Global Equity Correlation in International Markets

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Abstract

We present empirical evidence that the innovation in global equity correlation is a viable pricing factor in international markets. We develop a stylized model to motivate why this is a reasonable candidate factor and propose a simple way to measure it. We find that our factor has a robust negative price of risk and significantly improves the joint cross-sectional fits across various asset classes, including global equities, commodities, sovereign bonds, foreign exchange rates, and options. In exploring the pricing ability of our factor on the FX market, we also shed light on the link between international equity and currency markets through global equity correlations as an instrument for aggregate risks.

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1 Introduction

A central question in nancial economics is how to nd the pricing kernel across asset classes in international markets and how that kernel could be measured empirically. This article provides empirical evidence that the innovation in global equity correlation (henceforth *Corr*) is a common component of the marginal utility of international investors. We present empirical ndings that it is a priced risk factor in the cross-section of a wide array of asset classes including global equities, commodities, developed and emerging markets, sovereign bonds, foreign exchange rates, and options.

To motivate why *Corr* is a valid factor in international asset returns, we present a stylized consumption-based international asset pricing model in which the representative agent lation is negatively associated with the surplus consumption ratio (Campbell and Cochrane (1999)), higher during NBER recessionary periods, positively related to a model-implied time-varying risk aversion of Bekaert et al. (2019), and also positively correlated with the global and U.S. option-implied volatilities (Rey (2015)). Second, we focus on the *changes* in global correlation and show that it is negatively associated with global equity market returns, tends to increase more dramatically during large market declines[3] and is strongly positively associated with changes in the global and the U.S. option-implied volatilities and variance risk premia.[4]

Having established empirical support for the theoretical prediction that our factor is related to *GRA*, we start our empirical tests by examining the two-pass cross-sectional regression (henceforth, CSR) in a wide array of asset classes. We construct various sets of carry and momentum portfolios in different markets: 6 portfolios formed on equity index futures, 10 portfolios formed on commodity futures, 10 portfolios using 10-year Treasury bond total-return series, and 10 portfolios formed on foreign exchange rate futures. In addition to those, we construct 6 emerging market sovereign bond portfolios as in Borri and Verdelhan (2011), 18 equity index option portfolios as in Constantinides et al. (2013) and 60 global equity portfolios as in Hou et al. (2011).

We show that differences in exposure to *Corr* can explain the systematic variation in average excess returns across these sets of portfolios simultaneously. When the two-pass CSR is performed on each asset separately, we find that the power of the CSR test originates from all types of investment strategies yielding cross-sectional fit, ranging from 44% for the global equity portfolios to 90% for the option portfolios. The price of risk for our factor is economically and statistically significant under Shanken's (1992) estimation error adjustment as well as the misspecification error adjustment as in Kan et al. (2013). We also use CSR-GLS, Fama-MacBeth and GMM methods, and find that one standard deviation of cross-sectional differences in covariance to our factor explains about 2.5% to 5.7% per annum

[3]Equity returns become more internationally correlated after bad global fundamental shocks due to the asymmetric valuation effect that originates from higher level of risk aversion. This asymmetric response due to time variability in *GRA* is consistent with our model. It also relates our factor to the downside CAPM of Lettau et al. (2014) and intermediary capital shocks of He et al. (2017).

[4]See Rey (2015) and Bekaert and Hoerova (2016) for evidence on VIX and variance risk premia.

in the cross-sectional di erences in average return of 120 all-inclusive portfolios. A negative price of risk suggests that investors demand low risk premium for portfolios whose returns co-move with global equity correlation, since they provide a hedging opportunity against a sudden positive shock on the level of global risk aversion.

Regarding the concern related to a useless factor bias as in Kan and Zhang (1999), we follow several suggestions from their paper. We rst check that R^2 is statistically di erent from zero and con rm that our model is able to reject the null hypothesis of the misspeci ed model ($H0 : R^2 = 0$).[5] Second, we compare the single factor CAPM model with the extended two factor model augmented with *Corr*. By doing so, we show that the explanatory powers of two nested models are statistically di erent from each other and highlight the relative importance of the correlation factor. More speci cally, we nd that di erences in R^2 range from 22% (emerging market sovereign bonds) to 80% (global equity index futures) and those are statistically di erent from zero at a 5% rejection level in all asset classes except sovereign bonds. Third, the p-values from the F-test, a generalized version of Shanken's CSRT statistic which takes conditional heteroskedasticity and autocorrelated errors into account, suggest that the null hypothesis that all pricing errors are zero (*H0: all pricing error = 0*) cannot be rejected in all asset classes. These results suggest that the signi cance of our factor risk premium is not likely due to the useless factor bias.

The recent literature suggests that there are other risk factors that have some success in pricing the cross-section of returns in di erent asset classes (e.g., Lettau et al. (2014), He et al. (2017) and Yara et al. (2019)). It is, then, natural to explore how the pricing ability of *Corr* fares against these alternative models in explaining portfolios in multiple asset classes.[6] We do so not only with our benchmark 120 all-inclusive multi-asset portfolios as test assets but also with completely independent sets of test assets provided by He et al. (2017) (104 portfolios) and Asness et al. (2013) (48 portfolios).

We rst con rm their empirical results in our sample and nd that both the downside risk factor of Lettau et al. (2014) and the intermediary capital ratio factor of He et al.

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[5] We rely on the asymptotic distribution of the sample R^2

(2017) can explain the spreads in mean returns of multi-asset portfolios with R^2 ranging from 27% to 42%. Second, we include $Corr$ along with these factors and nd that the price of the covariance risk for $Corr$ is statistically di erent from zero in most cases. Using our benchmark all-inclusive multi-asset portfolios as test assets, the normalized price of covariance risk ranges from -2.81 to -3.43 per annum after controlling for the intermediary capital ratio factor and the downside risk factor, respectively. These estimates are similar to those of our main regression, and hence we conclude that the pricing power of our factor tum portfolios jointly as a test asset, di erences in R^2

who proposes a habit-based explanation for the forward premium puzzle. While our model is similar in that we leverage the external habit level to endogenously generate time-varying correlation of stock returns, our setup allows us to study one pricing kernel in which the risk aversion of a global representative agent plays a central role in pricing all assets. Our model also builds on Hassan (2013) and Martin (2013) as both papers highlight the role of country size in explaining heterogeneity of the stochastic properties of countries' exchange rates. An important distinction between this model and theirs is that we utilize N-country specification with greater focus given to the role of time-varying *GRA*. In our specification, the change in *GRA* is a common driver of returns across all assets in different countries. Since *GRA* is not observable and hence challenging to measure empirically, we illustrate in our model that the changes in co-movement across international equities can be a good proxy for the changes in *GRA*.

2.1 Global Risk Aversion

There are N countries with independent output streams ($D_{i;t}$) for each country i.[7] The growth rate and volatility of the output streams are the same across all countries: $dD_{i;t} = D_{i;t}(\ dt + \ dB_{i;t})\ \forall i$. There are two classes of agents in this economy. The first class is "Locals" who consume a fraction of 1 of their own country's output and do not consume foreign country's output. The second class is "Internationals" who consume the remaining fraction of each country's output. *Locals* do not participate in financial markets, therefore assets are priced by *Internationals*. *Internationals* maximize expected utility of the form: $E \int_{t=0}^{\infty} e^{\ t} ln(C_t \ X_t)dt$, where C_t denotes the aggregate consumption level of *Internationals* and X_t denotes the habit level at time t

The constant $_i$ controls the relative importance of good i for *Internationals* and the sum of $_i$ equals to one ($\sum_{i=1}^{N} \ _i = 1$).

The e ect of habit persistence on the agent's attitudes toward risk can be summarized by the inverse of the surplus/consumption ratio, which we denote $_t = C_t/(C_t \quad X_t)$. Analogously to Menzly et al. (2004), we assume that the dynamic of risk aversion coe cient for *Internationals* (*global risk aversion* or

$$S_{i;t} = \frac{e_{i;t} D_{i;t}}{e_{i;t} D_{i;t} + \sum_{n \neq i}^{N} e_{n;t} D_{n;t}} = \frac{\frac{1}{i} D_{i;t}^{\frac{}{1}}}{\sum_{n=1}^{N} \frac{1}{n} D_{n;t}^{\frac{}{1}}} \quad (4)$$

$$e_{i;t} = \frac{S_{i;t}}{S_{1;t}} \frac{D_{i;t}}{D_{1;t}}^{1} \quad (5)$$

De ning the size-weighted average of consumption shock as the global consumption shock ($dB_{g;t}$

other country's dividend shocks. This leads to increased *cross-valuation e ect*, hence higher expected co-movement across all international equity index returns. Therefore, the changes in the unobservable *GRA* reveal themselves through changes in the co-movement between observable returns of the international equity market indices.

2.2.2 Case 2: Substitutable goods

When goods in one country are (partially) substitutable for goods in another country (> 1), the size of the country is no longer constant ($S_{i,t} \neq \ _i$).

$$V_{i,t} \quad \frac{P_{i,t}}{D_{i,t}} = \frac{1}{S_{i,t}\ _t} E_t \int_t^{1} e^{\ (\ \ t)} \ S_{i,}\ d \tag{14}$$

The price-dividend ratio is an inverse function of the risk aversion as in Campbell and Cochrane (1999) as well as the size of the economy as in Cochrane et al. (2008).[10] To see what drives the covariance between two equity returns in this general case, we rst derive the unexpected component of equity returns. In this substitutable-goods case, it is given by

$$R_{i,t} \quad E_t[R_{i,t}] \ = \ \frac{\partial V_{i,t}/\partial \ _t}{V_{i,t}} \ (\ _t \quad) \ \frac{\partial V_{i,t}/\partial S_{i,t}}{V_{i,t}} \frac{1}{\ } S_{i,t} \sum_{n=1}^{N} S_{n,t} dB_{n,t}$$

$$+ \ \frac{\partial V_{i,t}/\partial S_{i,t}}{V_{i,t}} \frac{1}{\ } S_{i,t} + 1 \quad dB_{i,t} \tag{15}$$

where $\frac{\partial V_{i,t}/\partial \ _t}{V_{i,t}} < 0$ and $\frac{\partial V_{i,t}/\partial S_{i,t}}{V_{i,t}} < 0$. As in the case of non-substitutable goods in the previous section, Equation 15 illustrates that the asset return of country i reacts to the dividend shock of country j especially when the relative size of country j is large and the level of *GRA* is high. Given the term $\hat{\ }_t$ in Equation 15, this cross-country e ect is magni ed if *Internationals* have high risk aversion at time t.

[10]Cochrane et al. (2008) is a special case of this model. If the risk aversion is constant ($_t =$ and $= 0$), goods are perfectly substitutable ($= 1$) and only two countries exist in the world, the price-dividend ratio converges to the one in Cochrane et al. (2008).

$$V_{i,t} \ = \ \frac{1}{2\ S_{i,t}} \ 1 + \ \frac{1 \quad S_{i,t}}{S_{i,t}} \ ln(1 \quad S_{i,t}) \quad \frac{S_{i,t}}{1 \quad S_{i,t}} \ ln(S_{i,t})$$

Note that, in this case, there is no common driver that governs the time-variation of the valuation ratios across all countries. Instead, there exists the cross-sectional variation in $V_{i,t}$ through the relative size of country ($S_{i,t}$), and the valuation ratio is marginally time-varying through the time-variation in the distribution of relative sizes. In other words, a positive correlation can be endogenously generated in the model, but the model cannot generate the dynamics of the average co-movement among international equity returns.

In this substitutable-goods case, there is an additional channel of the *cross-valuation effect* through the changes in size ($\frac{\partial V_{i,t}/\partial S_{i,t}}{V_{i,t}}$ in Equation 15) besides the changes in *GRA* ($\frac{\partial V_{i,t}/\partial \gamma_t}{V_{i,t}}$ in Equation 15) as in Section 2.2.1. This additional channel of the *cross-valuation effect* shares the same intuition as in Cochrane et al. (2008)'s two trees model. To understand the mechanism behind this additional channel, let us assume that there exist only two countries (i and j) and no time-variation in *GRA* ($\Delta\gamma = 0$). In this case, if one country i has a negative dividend shock ($\Delta D_{i,t} < 0$), the relative size of country i would be decreased ($\Delta S_{i,t} < 0$). With only two countries in the world, the decrease in the relative size of country i automatically implies an increase in the relative size of country j ($\Delta S_{j,t} > 0$), hence there is negative innovation in the valuation ($\Delta V_{j,t} < 0$). This creates positive contemporaneous correlations among two equity indices through the *cross-valuation effect*: $Cov_t\left(\frac{dD_{i,t}}{D_{i,t}}, \frac{dV_{j,t}}{V_{j,t}}\right) + Cov_t\left(\frac{dV_{i,t}}{V_{i,t}}, \frac{dD_{j,t}}{D_{j,t}}\right) > 0$.[11]

Extending to N countries with N corresponding international equity indices shows that the *cross-valuation* channel cannot be a major determinant of the time-series variation in the *common* correlation among the N indices' returns. First of all, contrary to the two-tree case, the decrease in the relative size of country i cannot automatically imply an increase in the relative size of country j, since the initial effect on country i will be diluted to $N - 1$ countries. Second, there will be no time-series variations in the *average* correlation unless there are dramatic changes in the entire distribution of the size from one period to another.

