZAR1F	MSSARFL	MSSARF$
41.South Korea	KORSWON	KORSWO$	UKKRW1F	USKRW1F	MSKOREL	MSKORE$
42.Spain	SPANPES	SPANPE$	SPANP1F	USESP1F	MSSPANL	MSSPAN$
43.Sweden	SWEKRON	SWEKRO$	SWEDK1F	USSEK1F	MSSWDNL	MSSWDN$
44.Switzerland	SWISSFR	SWISSF$	SWISF1F	USCHF1F	MSSWITL	MSSWIT$
45.Taiwan	TAIWDOL	TAIWDO$	UKTWD1F	USTWD1F	MSTAIWL	MSTAIW$
46.Thailand	THABAHT	THABAH$	UKTHB1F	USTHB1F	MSTHAFL	MSTHAF$
47.Ukraine	UKRAINE	UKRAHY$	UKUAH1F	USUAH1F	MSUKRNL	MSUKRN$
48.UK		UKDOLLR		UKUSD1F	MSUTDKL	MSUTDK$
49.US	USDOLLR		USDOL1F		MSUSAML	MSUSAM$

Appendix II. Portfolio Construction

FX ALL: All 48 currencies

FX DM: Developed market currencies only (17 currencies)

Equity DM: Matched countries used in FX DM (17 indices: daily price data starts from Jan 1973)

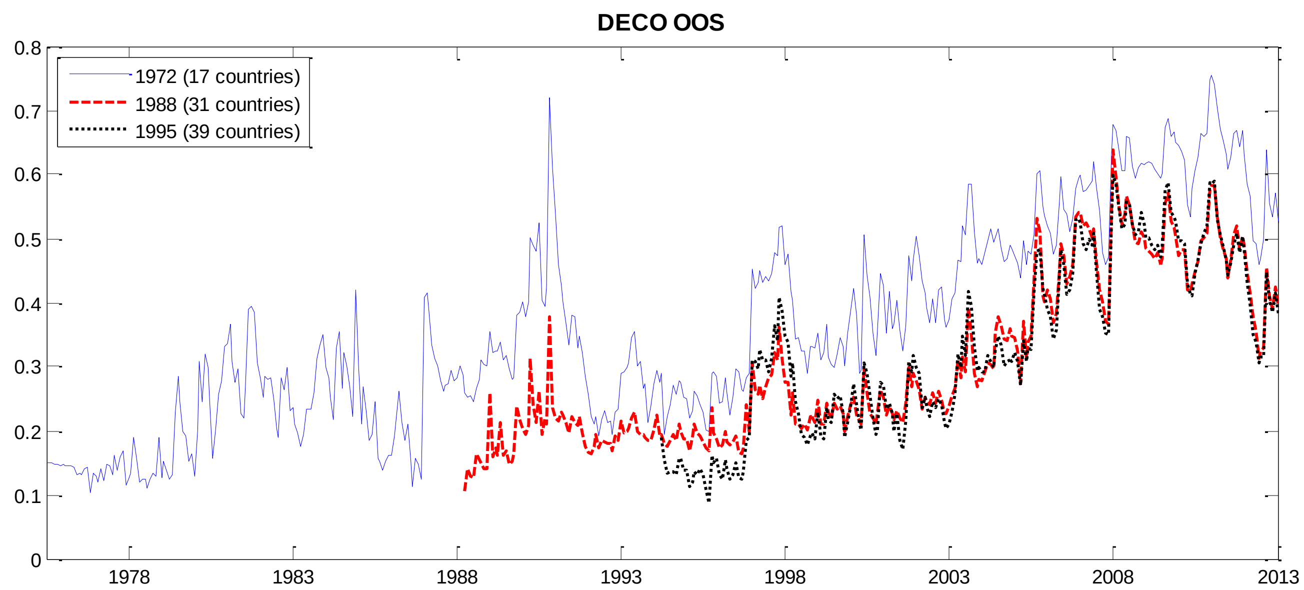
Equity 1988: All equity indices available from Jan 1988 (31 countries)

