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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 financial economics is how to find 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 $\Delta Corr$) is a common component of the marginal utility of international investors. We present empirical findings 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 $\Delta Corr$ is a valid factor in international asset returns, we present a stylized consumption-based international asset pricing model in which the representative agent is endowed with a habit utility. The model illustrates that the change in global risk aversion (henceforth *GRA*) is a common driver of returns across all assets in different countries. An increase in *GRA* makes equity returns in one country more responsive to another country's dividend shocks even when their dividend streams (cash flows) are independent of each other, thus inducing higher expected comovements across all international equity returns. Because *GRA* is not observable and is challenging to measure, our model illustrates that the change in the common correlation across international equity returns is a potential proxy and hence a viable candidate factor for our empirical exercise.[1]

We measure the correlation dynamics by computing bilateral intramonth correlations at the end of each month. Then we take the average of all the bilateral correlations to arrive at a global correlation level in a particular month.[2] The correlation innovation factor is constructed as the first difference of the global correlation. To confirm our theoretical motivation, we examine how the level and time variations of global equity correlation are related to known alternative proxies for *GRA*. First, we find that the *level* of global correlation is negatively associated with the surplus consumption ratio (Campbell and Cochrane 1999), higher during National Bureau of Economic Research (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 2013). 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 (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 $\Delta Corr$ 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 the estimation error adjustment of Shanken (1992) and the misspecification error adjustment as in Kan et al. (2013). We also use CSR-Generalized least squares (GLS), Fama-MacBeth, and Generalized method of moments (GMM) methods and find that one standard deviation of cross-sectional differences in covariance to our factor explains about 2.5%–5.7% per annum in the cross-sectional differences in average return of 120 all-inclusive portfolios. A negative price of risk suggests that investors demand low risk premium for portfolios whose returns comove with global equity correlation because 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 first check that R^2 is statistically different from zero and confirm that our model is able to reject the null hypothesis of the misspecified model ($H0: R^2 = 0$).[5] Second, we compare the single factor Capital asset pricing model (CAPM) model with the extended two factor model augmented with $\Delta Corr$. By doing so, we show that the explanatory powers of two nested models are statistically different from each other and highlight the relative importance of the correlation factor. More specifically, we find that differences in R^2 range from 22% (emerging market sovereign bonds) to 80% (global equity index futures) and those are statistically different 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 cross-sectional regression test (CSRT) statistic that takes conditional heteroskedasticity and autocorrelated errors into account, suggest that the null hypothesis that all pricing errors are zero (Hypothesis 0: all pricing error = 0) cannot be rejected in all asset classes. These results suggest that the significance of our factor risk premium is not likely because of 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 different asset classes (Lettau et al. 2014, He et al. 2017, Yara et al. 2021). It is then natural to explore how the pricing ability of $\Delta Corr$ fares against these alternative models in explaining portfolios in multiple asset classes.[6] We do so not only with our benchmark 120 all-inclusive multiasset 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 first confirm their empirical results in our sample and find that both the downside risk factor of Lettau et al. (2014) and the intermediary capital ratio factor of He et al. (2017) can explain the spreads in mean returns of multiasset portfolios with R^2 ranging from 27% to 42%. Second, we include $\Delta Corr$ along with these factors and find that the price of the covariance risk for $\Delta Corr$ is statistically different from zero in most cases. Using our benchmark all-inclusive multiasset 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 is not significantly affected by the inclusion of these factors. Furthermore, given the tight relationship between $\Delta Corr$ and these alternative factors, we note that the relative economic magnitude of $\Delta Corr$ is reduced when explaining the portfolios in He et al. (2017) and Asness et al. (2013) compared with our benchmark case.

To assess further the empirical relevance of our factor, we explore in detail the pricing ability in the foreign exchange (FX) markets as a special case. We choose the FX markets mainly because of the notorious difficulty in explaining both FX carry and momentum strategies simultaneously (Burnside et al. 2011b, Menkhoff et al. 2012b). Our aim is twofold. First, we provide ample evidence that the cross-sectional variations in the average excess returns across FX carry and momentum portfolios can be explained by different sensitivities to our correlation factor. Second, we contrast the pricing ability of our factor with respect to other factors proposed in the FX literature particularly for carry strategies.

More specifically, we construct various control risk factors discussed frequently in the currency literature. The list includes (i) a set of traded and nontraded factors constructed from FX data, (ii) a set of liquidity factors, and (iii) a set of global equity market risk factors. Consistent with the forward puzzle literature, we find that those factors have explanatory power over the cross section of carry portfolios with R^2 ranging from 58% for TED spread innovation to 92% for FX volatility factor. The same set of factors, however, fails to explain the cross section of momentum portfolios. We demonstrate that our factor not only improves the explanatory power across carry portfolios but can also explain the cross section of momentum portfolios. Relying on the asymptotic distribution of the sample R^2 in the second-pass CSR, we show that the explanatory power can be statistically and economically improved when our correlation factor is added to the models. Using FX carry and momentum portfolios jointly as a test asset, differences in R^2 with and without our factor range from 21% for the high-minus-low FX carry factor (Lustig et al. 2011) to 58% for the FX illiquidity factor (Mancini et al. 2013).

Overall, using a factor constructed from the equity market to explain abnormal return in the FX and international equity markets, we also shed light on the discussion of the linkage between international equity and FX markets through equity correlations as an instrument of the aggregate risk. This extant literature focuses mainly on international capital flows (Hau and Rey 2006, Cenedese et al. 2016). We show that global equity correlation is subsumed neither by global capital flows nor underlying commonalities in those trading activities but rather is closely associated with time-varying global risk aversion.

This paper is also related to the recent literature on correlation risk (Driessen et al. 2009, Mueller et al. 2017). For example, Driessen et al. (2009) show that the differential pricing of S&P 100 index option and the component individual stock options reveals important information on the price of correlation risk. We expand their arguments beyond the U.S. equity and options markets and show that the global equity correlation risk is priced across many international asset classes. In addition, by presenting empirical evidence that the correlation factor is strongly negatively correlated with both the global and the U.S. variance risk premium, this paper also contributes to the literature that highlights the role of variance risk premium in asset returns (Bekaert and Hoerova 2016, Della-Corte et al. 2016, Londono and Zhou 2017).

The rest of the paper is organized as follows: Section 2 illustrates the theoretical motivation for the global correlation innovation factor. Section 3 presents data and Section 4 describes our factor construction methodology and presents time-series analysis of the factor. Section 5 provides the main empirical cross-sectional testing results. A number of alternative tests and robustness checks are also performed in Section 5, and we conclude in Section 6.

2. Theoretical Motivation

In this section, we develop a stylized international asset pricing model. Our aim is to explain why innovations in the global equity correlation can be considered as a factor for international asset returns. Our theoretical motivation is closely related to Verdelhan (2010), who proposes a habit-based explanation for the forward premium puzzle. Although 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 use 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. Because *GRA* is not observable and hence challenging to measure empirically, we illustrate in our model that the changes in comovement 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: $dD_{i,t} = D_{i,t}(\mu dt + \sigma dB_{i,t})\forall i$. There are two classes of agents in this economy. The first class is *Locals* who consume a fraction of $1-\phi$ of their own country's output and do not consume foreign country's output. The second class is *Internationals* who consume the remaining fraction ϕ 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: $E[\int_{t=0}^{\infty} e^{-\delta t}\ln(C_t - X_t)dt]$, where C_t denotes the aggregate consumption level of *Internationals* and X_t denotes the habit level at time t. The goods in different countries are viewed as imperfect substitutes by *Internationals* and $\eta \in [1,\infty)$ captures the elasticity of intratemporal substitution between goods.

$$C_t = \left[\sum_{i=1}^{N} \theta_i^{\frac{1}{\eta}} D_{i,t}^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}. \tag{1}$$

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

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 $\gamma_t = C_t/(C_t - X_t)$. Analogously to Menzly et al. (2004), we assume that the dynamic of risk aversion coefficient for *Internationals* (*global risk aversion* or *GRA*) follows a mean-reverting process and depends entirely on innovations in global consumption growth:

$$d\gamma_t = \kappa(\bar{\gamma} - \gamma_t)dt - \alpha(\gamma_t - \lambda)\sigma(dc_t - E_t[dc_t]), \quad (2)$$

where c_t is log C_t, κ denotes the speed of mean reversion, $\bar{\gamma}$ and λ are the long-run mean and the lower bound for γ_t, respectively, and $\alpha > 0$ is the sensitivity of γ_t to the aggregate consumption shock to *Internationals*.

The real exchange rate $e_{i,t}$ is the intratemporal price of a unit of good i in units of good 1 (base country), and an increase in $e_{i,t}$ means an appreciation of the currency i. Because the relative price of good i with respect to good 1 is the ratio of the marginal utility of the consumption of good i and 1, we can denote the real exchange rate $e_{i,t}$ as follows:

$$e_{i,t} = \frac{\partial \ln(C_t - X_t)/\partial D_{i,t}}{\partial \ln(C_t - X_t)/\partial D_{1,t}} = \left(\frac{\theta_i}{\theta_1}\right)^{\frac{1}{\eta}}\left(\frac{D_{i,t}}{D_{1,t}}\right)^{-\frac{1}{\eta}}. \quad (3)$$

With $\eta < \infty$, the good in country i is an imperfect substitute for the goods in any other countries. Therefore, a negative supply shock to $D_{i,t}$ makes the good i more scarce to *Internationals*, and this scarcity of the good drives up the relative price of the good i. This relation suggests that the exchange rate $e_{i,t}$ appreciates when the relative supply of country i's good declines.

The level of the real exchange rate i is closely related to the size of country i. Defining the relative size of country i (denoted by $S_{i,t}$) as the dividend share of world output denominated in the base currency 1, the exchange rate i in Equation (3) can be rewritten as follows[8]:

$$S_{i,t} = \frac{e_{i,t}D_{i,t}}{e_{i,t}D_{i,t} + \sum_{n\neq i}^{N} e_{n,t}D_{n,t}} = \frac{\theta_i^{\frac{1}{\eta}} D_{i,t}^{\frac{\eta-1}{\eta}}}{\sum_{n=1}^{N} \theta_n^{\frac{1}{\eta}} D_{n,t}^{\frac{\eta-1}{\eta}}}, \quad (4)$$

$$e_{i,t} = \left(\frac{S_{i,t}}{S_{1,t}}\right)\left(\frac{D_{i,t}}{D_{1,t}}\right)^{-1}. \quad (5)$$

Defining the size-weighted average of consumption shock as the global consumption shock ($dB_{g,t} = \sum_{n=1}^{N} S_{n,t}dB_{n,t}$), the stochastic structure on *GRA* can be rewritten as follows:

$$d\gamma_t = \kappa(\bar{\gamma} - \gamma_t)dt - \alpha(\gamma_t - \lambda)\sigma \sum_{n=1}^{N} \frac{\theta_n^{\frac{1}{\eta}} D_{n,t}^{\frac{\eta-1}{\eta}}}{\sum_{n=1}^{N} \theta_n^{\frac{1}{\eta}} D_{n,t}^{\frac{\eta-1}{\eta}}} dB_{n,t}, \quad (6)$$

$$= \kappa(\bar{\gamma} - \gamma_t)dt - \alpha(\gamma_t - \lambda)\sigma \sum_{n=1}^{N} S_{n,t}dB_{n,t}. \quad (7)$$

Not every country's dividend shock has the same influence on the dynamics of *GRA*. Because large countries account for a larger share of the global consumption, shocks from those countries have a significant influence on the degree of *GRA* and the marginal utility of consumption. The marginal utility for each of the good (country) i is given by

$$\Lambda_{i,t} = e^{-\delta t}\partial \ln(C_t - X_t)/\partial D_{i,t} = e^{-\delta t}\gamma_t S_{i,t} D_{i,t}^{-1}$$
$$\frac{d\Lambda_{i,t}}{\Lambda_{i,t}} = E_t\left[\frac{d\Lambda_{i,t}}{\Lambda_{i,t}}\right] - \frac{\sigma}{\eta}dB_{i,t} + \frac{d\gamma_t}{\gamma_t} - E_t\left[\frac{d\gamma_t}{\gamma_t}\right] - \frac{\eta - 1}{\eta}\sigma dB_{g,t}. \quad (8)$$

The marginal utility has a common exposure to two factors: the unexpected changes in *GRA* $\left(\frac{d\gamma_t}{\gamma_t} - E_t[\frac{d\gamma_t}{\gamma_t}]\right)$ and the global consumption shock ($dB_{g,t}$).[9] Thus, a discount factor that is a linear function of the two factors suggests an expected return beta relationship of the form

$$E(R^i) = \upsilon + \lambda_{\Delta\gamma}\beta_{i,\Delta\gamma} + \lambda_g \beta_{i,g},$$

where $\beta_{i,\Delta\gamma}$ is the exposure of asset i's return to the unexpected changes in *GRA* and $\beta_{i,g}$ is the exposure to the global consumption shock.