While the effect on the *common* correlation from the changes in size is severely diluted, the effect from the changes in *GRA* is not marginalized even when the model is extended to N-trees. Increased *GRA* induces equity index returns in one country to be more responsive to other countries' dividend shocks, hence higher co-movements across international equity returns. The key mechanism behind the *cross-valuation effect*, therefore, is still through the changes in *GRA*, not through the changes in size, whether goods are substitutable or not.

[11] The *level* of bilateral correlation between two equities i and j depends on the size of two countries ($S_{i,t}$ and $S_{j,t}$) and *GRA* (γ_t). If country i is large, changes in the relative size of country i have a greater implication for the relative size of country j. Moreover, the larger country i is, the greater the influence on *GRA* from the country's dividend shock. Therefore, the *level* of bilateral correlation between two equities i and j is higher if the size of both countries is larger.

3 Data

3.1 Global Equities

Our international equity data consist of returns on equity indices, index futures, and individual stocks. We collect daily closing MSCI international equity indices for 39 countries both in U.S. dollars and in local currencies from Datastream. We use total returns in U.S. dollars as our base case.[12] The sample covers the period from January 1973 to December 2014. For index futures, we focus on equity index futures contracts with one-month maturity and we interpolate between the two nearest-to-maturity futures prices to compute synthetic one-month equity futures prices if an exact one-month contract is not available, following

The sample periods run from December 1973 to December 2014. We also have a dataset for sovereign bonds using the JP Morgan EMBI Global total return indices. The EMBI index is a market capitalization-weighted aggregate of Brady Bonds, Eurobonds, traded loans, and local market debt instruments issued by (quasi-) sovereign entities. We select the same 41 countries as in Borri and Verdelhan (2011) for the period from December 1993 to December 2014. The commodity futures price data are from Commodity Research Bureau (CRB) and the sample spans from January 1973 to December 2014. Lastly, the equity index option return series are obtained from Constantinides et al. (2013) for the period from April 1986 to January 2012.[15]

3.3 Spot and Forward Foreign Exchange Rates

Following Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011a), we blend two datasets of spot and forward exchange rates to span a longer time period. Both datasets are obtained from Datastream. The datasets consist of daily observations for bid/ask/mid spot and one month forward exchange rates for 44 currencies. Those bid/ask/mid exchange rates are quoted against the British pound and US dollar for the rst and second dataset, respectively. The rst dataset spans the period between January 1976 and December 2014 and the second dataset spans the period between December 1996 and December 2014. The sample period varies by currency. To blend the two datasets, we convert pound quotes in the rst dataset to dollar quotes by multiplying the GBP/Foreign currency units by the USD/GBP quotes for each of bid/ask/mid data. We sample the data on the last weekday of each month. In the empirical section, we carry out our analysis for the 44 countries as well as for a restricted database of only the 17 developed countries for which we have longer time series. The list of currencies is reported in Internet Appendix Table A1.

4 The global equity correlation factor

In our theoretical motivation, we show that the changes in risk aversion reveal themselves through changes in the correlation between observable returns of international equity indices. Moreover, the endogenous correlation through the valuation e ect is asymmetric, meaning

[15] See, http://pages.stern.nyu.edu/ asavov/alexisavov

that equity returns are much more correlated internationally subsequent to negative global fundamental shocks due to the higher risk aversion level. In this section, we construct a measure of international equity correlation innovation and examine its determinants. We empirically test whether $\Delta Corr$ is indeed closely related to (i) the level of GRA and (ii) the negative realization of global fundamental shocks.

4.1 Factor construction

We measure the correlation dynamics by computing bilateral intra-month correlations in each month's end using daily return series. Then, we take an average of all the bilateral correlations to arrive at a global correlation level of a particular month.[16] The correlation levels are plotted in the upper panel of Figure 1. The lower panel of the figure shows a time-series plot of $\Delta Corr$. We simply take the first difference in the time series of correlation to quantify the evolution of the co-movements.[17]

4.2 Time-series analysis on global equity correlation

Table 1 reports results from time-series regressions in which the level of the global equity correlation is regressed on various proxies of the GRA. First, in Model (1), we find that the global equity correlation is negatively associated with a surplus consumption ratio. We follow Watcher (2006) in order to construct a proxy for the surplus consumption at the monthly frequency: $Surplus_t = \frac{1-\phi}{1-\phi^{40}} \sum_{j=0}^{39} \phi^{j} \Delta c(t-j)$ where the decay factor $\phi = 0.96$.

risk aversion that is calculated from financial variables at monthly frequency. Model (3) shows that the correlation level is also positively correlated with their model-implied risk aversion.[18] Fourth, we use the global and the U.S. option-implied volatilities as alternative proxies of global risk aversion (e.g., Rey (2015)). For the global option-implied volatility, we apply Mark and Neuberger (2000) and Jiang and Tian (2005)'s methodology to option prices written on 16 developed stock market indices and extract the risk-neutral expectation of the return variation.[19] Our two proxies for the global implied volatility are the value-weighted and equal-weighted average of those countries' option implied volatility measures. We simply use the level of VIX index for the equivalent measure in the U.S. Models (4)-(6) in Table 1 present evidence that the global correlation loads strongly on all three measures of the global implied volatility. In summary, these pieces of evidence consistently point to a strong link between the level of correlation across international equity markets and global risk aversion.

4.3 Time-series analysis of global equity correlation innovation

Having established the existence of a connection between the level of correlation and global risk aversion, we next turn our attention to the innovation in the global equity correlation. We investigate its relation with the realization of global fundamental shocks and economic conditions. We use global equity market returns as a proxy for global fundamental shocks. In order to show the asymmetric reaction of the correlation through the valuation effect, we define large negative (positive) market returns as returns that are more than one standard deviation below (above) the mean of the global market returns. Our time-series regressions also include various proxies for global macro economic conditions. Those are global market-capitalization weighted average of term spreads (10-year minus 3-month yield), 3-month T-bill rates, and dividend yields. To examine if there are other important pre-determinants of $\Delta Corr$, we not only include contemporaneous changes in those variables, but also control for the level of macro economic conditions in the previous month $t-1$.

[18] See https://www.nancyxu.net/risk-aversion-index

[19] Those include S&P/ASX 200 for Australia, EURONEXT BEL-20 for Belgium, S&P/TSX60 for Canada, SMI for Switzerland, HS CHINA ENT for China, IBEX-35 for Spain, OMXH 25 for Finland, CAC 40 for France, FTSE 100 for the U.K., DAX for Germany, HANG SENG for Hong Kong, FTSE MIB for Italy, NIKKEI 225 for Japan, KOSPI 200 for Korea, AEX for Netherlands, TAIEX for Taiwan, and S&P 500 for the U.S. Index option data is from Option Metrics.

The dynamics of the average correlation can potentially be driven by correlated trading activities in the global equity market owing to significant prevalence of global institutional investors. The correlation risk may also reflect the global liquidity risk if the correlation only increases during pervasive liquidity dry-ups. Therefore, our tests include global turnover and liquidity innovations, and changes in the commonality in turnover as well as liquidity. We rely on the Amihud liquidity measure to capture liquidity risk and we follow Karolyi et al. (2012) for the commonality in turnover and liquidity.

Models (1)-(2) in Table 2 show that our correlation factor is negatively associated with global equity market returns and it tends to increase more dramatically during large market declines. These findings are consistent with our theoretical motivation in Section 2 that there is an asymmetric response of the correlation to global fundamental shocks induced by higher risk aversion rates. This asymmetric response also hints that our factor is closely related to the downside CAPM of Lettau et al. (2014). Moreover, we expect our factor is negatively associated with intermediary capital ratio due to a positive feedback loop between risk aversion and financial intermediaries' assets. For example, an increase in global risk aversion coincides with reductions in speculators' asset positions and unwinding of those assets in turn results in further speculators' capital losses and higher risk aversion. We confirm this negative relation in Model (3).

Throughout Models (1)-(3), we also examine whether global macro-economic states are pre-determinants of the correlation innovations. The regression results indicate that the effect of global macro-economic conditions on the correlation innovation is weak. *Corr* is not significantly related to global term spreads, risk-free yields, or dividend yields. Therefore, it is hard to conclude that the dynamic of the global equity correlation is mainly driven by the changes in global macro-economic fundamentals.

Similarly to macro-economic conditions, Model (4) shows that the correlation innovation is weakly related to innovations in other financial market conditions. A statistically insignificant relation between *Corr* and the global liquidity innovation in Model (4) suggests that the correlation risk cannot be subsumed by the global liquidity risk. A positive relation with the global turnover innovation highlights that *Corr* increases when there are excessive trading activities around the world. At the same time, a weak relation between *Corr* and correlated trading activities in Model (4) also implies that it is not mainly determined by common capital flows that originate from greater use of basket trading or prevalence of institutional investors. Overall, the evidence on the effect of global liquidity and global trading activity is mixed and their marginal contribution to the explanatory power of our factor is not economically significant.

We then examine the relation between the time variation of the global equity correlation and GRA in Models (5)-(8) of Table 2. In line with the empirical evidence from Table 1, we find that $\Delta Corr$ is positively correlated with innovations in GRA. Rey (2015) shows that the global financial cycle has tight connections with fluctuations in the risk-neutral volatility and proposes that it is closely related to risk aversion. We thus use changes in the global and the U.S. option-implied volatilities as proxies for GRA in Models (5) and (6), respectively.

The extant literature also highlights the role of the variance risk premium. For example, Bekaert and Hoerova (2016) suggest that the variance risk premium (henceforth VRP) houses a substantial amount of information about risk aversion in financial markets. Therefore, we construct two equivalent measures of VRP, the global and the U.S., defined as $VRP_t^{VW(US)} = RV_t^{VW(US)} - IVOL_t^{VW(US)}$ where $RV_t^{VW(US)}$ is the value-weighted average of realized return variances of 16 developed market indices (S&P 500 index) from month $t-1$ to t. We find evidence that $\Delta Corr$ is strongly negatively associated with both the global and the U.S. conditional VRP. This evidence is also closely related to the recent literature in the foreign exchange market in which researchers reveal the important role of VRP for currency returns (see Della-Corte et al. (2016) and Londono and Zhou (2017)).

Models (9)-(13) compare $\Delta Corr$ with the changes in correlations among many other asset classes. We compare the average of intra-country (internal) correlations with our factor, which is based on inter-country (external) correlations. To measure global intra-country equity correlations ($\Delta Corr_t^{Equity;Internal}$), we rely on the R^2 based measure to be consistent with the other commonality measures: liquidity and turnover commonalities.[20]

[20] The global commonality in returns ($Corr_{i;t}^{Equity;Internal}$) for each stock is the R^2s from the following within-month regression: $Ret_{i;t;d} = \alpha_{i;d} + \sum_{j=-1}^{1} b_{i;t;j} Ret_{w;t;d+j} + \epsilon_{i;t;d}$, where $Ret_{w;t;d}$ denotes the global equity return. $\Delta Corr_t^{Equity;Internal}$ is the change (the first differences) in the value-weighted average of the commonality in returns across all countries. Note that market microstructure issues such as different time zones and stale prices of smaller countries can be mitigated for the internal correlation measure.

$Corr_t^{Treasury\ Bond}$, $Corr_t^{FX\ USD}$ and $Corr_t^{Commodity}$ are the changes in the correlation among 10-year treasury total returns, FX returns against USD, and returns on commodity futures, respectively. The statistically signi cant beta coe cient of 0.91 in Model (9) presents evidence that the average intra-country and inter-country equity correlations are closely related, which can be interpreted as evidence of a common driver of global equity correlations.[21] Models (10) to (12) show that the factor is also positively, albeit rather weakly, related to correlations of FX returns against USD, 10 year treasury total returns and commodity returns. Model (13) illustrates that the global equity correlation is associated with correlation of FX returns against USD, but not related to correlation of FX returns against other base currencies (average of all the remaining 43 currencies in our dataset). This nding indicates that the U.S. dollar plays a special role in the international market as a barometer of international investors' risk appetite.[22]

5 Asset pricing model and empirical testing

In this section, we present empirical evidence that $Corr$ is a priced risk factor in the cross-section of portfolios in multiple asset classes and that it simultaneously explains the systematic variation in average excess returns across those sets of portfolios.

5.1 Methods: Two-pass cross-sectional (CSR) regression

To test whether our factor is a priced risk factor in the cross-section of currency portfolios, we utilize the two-pass cross-sectional regression (CSR-OLS) method. For statistical signi - cance of the price of beta or covariance, we report the statistical measures of Kan, Robotti, and Shanken (2013) throughout the main analysis of this paper. While we investigate both the price of covariance risk and the price of beta risk in our empirical tests, we only report

[21] Consistent with this time-series regression result, our cross-sectional asset pricing test results also hold for the intra-country correlation. However, we nd that the price of covariance risk is lower than that estimated from our benchmark (inter-country) global equity correlation factor, which highlights the importance of the international dimension in the factor construction.