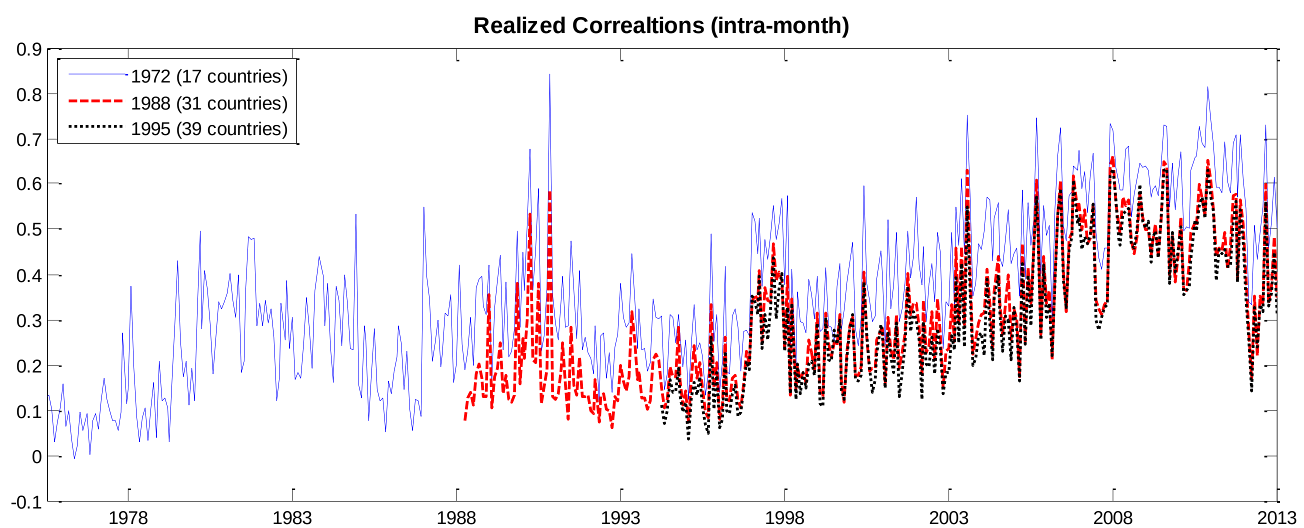
Equity 1995: All equity indices available from Jan 1995 (39 countries)

17 countries	17 countries
FX DM (1976)	**Equity DM (1973)**
1.Australia	1.Australia
2.Austria	2.Austria
3.Belgium	3.Belgium
6.Canada	6.Canada
10.Denmark	10.Denmark
12.Euro erea	12.Euro erea
14.France	14.France
15.Germany	15.Germany
24.Italy	24.Italy
25.Japan	25.Japan
29.Netherlands	29.Netherlands
30.New Zealand	
31.Norway	31.Norway
42.Spain	42.Spain
43.Sweden	43.Sweden
44.Switzerland	44.Switzerland
48.UK	48.UK
	49.US

31 Countries	39 Countries
Equity (1988 ~)	**Equity (1995 ~)**
1.Australia	1.Australia
2.Austria	2.Austria
3.Belgium	3.Belgium
4.Brazil	4.Brazil
6.Canada	6.Canada
	9.Czech Repulbic
10.Denmark	10.Denmark
	11.Egypt
13.Finland	13.Finland
14.France	14.France
15.Germany	15.Germany
16.Greece	16.Greece
17.Hong Kong	17.Hong Kong
	18.Hungary
	20.India
21.Indonesia	21.Indonesia
22.Ireland	22.Ireland
	23.Israel
24.Italy	24.Italy
25.Japan	25.Japan
27.Malaysia	27.Malaysia
28.Mexico	28.Mexico
29.Netherlands	29.Netherlands
30.New Zealand	30.New Zealand
31.Norway	31.Norway
32.Philippines	32.Philippines
	33.Poland
34.Portugal	34.Portugal
	35.Russia
37.Singapore	37.Singapore
	40.South Africa
41.South Korea	41.South Korea
42.Spain	42.Spain
43.Sweden	43.Sweden
44.Switzerland	44.Switzerland
45.Taiwan	45.Taiwan
46.Thailand	46.Thailand
48.UK	48.UK
49.US	49.US

Appendix II. Figure 1





Appendix II. Figure 2