2.2. Global Equity Correlations

Equation (8) shows that the dynamic of *GRA* is a common component of the marginal utility of assets and as such it affects the pricing of any assets across all countries. However, *GRA* is not observable and is hard to measure in empirical settings. In this section, we consider the following two cases and show that the changes in *GRA* reveal themselves through changes in the common correlation between observable international equity returns.

2.2.1. Case 1: Nonsubstitutable Goods. In our economy, the price of any international equity indices is given by

$$P_{i,t} = E_t\left[\int_t^\infty e^{-\delta(\tau - t)} \frac{\partial U/\partial D_{i,\tau}}{\partial U/\partial D_{i,t}} D_{i,\tau} d\tau\right].$$

In a special case in which goods are not substitutable ($\eta = 1$), the size of the economy from Equation (4) becomes constant and equal to the relative importance of goods in country i for *Internationals* ($S_{i,t} = \theta_i$). Moreover, a closed-form solution for the price-dividend ratio ($V_{i,t}$) of the equity index of country i can also be obtained as follows:

$$V_{i,t} \equiv \frac{P_{i,t}}{D_{i,t}} = \frac{1}{\delta + \kappa} + \frac{\kappa\bar{\gamma}}{(\delta + \kappa)\delta\gamma_t}. \quad (9)$$

In this special case, the price-dividend ratio is the same across all countries, and the time-variation of the ratio is solely driven by the dynamics of *GRA*. The higher *GRA*, the lower the price-dividend ratio as prices are depressed relative to dividends because of higher discount rates.

The instantaneous equity return $R_{i,t}$ expressed in terms of the price-dividend ratio is

$$R_{i,t} = \frac{dt}{V} + \frac{dV_{i,t}}{V_{i,t}} + \frac{dD_{i,t}}{D_{i,t}} + \frac{dD_{i,t}dV_{i,t}}{D_{i,t}V_{i,t}}. \tag{10}$$

The return is composed of the dividend yield, the relative change in valuation, the dividend growth, and the cross-product of valuation and dividend growths. Substituting Equation (9) into Equation (10), the equity returns can be denoted as follows:

$$R_{i,t} - E_t[R_{i,t}] = \hat{\gamma}_t\sigma\sum_{n=1}^{N}\theta_n dB_{n,t} + \sigma dB_{i,t}, \tag{11}$$

where $\hat{\gamma}_t \equiv \frac{\kappa\bar{\gamma}}{(\delta\gamma_t+\kappa\bar{\gamma})\gamma_t}\alpha(\gamma_t - \lambda)$, which is an increasing function of γ_t. Equation (11) illustrates that equity returns of country *i* are positively associated not only with the consumption shock of it itself, country *i*, but also with the consumption shocks from all the other countries. In other words, returns of any two international equity indices are correlated even though their dividend streams are independent. The sensitivity of asset return *i* to the dividend shock from country *j* depends on two terms: γ_t and θ_j. The larger the relative size of country *j*, the more influential its consumption shock is to the asset returns of country *i*. This cross-country effect is magnified if *Internationals* have high risk aversion at time *t*.

We decompose the covariance between two returns of international equity indices as follows ($\mathrm{Cov}_{i,j,t} \equiv \mathrm{Cov}_t(R_{i,t}, R_{j,t})$):

$$\mathrm{Cov}_{i,j,t} = \mathrm{Cov}_t\left(\frac{dD_{i,t}}{D_{i,t}}, \frac{dD_{j,t}}{D_{j,t}}\right) + \mathrm{Cov}_t\left(\frac{dD_{i,t}}{D_{i,t}}, \frac{dV_{j,t}}{V_{j,t}}\right) + \mathrm{Cov}_t\left(\frac{dV_{i,t}}{V_{i,t}}, \frac{dD_{j,t}}{D_{j,t}}\right) + \mathrm{Cov}_t\left(\frac{dV_{i,t}}{V_{i,t}}, \frac{dV_{j,t}}{V_{j,t}}\right)$$

Returns of any two international equity indices can be positively correlated through the *cross-valuation effect*, defined as $\mathrm{Cov}_t(\frac{dD_{i,t}}{D_{i,t}}, \frac{dV_{j,t}}{V_{j,t}}) + \mathrm{Cov}_t(\frac{dV_{i,t}}{V_{i,t}}, \frac{dD_{j,t}}{D_{j,t}})$, even though the underlying cash flows are not correlated. More specifically, if one country *i* has a negative dividend shock ($\Delta D_{i,t} < 0$), this shock induces *Internationals* to have higher risk aversion ($\Delta\gamma_t > 0$). The higher risk aversion has negative impact not only on the valuation level of equity index *i* ($\Delta V_{i,t} < 0$) but also on the valuation of equity index *j* ($\Delta V_{j,t} < 0$). Both valuations are affected at the same time by a dividend shock in a single country because *Internationals* are the ones who price equities altogether.

Closed-form solutions for the covariance between any two international equity index returns ($Cov_{i,j,t}$) and the cross-sectional average of those covariances at each time *t* ($\overline{\mathrm{Cov}_t}$) can be obtained as follows:

$$\mathrm{Cov}_{i,j,t} = \hat{\gamma}_t^2\sigma^2\sum_{n=1}^{N}\theta_n^2 + \hat{\gamma}_t\sigma^2(\theta_i + \theta_j), \tag{12}$$

$$\overline{\mathrm{Cov}_t} = \left(N\overline{\theta^2}\hat{\gamma}_t + 2\overline{\theta}\right)\sigma^2\hat{\gamma}_t, \tag{13}$$

where $\overline{\theta} = \frac{1}{N}\sum_{n=1}^{N}\theta_n$ and $\overline{\theta^2} = \frac{1}{N}\sum_{n=1}^{N}\theta_n^2$. Equation (13) suggests that the common components in the comovement of international equity indices are positively associated with the level of *GRA*.

When a country experiences low (or negative) dividend shock, this shock increases *GRA*. Increased *GRA* induces equity index returns in one country to be more responsive to another country's dividend shocks. This leads to increased *cross-valuation effect*, hence higher expected comovement across all international equity index returns. Therefore, the changes in the unobservable *GRA* reveal themselves through changes in the comovement 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 ($\eta > 1$), the size of the country is no longer constant ($S_{i,t} \neq \theta_i$).

$$V_{i,t} \equiv \frac{P_{i,t}}{D_{i,t}} = \frac{1}{S_{i,t}\gamma_t}E_t\left[\int_t^{\infty} e^{-\delta(\tau-t)}\gamma_\tau S_{i,\tau}d\tau\right]. \tag{14}$$

The price-dividend ratio is an inverse function of the risk aversion as in Campbell and Cochrane (1999) and 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 first derive the unexpected component of equity returns. In this substitutable-goods case, it is given by

$$R_{i,t} - E_t[R_{i,t}] = \left(-\frac{\partial V_{i,t}/\partial\gamma_t}{V_{i,t}}\alpha(\gamma_t - \lambda) - \frac{\partial V_{i,t}/\partial S_{i,t}}{V_{i,t}}\frac{\eta-1}{\eta}S_{i,t}\right)\sigma\sum_{n=1}^{N}S_{n,t}dB_{n,t} + \left(\frac{\partial V_{i,t}/\partial S_{i,t}}{V_{i,t}}\frac{\eta-1}{\eta}S_{i,t} + 1\right)\sigma dB_{i,t}, \tag{15}$$

where $\frac{\partial V_{i,t}/\partial\gamma_t}{V_{i,t}} < 0$ and $\frac{\partial V_{i,t}/\partial S_{i,t}}{V_{i,t}} < 0$. As in the case of nonsubstitutable 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 $\hat{\gamma}_t$ in Equation (15), this cross-country effect is magnified if *Internationals* have high risk aversion at time t.

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 the two-trees model of Cochrane et al. (2008). 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* ($\alpha = 0$). 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*: $\mathrm{Cov}_t\left(\frac{dD_{i,t}}{D_{i,t}}, \frac{dV_{j,t}}{V_{j,t}}\right) + \mathrm{Cov}_t\left(\frac{dV_{i,t}}{V_{i,t}}, \frac{dD_{j,t}}{D_{j,t}}\right) > 0$.[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, because 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, and hence higher comovements across international equity returns. The key mechanism behind the *cross-valuation effect*, therefore, is still through the changes in *GRA*, and not through the changes in size, whether goods are substitutable or not.

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 Morgan Stanley Capital International (MSCI) 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 Koijen et al. (2018). The sample is from Commodity Research Bureau (CRB) and covers the period from December 1990 to December 2014.

For individual stock returns and other financial variables, we follow Hou et al. (2011) to obtain prices and total returns series, book-to-market (B/M), cash flow-to-price (C/P), dividend-to-price (D/P), earnings-to-price (E/P), market value of equity (Size), and daily trading volumes (VO) from Datastream. After applying several screening procedures as suggested by Ince and Porter (2006),[13] our final sample encompasses 64,655 stocks from 33 countries from July 1981 to December 2014. The country lists are reported in Table A1 in the online appendix.

3.2. Bonds, Commodities, and Options

For sovereign bonds, 10-year treasury bond total return indices from 45 countries are obtained from Global Financial Data (GFD),[14] and they are denominated in local currencies. The sample periods run from December 1973 to December 2014. We also have a data set for sovereign bonds using the JP Morgan EMBI Global total return indices. The EMBI Global 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 CRB, and the sample spans from January 1973 to December 2014. Last, 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 et al. (2011a), we blend two data sets of spot and forward exchange rates to span a longer time period. Both data sets are obtained from Datastream. The data sets consist of daily observations for bid/ask/mid spot and one-month forward exchange rates for 44 currencies. Those bid/ask/mid exchange rates are quoted against the British pound (GBP) and U.S. dollar (USD) for the first and second data set, respectively. The first data set spans the period between January 1976 and December 2014 and the second data set spans the period between December 1996 and December 2014. The sample period varies by currency. To blend the two data sets, we convert pound quotes in the first data set to dollar quotes by multiplying the GBP/Foreign currency units by the USD/GBP quotes for each of bid/ask/mid data. 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 Table A1 in the online appendix.