[22] Panel A of Figure A1 in Internet Appendix compares $Corr$ with the correlation of FX returns against USD and the average correlation of FX returns against all other base currencies. Panel B of Figure A1 plots the correlation of 10 year treasury bond total returns with the FX correlation. Panel B illustrates that the correlation of treasury bond returns is almost entirely driven by the correlation of FX returns.

the price of covariance risk.[23] We report the details of the estimation methodology of these statistics in Section B of Internet Appendix.

5.2 Test assets: All-inclusive asset classes

Our theoretical motivation suggests that the change in GRA is a common component of the marginal utility for all countries and hence it affects the pricing of any assets across all countries. In Section 4, we empirically show that $Corr$ can be a good proxy for the change in GRA. In this section, we explore whether the global equity correlation innovation factor is a priced risk factor in the cross-section of global equities, commodities, sovereign bonds, foreign exchanges, and options markets, and we examine the economic relevance of our factor in explaining expected returns in those wider array of asset classes.

More specifically, we first construct various sets of carry and momentum portfolios in the following markets: 6 portfolios formed on equity index futures, 10 portfolios formed on commodity futures, 10 portfolios formed on foreign exchange rate futures, and 10 portfolios using 10-year treasury bond total-return series.[24] We follow Koijen et al. (2018) to implement the global equity index carry strategy via index futures, sorted on the slope between spot and one-month futures price. Similarly, we implement the global bond carry strategy via 10-year treasury bonds, sorted on the yield spread between 10-year and 3-month bond yields. For the commodity carry portfolios, we follow Yang (2013) and sort 30 commodities based beta as in Borri and Verdelhan (2011). For option portfolios, a panel of leverage-adjusted monthly returns of 18 option portfolios split across type (9 call and 9 put portfolios), each with targeted time to maturity (30, 60, or 90 days), and moneyness (90, 100, or 110) as in Constantinides et al. (2013). The global equity portfolios by Hou et al. (2011) are formed on 64,655 stocks from 33 countries, sorted on the basis of book-to-market (B/M), cash ow-to-price (C/P), dividend-to-price (D/P), earnings-to-price (E/P), market value of equity (Size), and momentum (MoM). We generate 10 portfolios for each type of the sorting variables. The summary statistics of those 120 portfolios are presented in Table 3.

5.3 CSR results: All-inclusive asset classes

Table 4 reports cross-sectional asset pricing test results for the two-factor model based on the global equity risk premium (Ret_{Global}) and the global equity correlation innovation ($Corr$). From Panel A to Panel G, we run CSR-OLS on each of the asset classes separately, while we employ an all-inclusive approach to test various asset classes in a joint cross-section from Panel H to I. Given the dominant number of portfolios for global equities compared to the other asset classes, we rst run CSR on the all-inclusive portfolios (60 in total) without global equities in Panel H, then we augment those all-inclusive portfolios with global equities and test on the aggregate portfolios (120 in total) in Panal I. In each panel, the market price of covariance risk ( ) is presented rst, followed by the price of covariance risk normalized by standard deviation of the cross-sectional covariances ($_{norm}$) and the corresponding t-statistics ($t\text{-}ratio_{krs}$) under Shanken's (1992) estimation error adjustment as well as the misspeci cation error adjustment of Kan et al. (2013).[25]

We expect our correlation innovation factor to be negatively priced since it is positively associated with marginal utility of consumption for *Internationals*. In Table 4, we nd that the price of covariance risk is negative in all cases, and $_{norm}$ varies from -2.42% (for the foreign exchange rates) to -7.31% (for the options) per annum. The negative price

[25] Kan, Robotti, and Shanken (2013) show empirically that misspeci cation-robust standard errors are substantially higher when a factor is a non-traded factor. That is because the e ect of misspeci cation adjustment on the asymptotic variance of beta risk is potentially large due to the variance of residuals generated from projecting the non-traded factor on the returns. It is thus important to note that our correlation factor, while not being traded, has a highly signi cant t-ratio.

of covariance risk confirms our hypothesis that investors demand a low risk premium for portfolios whose returns co-move with $\Delta Corr$, as they provide hedging opportunity against a sudden positive shock on the level of risk aversion of global investors.

To further analyze the fit of our model, we present pricing errors of the asset pricing model with our global equity correlation as a risk factor in Figure 2. The realized actual excess returns are on the horizontal axis and the model predicted average excess returns are on the vertical axis. The figure shows that the asset pricing model produces R^2 ranging from 44% to 90%, and our correlation factor contributes to the benchmark global CAPM model with a minimum increment of 20% in R^2. Overall, Figure 2 illustrates that the cross-sectional dispersion across mean returns generated by our model fits the actual realization of mean excess returns well across portfolios constructed from various asset classes.

Panels H and I in Table 4 and Figure 2, in which we use all 60 and 120 all-inclusive portfolios respectively, also confirm the ability of $\Delta Corr$ to price multiple asset classes. 61% and 30% increases in R^2 are both statistically significant with p-values less than 0.01. The generalized χ^2 test shows that the model with our correlation factor cannot be rejected, while the benchmark global CAPM model is rejected for both test assets at a 5% rejection level. We conclude that $\Delta Corr$ can jointly rationalize a number of cross-sectional asset returns.

Regarding the concern related to a useless factor bias as in Kan and Zhang (1999), we

risk aversion rates of the marginal investor and asset prices. For example, an increase in global risk aversion coincides with reductions in speculators' asset positions. Unwinding of those assets further depresses asset prices, exacerbating speculators' capital losses, and inducing greater risk aversion. Rey (2015) also notes that the e ective risk appetite of the market is related to the leverage of nancial market intermediaries. This mechanism is an important positive feedback loop between greater credit supply, asset price in ation, and risk aversion. To the extent that there exists a positive feedback loop for nancial intermediaries, we expect negative correlation between the intermediary capital ratio of He et al. (2017) and our factor, which is consistent with our empirical nding in Section 4.2.

We test the marginal contribution of $Corr$ in explaining the cross-sectional variation of returns of multiple asset classes. We do so not only with our benchmark all-inclusive multi-asset portfolios (120 portfolios) as test assets but also with completely independent sets of test assets provided by He et al. (2017) (104 portfolios)[28] and Asness et al. (2013) (48 portfolios)[29] in Panels A, B, and C of Table 5, respectively. In each panel of Table 5, we rst run CSR separately based on each of two alternative factor models of Lettau et al. (2014) and He et al. (2017) (Model 1). We then include *Value-everywhere* and *Momentum-everywhere* factors as a control in examining the portfolios of Asness et al. (2013), since value and momentum are the sole criteria considered in constructing their test assets. The speci cation for the CSR test is the same as in Table 4.

The rst column of Table 5 reports the name of variables to be controlled in each regression. We present misspeci cation robust t-ratios for the price of covariance risk ($tratio_{krs}$) and p-values for the R^2 ($pval_{R^2=0}$) for each of the control factors. Consistent with the empirical results in the literature, we con rm in our sample that both the downside risk factor ($DR\text{-}CAPM$) and the intermediary capital ratio factor (IC^{HKM}) can explain the spreads in mean returns of multi-asset portfolios with R^2

Second, we explore di erent asset pricing test methodologies and present the asset pricing test results in Table 7. Regarding asset pricing methodologies, we rst employ two-pass OLS regression (CSR-OLS) in Panel A. Given that our factor is a non-traded factor, we

A4 in the Internet Appendix reports non-overlapping time-series regression results with *k*-

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 FX portfolios since it captures the common uctuations of the U.S. dollar against a broad basket of currencies. Therefore, we use *DOL* as a control variable instead of the global CAPM (Ret_{Global}) in this section.

Table 9 presents the results of the second pass CSR using two factors: *DOL* and *Corr*. We rst examine carry and momentum portfolios separately to understand whether the explanatory power of the cross-sectional di erences in mean return is mainly driven by one particular type of strategy. Then, we jointly estimate the price of covariance risk using the combined assets: *FX 10* portfolios.

In Section 5.3, we show that *Corr* factor is negatively priced across many asset classes including the foreign exchange market. We con rm the empirical result in Panel A of Table 9 that *Corr* is negatively priced after controlling for the dollar risk factor instead of the global equity risk premium. Moreover, the price of covariance risk is statistically signi cant with a high level of R^2 regardless of whether the cross-sectional regression is performed on carry and momentum portfolios separately or jointly. With respect to *FX 10* portfolios in the table, the price of covariance risk is statistically signi cant under Shanken's (1992) estimation error adjustment as well as the misspeci cation error adjustment, with t-ratio of -3.48 ($t\text{-}ratio_s$) and -3.20 ($t\text{-}ratio_{krs}$) respectively.[37] As in Section 5.3, we also take an additional step to tackle the issue of useless factor bias in Kan and Zhang (1999). We do this by checking that the betas to to (1999 [(T)82(ab9 [(T388(sig3(error)-413(adju 0 -413(59(w)204 Td [

could yield statistically and economically significant cross-sectional fit with OLS R^2 of 96%, 86% and 82% for carry only, momentum only, and *FX 10* portfolios, respectively.

We next ask whether our asset pricing results are driven by our choice of the portfolio construction strategy. To address this issue, we construct alternative sets of carry and momentum portfolios and Panel B of Table 9 reports the asset pricing results using those test assets. To construct the alternative FX portfolios, we sort currencies based on their 10-year interest rate differentials instead of 1-month forward discount for carry, and sort on their excess returns over the last 1-month instead of 3-months for momentum. To show the validity of the alternative portfolios as test assets, we report annualized average return differentials between high and low portfolios (*HML Spread* in Table 9) and associated *p-values* under the null hypothesis that *HML Spread* is not statistically different from zero (*H0: HML spread = 0*). Lastly, we perform Patton and Timmermann (2010)'s monotonicity test and find that average portfolio returns are monotonically increasing with underlying characteristics (*Monotonicity p-val*). Using these alternative sets of FX portfolios, *Corr* can still yield a similar level of cross-sectional fit with OLS R^2 of 91%, 78% and 79% for Carry only, Momentum only, and *FX 10* portfolios respectively.

In Table 10, we test whether the inclusion of our correlation factor improves the explanation of carry and momentum portfolios after controlling for factors discussed in the FX literature. Those factors include i) FX volatility innovations from Menkhoff et al. (2012a), ii) FX correlation innovation from Mueller et al. (2017), iii) the TED spread, iv) the global average bid-ask spread from Mancini et al. (2013), v) the global liquidity measure from Karolyi et al. (2012), vi) the global Fama-French 3 factors, vii) the global momentum factor, and high-minus-low risk factors from excess returns of portfolios sorted on interest differentials, viii) the FX carry factor from Lustig et al. (2011), and sorted on past returns, ix) the FX momentum factor of Menkhoff et al. (2012b).

Consistent with the empirical results from the FX literature, we find in Table 10 that the FX volatility, the FX illiquidity, and the FX carry factors can explain the spreads in mean returns of carry portfolios with R^2 ranging from 35% for the TED spread factor to 72 % for the FX carry factor. The factor price is statistically significant under a misspecification robust cross-sectional regression, and has the expected signs, that is, negative for the FX illiquidity and the FX volatility factors and positive for the FX carry factor.

We then include our correlation factor along with other factors described above to evaluate the relative importance across those factors (Table 10, Model 2). We find that the prices of the covariance risk for our correlation factor are statistically significantly different from zero in all cases. For the economic magnitude of the pricing power, $\Delta Corr$ factor dominates each of the control variables. The normalized price of covariance risk (λ_{norm}) ranges from -1.83 to -2.90 after controlling for SMB_{Global} and ΔFX_{Vol}, respectively. These estimates are similar to the estimates from Table 9, and hence the pricing power of our factor is not affected by the inclusion of other factors in the previous literature.[38] Contrary to that, we find that none of the control variables has statistically significant price of risk, with the highest level of t-ratio of 1.26 for SMB_{Global} factor. The significance of our factor after controlling for ΔFX_{Corr} also suggests that the pricing power of $\Delta Corr$ is mainly driven by co-movements in international equity returns, not by the correlation dynamics in the FX market.

5.7 Correlation innovation and volatility innovation

An increase in the perception of aggregate risk is associated with the common component in the comovement of international equity market portfolio returns, and it is unobservable in practice. The changes in the common variation can be sourced from two parts: innovations in average volatility and innovations in average correlation. The two components tend to be correlated,[39] hence we analyze the source of pricing power in the cross-section of returns.

To investigate this, we construct the global equity volatility innovation factor by using the first difference in aggregate volatility. The aggregate volatility is measured by averaging intra-month realized volatilities for all MSCI international equity market indices to be consistent with our correlation factor. We design two empirical tests to identify the source of explanatory power. In the first test, we orthogonalize our correlation innovation factor ($\Delta Corr$) against the global equity volatility innovation factor (ΔVol). We then perform

CSR-OLS on 120 all-inclusive multi-asset portfolios as well as $FX10$ portfolios using the correlation residual factor ($Corr_{resid}$) after controlling for the e ect of Vol. In the second test, Vol is orthogonalized against $Corr$ and the volatility residual factor (Vol_{resid}) is used jointly with $Corr$

References

Akram F, Rime D, Sarno L, 2008. Arbitrage in the foreign exchange market: Turning on the microscope. *Journal of International Economics* 76, 237{253.

Asness CS, Moskowitz TJ, Pedersen LH, 2013. Value and Momentum Everywhere. *Journal of Finance* 68, 929{985.