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 effect is asymmetric, meaning that equity returns are much more correlated internationally subsequent to negative global fundamental shocks because of 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.

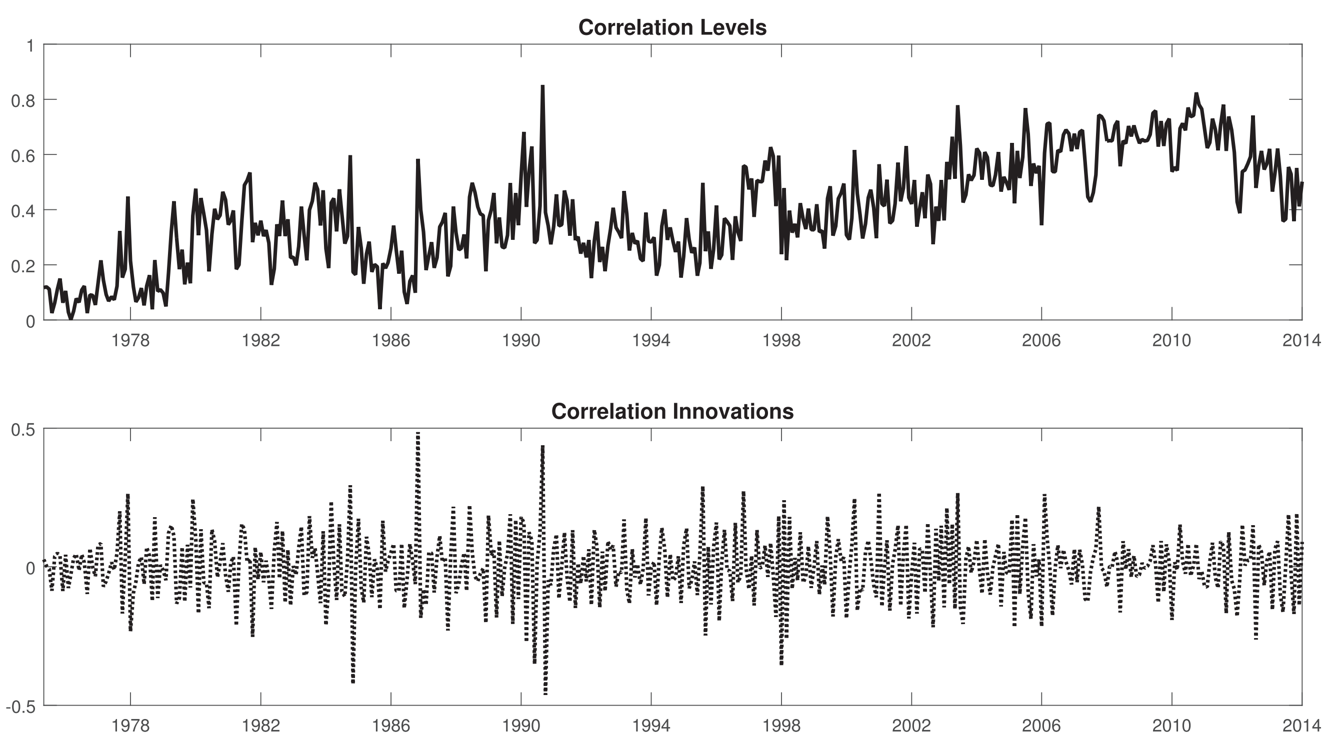
4.1. Factor Construction

We measure the correlation dynamics by computing bilateral intramonth 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 comovements.[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) to construct a proxy for the surplus consumption at the monthly frequency: $Surplus_t = \frac{1-\Psi}{1-\Psi^{40}} \sum_{j=0}^{39} \Psi^j \Delta c(t-j)$, where the decay factor $\Psi = 0.96$. Monthly aggregate consumption is the seasonally adjusted per capital expenditures on nondurables and services from National Income and Product Accounts (NIPA). Second, because of the counter-cyclical nature of the willingness to take a risk, we investigate the relation with a recession and find that

Figure 1. Correlation Innovation Factors



Notes. The upper panel of the figure shows a time-series plot of the global equity correlation levels. The correlation level is measured by computing bilateral intramonth 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 ($\Delta Corr$). The correlation innovations are measured by taking first difference of each of the correlation levels. The sample covers the period March 1976 to December 2014.

the level of global correlation is higher during the NBER recession periods (model 2). Third, Bekaert et al. (2019) propose a measure of time-varying 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 (Rey 2013). For the global option-implied volatility, we apply the methodology of Mark and Neuberger (2000) and Jiang and Tian (2005) 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 United States. 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.

Table 1. Time-Series Regression with the Level of Correlation

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

Notes. 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) to construct a proxy for the surplus consumption at monthly frequency: $Surplus_t = \frac{1-\Psi}{1-\Psi^{40}} \sum_{j=0}^{39} \Psi^j \Delta c(t-j)$ where the decay factor $\Psi = 0.96$. *Recession* is the NBER's recession indicators. RA^{BEX} is the Bekaert et al. (2019) 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 the methodology of Mark and Neuberger (2000) and Jiang and Tian (2005) 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 United States. The heteroskedasticity and autocorrelation adjusted t ratio with automatic lag selection from Newey-West (1994) are reported in parentheses.

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. 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 macroeconomic 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 predeterminants of $\Delta Corr$, we not only include contemporaneous changes in those variables but also control for the level of macroeconomic conditions in the previous month $t-1$.

The dynamics of the average correlation can potentially be driven by correlated trading activities in the global equity market because of 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 and 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 and 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 because of 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.

Table 2. Time-Series Regression with the Innovation of Correlation

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Panel A: Global equity market returns													
Ret_t	−0.391***		−0.167	−0.234	−0.270	−0.040	−0.303	−0.308	0.077	−0.546***	−0.382***	−0.352***	−0.390***
$Ret_t^{Down,Large}$		−0.487***											
Ret_t^{Small}		−0.290											
$Ret_t^{Up,Large}$		−0.387***											
IC_t^{HKM}			−0.280***										
Panel B: Global macro conditions													
$Term_{t-1}$	3.686	4.203	4.379	11.004	11.360	7.735	4.967	4.527	3.289	15.228	10.119	10.437	7.332
RF_{t-1}	1.594	1.848	2.041	3.679	0.652	1.962	0.477	0.744	1.510	2.373	3.709	3.441	2.804
$Div\ Yield_{t-1}$	−0.007	−0.008	−0.010	−0.012	−0.013	−0.008	−0.002	0.001	−0.002	−0.002	−0.013	−0.011	−0.009
$\Delta Term_t$	18.512	17.834	13.597	12.301	−1.729	3.347	−2.855	11.810	−2.746	31.754	−10.252	6.322	15.684
ΔRF_t	16.074	17.259	16.269	26.805	12.746	26.212	8.334	4.006	18.933	56.671	14.669	27.300	28.432
$\Delta Div\ Yield_t$	0.036	0.034	−0.008	0.101	−0.090	−0.136	−0.082	−0.085	0.056	−0.178	0.124	0.092	0.095
Panel C: Global capital market conditions													
$\Delta GlobalLiquidity_t$				−0.006	0.018	−0.015	0.031	0.027	0.009	0.037	−0.009	−0.003	−0.006
$\Delta GlobalTurnover_t$				0.042***	0.037***	0.030***	0.032***	0.032***	0.005	0.051***	0.039***	0.035***	0.042***
$\Delta R^2_{Liq,t}$				−0.060	−0.181	−0.170	−0.131	−0.105	−0.086	−0.395	−0.093	−0.035	−0.060
$\Delta R^2_{Turn,t}$				0.167	0.111	0.152	0.123	0.124	0.070	0.117	0.177	0.144	0.161
Panel D: Global risk aversion													
$\Delta IVOL_t^{VW}$					0.412***								
$\Delta IVOL_t^{US}$						0.445***							
VRP_t^{VW}							−0.372***						
VRP_t^{US}								−0.390***					
Panel E: Other correlation innovations													
$\Delta Corr_t^{Equity,Internal}$									0.910***				
$\Delta Corr_t^{Treasury\ Bond}$										0.246***			
$\Delta Corr_t^{FXUSD}$											0.304***		
$\Delta Corr_t^{Commodity}$												0.201***	
$\Delta Corr_t^{FXALL}$													0.146
R^2	0.029	0.032	0.042	0.068	0.082	0.077	0.119	0.112	0.243	0.135	0.120	0.081	0.071

Notes. The table reports results from time-series regressions in which $\Delta Corr$ is regressed on various proxies of the change in *GRA*. Ret_t is the global market-capitalization weighted average of equity index returns. We define $Ret_t^{Down,Large}$ ($Ret_t^{Up,Large}$) as returns that are more than one standard deviation below (above) the unconditional mean of the global market returns. Ret_t^{Small} is defined as returns that are within one standard deviation of the mean market returns. IC_t^{HKM} is the intermediary capital risk factor of He et al. (2017). $Term_t$, RF_t, and $Div\ Yield_t$ are the global market-capitalization weighted average of term spreads (10-year minus 3-month yield), 3-month T-bill rates, and aggregate dividend yields, respectively. We follow the measure of Karolyi et al. (2012) of country-level liquidity and turnover. $\Delta Global\ Liquidity_t$ ($\Delta Global\ Turnover_t$) is the market-value weighted average of the liquidity (turnover) innovation for all stocks across countries. Similarly, $\Delta R^2_{liq,t}$ ($\Delta R^2_{Turn,t}$) is the first differences in the market-value weighted average of the commonality in liquidity (turnover) across countries. $\Delta IVOL^{VW(US)}$ is the change in the global (the U.S.) option-implied volatility measure. The equivalent measure of the global (U.S.) variance risk premium is defined as $VRP_t^{VW(US)} = RV_t^{VW(US)} - IVOL_t^{VW(US)}$. $\Delta Corr_t^{Equity,\ Internal}$ is the change in the market-value weighted average of intracountry correlations. $\Delta Corr_t^{Treasury\ \ Bond}$, $\Delta Corr_t^{FX\ USD}$, $\Delta Corr_t^{Commodity}$, $\Delta Corr_t^{FX\ ALL}$ is the change in correlations among 10 year treasury total returns, FX returns against USD, returns on commodity futures, and FX returns against all other base currencies, respectively.

*, **, and ***Significant at 10%, 5%, and 1%, respectively.

Throughout models 1–3, we also examine whether global macroeconomic states are predeterminants of the correlation innovations. The regression results indicate that the effect of global macroeconomic conditions on the correlation innovation is weak. The term $\Delta Corr$ 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 macroeconomic fundamentals.