Bekaert G, Engstrom EC, Xu NR, 2019. The Time Variation of Risk Appetite and Uncertainty. Working paper, Columbia University, New York.

Bekaert G, Hoerova M, 2016. What do asset prices have to say about risk appetite and uncertainty? *Journal of Banking and Finance* 67, 103{118.

Borri N, Verdelhan A, 2011. Sovereign Risk Premia. Working paper, Massachusetts Institute of Technology, Cambridge.

Brunnermeier MK, Nagel S, Pedersen LH, 2009. Carry Trades and Currency Crashes. *NBER Macroeconomics Annual* 23, 313{347.

Burnside C, Eichenbaum M, Kleshchelski I, Rebelo S, 2011a. Do Peso Problems Explain the Returns to the Carry Trade? *Review of Financial Studies* 24, 853{891.

Burnside C, Eichenbaum M, Rebelo S, 2011b. Carry Trade and Momentum in Currency Markets. *Annual Review of Financial Economics* 3, 511{535.

Campbell JY, Cochrane JH, 1999. By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior. *Journal of Political Economy* 107, 205{251.

Cenedese G, Payne R, Sarno L, Valente G, 2016. What Do Stock Markets Tell Us about Exchange Rates? *Review of Finance* 20, 1045{1080.

Cochrane JH, Longsta FA, Santa-Clara P, 2008. Two Trees. *Review of Financial Studies* 21, 347{385.

Constantinides GM, Jackwerth JC, Savov A, 2013. The Puzzle of Index Option Returns. *Review of Asset Pricing Studies* 3, 229{257.

Della-Corte P, Ramadorai T, Sarno L, 2016. Volatility risk premia and exchange rate predictability. *Journal of Financial Economics* 120, 21{40.

Driessen J, Maenhout PJ, Vilkov G, 2009. The Price of Correlation Risk: Evidence from Equity Options. *Journal of Finance* 64, 1377{1406.

Dumas B, Solnik B, 1995. The World Price of Foreign Exchange Risk. *Journal of Finance* 50, 445{479.

Engle R, Kelly B, 2012. Dynamic Equicorrelation. *Journal of Business and Economic Statistics* 30, 212{228.

Fama EF, French KR, 1998. Value versus Growth: The International Evidence. *Journal of Finance* 53, 1975{1999.

Hansen LP, 1982. Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica*

Mancini L, Ranaldo A, Wrampelmeyer J, 2013. Liquidity in the Foreign Exchange Market: Measurement, Commonality, and Risk Premiums. *Journal of Finance* 68, 1805{1841.

Mancini-Gri oli T, Ranaldo A, 2011. Limits to arbitrage during the crisis: funding liquidity constraints and covered interest parity. Swiss National Bank Working paper.

Mark BJ, Neuberger A, 2000. Option Prices, Implied Price Processes, and Stochastic Volatility. *Journal of Finance* 55, 839{866.

Martin I, 2013. The Forward Premium Puzzle in a Two-Country World. National Bureau of Economic Research Working paper.

Menkho L, Sarno L, Schmeling M, Schrimpf A, 2012a. Carry Trades and Global Foreign Exchange Volatility. *Journal of Finance* 67, 681{718.

Menkho L, Sarno L, Schmeling M, Schrimpf A, 2012b. Currency Momentum Strategy. *Journal*

Figure 1: Correlation innovation factors

The upper panel of the gure shows a time-series plot of the global equity correlation levels. The correlation level is measured by computing bilateral intra-month correlations at each month's end using daily return series. Then, we take an average of all the bilateral correlations to arrive at a global correlation level of a particular month. The lower panel shows a time-series plot of the global equity correlation innovations (Corr). The correlation innovations are measured by taking rst di erence of each of the correlation levels. The sample covers the period March 1976 to December 2014.

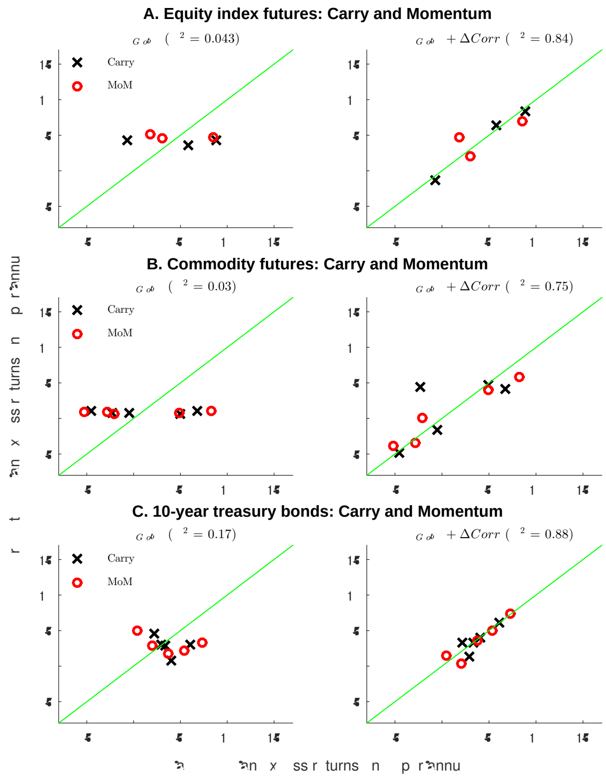

Figure 2: Pricing errors plot: by asset classes (Cont.)

The gure presents the pricing errors of the asset pricing model with the global equity risk premium (Ret_{Global}) and the global equity correlation innovation ($Corr$) factor. The realized actual excess returns are on the horizontal axis and the model predicted average excess returns are on the vertical axis. The test assets are 6 carry and momentum portfolios formed on equity index futures in Panel A (Koijen et al. (2018)), 10 portfolios using commodity futures in Panel B (Yang (2013)), 10 portfolios using 10-year treasury bond total-return series in Panel C, 6 emerging market sovereign bond portfolios sorted on bond beta and credit rating in Panel D (Borri and Verdelhan (2011)), 18 index option portfolios sorted on maturity and moneyness in Panel E (Constantinides et al. (2013)), 10 carry and momentum portfolios formed on foreign

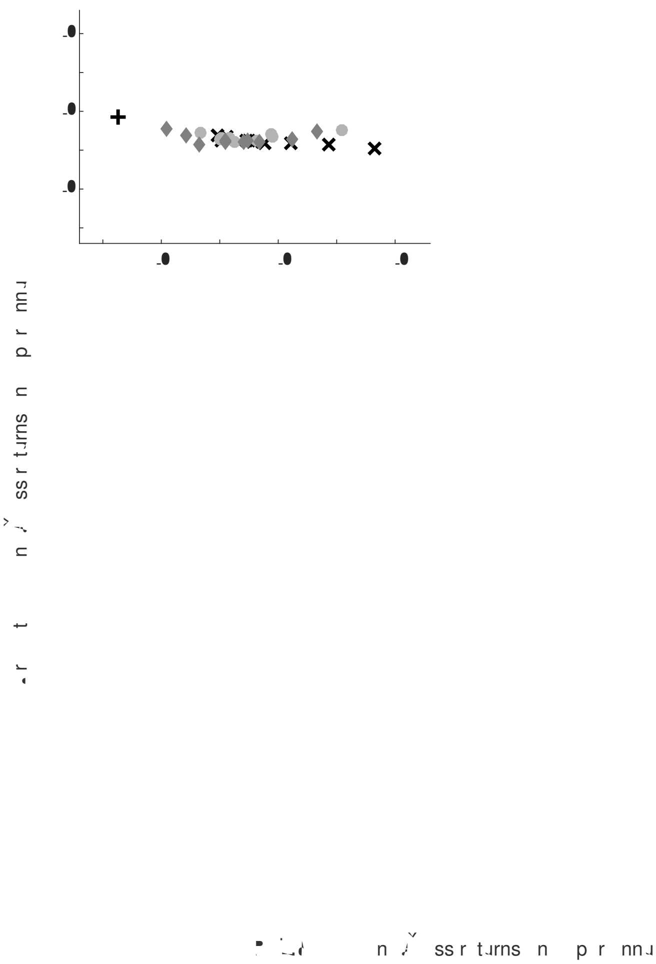

Figure 2: Pricing errors plot: by asset classes (Cont.)

Figure 3: Pricing errors plot: with FF and HKK factors

The gure presents the pricing errors of the asset pricing model with the global

Table 1: Time-series regression with the level of correlation

The table reports results from time-series regressions in which the level of global equity correlation is regressed on various proxies of *GRA*. We follow Watcher (2006) in order to construct a proxy for the surplus consumption at monthly frequency: $Surplus_t = \frac{1}{1 \quad ^{40}} \sum_{j=0}^{39} \; ^{j} \quad c(t \quad j)$ where the decay factor $\quad = 0{:}96$. *Recession* is the NBER's recession indicators. RA^{BEX} is Bekaert et al. (2019)'s model-implied measure of time-varying risk aversion which is calculated from financial variables at monthly frequency. $IVOL^{VW}$ ($IVOL^{EW}$) is the global option-implied volatility measure, defined as the value-weighted (equal-weighted) average of 16 developed market countries' option implied volatilities. We apply Mark and Neuberger (2000) and Jiang and Tian (2005)'s methodology in order to extract the risk-neutral expectation of the return variation from option prices written on stock market indices. $IVOL^{US}$ is the level of VIX index for the equivalent measure of the risk-neutral expectation of the return variation in the U.S. *10%, **5%, ***1% significance.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Surplus	-0.620					
	(-3.29)					
Recession		0.071				
		(2.78)				
RA^{BEX}			0.074			
			(3.37)			
$IVOL^{VW}$				0.519		
				(3.42)		
$IVOL^{EW}$					0.487	
					(3.01)	
$IVOL^{US}$						0.654
						(3.87)
R^2	0.106	0.063	0.016	0.089	0.082	0.096

Table 2: Time-series regression with the innovation of correlation

Table 3: Summary statistics of test assets

	Mean	Std	Skew	Sharpe			
Panel A. Equity index futures							
Carry portfolios (KMPV, 2016)							
Low Carry	-0.73	19.19	-0.54	-0.04			
Medium	5.81	16.20	-0.83	0.36			
High Carry	8.88	19.91	-0.39	0.45			
Momentum portfolios							
Low Momentum	1.79	25.65	-0.73	0.07			
Medium	3.03	20.61	-1.27	0.15			
High Momentum	8.55	21.47	-1.19	0.40			
Panel B. Commodity futures							
Carry portfolios (Yang, 2013)							
Low Carry	-4.54	18.11	0.57	-0.25			
2	-0.49	16.17	0.21	-0.03			
3	-2.26	17.15	-0.44	-0.13			
4	6.79	18.51	-0.25	0.37			
High Carry	4.96	16.98	-0.70	0.29			
Momentum portfolios							
Low Momentum	-5.22	17.61	0.29	-0.30			
2	-2.83	16.81	0.33	-0.17			
3	-2.05	15.09	-0.10	-0.14			
4	4.93	17.64	0.32	0.28			
High Momentum	8.27	22.11	-0.82	0.37			
Panel C. 10-year treasury bond total return series							
Carry portfolios							
Low Carry	2.18	11.72	-2.80	0.19			
2	2.90	10.60	0.07	0.27			
3	3.35	11.56	0.04	0.29			
4	4.03	11.00	-0.19	0.37			
High Carry	6.08	10.81	-0.31	0.56	20.61	-1.27	0.15
High Momentum	8.55	21.47	-1.19	0.40			

Table 4: Cross-sectional regression (CSR) tests

The table reports cross-sectional pricing results for the factor model based on the global equity risk premium (Ret_{Global}) and the global equity correlation innovation ($Corr$) factors. The test assets are 6 carry and momentum portfolios formed on equity index futures in Panel A (Koijen et al. (2018)), 10 portfolios using commodity futures in Panel B (Yang (2013)), 10 portfolios using 10-year treasury bond total-return series in Panel C, 6 emerging market sovereign bond portfolios sorted on bond beta and credit rating in Panel D (Borri and Verdelhan (2011)), 18 index option portfolios sorted on maturity and moneyness in Panel E (Constantinides et al. (2013)), 10 carry and momentum portfolios formed on foreign exchange rate futures in Panel F (Menkho et al. (2012b)), and 60 global equity portfolios sorted on size, B/M, C/P, D/P, E/P, and momentum using international stocks in Panel G (Hou et al. (2011)). All 60 (120) portfolios without (with) the global equity portfolios are used in Panel H (Panel I). The normalized price of covariance risk $_{norm}$, and the misspeci cation-robust t-ratios ($t\text{-}ratio_{krs}$) are reported in parentheses. The p-value for the test of the statistical signi cance of R^2 under $H0: R^2 = 0$, the p-value for approximate nite sample p-value of Shanken's CSRT statistic (a generalized ^{2} test), and the p-value for the test of di erences in R^2 between two nested models under $H0: R^2_{Model1} = R^2_{Model2}$ are reported in square brackets (Kan et al. (2013)).

	A. Equity index futures			*B. Commodity futures*			*C. 10-year treasury bonds*		
Model	(1)	(2)		(1)	(2)		(1)	(2)	
Factor	Ret_{Global}	Ret_{Global}	Corr	Ret_{Global}	Ret_{Global}	Corr	Ret_{Global}	Ret_{Global}	Corr
	1.67	-6.52	-13.53	1.59	-4.49	-12.07	27.66	13.90	-19.62
$_{norm}$	0.52	-2.04	-3.96	0.17	-0.49	-4.12	3.08	1.55	-3.23
t-ratio$_{krs}$	(0.92)	(-1.26)	(-1.83)	(0.40)	(-0.67)	(-2.34)	(2.71)	(1.04)	(-2.12)
R^2	0.04	0.84		0.03	0.75		0.17	0.88	
pval (R^2 = 0)	0.57	[0.01]		[0.73]	[0.00]		[0.34]	[0.01]	
^{2}	0.07	0.00		0.05	0.01		0.03	0.00	
pval (all pricing error = 0)	[0.01]	[0.90]		[0.00]	[0.77]		[0.14]	[0.99]	
pval ($R^2_{Model1} = R^2_{Model2}$)		[0.05]			[0.03]			[0.04]	

	D. EMBI global indices			*E. Options*			*F. Foreign Exchange*		
Model	(1)	(2)		(1)	(2)		(1)	(2)	
Factor	Ret_{Global}	Ret_{Global}	Corr	Ret_{Global}	Ret_{Global}	Corr	Ret_{Global}	Ret_{Global}	Corr
	7.63	0.43	-12.21	4.16	-2.78	-10.97	9.07	-3.26	-17.37
$_{norm}$	3.66	0.21	-3.82	1.57	-1.05	-7.31	0.67	-0.24	-2.42
t-ratio$_{krs}$	(1.60)	(0.06)	(-1.62)	(2.54)	(-0.81)	(-2.17)	(1.21)	(-0.22)	(-3.17)
R^2	0.62	0.84		0.20	0.90		0.06	0.83	
pval (R^2 = 0)	[0.02]	[0.01]		[0.00]	[0.00]		[0.31]	[0.00]	
^{2}	0.04	0.01		0.23	0.10		0.11	0.01	
pval (all pricing error = 0)	[0.12]	[0.75]		[0.00]	[0.02]		[0.00]	[0.64]	
pval ($R^2_{Model1} = R^2_{Model2}$)		[0.13]			[0.02]			[0.00]	

	G. Global equities			*H. All-inclusive w/o Global equities*			*I. All-inclusive w/ Global equities*		
Model	(1)	(2)		(1)	(2)		(1)	(2)	
Factor	Ret_{Global}	Ret_{Global}	Corr	Ret_{Global}	Ret_{Global}	Corr	Ret_{Global}	Ret_{Global}	Corr
	4.28	-3.63	-16.16	1.88	-3.58	-10.42	2.47	-1.86	-9.45
$_{norm}$	1.09	-0.93	-3.01	2.09	-3.98	-7.65	2.75	-2.07	-5.70
t-ratio$_{krs}$	(2.22)	(-0.87)	(-2.45)	(0.97)	(-1.21)	(-2.58)	(1.24)	(-0.72)	(-3.13)
R^2	0.14	0.44		0.01	0.62		0.04	0.33	
pval (R^2 = 0)	[0.08]	[0.02]		[0.76]	[0.03]		[0.55]	[0.07]	
^{2}	0.42	0.18		0.69	0.38		0.94	0.75	
pval (all pricing error = 0)	[0.00]	[0.76]		[0.00]	[0.38]		[0.05]	[0.52]	
pval ($R^2_{Model1} = R^2_{Model2}$)		[0.02]			[0.01]			[0.00]	

Table 5: CSR tests with alternative test assets and factors

This table reports the price of covariance risk from *CSR-OLS* tests based on the global equity risk premium (Ret_{Global}), a control factor, and the global equity correlation innovation factor ($Corr$). The normalized price of covariance risk $_{norm}$, and the misspeci cation-robust t-ratios ($t\text{-}ratio_{krs}$) are reported in parentheses. P-values from the test of the statistical signi cance of R^2 under $H0 : R^2 = 0$ and the p-values from the test of di erences in R^2 between two nested models under R M ot76-72 (or) -21

Table 6: Moments of correlation innovation factors

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

Panel A. Correlation Level

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

Panel B. Correlation Innovation

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

Table 7: Alternative factors and asset pricing tests

This table reports the price of covariance risk for the global equity correlation innovation factors from the various forms of asset pricing models. The test assets are 120 all-inclusive portfolios portfolios. *CSR-OLS* (*CSR-GLS*) is the two-pass cross-sectional *OLS* (*GLS*) regression. In the rst pass, we run time-series regressions to estimate each asset's beta to the risk factors. In the second pass, we run cross-sectional regression where test assets' average returns are regressed against the estimated betas to determine the risk premium of each factor. For *Fama-MacBeth In-Sample*, the rst pass regression is the same as *CSR-OLS*. In the second pass, we run cross-sectional regressions at each time period. The risk premium of each factor is determined to be the average price of risk across time. For *Fama-MacBeth Rolling 60M*, we run time-series regressions with rolling 60-month windows to estimate each asset's time-varying beta to the risk factors. At each time period, in the second pass, we run cross-sectional regressions and the risk premium of each factor is determined to be the average price of risk across time. For *GMM*, we measure the price of risk

Table 8: Summary statistics of test assets in the FX market

The table reports statistics for the annualized excess currency returns of currency portfolios sorted as follows. Carry is currency portfolios sorted on last month's forward discounts with one-month maturity (Panel A), and Momentum is currency portfolios sorted on their excess return over the last 3 months (Panel B). All portfolios are rebalanced at the end of each month and the excess returns are adjusted for transaction costs (bid-ask spread). Portfolio 1 contains the 20% of currencies with the lowest interest di erentials (or past returns), while portfolio 5 contains currencies with the highest interest di erentials (or past returns). HML denotes di erences in returns between portfolio 5 and 1. We use 3-month treasury-bill yield for Tbill Yield, and the percentage of GDP relative to the total sum of GDP for the size. The excess returns cover the period March 1976 to December 2014.

Panel A. Carry: Portfolios Sorted on Forward Discounts

	All Countries (44)						Developed Countries (17)					
	Low	2	3	4	High	HML	Low	2	3	4	High	HML
Mean	-1.67	0.10	1.91	3.39	5.10	6.77	-0.88	-0.77	1.25	2.58	4.48	5.37
Median	-1.49	1.40	2.35	4.75	9.21	9.90	-0.52	1.54	2.41	3.92	5.24	9.39
Std. Dev	9.14	9.13	8.45	8.92	10.07	7.95	10.02	9.79	9.08	9.56	10.73	9.33
Skewness	-0.10	-0.43	0.00	-0.44	-1.05	-1.84	0.05	-0.16	-0.16	-0.42	-0.40	-0.58
Kurtosis	4.41	4.66	4.12	4.65	6.99	6.25	3.77	3.90	4.08	5.05	5.00	4.91
Sharpe Ratio	-0.18	0.01	0.23	0.38	0.51	0.85	-0.09	-0.08	0.14	0.27	0.42	0.58
AR(1)	0.03	0.01	0.04	0.07	0.13	0.14	0.00	0.06	0.05	0.06	0.08	0.08
Tbill Yield	2.56	4.11	5.49	7.27	10.15	7.59	2.17	3.71	4.85	5.93	7.96	5.80
Size	4.46	3.57	2.01	1.80	1.48	-2.98	10.02	9.06	5.09	5.64	2.88	-7.14

Panel B. Momentum: Portfolios Sorted on Past Excess Returns

	All Countries (44)						Developed Countries (17)					
	Low	2	3	4	High	HML	Low	2	3	4	High	HML
Mean	-1.29	-0.18	1.50	2.79	6.29	7.58	-1.32	1.58	1.24	1.84	3.69	5.01
Median	-0.27	1.27	2.21	3.19	6.46	7.34	-0.49	2.45	2.55	3.21	4.96	6.38
Std. Dev	9.63	9.29	9.21	9.00	9.01	8.23	9.90	10.04	10.32	9.85	9.47	9.37
Skewness	-0.20	-0.40	-0.20	-0.27	-0.26	-0.14	-0.12	-0.18	-0.34	-0.13	-0.14	-0.03
Kurtosis	4.67	4.63	4.50	4.16	4.55	3.84	5.18	4.27	4.02	3.90	4.11	4.03
Sharpe Ratio	-0.13	-0.02	0.16	0.31	0.70	0.92	-0.13	0.16	0.12	0.19	0.39	0.53
AR(1)	0.04	0.06	0.01	0.05	0.06	-0.08	0.04	0.04	0.06	0.00	0.02	-0.06
Tbill Yield	5.57	5.50	5.80	6.25	7.67	2.10	4.11	4.60	5.01	5.22	5.41	1.30
Size	3.38	2.98	2.90	2.57	2.39	-0.99	9.84	6.41	5.39	5.35	5.94	-3.90

Table 9: CSR tests in the FX market

The table reports cross-sectional pricing results for the factor model based on the dollar risk factor (DOL) and the global equity correlation innovation ($Corr$) measured by taking the rst di erence on the average intra-month bilateral correlations. The test assets are a set of carry portfolios (1-5), and a set of momentum portfolios (1-5). For the carry portfolios, currencies are sorted into portfolios on the basis of 1-month (10-year) maturity interest rate di erentials embedded in the forward contract in Panel A (Panel B). For the momentum portfolios, currencies are sorted into portfolios on the basis of their past 3-month (1-month) excess returns (Panel B). The market price of covariance risk , and the price of covariance risk normalized by standard deviation of the cross-sectional covariances $_{norm}$ are reported. Shanken (1992)'s t-ratios under correctly speci ed models accounting for the errors-in-variables problem (*t-ratio*$_s$) and Kan et al. (2013)'s misspeci cation-robust t-ratios (*t-ratio*$_{krs}$) are reported in parentheses. The p-value for the test of $H0$: R^2 = 0, the p-value for approximate nite sample p-value of Shanken's CSRT statistic (a generalized ^{2} test) and the p-value for the test of H0: $j\ _5\quad _1j$ = 0 (Patton and Timmermann (2010)) are reported in square brackets. We also report the average annualized returns for HML portfolios (*HML Spread*), the p-value for the test of H0: *HML Spread = 0*, and the p-value for the monotonic relationship test from Patton and Timmermann (2010).

Panel A. Benchmark portfolios

Test assets	Carry only		Momentum only		Both	
Factor	DOL	Corr	DOL	Corr	DOL	Corr
	3.39	-26.33	0.93	-16.08	1.50	-18.70
$_{norm}$	0.06	-2.60	0.04	-2.67	0.05	-2.39
t-ratio$_{fm}$	(1.53)	(-5.52)	(0.46)	(-6.29)	(0.74)	(-7.89)
t-ratio$_s$	(0.47)	(-1.78)	(0.21)	(-3.32)	(0.30)	(-3.48)
t-ratio$_{krs}$	(0.40)	(-1.68)	(0.19)	(-2.89)	(0.27)	(-3.20)
R^2	0.96		0.86		0.82	
pval (R^2 = 0)	[0.00]		[0.00]		[0.00]	
^{2}	0.001		0.006		0.011	
pval (all pricing error = 0)	[0.81]		[0.28]		[0.65]	
Beta spread	0.015		0.019			
pval (Beta spread = 0)	[0.04]		[0.03]			
HML spread	6.77		7.58			
pval (HML spread = 0)	[0.00]		[0.00]			
pval (Monotonicity)	[0.00]		[0.00]			

Panel B. Alternative portfolios

Test assets	Carry only		Momentum only		Both	
Factor	DOL	Corr	DOL	Corr	DOL	Corr
	1.06	-15.69	3.35	-21.05	2.18	-18.96
$_{norm}$	0.04	-1.41	0.15	-2.38	0.12	-1.81
t-ratio$_{fm}$	(0.50)	(-3.96)	(1.50)	(-5.03)	(1.05)	(-6.21)
t-ratio$_s$	(0.23)	(-1.87)	(0.56)	(-1.92)	(0.43)	(-2.51)
t-ratio$_{krs}$	(0.20)	(-1.85)	(0.51)	(-1.86)	(0.37)	(-2.49)
R^2	0.91		0.78		0.79	
pval (R^2 = 0)	[0.00]		[0.04]		[0.00]	
^{2}	0.001		0.002		0.004	
pval (all pricing error = 0)	[0.83]		[0.60]		[0.96]	
Beta spread	0.008		0.015			
pval (Beta spread = 0)	[0.13]		[0.06]			
HML spread	4.45		7.28			
pval (HML spread = 0)	[0.00]		[0.00]			
pval (Monotonicity)	[0.00]		[0.00]			

Table 10: CSR tests including other factors in the FX market

This table reports the price of covariance risk from *CSR-OLS* tests based on the dollar risk factor (DOL), a control factor, and our global equity correlation innovation factors (Corr). The test assets are *FX 10* portfolios: the set of carry and momentum portfolios. The price of covariance risks normalized by standard deviation of the cross-sectional covariances ($_{norm}$) are reported. The misspeci cation-robust t-ratio (t $ratio_{krs}$) from Kan et al. (2013) and the p-values for the test of $H0 : R^2 = 0$ are reported in parentheses and in square brackets, respectively. The control factors are described as follows. FX_{VOL}: the aggregate FX volatility innovations (Menkho et al. (2012a)), FX_{CORR}: the aggregate FX correlation innovations (Mueller et al. (2017)), TED: TED spread innovation, FX_{BAS}: innovations to the aggregate FX bid-ask spreads (Mancini et al. (2013)), LIQ_{Global}: the global liquidity innovation (Karolyi et al. (2012)), MRP_{Global}: the global market risk premium, SMB_{Global}: the global size premium, HML_{Global}: the global value premium, MoM_{Global}: the global momentum factor, HML_{Carry}: the high-minus-low FX carry factor (Lustig et al. (2011)), HML_{MoM}: the high-minus-low FX momentum factor. The p-value for the test of the statistical signi cance of R^2 under $H0 : R^2 = 0$ and the p-value for the test of di erences in R^2 between two nested models under $H0 : R^2_{Model1} = R^2_{Model2}$ are reported in square brackets (Kan et al. (2013)).