Similar to macroeconomic conditions, model 4 shows that the correlation innovation is weakly related to innovations in other financial market conditions. A statistically insignificant relation between $\Delta Corr$ 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 $\Delta Corr$ increases when there are excessive trading activities around the world. At the same time, a weak relation between $\Delta Corr$ 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 (2013) 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 (*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 United States, 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 (Della-Corte et al. 2016, 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 intracountry (internal) correlations with our factor, which is based on intercountry (external) correlations. To measure global intracountry 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] The variables $\Delta Corr_t^{Treasury\ Bond}$, $\Delta Corr_t^{FX\ USD}$, and $\Delta Corr_t^{Commodity}$ are the changes in the correlation among 10-year treasury total returns, FX returns against USD, and returns on commodity futures, respectively. The statistically significant beta coefficient of 0.91 in model 9 presents evidence that the average intracountry and intercountry equity correlations are closely related, which can be interpreted as evidence of a common driver of global equity correlations.[21] Models 10–12 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 data set). This finding indicates that the USD 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 $\Delta Corr$ 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 CSR

To test whether our factor is a priced risk factor in the cross section of currency portfolios, we use the two-pass cross-sectional regression (CSR-OLS) method. For statistical significance of the price of beta or covariance, we report the statistical measures of Kan et al. (2013) throughout the main analysis of this paper. Although we investigate both the price of covariance risk and the price of beta risk in our empirical tests, we only report the price of covariance risk.[23] We report the details of the estimation methodology of these statistics in Section B of the online 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 $\Delta Corr$ 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 on the basis spread, which is the log difference between 1-month and the 12-month futures prices divided by the difference in maturity. We define momentum as the cumulative return from month $t-12$ to $t-2$ while skipping month $t-1$ return for all three asset classes.

In addition to those carry and momentum portfolios, we construct 6 emerging market sovereign bond portfolios, 18 equity index option portfolios, and 60 global equity portfolios. To construct the emerging market sovereign bond portfolios, JP Morgan EMBI Global total return indices are sorted first by the credit rating of country and then by bond 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 B/M, C/P, D/P, E/P, Size, and MoM. We generate 10 portfolios for each type of sorting variable. 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 ($\Delta Corr$). From panel A to panel G, we run CSR-OLS on each of the asset classes separately, whereas we use an all-inclusive approach to test various asset classes in a joint cross section from panels H to I. Given the dominant number of portfolios for global equities compared with the other asset classes, we first 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 panel I. In each panel, the market price of covariance risk (λ) is presented first, followed by the price of covariance risk normalized by standard deviation of the cross-sectional covariances (λ_{norm}) and the corresponding t-statistics ($t\text{-}ratio_{krs}$) under the estimation error adjustment of Shanken (1992) and the misspecification error adjustment of Kan et al. (2013).[25]

We expect our correlation innovation factor to be negatively priced because it is positively associated with marginal utility of consumption for *Internationals*. In Table 4, we find that the price of covariance risk is negative in all cases, and λ_{norm} varies from −2.42% (for the foreign exchange rates) to −7.31% (for the options) per annum. The negative price of covariance risk confirms our hypothesis that investors demand a low-risk premium for portfolios whose returns comove 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 $p < 0.01$. The generalized χ^2 test shows that the model with our correlation factor cannot be rejected, whereas 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 follow several suggestions from their paper. We first check that R^2 is statistically different from zero. The p values of the test ($pval_{R^2=0}$ in Table 4) suggest that the model has statistically significant explanatory power for the cross section of expected returns in all asset classes under the null hypothesis of the misspecified model ($H0: R^2 = 0$). Second, we compare the single factor CAPM model (model 1) and the extended two-factor

Table 3. Summary Statistics of Test Assets

	Mean	Standard deviation	Skew	Sharpe
Panel A: Equity index futures				
Carry portfolios (Koijen et al. 2018)				
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				
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
Momentum portfolios				
Low momentum	0.41	12.21	−1.53	0.03
2	2.03	10.72	−0.12	0.19
3	3.71	10.75	−0.04	0.35
4	5.39	11.20	−0.23	0.48
High momentum	7.29	10.29	−0.43	0.71
Panel D: EMBI global indices (Borri and Verdelhan 2011)				
Low beta: High rating	−1.12	9.53	−2.34	−0.12
Low beta: Medium rating	1.03	10.97	−3.26	0.09
Low beta: Low rating	3.40	16.37	−3.95	0.21
High beta: High rating	4.05	9.35	−0.96	0.43
High beta: Medium rating	7.92	11.77	−1.61	0.67
High beta: Low rating	11.37	19.60	−2.00	0.58
Panel E: Options (Constantinides et al. 2013)				
Call: M = 30 and K = 90	1.70	14.68	−0.31	0.12
Call: M = 30 and K = 100	−1.31	14.36	0.00	−0.09
Call: M = 30 and K = 110	−4.15	13.93	1.40	−0.30
Call: M = 60 and K = 90	1.82	14.55	−0.28	0.12
Call: M = 60 and K = 100	−0.76	14.41	−0.01	−0.05
Call: M = 60 and K = 110	−3.47	14.21	0.87	−0.24
Call: M = 90 and K = 90	2.10	14.40	−0.25	0.15
Call: M = 90 and K = 100	0.46	14.36	0.01	0.03
Call: M = 90 and K = 110	−1.24	14.55	0.47	−0.09
Put: M = 30 and K = 90	22.55	21.36	−1.65	1.06
Put: M = 30 and K = 100	8.50	17.35	−1.01	0.49
Put: M = 30 and K = 110	4.78	15.64	−0.59	0.31

Table 3. (Continued)

	Mean	Standard deviation	Skew	Sharpe
Panel E: Options (Constantinides et al. 2013)				
Put: M = 60 and K = 90	14.42	20.37	−1.39	0.71
Put: M = 60 and K = 100	7.46	17.19	−0.98	0.43
Put: M = 60 and K = 110	4.34	15.86	−0.65	0.27
Put: M = 90 and K = 90	9.33	19.78	−1.25	0.47
Put: M = 90 and K = 100	6.56	17.18	−0.96	0.38
Put: M = 90 and K = 110	4.60	15.96	−0.71	0.29
Panel F.1: Global equities, size (Hou et al. 2011)				
Small	18.23	20.23	−0.63	0.90
2	14.37	19.17	−0.85	0.75
3	11.08	18.50	−0.91	0.60
4	8.85	18.09	−0.99	0.49
5	7.88	18.05	−1.04	0.44
6	7.49	18.39	−1.01	0.41
7	7.31	18.17	−1.08	0.40
8	5.18	17.94	−1.04	0.29
9	5.63	17.83	−1.00	0.32
Big	4.83	16.23	−0.87	0.30
Panel F.2: Global equities, B/M (Hou et al. 2011)				
Low B/M	3.39	17.55	−1.19	0.19
2	5.16	15.62	−0.91	0.33
3	5.07	15.77	−0.83	0.32
4	6.30	15.79	−0.74	0.40
5	5.84	17.10	−0.95	0.34
6	5.60	17.41	−0.83	0.32
7	8.16	16.99	−0.43	0.48
8	9.52	19.33	0.05	0.49
9	9.35	21.16	−0.45	0.44
High B/M	15.41	24.70	0.20	0.62
Panel F.3: Global equities, C/P (Hou et al. 2011)				
Low C/P	5.44	17.55	−0.69	0.31
2	0.42	21.56	−0.92	0.02
3	2.18	18.08	−0.89	0.12
4	3.23	15.07	−0.76	0.21
5	5.52	15.25	−0.76	0.36
6	7.09	15.30	−1.11	0.46
7	7.36	15.71	−0.93	0.47
8	8.34	15.19	−1.11	0.55
9	11.22	16.77	−0.87	0.67
High C/P	13.30	19.64	−1.21	0.68
Panel F.4: Global equities, D/P (Hou et al. 2011)				
Low D/P	−3.72	21.89	−1.05	−0.17
2	0.98	18.75	−0.99	0.05
3	2.80	16.69	−0.81	0.17
4	5.10	15.29	−0.81	0.33
5	5.70	14.46	−1.02	0.39
6	7.53	14.94	−0.95	0.50
7	7.79	14.39	−0.89	0.54
8	9.08	15.01	−0.49	0.60
9	10.40	15.77	−0.77	0.66
High D/P	12.79	19.23	−0.94	0.67
Panel F.5: Global equities, E/P (Hou et al. 2011)				
Low E/P	5.46	17.50	−0.69	0.31

Table 3. (Continued)

	Mean	Standard deviation	Skew	Sharpe
Panel F.5: Global equities, E/P (Hou et al 2011)				
2	−0.03	21.66	−0.92	0.00
3	2.39	18.20	−0.88	0.13
4	3.27	15.07	−0.69	0.22
5	5.21	15.14	−0.79	0.34
6	7.15	15.31	−1.03	0.47
7	7.56	15.64	−0.84	0.48
8	8.45	15.24	−1.25	0.55
9	10.71	16.68	−0.89	0.64
High E/P	13.04	19.54	−1.23	0.67
Panel F.6: Global equities, momentum (Hou et al. 2011)				
Low momentum	−1.31	33.25	−0.29	−0.04
2	0.38	23.83	−0.57	0.02
3	2.57	20.34	−0.84	0.13
4	2.09	18.35	−1.48	0.11
5	4.77	15.30	−0.80	0.31
6	4.95	14.32	−1.01	0.35
7	5.82	13.78	−0.98	0.42
8	6.72	14.46	−0.79	0.47
9	7.25	16.35	−0.79	0.44
High momentum	10.74	21.43	−0.42	0.50

model augmented with $\Delta Corr$ (model 2) in Table 4. By doing so, we explore that the explanatory power of two nested models are statistically different from each other and ask what the relative importance of $\Delta Corr$ factor is. Table 4 shows that augmenting the correlation innovation factor significantly improves the joint cross-sectional fits across various asset classes. Differences in R^2 are 80%, 72%, 71%, 22%, 70%, 77%, and 30% from panels A to G, respectively, and R^2s are also statistically different from each other at a 5% rejection level except emerging market sovereign bonds in panel D ($pval$ = 13%).[26] Third, the p values from the F test, a generalized version of Shanken's CSRT statistic (χ^2 in Table 4) that allows for conditional heteroskedasticity and autocorrelated errors, show that the null hypothesis that all pricing errors are zero (Hypothesis 0: all pricing error = 0) cannot be rejected, except the case of option portfolios. These results suggest that the significance of our factor risk premium is unlikely because of the useless factor bias. Last, another test is to use independent test assets to examine the robust significance of the risk premium associated with our correlation factor.[27] We explore this idea in depth in the next section.

5.4. Alternative Test Assets and Factor Models

The recent literature suggests that there are other risk factors that price the cross section of returns in different asset classes. For example, Lettau et al. (2014) show that exposure to downside risk can jointly reconcile the cross section of multiple asset classes including equity, equity index options, commodity, sovereign bond, and currency returns. Similarly, He et al. (2017) suggest that financial intermediaries' net worth is a key determinant of its marginal value of wealth and present evidence that shocks to the equity capital ratio of financial intermediaries possess significant explanatory power for the cross-sectional variation in expected returns in many asset markets. In this section, we explore how well $\Delta Corr$ fares against the pricing ability of these alternative models in explaining multiasset class portfolios. Moreover, we examine whether the factor can improve the pricing ability using not only our benchmark 120 all-inclusive portfolios but also independent sets of test assets.

The economic intuition behind the pricing model using our global equity correlation factor is closely associated with that of Lettau et al. (2014) and He et al. (2017). First, equity returns become more internationally correlated after bad global fundamental shocks because of the asymmetric valuation effect that originates from a higher level of risk aversion. Therefore, as we pointed out in our empirical time-series analysis in Section 4.2, the global equity correlation is positively associated with the downside return of global equity market portfolios. Second, Brunnermeier et al. (2009) show that there is a feedback loop between 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 (2013) also notes that the effective risk appetite of the market is related to the leverage of financial market intermediaries. This mechanism is an important positive feedback loop between greater credit supply, asset price inflation, and risk aversion. To the extent that there exists a positive feedback loop for financial intermediaries, we expect negative correlation between the intermediary capital ratio of He et al. (2017) and our factor, which is consistent with our empirical finding in Section 4.2.