		Model 1			Model 2				
Control Factor	*Statistics*	*DOL*	*Control Factor*	R^2_{Model1} pval($R^2 = 0$)	*DOL*	*Control Factor*	Corr	R^2_{Model2} pval($R^2 = 0$)	Di erence in R^2 pval($R^2_{Model2} = R^2_{Model1}$)
Panel A. FX volatility & correlation factors									
FX_{Vol}	$_{norm}$	0.02	-1.68	0.68	0.09	0.45	-2.90	0.94	0.26
	t-ratio$_{krs}$	(0.15)	(-1.97)	[0.00]	(0.59)	(0.49)	(-2.74)	[0.00]	[0.06]
FX_{Corr}	$_{norm}$	0.01	-1.64	0.50	0.04	-0.53	-2.30	0.92	0.42
	t-ratio$_{krs}$	(0.06)	(-2.04)	[0.01]	(0.27)	(-0.78)	(-2.54)	[0.00]	[0.02]
Panel B. Liquidity factors									
TED	$_{norm}$	0.00	-0.82	0.35	0.12	0.55	-2.83	0.93	0.58
	t-ratio$_{krs}$	(0.03)	(-0.80)	[0.12]	(0.78)	(0.86)	(-2.91)	[0.00]	[0.01]
FX_{BAS}	$_{norm}$	0.09	0.04	0.36	0.07	0.31	-2.65	0.94	0.58
	t-ratio$_{krs}$	(1.32)	(0.04)	[0.11]	(0.47)	(0.48)	(-3.09)	[0.00]	[0.00]
LIQ_{Global}	$_{norm}$	0.07	1.83	0.59	0.14	-0.59	-2.89	0.97	0.38
	t-ratio$_{krs}$	(0.47)	(2.64)	[0.00]	(0.70)	(-0.43)	(-2.04)	[0.00]	[0.09]
Panel C. Global equity factors									
MRP_{Global}	$_{norm}$	0.34	1.23	0.46	0.26	-0.57	-2.91	0.93	0.47
	t-ratio$_{krs}$	(1.66)	(1.93)	[0.00]	(0.88)	(-0.69)	(-2.84)	[0.00]	[0.01]
SMB_{Global}	$_{norm}$	0.05	2.32	0.70	0.00	1.25	-1.83	0.98	0.28
	t-ratio$_{krs}$	(0.24)	(2.11)	[0.00]	(0.01)	(1.26)	(-1.58)	[0.00]	[0.12]
HML_{Global}	$_{norm}$	0.06	1.34	0.52	0.06	-0.65	-2.87	0.91	0.39
	t-ratio$_{krs}$	(0.66)	(1.65)	[0.00]	(0.39)	(-0.69)	(-2.76)	[0.00]	[0.01]
MoM_{Global}	$_{norm}$	0.04	-0.52	0.36	0.09	0.68	-2.72	0.93	0.57
	t-ratio$_{krs}$	(0.60)	(-0.80)	[0.02]	(0.61)	(0.93)	(-2.95)	[0.00]	[0.01]
Panel D. FX carry & momentum factors									
HML_{Carry}	$_{norm}$	0.09	1.77	0.72	0.07	-0.34	-2.81	0.92	0.21
	t-ratio$_{krs}$	(1.27)	(2.92)	[0.00]	(0.41)	(-0.36)	(-2.69)	[0.00]	[0.10]
HML_{MoM}	$_{norm}$	0.10	2.03	0.55	0.08	0.73	-2.13	0.95	0.40
	t-ratio$_{krs}$	(1.56)	(5.16)	[0.01]	(0.61)	(1.04)	(-2.39)	[0.00]	[0.02]

Table 11: CSR tests with volatility innovation factor

This table reports the price of covariance risk ( ) for the global equity volatility (Vol) and the global correlation innovation ($Corr$) factors from the various forms of asset pricing models. The global equity volatility innovation factor is measured by taking the rst di erence on the average intra-month volatility for all MSCI international equity indices. In Panel A, we orthogonalize our correlation innovation factor against the global volatility innovation factor. In Panel B, the global volatility innovation factor is orthogonalized against our correlation innovation factor. The cross-sectional asset pricing tests are similar to those in Table 4. The test assets are 120 all-inclusive portfolios (Subpanel 1) and *FX 10* portfolios (Subpanel 2). The price of covariance risks normalized by standard deviation of the cross-sectional betas ($_{norm}$) and the misspeci cation robust t-ratios from Kan et al. (2013) are reported in parentheses. The p-value for the test of the statistical signi cance of R^2 under $H0 : R^2 = 0$ and the p-value for the test of di erences in R^2 between two nested models under $H0 : R^2_{Model1} = R^2_{Model2}$ are reported in square brackets. The sample covers the period March 1976 to December 2014.

Panel A. Correlation Residual

	Model 1			Model 2				
Statistics	*Control Factor*	Vol	R^2_{Model1}	*Control Factor*	Vol	$Corr_{resid}$	R^2_{Model2}	Di erence in R^2 pval($R^2_{Model2} = R^2_{Model1}$)
1. All-inclusive w/ Global equities								
$_{norm}$	-2.75	-6.14	0.29	-4.72	-5.63	-3.59	0.48	0.19
t-ratio$_{krs}$	(-1.21)	(-2.75)	0.08	(-1.51)	(-2.80)	(-2.00)	[0.02]	[0.01]
2. FX only								
$_{norm}$	0.16	-1.48	0.57	0.15	-1.90	-2.11	0.84	0.28
t-ratio$_{krs}$	(1.18)	(-2.50)	0.00	(0.68)	(-2.24)	(-2.71)	[0.00]	[0.02]

Panel B. Volatility Residual

	Model 1			Model 2				
Statistics	*Control Factor*	Corr	R^2_{Model1}	*Control Factor*	Vol_{resid}	Corr	R^2_{Model2}	Di erence in R^2 pval($R^2_{Model2} = R^2_{Model1}$)
1. All-inclusive w/ Global equities								
$_{norm}$	-2.07	-5.70	0.33	-4.61	-3.52	-5.42	0.40	0.08
t-ratio$_{krs}$	(-0.72)	(-3.13)	0.06	(-1.41)	(-1.10)	(-2.53)	[0.02]	[0.28]
2. FX only								
$_{norm}$	0.05	-2.39	0.82	0.08	-0.34	-2.32	0.83	0.01
t-ratio$_{krs}$	(0.27)	(-3.48)	0.00	(0.43)	(-0.45)	(-3.36)	[0.00]	[0.66]

Internet Appendix for

Global Equity Correlation in International Markets

In this Internet Appendix, we describe the details of portfolio construction methodologies for both carry and momentum in the FX market (Section A), present the details of two-pass cross-sectional asset pricing model (Section B), report a summary of the DECO model (Section C), provide the description of the GMM methodology and its underlying assumptions (Section D), describe our theoretical motivation and further implications of the FX carry portfolios (Section E), check robustness of empirical results in the FX market (Section F), and show some proofs for our theoretical motivation (Section G).

A Portfolio construction in the foreign exchange market

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

A.1 Spot and excess returns for foreign exchange rates

We use e and f to denote the log of the spot and forward nominal exchange rate measured in home currency (USD) per foreign currency, respectively. An increase in e_i means an appreciation of the foreign currency i. Following Lustig and Verdelhan (2007), we de ne the log excess return ($RX_{i;t+1}$) of the currency i at time $t+1$ as

$$RX_{i;t+1} = \quad e_{i;t+1} + r^f_{i;t} \quad r^f_{us;t} \quad e_{i;t+1} \quad f_{i;t} \tag{16}$$

where $r^f_{i;t}$ and $r^f_{us;t}$ denote the foreign and domestic nominal risk-free rates over a one-period horizon. This is the return on buying a foreign currency (f_i) in the forward market at time t and then selling it in the spot market at time $t+1$. Since the forward rate satis es the covered interest parity under normal conditions (see, Akram et al. (2008)), it can be denoted as $f_{i;t} = log(1 + r^f_{us;t}) - log(1 + r^f_{i;t}) + e_{i;t}$.[1] Therefore, the forward discount is a proxy for the interest rate differential ($e_{i;t} - f_{i;t} \approx r^f_{i;t} - r^f_{us;t}$) which enables us to compute currency excess returns using forward contracts.

A.2 Carry portfolios

Carry portfolios are the portfolios where currencies are sorted on the basis of their interest rate differentials. Following Menkhoff et al. (2012a), we construct 5 FX carry portfolios. Portfolio 1 contains the 20% of currencies with the lowest interest rate differentials against

($^{In\ \ Stay}_{long;t+1} = q^{mid}_{t+1} \quad f^{ask}_{t}$). A similar calculation is for a short position as well (with opposite signs while swapping bids and asks). Theses magnitudes are similar to the levels reported in the carry literature. As described in Brunnermeier et al. (2009) and Burnside et al. (2011a), we observe a decreasing skewness pattern as we move from a low interest rate to a high interest rate currency portfolio. Moreover, consistent with our theoretical motivation in Section 2, we discover that the relative size of countries in the high-interest portfolio is smaller than those in the low-interest portfolio. In Table 8, we empirically measure the relative size of country as the percentage of GDP relative to the total sum of GDP at each time t and show this negative relation between interest rates and country sizes.

A.3 Momentum portfolios

Momentum portfolios are the portfolios where currencies are sorted on the basis of past returns. We form momentum portfolios sorted on the excess currency returns over a period of three months, as de ned in Equation 16. Portfolio 1 contains the 20% of currencies with the lowest excess returns, while portfolio 5 contains the 20% of currencies with the highest excess returns over the last three months. As portfolios are rebalanced at the end of every month, formation and holding periods considered in this paper are three and one months, respectively. We consider the previous three months for the formation period because we generally nd highly signi cant excess returns from momentum strategies with a relatively short time horizon as documented in Menkho et al. (2012b).

Panel B of Table 8 reports the descriptive statistics for momentum portfolios. There is a strong pattern of increasing average excess return from portfolio 1 (loser) to portfolio 5 (winner). Unlike carry portfolios, we do not observe a decreasing skewness pattern from low to high momentum portfolios. A traditional momentum trade portfolio (HML_{MoM}) where investors borrow money from low momentum countries and invest in high momentum countries' money markets yields average excess return of 7.6% and 5.0% per annum after transaction costs for ALL and DM currencies respectively.

We nd that the returns from currency momentum trades are seemingly unrelated to the returns from carry trades since unconditional correlation between returns of the two trades is about 0.02. The weak relationship holds regardless of the choice of formation period for momentum strategy since momentum strategy is mainly driven by favorable spot rate changes, not by interest rate differentials. Menkhoff et al. (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.[2] In this paper we also confirm that, using a different sample of countries and different time intervals, the factors that the later papers investigate are indeed unable to explain carry and momentum portfolios. In addition, those two strategies are not correlated unconditionally. However, consistent with our theory, we find that returns of carry and momentum strategies conditionally co-move together when we observe positive innovations in the global equity correlation.

B 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

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

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

If the K factor asset pricing model holds, the expected returns of the N assets are given by $\mu_R = X\gamma$, where $X = [1_N, \beta]$ and $\gamma = [\gamma_0, \gamma_1']'$ is a vector consisting of the zero-beta rate and risk premia on the K factors. In a constant beta case, the two-pass cross-sectional regression

[2] Burnside et al. (2011b) similarly argue that it is difficult to explain carry and momentum strategies simultaneously. They argue that the high excess returns should be understood with high transaction costs due to high bid-ask spreads.