We test the marginal contribution of $\Delta Corr$ in explaining the cross-sectional variation of returns of multiple asset classes. We do so not only with our benchmark all-inclusive multiasset 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–C of Table 5, respectively. In each panel of Table 5, we first 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

Table 4. CSR Tests

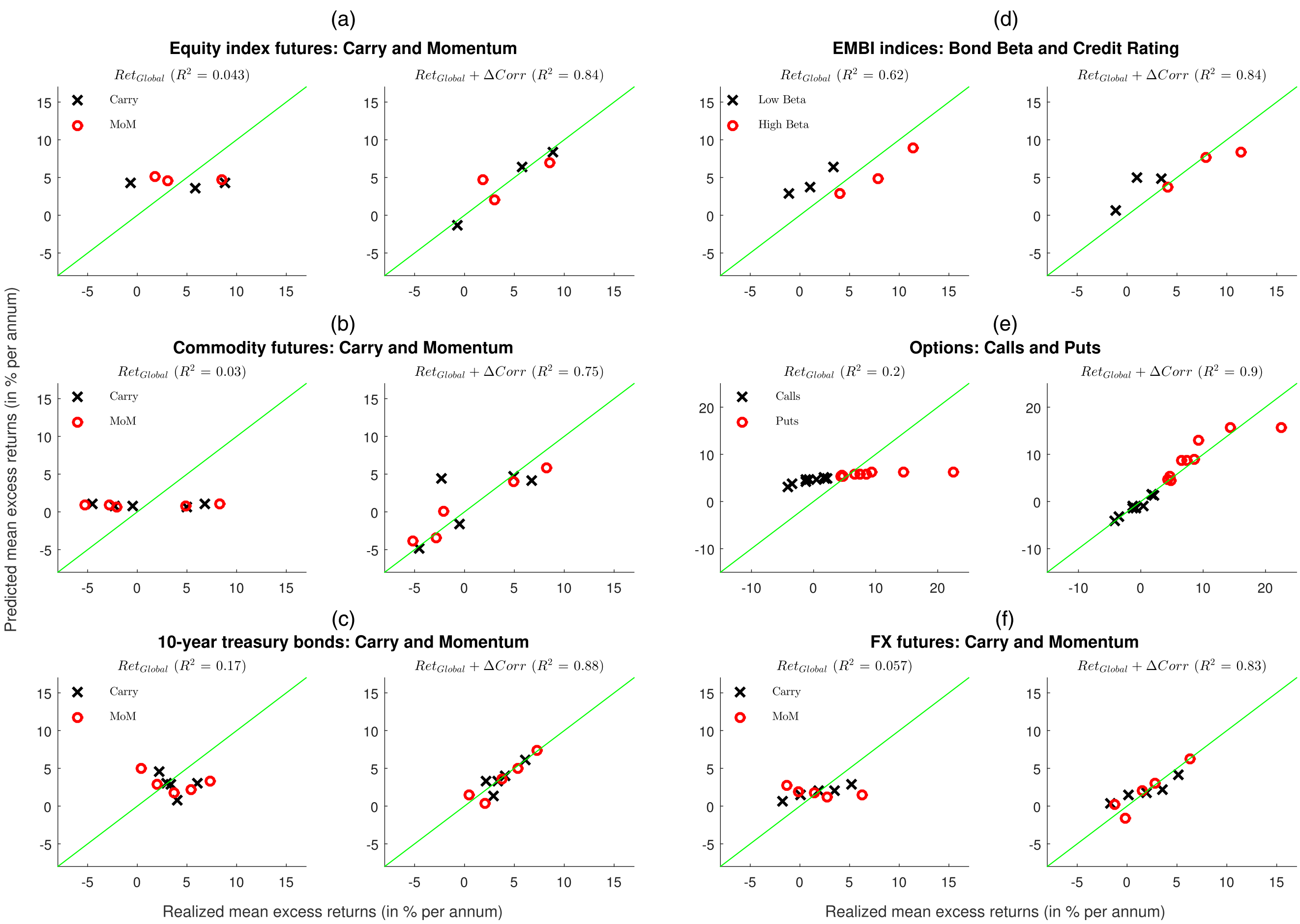
Factor	A. Equity index futures (1) Ret_{Global}	A. (2) Ret_{Global}	A. (2) $\Delta Corr$	B. Commodity futures (1) Ret_{Global}	B. (2) Ret_{Global}	B. (2) $\Delta Corr$	C. 10-year treasury bonds (1) Ret_{Global}	C. (2) Ret_{Global}	C. (2) $\Delta Corr$
λ	1.67	−6.52	−13.53	1.59	−4.49	−12.07	27.66	13.90	−19.62
λ_{norm}	0.52	−2.04	−3.96	0.17	−0.49	−4.12	3.08	1.55	−3.23
$t\text{-}ratio_{krs}$	(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]	
χ^2	0.07	0.00		0.05	0.01		0.03	0.00	
$pval_{Pricing\ error=0}$	[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 (1) Ret_{Global}	D. (2) Ret_{Global}	D. (2) $\Delta Corr$	E. Options (1) Ret_{Global}	E. (2) Ret_{Global}	E. (2) $\Delta Corr$	F. Foreign exchange (1) Ret_{Global}	F. (2) Ret_{Global}	F. (2) $\Delta Corr$
λ	7.63	0.43	−12.21	4.16	−2.78	−10.97	9.07	−3.26	−17.37
λ_{norm}	3.66	0.21	−3.82	1.57	−1.05	−7.31	0.67	−0.24	−2.42
$t\text{-}ratio_{krs}$	(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]	
χ^2	0.04	0.01		0.23	0.10		0.11	0.01	
$pval_{Pricing\ error=0}$	[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]	

Factor	G. Global equities (1) Ret_{Global}	G. (2) Ret_{Global}	G. (2) $\Delta Corr$	H. All-inclusive w/o global equities (1) Ret_{Global}	H. (2) Ret_{Global}	H. (2) $\Delta Corr$	I. All-inclusive w/ global equities (1) Ret_{Global}	I. (2) Ret_{Global}	I. (2) $\Delta Corr$
λ	4.28	−3.63	−16.16	1.88	−3.58	−10.42	2.47	−1.86	−9.45
λ_{norm}	1.09	−0.93	−3.01	2.09	−3.98	−7.65	2.75	−2.07	−5.70
$t\text{-}ratio_{krs}$	(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]	
χ^2	0.42	0.18		0.69	0.38		0.94	0.75	
$pval_{Pricing\ error=0}$	[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]	

Notes. 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 ($\Delta Corr$) 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 (Menkhoff 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 it normalized price of covariance risk λ_{norm}, and the misspecification-robust t ratios ($t\text{-}ratio_{krs}$) are reported in parentheses. The p value for the test of the statistical significance of R^2 under $H0: R^2 = 0$, the p value for approximate finite sample p value of Shanken's CSRT statistic (a generalized χ^2 test), and the p value for the test of differences in R^2 between two nested models under $H0: R^2_{Model1} = R^2_{Model2}$ are reported in square brackets (Kan et al. 2013).

Figure 2. (Color online) Pricing Errors Plot by Asset Classes



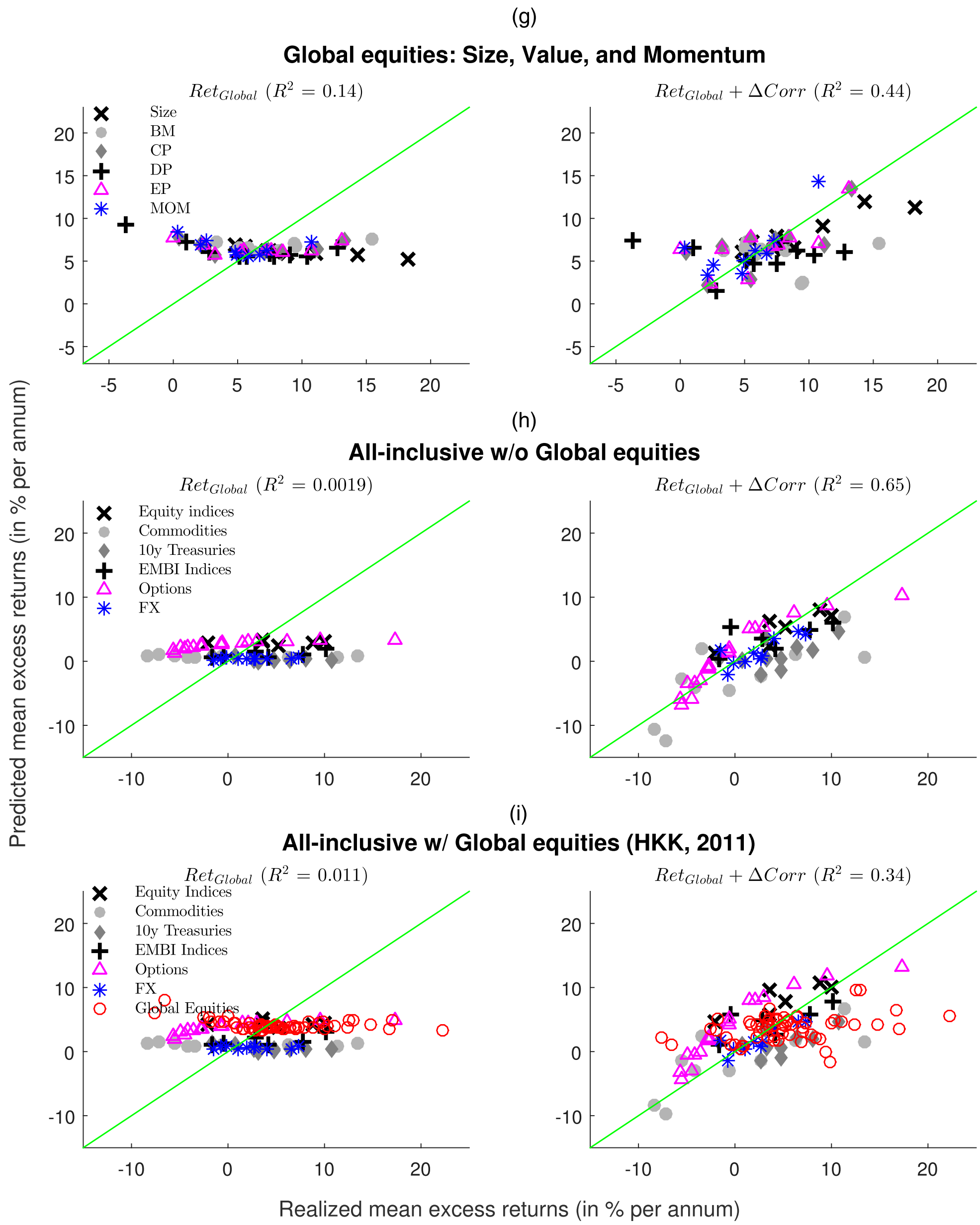
Asness et al. (2013), because value and momentum are the sole criteria considered in constructing their test assets. The specification for the CSR test is the same as in Table 4.

The first column of Table 5 reports the name of variables to be controlled in each regression. We present misspecification robust t-ratios for the price of covariance risk ($t - ratio_{krs}$) 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 confirm in our sample that both the downside risk factor (*DR-CAPM*) and the intermediary capital ratio factor (IC^{HKM}) can explain the spreads in mean returns of multiasset portfolios with R^2 ranging from 27% to 42% depending on the model specifications. The factor price is statistically significant under the misspecification robust CSR, and has the expected sign, that is, positive for all four alternative factors.

We then include our correlation factor along with the factors described above to evaluate the relative importance of our factor (model 2 of Table 4). We find that the price of the covariance risk for $\Delta Corr$ is statistically significantly different from zero in all cases except the Asness et al. (2013) portfolios with the downside risk or *Momentum-everywhere* as a controlling factor. For the economic magnitude of the pricing power, we have mixed results in terms of dominance of explanatory power for $\Delta Corr$ with respect to each of the other control variables. Using our benchmark all-inclusive multiasset portfolios as test assets in panel A, the normalized price of covariance risk (λ_{norm}) ranges from −2.81 to −3.43 after controlling for IC^{HKM} and *DR-CAPM*, respectively. These estimates are similar to those of our main regression in Table 4, and thus the pricing power of our factor is not affected by the inclusion of other factors. However, we also note that the economic magnitude of the pricing ability of $\Delta Corr$ is weaker than our benchmark case in explaining the portfolios of He et al. (2017) and Asness et al. (2013) after controlling for those alternative factors.[30]

Model 2 nests model 1 in each panel of the table; hence, the R^2s of the larger model should exceed those of the smaller model. We formally test whether R^2s of these two nested models are statistically different from each other under the assumption that the models

Figure 2. (Continued)



Notes. The figure presents the pricing errors of the asset pricing model with the global equity risk premium (Ret_{Global}) and the global equity correlation innovation ($\Delta Corr$) 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 (a) (Koijen et al. 2018), 10 portfolios using commodity futures in (b) (Yang 2013), 10 portfolios using 10-year treasury bond total-return series in (c), 6 emerging market sovereign bond portfolios sorted on bond beta and credit rating in (d) (Borri and Verdelhan 2011), 18 index option portfolios sorted on maturity and moneyness in (e) (Constantinides et al. 2013), 10 carry and momentum portfolios formed on foreign exchange rate futures in (f) (Menkhoff 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 (g) (Hou et al. 2011). For (h) ((i)), the test assets are 60 (120) all-inclusive portfolios without (with) global equity portfolios. The estimation results are based on the two-pass OLS-CSR test.

are potentially misspecified.[31] The last column of Table 5 shows that differences in R^2 of the cross-sectional regression are about 4% to 9%, and those are statistically different from the nested models without $\Delta Corr$. These incremental contributions in explanatory power are relatively small compared with those in our benchmark case in Table 4 in which we only control for the global equity risk factor (Ret_{Global}). This empirical result can be reconciled with the tight empirical and theoretical relationship between $\Delta Corr$ and the other factors.

Last, we perform CSR tests jointly with the global version of the three factors of Fama and French (1998) (*FF* three-factors model) and the three factors of Hou

Table 5. CSR Tests with Alternative Test Assets and Factors

		Model 1			Model 2				
Control factor	Statistics	Ret_{Global}	Control factor	$R^2_{Model\ 1}$ $pval_{R^2=0}$	Ret_{Global}	Control factor	$\Delta Corr$	$R^2_{Model\ 2}$ $pval_{R^2=0}$	Difference in R^2 $pval_{R^2_{Model1}=R^2_{Model2}}$
Panel A: All-inclusive w/ global equities (120 portfolios)									
IC^{HKM}	λ_{norm}	−1.65	4.24	0.31	0.37	2.31	−3.43	0.38	0.07
	$t\text{-}ratio_{krs}$	(−0.73)	(3.03)	[0.08]	(1.04)	(2.07)	(−2.95)	[0.03]	[0.02]
$DR\text{-}CAPM$	λ_{norm}	−1.01	3.11	0.30	−0.33	2.56	−2.81	0.37	0.07
	$t\text{-}ratio_{krs}$	(−1.32)	(3.24)	[0.12]	(−1.39)	(2.44)	(−3.07)	[0.05]	[0.01]
Panel B: HKM portfolios w/o CDS (104 portfolios)									
IC^{HKM}	λ_{norm}	1.26	3.66	0.42	1.42	4.69	−1.60	0.47	0.05
	$t\text{-}ratio_{krs}$	(1.74)	(2.75)	[0.04]	(1.76)	(2.51)	(−2.22)	[0.03]	[0.04]
$DR\text{-}CAPM$	λ_{norm}	−1.70	2.18	0.38	1.72	2.52	−1.50	0.42	0.04
	$t\text{-}ratio_{krs}$	(−1.29)	(2.01)	[0.02]	(0.27)	(2.86)	(−2.29)	[0.01]	[0.05]
Panel C: AMP portfolios (48 portfolios)									
IC^{HKM}	λ_{norm}	−1.41	3.95	0.27	−0.34	2.41	−1.84	0.36	0.09
	$t\text{-}ratio_{krs}$	(−0.26)	(2.46)	[0.02]	(−0.29)	(2.30)	(−2.08)	[0.01]	[0.01]
$DR\text{-}CAPM$	λ_{norm}	1.11	1.86	0.27	1.09	2.30	−1.19	0.33	0.06
	$t\text{-}ratio_{krs}$	(1.63)	(2.16)	[0.03]	(1.04)	(2.27)	(−1.18)	[0.03]	[0.20]
$Value^{AMP}$	λ_{norm}	−0.01	2.46	0.28	−0.08	2.23	−1.56	0.35	0.07
	$t\text{-}ratio_{krs}$	(−0.87)	(2.41)	[0.13]	(−0.55)	(2.21)	(−2.13)	[0.07]	[0.01]
$Momentum^{AMP}$	λ_{norm}	0.88	2.63	0.30	0.64	2.31	−1.81	0.35	0.05
	$t\text{-}ratio_{krs}$	(1.20)	(2.58)	[0.04]	(2.06)	(2.07)	(−1.38)	[0.11]	[0.18]

Notes. 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 ($\Delta Corr$). The it normalized price of covariance risk λ_{norm}, and the misspecification-robust t ratios ($t\text{-}ratio_{krs}$) are reported in parentheses. p Values from the test of the statistical significance of R^2 under $H0 : R^2 = 0$ and the p values from the test of differences in R^2 between two nested models under $H0 : R^2_{Model1} = R^2_{Model2}$ are reported in square brackets (Kan et al. 2013), respectively. As controlling factors, we use the intermediary capital ratio factor (IC^{HKM}) of He et al. (2017), the downside risk factor *DR-CAPM* of Lettau et al. (2014), and *Value-everywhere* and *Momentum-everywhere* factors ($Value^{AMP}$ and $Momentum^{AMP}$) of Asness et al. (2013). The test assets in panel A are 120 all-inclusive portfolios: 6 portfolios formed on equity index futures, 10 portfolios formed on commodity futures, 10 portfolios formed on foreign exchange rate futures, 10 portfolios using 10-year treasury bond total-return series, 6 emerging market sovereign bond portfolios, 18 equity index option portfolios, and 60 global equity portfolios. The test assets in panel B are 104 portfolios from He et al. (2017): Fama-French 25 size-value sorted portfolios, 10 maturity sorted U.S. government bonds, 10 yield spread sorted U.S. corporate bonds, 6 sovereign bonds, 18 moneyness and maturity sorted S&P 500 index options, 23 commodities, and 12 carry and momentum sorted foreign exchange rates. The test assets in panel C are the 48 portfolios of Asness et al. (2013): 6 value and momentum portfolios constructed from the U.S. stock market, the U.K. stock market, European stock market, Japanese stock market, international equity indices, foreign exchange rates, fixed income securities, and commodities.

et al. (2011), which include the global market, the global C/P, and the global momentum factors (*HKK* three-factors model). This setup allows us to find the incremental contribution of our factor in explaining the joint cross-section of 120 all-inclusive portfolios in addition to those two sets of three-factors models. Panel (b) (panel (d)) of Figure 3 shows that the *FF* (*HKK*) three-factors model contributes to the benchmark global CAPM model with an increment of 30% (29%) in R^2. After adding $\Delta Corr$ factor to those alternative pricing models, panels (c) and (e) of Figure 3 show that the extended four-factor models now explain 43% and 50% of the joint variation in returns of 120 all-inclusive portfolios, respectively. This evidence further confirms that $\Delta Corr$ improves the cross-sectional fit in economically and statistically significant ways even after controlling for *FF*'s or *HKK*'s three factors.

5.5. Robustness

In this section, we explore various empirical measures of our correlation factor. Given that the United States plays a dominant role in financial markets, it is prudent to emphasize the marginal effect of different weighting on our correlation measure. To illustrate this, we construct four other measures of the aggregate intramonth correlation level: $Corr_{GDP}$, $Corr_{MKT}$, $Corr_{LOC}$, and $Corr_{OOS}$. The correlation level for $Corr_{GDP}$ ($Corr_{MKT}$) is estimated by computing the GDP-weighted (market capitalization–weighted) average over all bilateral correlations at the end of each month using the previous quarter's dollar values of GDP (market capitalization). The level for $Corr_{LOC}$ is the equally weighted average of bilateral correlation using index returns in local currency units. Lastly, we consider a model-based correlation measure ($Corr_{OOS}$), which relies on the Dynamic Equicorrelation (DECO) model of Engle and Kelly (2012).[32] In Table 6, we verify that the averages of correlation innovation factors are all close to zero and highly correlated to each other. These results suggest that different weighting schemes across countries do not have a significant effect on the construction of our factor.

Second, we explore different asset pricing test methodologies and present the asset pricing test results in Table 7. Regarding asset pricing methodologies, we first use CSR-OLS in panel A. Given that our factor is a nontraded factor, we use CSR-OLS as our main methodology because it has a direct interpretation of the cross-sectional R^2, and it allows us to make proper adjustments for beta estimation errors and misspecification errors. In this section, we also run two-pass CSR-GLS in panel B,[33] the Fama-MacBeth regression under both constant beta and time-varying beta assumption in panels C and D respectively,[34] and use GMMs methods of Hansen (1982) and Dumas and Solnik (1995) in panel E.[35]