(CSR) method rst obtains estimates ^ by running the following multivariate regression:

$$R_t = + f_t + {}_t; \quad t = 1; \quad ; T$$

^

where $_t = [_{0t}; (_{1t} \quad f_t)^0]^0; \quad = [_0; (_1 \quad _f)^0]^0; \; u_t = e^0 W (R_t \quad _R); \; w_t = {}^0_1 V$

where μ_i denotes the unconditional mean, $\sigma^2_{i;t}$ the conditional variance, $z_{i;t}$ a standard normal random variable, ω_i the constant term, α_i the sensitivity to the squared innovation, and β_i the sensitivity to the previous conditional variance. Since the covariance is just the product of correlations and standard deviations, we can write the covariance matrix (Σ_t) of the returns at time t as $\Sigma_t = D_t R_t D_t$ where D_t has the standard deviations ($\sigma_{i;t}$) on the diagonal and zero elsewhere, and R_t is an $n \times n$ conditional correlation matrix of standardized returns (z_t) at time t. Depending on the specification of the dynamics of the correlation matrix, DCC correlation (R_t^{DCC}) and DECO correlation (R_t^{DECO}) can be separated. Let Q_t denote the conditional covariance matrix of z_t.

$$Q_t = (1 - \alpha_Q - \beta_Q)\overline{Q} + \alpha_Q Q_{t-1}^{*\frac{1}{2}} z_{t-1} z_{t-1}' Q_{t-1}^{*\frac{1}{2}} + \beta_Q Q_{t-1} \quad (21)$$

$$R_t^{DCC} = Q_t^{*-\frac{1}{2}} Q_t Q_t^{*-\frac{1}{2}} \quad (22)$$

$$\rho_t = \frac{1}{n(n-1)}(\iota' R_t^{DCC} \iota - n) \quad (23)$$

$$R_t^{DECO} = (1 - \rho_t) I_n + \rho_t J_{n \times n} \quad (24)$$

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, 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, ι 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.

D GMM method

Following Dumas and Solnik (1995), we assume that the marginal rate of substitution between returns from time t to $t + 1$ has the form

$$M_{t+1} = \frac{1 - \delta_{0;t} - \delta_{F;t} R_{F;t+1}}{1 + i_t};$$

investor who borrows funds at a domestic risk-free rate (country 1), converts them to a foreign currency, lends them at foreign risk free rate at time t, and converts the money back to domestic currency at time $t + h$ (after in nitesimally small time h) once the investor collects the money from a foreign borrower. The FX carry portfolios are the portfolios where currencies are sorted on the basis of interest rates of their respective countries. Therefore, to better understand drivers of carry portfolios' expected returns, it is important to investigate determinants of underlying countries' risk free rates in our model.

Starting from a simplistic one-tree (one-country) model, assuming that there is no dynamics in *GRA* ($_t$ = and = 0), the risk-free rate is composed of the standard discount rate ( ), dividend growth ( ), and precautionary saving (^{2}) e ects: $r^f_{i;t}$ = + ^{2}.

If we extend the number of trees to N

to hedge against shocks that a ect the aggregate consumption of *Internationals*, leading to the higher *dispersion* of the interest rates across countries.[3]

Using Equation 25 for the interest rate, the excess return of a currency ($RX_{i;t}$) becomes,

$$RX_{i;t} = {}^{2}dt \quad \frac{^{2}}{} \quad \frac{_t}{_t} + \frac{1}{} \quad (S_{i;t} \quad S_{1;t})dt \quad -dB_{i;t} + -dB_{1;t} \qquad (26)$$

Equation 25 shows that the cross-sectional variation of the interest rate originates from the cross-sectional variation of relative size ($S_{i;t}$) at time t. Therefore, in our setup, as also noted in Hassan (2013), sorting currencies by interest rates is similar to sorting by country size. The low-interest currency portfolio consists of the currencies of large countries.[4] Equation 26 shows that the expected return of currency is negatively associate with the relative size of country.

Now we turn to the model intuition why the low-interest currencies, or currencies of small-size countries, earn low excess return on average. When a large country experiences a low (or negative) dividend shock, the relative scarcity of goods drives up the relative price of goods in the large country, meaning that the real exchange rate for that country appreciates. The appreciation of the real exchange rate leads to the high (or positive) realization of excess return of the large country's currency. Since large countries account for a larger share of the global consumption, the changes in *GRA* are signi cantly in uenced by the dividend shocks from those large countries. When large countries experience low dividend shocks, *GRA* increases and currencies of large countries appreciate as well. This suggests that times that we observe positive innovations in correlation across international equities overlap with times that we observe the high (or positive) realization of excess return of large countries' currencies. Therefore, the risk-free bonds denominated in currencies of large economies are expensive because they provide a hedge against shocks that a ect *GRA*.

[3]We can understand this relationship more clearly from the special case in which the goods are not substitutable (= 1). In this case, the interest rate is: $r^f_{i;t} = \quad + \quad {}^2 \quad \frac{_t}{_t} \quad {}^2 \quad \frac{_t}{_t} \quad _i$. Procyclical interest rates imply that the precautionary saving term (${}^2 \frac{_t}{_t} \; _i$) is larger than the intertemporal substitution term ($\frac{_t}{_t}$). Therefore, the higher the $_t$ is, the lower the $r^f_{i;t}$ for all countries i. Moreover, given the cross-country dispersion of $_i$, the higher $_t$ ampli es this dispersion, leading to the greater dispersion of $r^f_{i;t}$ across countries.

[4]We discuss this relation further in Section A.2 and show empirical results in Table 8.

sion with time-varying beta, and employ generalized method moments (GMM) methods of Hansen (1982) and Dumas and Solnik (1995).

Table A6 presents results for these alternative cross-sectional asset pricing tests on the FX portfolios. In each panel, we perform one of the tests illustrated above and present the price of covariance risk ( ), the price of beta risk normalized by standard deviation of the cross-sectional covariances ($_{norm}$), and corresponding t-ratios in parentheses. In each column, we use one of the five different measures of our correlation innovation factor. Overall, our results show that we have similar estimates of the price of risk across different factor construction and asset pricing methodologies. On average, one standard deviation of cross-sectional differences in covariance exposure to our factor can explain about 2% per annum in the cross-sectional differences in mean return of *FX 10* portfolios.

Lastly, we perform a number of other robustness checks associated with outliers, different sampling periods, an alternative measure of innovations, different frequency of data, and base currency other than USD. In Panel A of Table A7, we winsorize the correlation innovation series at the 90% level. In Panel B, we pick a time period before the financial crisis, from March 1976 to December 2006, since the large positive innovations during the crisis period can potentially drive the CSR testing results. Panel C reports the estimation results with an AR(2) shock and Panel D reports the results using weekly data series.[6] Lastly, we also consider portfolios constructed from a different base currency, *EUR* and *JPY* denomination for Panels E and F, respectively. To be consistent with our baseline logic to include *DOL* in the benchmark case, we include *EUR* and *JPY* factors in the respective model.[7] We generally find that the results are robust to the other specifications as well.

[6] For forward exchange rates, we use forward contract with a maturity of one week to properly account for the interest rate differentials in the holding period. The weekly sample covers the period from October 1997 to December 2014.

[7] *DOL* is designed to capture the common fluctuations of the U.S. dollar against a broad basket of currencies in the FX portfolios.

G Proofs

Internationals maximize expected utility of the form,

$$U(D_{1;t}, \dots, D_{N;t}) = E \int_{t=0}^{\infty} e^{-\rho t} \ln(C_t - X_t)\,dt \tag{27}$$

where C_t denotes the aggregate consumption level of *Internationals* and X_t denotes the habit level at time t. The effect of habit persistence on the agent's attitudes toward risk can be summarized by the inverse of the surplus/consumption ratio, which we denote $\Gamma_t = C_t/(C_t - X_t)$.

$$C_t = \left(\sum_{i=1}^{N} \alpha_i^{\frac{1}{\varepsilon}} D_{i;t}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{28}$$

$$\ln C_t = c_t = \frac{\varepsilon}{\varepsilon-1} \ln \left(\sum_{i=1}^{N} \alpha_i^{\frac{1}{\varepsilon}} D_{i;t}^{\frac{\varepsilon-1}{\varepsilon}} \right) \tag{29}$$

$$dD_{i;t} = D_{i;t}(\mu\, dt + \sigma\, dB_{i;t}) \tag{30}$$

where α_i controls the relative importance of good i for *Internationals*, $\varepsilon \in [1, \infty)$ captures the elasticity of intratemporal substitution between goods, and the sum of α_i equals to one ($\sum_{i=1}^{N} \alpha_i = 1$).

The dynamics of the aggregate consumption is as follows.

$$dc_t = \Bigg[\mu + \frac{\sigma^2}{2} \sum_{i=1}^{N} \frac{\frac{\varepsilon-1}{\varepsilon}\, \alpha_i^{\frac{1}{\varepsilon}} D_{i;t}^{\frac{\varepsilon-1}{\varepsilon}}}{\sum_{i=1}^{N} \alpha_i^{\frac{1}{\varepsilon}} D_{i;t}^{\frac{\varepsilon-1}{\varepsilon}}} \; \frac{\varepsilon-1}{\varepsilon}\, \alpha_i^{\frac{2}{\varepsilon}} D_{i;t}^{\frac{2\varepsilon-2}{\varepsilon}} \dots$$

denote the real exchange rate $e_{i;t}$ as follows.

$$S_{i;t} = \frac{e_{i;t}D_{i;t}}{e_{i;t}D_{i;t} + \sum_{n \neq i}^{N} e_{n;t}D_{n;t}} = \frac{{}_{i}^{\frac{1}{}} D_{i;t}^{\frac{1}{}}}{\sum_{n=1}^{N} {}_{n}^{\frac{1}{}} D_{n;t}^{\frac{1}{}}} \quad (31)$$

$$e_{i;t} = \left(\frac{i}{1}\right)^{\frac{1}{}} \left(\frac{D_{i;t}}{D_{1;t}}\right)^{\frac{1}{}} = \frac{S_{i;t}}{S_{1;t}} \left(\frac{D_{i;t}}{D_{1;t}}\right)^{1} \quad (32)$$

The dynamic of risk aversion coe cient for *Internationals* ( ) follows a mean-reverting process and depends entirely on innovations in global consum tion growth.

$$d\ _{t} = (\ \ _{t})dt\ (\ _{t}\ )\ (dc_{t}\ E$$

$$\frac{d \quad_{i;t}}{\quad_{i;t}} = \quad dt + \frac{dU_{i;t}}{U_{i;t}}$$

$$= \quad + \frac{\quad^2}{\quad} + \quad \frac{\quad_t}{\quad_t} + \quad \frac{\quad_t}{\quad_t} \quad \frac{1}{\quad} + \frac{1}{\quad} \quad ^2 \Bigg)^2 \quad ^2 \sum_{n=1}^{N} S_{n;t}^2$$

$$+ \frac{1}{\quad} \quad \frac{\quad_t}{\quad_t} + \frac{1}{\quad} \quad ^2 S_{i;t} \quad dt \quad - dB_{i;t}$$

$$\frac{\quad_t}{\quad_t} + \frac{1}{\quad} \quad \sum_{n=1}^{N} S_{n;t} dB_{n;t}$$

$$= E_t \quad \frac{d \quad_{i;t}}{\quad_{i;t}} \quad - dB_{i;t} + \frac{d \quad_t}{\quad_t} \quad E_t \quad \frac{d \quad_t}{\quad_t} \quad \frac{1}{\quad} \quad \sum_{n=1}^{N} S_{n;t} dB_{n;t}$$

$$= E_t \quad \frac{d \quad_{i;t}}{\quad_{i;t}} \quad - dB_{i;t} + \frac{d \quad_t}{\quad_t} \quad E_t \quad \frac{d \quad_t}{\quad_t} \quad \frac{1}{\quad} \quad dB_{g;t} \tag{35}$$

In our economy, the price of any international equity indices is given by

$$P_{i;t} = E_t \int_t^{1} e^{(\quad t)} \frac{\partial U / \partial D_{i;}}{\partial U / \partial D_{i;t}} D_{i;} \, d$$

$$= E_t \left[\int_t^{1} e^{(\quad t)} \frac{\sum_{i=1}^{N} \frac{1}{i} D_{i;}^{\frac{\quad 1}{\quad}} \quad ^1 \quad \frac{1}{i} D_{i;}^{\frac{\quad 1}{\quad}}}{\quad_t \sum_{i=1}^{N} \frac{1}{i} D_{i;t}^{\frac{\quad 1}{\quad}} \quad ^1 \quad \frac{1}{i} D_{i;t}^{\frac{\quad 1}{\quad}}} D_{i;} \, d \right]$$

$$\frac{P_{i;t}}{D_{i;t}} = \frac{D_{i;t}^{\frac{1}{\quad}} \quad \sum_{i=1}^{N} \frac{1}{i} D_{i;t}^{\frac{\quad 1}{\quad}}}{\quad_t} E_t \left[\int_t^{1} e^{(\quad t)} \quad \left(\sum_{i=1}^{N} \frac{1}{i} D_{i;}^{\frac{\quad 1}{\quad}} \right)^{1} D_{i;} \, d \right]$$

$$= \frac{1}{S_{i;t} \quad_t} E_t \int_t^{1} e^{(\quad t)} \quad S_{i;} \, d \tag{36}$$

In a special case in which goods are not substitutable (

Itô's lemma,

$$d(e^{t}{}_{t}) = e^{t}{}_{t} + e^{t} d_{t} \tag{38}$$

$$= e^{t}{}_{t} + e^{t}(({}_{t})dt ({}_{t}) \sum_{n=1}^{N} {}_{n} dB_{n;t})$$

$$= e^{t} dt \quad e^{t} ({}_{t}) \sum_{n=1}^{N} {}_{n} dB_{n;t}$$

By taking integral on both sides and solving for ${}_{t}$,

$$_{t} = e^{t}{}_{0} + (1 \quad e^{t}) \quad e^{t} \int_{0}^{t} e^{s} ({}_{s}) \sum_{n=1}^{N} {}_{n} dB_{n;s} \tag{39}$$

$$E_{t}[\quad] = e \quad {}_{0} + (1 \quad e \quad) \quad e \quad E_{t}[\int_{0} e^{s} ({}_{s}) \sum_{n=1}^{N} {}_{n} dB_{n;s}] \tag{40}$$