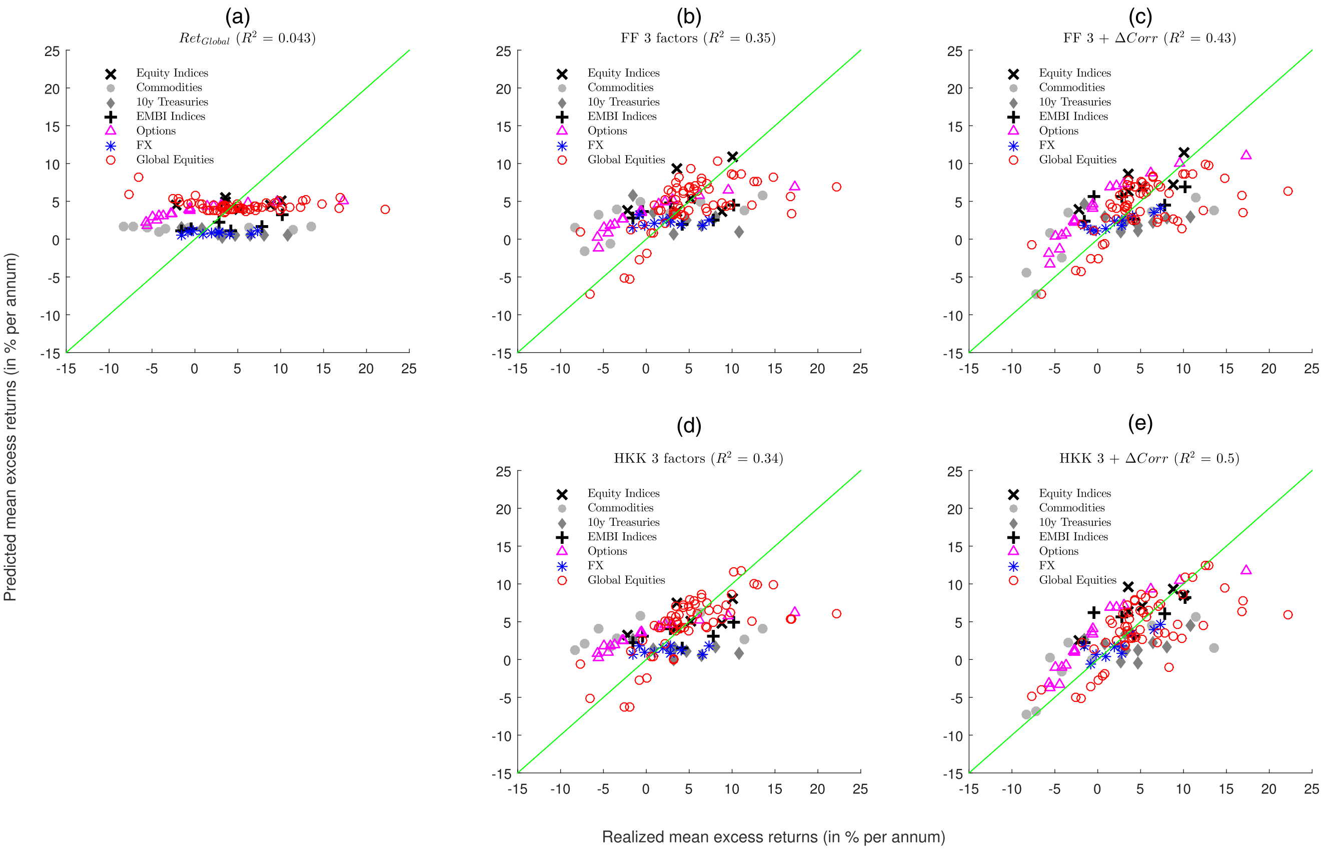
In each panel of Table 7, we perform one of the tests illustrated previously and present the price of covariance risk (λ), the price of beta risk normalized by standard deviation of the cross-sectional covariances (λ_{norm}), and corresponding *t* ratios in parentheses. In each column, we use one of the five different measures of our correlation innovation factor. Overall, our results show that we have robust estimates of the price of risk across different factor construction and asset pricing methodologies. The economic significance of the price of risk is stronger under the equally-weighted correlation measures. This evidence suggests that the cross-country correlations taken from smaller countries may be a better proxy for correlations coming from the discount rate channel, as implied by the Lucas orchard model of Martin (2013). On average, one standard deviation of cross-sectional differences in covariance exposure to our factor can explain about 3.5% per annum in the cross-sectional differences in mean return of 120 multiasset portfolios.

Last, as increases in global equity correlation implies greater perception of risk of a global representative agent, it should forecast future stock market excess returns. Table A4 in the online appendix reports nonoverlapping time-series regression results with *k*-month forecasting horizon in which the dependent (independent) variable is the excess return of global stock market (detrended level of the global equity correlation).[36] We find that the global equity correlation positively predicts future excess global stock market returns up to six-month horizons. The predictability is also economically significant. Using three-month forecast horizon as an example, a one standard deviation increase in the global equity correlation predicts 1.23% additional global stock market excess return over the following quarter.

5.6. A Special Case: Carry and Momentum Strategies in the FX Market

Carry and momentum trades are widely known strategies in the FX market. As the strategies draw more attention from global investors, there have been recent developments to create benchmark indices and ETFs reflecting their popularity. Despite the popularity, it has proven rather challenging to explain those excess returns through traditional equity-based risk factor exposures. Moreover, carry and momentum strategies seemingly have differential risk exposures, and thus it is difficult to provide risk-based explanations simultaneously (Burnside et al. 2011b, Menkhoff et al. 2012b). For this reason, we examine FX carry and momentum portfolios as a separate piece of testing ground and aim to show that the cross-sectional variations in their average excess returns can be

Figure 3. (Color online) Pricing Errors Plot with FF and HKK Factors



Notes. The figure presents the pricing errors of the asset pricing model with the global *FF* three-factors (*HKK* three-factors) augmented with the global equity correlation innovation ($\Delta Corr$) 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 120 all-inclusive portfolios, which consist of 6 carry and momentum portfolios formed on equity index futures (Koijen et al. 2018), 10 portfolios using commodity futures (Yang 2013), 10 portfolios using 10-year treasury bond total-return series, 6 emerging market sovereign bond portfolios sorted on bond beta and credit rating (Borri and Verdelhan 2011), 18 index option portfolios sorted on maturity and moneyness (Constantinides et al. 2013), 10 carry and momentum portfolios formed on foreign exchange rate futures (Menkhoff et al. 2012b), and 60 global equity portfolios sorted on size, B/M, C/P, D/P, E/P, and momentum using international stocks (Hou et al. 2011). The estimation results are based on the CSR-OLS test.

explained by different sensitivities to our correlation factor. We also test whether our factor explains significant excess returns of carry and momentum strategies not only jointly but also separately.

Carry and momentum portfolios are the portfolios where currencies are sorted based on their interest rate differentials and past returns, respectively. We refer to all the resulting portfolios as *FX 10* portfolios. The summary statistics of *FX 10* portfolios are presented in Table 8, and the details of portfolio construction methodologies for both carry and momentum are described in Section A of the online appendix.

We follow the convention in the foreign exchange literature (Lustig et al. 2011) to include the dollar risk factor (*DOL*) in all the main empirical asset pricing tests. *DOL* is the aggregate FX market return available to a U.S. investor and it is measured simply by averaging all excess returns available in the FX data at each point in time. Although *DOL* does not explain any of the cross-sectional variations in expected returns, it plays an important role for FX portfolios because it captures the common fluctuations of the USD 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 $\Delta Corr$. We first examine carry and momentum portfolios separately to understand whether the explanatory power of the cross-sectional differences 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 $\Delta Corr$ factor is negatively priced across many asset classes including the foreign exchange market. We confirm the empirical result in panel A of Table 9 that $\Delta Corr$ 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 significant

Table 6. Moments of Correlation Innovation Factors

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

Notes. This table reports sample statistics of global equity correlation innovation factors. From the first to the third columns, the correlation levels are measured by computing bilateral intramonth correlations using daily return series of international MSCI equity indices (in USD). 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 intramonth 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 first difference of each of the correlation level series. The sample covers the period March 1976 to December 2014.

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 significant under the estimation error adjustment of Shanken (1992) and the misspecification error adjustment, with a *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 the correlation factor between high and low portfolios are significantly different from each other (*Beta Spread* in Table 9). The *p* values of the test of Patton and Timmermann (2010) under the null hypothesis of zero beta spread ($H0 : |\beta_5 - \beta_1| = 0$) show that the beta spreads are statistically different from zero at a 5% rejection level for both carry and momentum portfolios. Overall, we have high explanatory power over the cross section of average returns across carry and momentum portfolios. We find that $\Delta Corr$ 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 thee average annualized average returns for High Minus Low portfolios (*HML Spread* in Table 9), and associated *p* values under the null hypothesis that *HML Spread* are not statistically different from zero. Last, we perform the monotonicity test of Patton and Timmermann (2010) and find that average portfolio returns are monotonically increasing with underlying characteristics ($pval_{Monotonicity}$). Using these alternative sets of FX portfolios, $\Delta Corr$ 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 three 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, and (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

Table 7. Alternative Factors and Asset Pricing Tests

	1. *Corr*		2. $Corr_{GDP}$		3. $Corr_{MKT}$		4. $Corr_{LOC}$		5. $Corr_{OOS}$	
	Ret_{Global}	$\Delta Corr$	Ret_{Global}	$\Delta Corr_{GDP}$	Ret_{Global}	$\Delta Corr_{MKT}$	Ret_{Global}	$\Delta Corr_{LOC}$	Ret_{Global}	$\Delta Corr_{OOS}$
Panel A: CSR-OLS										
λ	−1.86	−9.45	1.53	−4.69	1.58	−4.67	−2.71	−5.81	−3.02	−16.33
λ_{norm}	−2.07	−5.70	1.70	−2.92	1.75	−2.99	−3.01	−6.55	−3.35	−6.70
$t\text{-}ratio_{krs}$	(−0.72)	(−3.13)	(0.75)	(−2.14)	(0.77)	(−2.17)	(−0.92)	(−2.64)	(−1.15)	(−3.01)
Panel B: CSR-GLS										
λ	−1.16	−4.21	−0.01	−2.60	0.03	−2.50	−4.21	−4.97	−3.04	−10.75
λ_{norm}	−1.29	−2.94	−0.01		0.03		−4.68		−3.38	−4.41
$t\text{-}ratio_{krs}$	(−0.65)	(−3.69)	(−0.01)		(0.02)		(−2.04)		(−1.56)	(−4.62)
Panel C: Fama-MacBeth in-sample										
λ	4.41	−12.99	5.00	−4.66	4.96	−4.02	4.78	−7.04	4.74	−14.33
λ_{norm}	3.62	−3.52	4.11	−2.42	4.09	−2.28	3.87	−2.33	3.85	−2.88
t-ratio	(2.62)	(−5.08)	(3.11)	(−3.72)	(3.12)	(−3.12)	(2.88)	(−4.30)	(2.91)	(−4.21)
Panel D: Fama-MacBeth rolling 60M										
λ	4.52	−3.56	4.93	−2.35	5.05	−2.42	4.68	−2.06	4.28	−6.53
λ_{norm}	3.94	−2.53	4.26	−1.19	4.36	−1.25	4.02	−1.39	3.69	−1.57
t-ratio	(2.41)	(−4.31)	(2.66)	(−1.57)	(2.75)	(−1.41)	(2.48)	(−2.05)	(2.19)	(−3.34)
Panel E: GMM										
λ	−2.09	−9.56	1.38	−3.75	1.43	−3.78	−2.93	−5.96	−3.35	−16.75
λ_{norm}	−2.33	−5.82	1.53	−1.97	1.60	−2.06	−3.26	−6.68	−3.74	−6.95
t-ratio	(−0.64)	(−3.15)	(0.52)	(−1.93)	(0.54)	(−1.91)	(−1.14)	(−3.42)	(−1.32)	(−2.33)

Notes. 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 first pass, we run time-series regressions to estimate each asset's beta to the risk factors. In the second pass, we run CSRs 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 first pass regression is the same as *CSR-OLS*. In the second pass, we run CSRs 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 CSRs, 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 by specifying the pricing kernel to be a linear function of the risk factors (see Section D of the online appendix). The misspecification robust t ratios from Kan et al. (2013) are reported in parentheses for *CSR-OLS* and *CSR-GLS*. The heteroskedasticity and autocorrelation adjusted t ratio with automatic lag selection from Newey-West (1994) are reported in parentheses for *Fama-MacBeth* and *GMM*. The sample covers the period March 1976 to December 2014.