By the martingale property of Itô's integral, $E_{t}\left[\int_{0} e^{s} ({}_{s}) \sum_{n=1}^{N} {}_{n} dB_{n;s}\right] = \int_{0}^{t} e^{s} ({}_{s}) \sum_{n=1}^{N} {}_{n} dB_{n;s}$. Then, (40) becomes

$$E_{t}[\quad] = e \quad {}_{0} + (1 \quad e \quad) \quad e \quad \int_{0}^{t} e^{s} ({}_{s}) \sum_{n=1}^{N} {}_{n} dB_{n;s} \tag{41}$$

$$= e \quad {}_{0} + (1 \quad e \quad) \quad e^{\quad + \; t \quad t} \int_{0}^{t} e^{s} ({}_{s}) \sum_{n=1}^{N} {}_{n} dB_{n;s}$$

$$= e^{\quad + \; t}({}_{t} \quad + \quad e^{\quad t}) = e \quad e^{t}({}_{t} \quad) +$$

Combining (37) with (41), we have

$$\frac{P_{i;t}}{D_{i;t}} = \frac{e^{t}}{{}_{t}} \int_{t}^{1} e \quad (e \quad e^{t}({}_{t} \quad) + \quad)d \tag{42}$$

$$= \frac{e^{t}}{{}_{t}}[\int_{t}^{1} e^{(\; + \;)} e^{t}({}_{t} \quad)d \quad + \int_{t}^{1} e \quad d \quad]$$

$$= \frac{1}{\quad + \quad} \quad \frac{}{{}_{t}(\quad + \quad)} + \frac{}{{}_{t}}$$

Therefore, a closed-form solution for the price-dividend ratio ($V_{i;t}$) of the equity index of

By dividing this by $V_{i;t}$

$$\frac{dV_{i;t}}{V_{i;t}} = \frac{\frac{}{_t^2\ (\ +\ )} d\ _t + \frac{}{_t^3\ (\ +\ )} d\ _t d\ _t}{V_{i;t}} \tag{50}$$

Then, an unexpected shock to the process above is

$$\frac{dV_{i;t}}{V_{i;t}} \quad E_t[\frac{dV_{i;t}}{V_{i;t}}] = \frac{}{V_{i;t}\ _t^2\ (\ +\ )}(d\ _t \quad E_t[\ _t]) \tag{51}$$

$$= \frac{}{\frac{_t\ +}{_t\ (\ +\ )}\ _t^2\ (\ +\ )}\ (\ _t\ \quad)\sum_{n=1}^{N}\ _n ds3000$$

Revisiting Equation 35, the marginal utility for each of the good (country) i has a common exposure to two factors: the unexpected changes in *GRA* ($\frac{d\gamma_t}{\gamma_t} - E_t\left[\frac{d\gamma_t}{\gamma_t}\right]$) and the global consumption shock ($dB_{g;t}$). In the empirical sections of our paper, however, we use the global stock market return as a control variable since the marginal utility can be also rewritten as a function of two factors: unexpected changes in *GRA* and the global stock market return ($R_{g;t} - E_t[R_{g;t}]$), which is the size-weighted average of stock market returns ($\sum_{n=1}^{N} S_{n;t}(R_{n;t} - E_t[R_{n;t}])$). When goods in one country are (partially) substitutable for goods in another country ($\phi > 1$), the size of the country is no longer constant ($S_{i;t} \neq \alpha_i$). In this substitutable-goods case, the unexpected component of equity returns is given by

$$
\begin{aligned}
R_{i;t} - E_t[R_{i;t}] &= \left(\frac{\partial V_{i;t}/\partial \gamma_t}{V_{i;t}}(\gamma_t - \ldots) - \frac{\partial V_{i;t}/\partial S_{i;t}}{V_{i;t}}\frac{1}{\phi}S_{i;t}\right)\sigma\sum_{n=1}^{N} S_{n;t}dB_{n;t} \\
&\quad + \left(\frac{\partial V_{i;t}/\partial S_{i;t}}{V_{i;t}}\frac{1}{\phi}S_{i;t} + 1\right)\sigma\, dB_{i;t} \\
&= \tilde{\beta}_{i;t}\sigma\sum_{n=1}^{N} S_{n;t}dB_{n;t} + \beta_{i;t}\sigma\, dB_{i;t} \\
&= \tilde{\beta}_{i;t}\sigma\, dB_{g;t} + \beta_{i;t}\sigma\, dB_{i;t}
\end{aligned}
\tag{56}
$$

where $\tilde{\beta}_{i;t} \equiv \frac{\partial V_{i;t}/\partial \gamma_t}{V_{i;t}}(\gamma_t - \ldots) - \frac{\partial V_{i;t}/\partial S_{i;t}}{V_{i;t}}\frac{1}{\phi}S_{i;t}$, which is an increasing function of γ_t, and $\beta_{i;t} \equiv \frac{\partial V_{i;t}/\partial S_{i;t}}{V_{i;t}}\frac{1}{\phi}S_{i;t}+1$. Using Equation 56, the global stock market return ($R_{g;t} - E_t[R_{g;t}]$), which is the size-weighted average of stock market returns, is as follows.

$$
\begin{aligned}
R_{g;t} - E_t[R_{g;t}] &= \sum_{n=1}^{N} S_{n;t}(R_{n;t} - E_t[R_{n;t}]) \\
&= \sum_{n=1}^{N} S_{n;t}\tilde{\beta}_{n;t}\sigma\, dB_{g;t} + \sum_{n=1}^{N} S_{n;t}\beta_{n;t}\sigma\, dB_{n;t}
\end{aligned}
\tag{57}
$$

Then, the marginal utility for each good (country) i is

$$
\begin{aligned}
\frac{d\Lambda_{i;t}}{\Lambda_{i;t}} &= E_t\left[\frac{d\Lambda_{i;t}}{\Lambda_{i;t}}\right] - \gamma\sigma dB_{i;t} + \frac{1}{\sum_{n=1}^{N} S_{n;t}\tilde{\beta}_{n;t}}\sum_{n=1}^{N} S_{n;t}\beta_{n;t}\sigma\, dB_{n;t} \\
&\quad + \left(\frac{d\gamma_t}{\gamma_t} - E_t\left[\frac{d\gamma_t}{\gamma_t}\right]\right) - \frac{1}{\sum_{n=1}^{N} S_{n;t}\tilde{\beta}_{n;t}}[R_{g;t} - E_t[R_{g;t}]]
\end{aligned}
\tag{58}
$$

Figure A1: Correlation comparison

Panel A compares the global equity correlation ($Corr$) with the correlation of FX returns against USD ($Corr^{FX\ USD}$) and the average correlation of FX returns against all other base currencies ($Corr^{FX\ ALL} = \frac{1}{N}\sum_{Base=1}^{N} Corr^{FX\ Base}$). Panel B plots the correlation of 10 year treasury bond total returns ($Corr^{Treasury\ Bond}$) together with the FX correlation against USD ($Corr^{FX\ USD}$).

Figure A2: Pricing error plot: Other factors in the FX market

The gure presents the pricing errors of the asset pricing models with the selected risk factors from the list described in Section 5.6 of the paper. The realized actual excess returns are on the horizontal axis and the model predicted average excess returns are on the vertical axis. The test assets are *FX 10* portfolios: the set of carry portfolios (5) and momentum portfolios (5). We use our global equity correlation innovation factor (*Corr*) in Panel A, the FX volatility innovation factor in Panel B, the FX correlation innovation factor in Panel C, the high-minus-low carry factor in Panel D, the high-minus-low momentum factor in Panel E, and the global equity market factor in Panel F. The estimation results are based on OLS CSR test. The sample covers the period March 1976 to December 2014.

Table A1: Country selection

This table shows the list of countries in our dataset for various asset classes. The country is included in each dataset if it is checked (V). Panels A and B show the availability of FX spot and futures data for both developed and emerging markets and developed markets only, respectively. Panel C is MSCI equity market indices (total return series) from Datastream. Panel D is the equity futures contract with one-month maturity from Commodity Research Bureau (CRB). Panel E is individual stock data (total return series and various nancial variables) from Datastream. Panels F and G show 3-month treasury bill yields and 10-year treasury bond total return indices, and both series are obtained from Global Financial Data (GFD). Panel H

Table A2: Cross-sectional regression tests (Intercept)

The table reports cross-sectional pricing results for the factor model based on the global equity risk premium (Ret_{Global}) and the global equity correlation innovation ($Corr$) factors. The test assets are 6 carry and momentum portfolios formed on equity index futures in Panel A (Koijen et al. (2018)), 10 portfolios using commodity futures in Panel B (Yang (2013)), 10 portfolios using 10-year treasury bond total-return series in Panel C, 6 emerging market sovereign bond portfolios sorted on bond beta and credit rating in Panel D (Borri and Verdelhan (2011)), 18 index option portfolios sorted on maturity and moneyness in Panel E (Constantinides et al. (2013)), 10 carry and momentum portfolios formed on foreign exchange rate futures in Panel F (Menkho et al. (2012b)), and 60 global equity portfolios sorted on size, B/M, C/P, D/P, E/P, and momentum using international stocks in Panel G (Hou et al. (2011)). All 60 (120) portfolios without (with) the global equity portfolios are used in Panel H (Panel I). The normalized price of covariance risk $_{norm}$, and the misspeci cation-robust t-ratios ($t\text{-}ratio_{krs}$) are reported in parentheses. The p-value for the

Table A3: Cross-sectional regression tests (Sample split)

The table reports cross-sectional pricing results for the factor model based on the global equity risk premium (Ret_{Global}) and the global equity correlation innovation ($Corr$) factors. The test assets are 120 all-inclusive

Table A4: Predicting global stock market return

The table reports non-overlapping time-series regression results. The dependent variable is the return of value-weighted global stock market excess return with k-month horizon ($Ret_{global;t+1:t+k}$). Independent variable is a detrended level of the global equity correlation at time t ($Corr_{detrended;t}$). The correlation level is measured by computing bilateral intra-month correlations at each month's end using daily return series. Then, we take an average of all the bilateral correlations to arrive at a global correlation level ($Corr_t$) of a particular month. In order to detrend the level of correlation, in Panel A, we run the following time-series regression: $Corr_t = \quad + \quad t + \quad_t$ and we define the residual of the regression ($_t$) as a detrended level of the global equity correlation ($Corr_{detrended;t}$). In Panel B, we subtract 12-month EMA (exponential moving average) from the level of correlation. Newey-West t-statistics with six lags are reported in parentheses. The sample covers the period March 1976 to December 2014.

Panel A. Linear Detrending

Horizon	*Intercept*	*t-stat*	$Corr_{detrended}$	*t-stat*	R^2
1	0.006	(2.492)	0.024	(1.541)	0.015
2	0.012	(2.365)	0.099	(2.527)	0.031
3	0.018	(2.511)	0.135	(2.424)	0.037
4	0.025	(2.393)	0.163	(2.204)	0.038
5	0.031	(2.603)	0.144	(1.805)	0.032
6	0.036	(2.452)	0.305	(2.510)	0.065
7	0.042	(2.430)	0.093	(1.102)	0.019
8	0.049	(2.368)	0.195	(1.377)	0.027

Table A5: CSR tests in the FX market with developed countries

The table reports cross-sectional pricing results for the factor model based on the dollar risk factor (DOL)

Table A6: Alternative factors and asset pricing tests in the FX market

This table reports the price of covariance risk for the global equity correlation innovation factors from the various forms of asset pricing models. The test assets are *FX 10* portfolios: the set of carry and momentum portfolios. *CSR-OLS* (*CSR-GLS*) is the two-pass cross-sectional *OLS* (*GLS*) regression. In the rst pass, we run time-series regressions to estimate each asset's beta to the risk factors. In the second pass, we run cross-sectional regressions where test assets' average returns are regressed against the estimated betas to determine the risk premium of each factor. For *Fama-MacBeth Rolling 60M*, we run time-series regressions with rolling 60-month windows to estimate each asset's time-varying beta to the risk factors. At each

Table A7: CSR tests in the FX market: Robustness

This table reports the cross-sectional pricing results based on the dollar risk factor (*DOL*) and the global equity correlation innovation factor (Corr). The test assets are the set of Carry 5 and Momentum 5 (*FX 10*) portfolios. The winsorized correlation innovation series (at the 10% level) is used for Panel A, and the pre-financial crisis period (from March 1976 to December 2006) is chosen for Panel B. For Panel C, AR(2) instead of the first difference is used to measure the correlation innovations. Data are monthly and the sample covers the period March 1976 to December 2014. For Panel D, both factors (*DOL* and Corr) and test assets (*FX 10* portfolios) are constructed from weekly data series. Weekly sample covers the period October 1997 to December 2014. For Panel E (Panel F), *FX 10* portfolios are constructed using the euro (yen) as a base currency. To capture the common fluctuations of the euro (yen) against a broad basket of currencies, we add *EUR* (*JPY*) factor instead of *DOL* factor. The prices of covariance risks normalized