Table 8. Summary Statistics of Test Assets in the FX Market

	All countries (44)						Developed countries (17)					
	Low	2	3	4	High	HML	Low	2	3	4	High	HML
Panel A: Carry: Portfolios sorted on forward discounts												
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
Standard deviation	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												
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
Standard deviation	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

Notes. 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 three 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 differentials (or past returns), whereas portfolio 5 contains currencies with the highest interest differentials (or past returns). HML denotes differences in returns between portfolio 5 and 1. We use three-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.

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 the 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 comovements in international equity returns and 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 using the first difference in aggregate volatility. The aggregate volatility is measured by averaging intramonth realized volatilities for all MSCI 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 multiasset portfolios and $FX10$ portfolios using the correlation residual factor ($\Delta Corr_{resid}$) after controlling for the effect of ΔVol. In the second test, ΔVol is orthogonalized against $\Delta Corr$ and the volatility residual factor (ΔVol_{resid}) is used jointly with $\Delta Corr$. The results from the formal test are shown in panel A and those from the latter test are shown in panel B of Table 11.

Panel A shows that the price of risk to our correlation factor $\Delta Corr_{resid}$ is economically and statistically significant after orthogonalizing the volatility components. Although ΔVol still remains significant,

Table 9. CSR Tests in the FX Market

	Carry only		Momentum only		Both	
Factor	*DOL*	$\Delta Corr$	*DOL*	$\Delta Corr$	*DOL*	$\Delta Corr$
			Panel A: Benchmark portfolios			
λ	3.39	−26.33	0.93	−16.08	1.50	−18.70
λ_{norm}	0.06	−2.60	0.04	−2.67	0.05	−2.39
$t\text{-}ratio_{fm}$	(1.53)	(−5.52)	(0.46)	(−6.29)	(0.74)	(−7.89)
$t\text{-}ratio_{s}$	(0.47)	(−1.78)	(0.21)	(−3.32)	(0.30)	(−3.48)
$t\text{-}ratio_{krs}$	(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]	
χ^2	0.001		0.006		0.011	
$pval_{Pricing\ error=0}$	[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			
λ	1.06	−15.69	3.35	−21.05	2.18	−18.96
λ_{norm}	0.04	−1.41	0.15	−2.38	0.12	−1.81
$t\text{-}ratio_{fm}$	(0.50)	(−3.96)	(1.50)	(−5.03)	(1.05)	(−6.21)
$t\text{-}ratio_{s}$	(0.23)	(−1.87)	(0.56)	(−1.92)	(0.43)	(−2.51)
$t\text{-}ratio_{krs}$	(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]	
χ^2	0.001		0.002		0.004	
$pval_{Pricing\ error=0}$	[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]			

Notes. The table reports cross-sectional pricing results for the factor model based on the dollar risk factor (*DOL*) and the global equity correlation innovation ($\Delta Corr$) measured by taking the first difference on the average intramonth 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 differentials 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 λ and the price of covariance risk it normalized by standard deviation of the cross-sectional covariances λ_{norm} are reported. The t ratios of Shanken (1992) under correctly specified models accounting for the errors-in-variables problem ($t\text{-}ratio_s$) and the misspecification-robust t ratios of Kan et al. (2013) ($t\text{-}ratio_{krs}$) are reported in parentheses. The p value for the test of $H0: R^2 = 0$, the p value for approximate finite sample p value of Shanken's CSRT statistic (a generalized χ^2 test), and the p value for the test of Hypothesis 0: $|\beta_5 - \beta_1| = 0$ (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 Hypothesis 0: *HML Spread* = 0, and the p value for the monotonic relationship test from Patton and Timmermann (2010).

the cross-sectional fit on 120 all-inclusive ($FX10$) portfolios can be improved by 19% (28%) by adding $\Delta Corr_{resid}$, and this difference in R^2 is also statistically significant. However, the opposite is not true. In panel B, the global equity volatility innovation (ΔVol) does not have pricing power after removing the correlation component. The t ratios drop to −1.10 (−0.45) from −2.80 (−2.24) and the difference in R^2 becomes marginal 8% (1%) when the test is performed in 120 all-inclusive ($FX10$) portfolios. Therefore, we conclude that innovations in the average correlation rather than volatility reveal changes in the true perception of aggregate risk more clearly. This finding is also consistent with Driessen et al. (2009) that the correlation risk is priced but not the average of all individual variance risk in the cross-section of option returns.

Table 10. CSR Tests Including Other Factors in the FX Market

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

Notes. 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 ($\Delta Corr$). 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 (λ_{norm}) are reported. The misspecification-robust t ratio ($t\text{-}ratio_{krs}$) 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: ΔFX_{VOL}, the aggregate FX volatility innovations (Menkhoff et al. 2012a); ΔFX_{CORR}, the aggregate FX correlation innovations (Mueller et al. 2017); ΔTED, TED spread innovation; ΔFX_{BAS}, innovations to the aggregate FX bid-ask spreads (Mancini et al. 2013); ΔLIQ_{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 significance of R^2 under $H0: R^2 = 0$ and the p value for the test of differences in R^2 between two nested models under $H0: R^2_{Model1} = R^2_{Model2}$ are reported in square brackets (Kan et al. 2013).

Table 11. CSR Tests with Volatility Innovation Factor

	Model 1			Model 2				
Statistics	Control factor	ΔVol	R^2_{Model1} $pval_{R^2=0}$	Control factor	ΔVol	$\Delta Corr_{\text{resid}}$	R^2_{Model2} $pval_{R^2=0}$	Difference in R^2 $pval_{R^2_{Model1}=R^2_{Model2}}$
Panel A: Correlation residual								
Subpanel 1: All-inclusive w/ global equities								
λ_{norm}	–2.75	–6.14	0.29	–4.72	–5.63	–3.59	0.48	0.19
$t\text{-}ratio_{krs}$	(–1.21)	(–2.75)	[0.08]	(–1.51)	(–2.80)	(–2.00)	[0.02]	[0.01]
Subpanel 2: FX only								
λ_{norm}	0.16	–1.48	0.57	0.15	–1.90	–2.11	0.84	0.28
$t\text{-}ratio_{krs}$	(1.18)	(–2.50)	[0.00]	(0.68)	(–2.24)	(–2.71)	[0.00]	[0.02]
Panel B: Volatility residual								
Subpanel 1: All-inclusive w/ global equities								
λ_{norm}	–2.07	–5.70	0.33	–4.61	–3.52	–5.42	0.40	0.08
$t\text{-}ratio_{krs}$	(–0.72)	(–3.13)	[0.06]	(–1.41)	(–1.10)	(–2.53)	[0.02]	[0.28]
Subpanel 2: FX only								
λ_{norm}	0.05	–2.39	0.82	0.08	–0.34	–2.32	0.83	0.01
$t\text{-}ratio_{krs}$	(0.27)	(–3.48)	[0.00]	(0.43)	(–0.45)	(–3.36)	[0.00]	[0.66]

Notes. This table reports the price of covariance risk (λ) for the global equity volatility (ΔVol) and the global correlation innovation ($\Delta Corr$) factors from the various forms of asset pricing models. The global equity volatility innovation factor is measured by taking the first difference on the average intramonth volatility for all MSCI 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 (λ_{norm}) and the misspecification robust t ratios from Kan et al. (2013) are reported in parentheses. The p value for the test of the statistical significance of R^2 under $H0: R^2 = 0$ and the p value for the test of differences 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.

6. Conclusion

Although the asset pricing literature echoes the importance of understanding the main drivers of the pricing kernel across markets and asset classes, the list of robust candidates is still short. In this paper, we build a simple model to motivate that the innovation in correlation across equity markets is a good proxy for the global risk aversion and a viable pricing factor across markets and asset classes. We present a series of empirical results supporting that our factor explains the cross-sectional differences in excess returns of a wide array of asset classes including global equities, commodities, developed and emerging market sovereign bonds, foreign exchange rates, and options. By showing that a factor constructed from the international equity market can explain abnormal returns in various markets, we shed some light on the discussion of the linkage between markets and their risk premia.

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Endnotes

[1] The correlation-based factor as a measure of the aggregate risk can also be motivated by the analysis in Pollet and Wilson (2010). They document that because the aggregate wealth portfolio is a common component of all assets, the changes in the true aggregate risk reveal themselves through changes in the correlation between observable stock returns. Therefore, an increase in the aggregate risk must be associated with increased tendency of comovements across international equity indices.

[2] Given that the United States plays a dominant role in financial markets, we construct two alternative measures of the aggregate intramonth correlation levels: GDP and market capitalization weighted average of all bilateral correlations. We show that different weightings do not have a large effect on the pricing power of our factor.

[3] Equity returns become more internationally correlated after bad global fundamental shocks because of the asymmetric valuation effect that originates from higher level of risk aversion. This asymmetric response because of 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 (2013) and Bekaert and Hoerova (2016) for evidence on VIX and variance risk premia.

[5] We rely on the asymptotic distribution of the sample R^2 in the second-pass CSR as the basis for this specification test.

[6] We thank an anonymous referee for this suggestion.

[7] Although the independence is not necessary in our setting, we use it for two reasons. First, it simplifies the notations. Second, it reveals that we can endogenously generate correlation dynamics even in the absence of correlated dividend.

[8] When goods in one country is not substitutable from goods in other countries ($\eta = 1$), $S_{i,t}$ becomes constant ($S_{i,t} = \theta_i$). In this case, the relative price of good i increase just enough to compensate a negative supply shock to $D_{i,t}$. Therefore, the relative size of economy in a common base currency always remains constant as in Hassan (2013). In the other extreme case, when goods are perfectly substitutable ($\eta = \infty$), the prices are the same across all countries, and the exchange rate is constant ($e_{i,t} = 1$). With $\eta = \infty$, the relative size of country i is simply the dividend share $S_{i,t} = \frac{D_{i,t}}{\sum_{n=1}^{N} D_{n,t}}$, as in Cochrane et al. (2008).

[9] In the empirical sections of our paper, we use the global stock market return as a control variable because the marginal utility can also be 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 ($\sum_{n=1}^{N} S_{n,t}(R_{n,t} - E_t[R_{n,t}])$). In the online appendix, we show that Equation (8) can be noted as follows: $\frac{d\Lambda_{i,t}}{\Lambda_{i,t}} = E_t\left[\frac{d\Lambda_{i,t}}{\Lambda_{i,t}}\right] - \frac{\sigma}{\eta} dB_{i,t} + \frac{(\eta-1)\sum_{n=1}^{N} S_{n,t}\kappa_{n,t}\sigma dB_{n,t}}{\eta \sum_{n=1}^{N} S_{n,t}\tilde{\gamma}_{n,t}} + \left[\frac{d\gamma_t}{\gamma_t} - E_t\left[\frac{d\gamma_t}{\gamma_t}\right]\right] - \frac{\eta-1}{\eta\sum_{n=1}^{N} S_{n,t}\tilde{\gamma}_{n,t}}\left[R_{g,t} - E_t[R_{g,t}]\right]$.

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

$$V_{i,t} = \frac{1}{2\delta S_{i,t}}\left[1 + \left(\frac{1-S_{i,t}}{S_{i,t}}\right)\ln(1 - S_{i,t}) - \left(\frac{S_{i,t}}{1-S_{i,t}}\right)\ln(S_{i,t})\right]$$

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 comovement among international equity returns.

[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.

[12] The choice of countries is dictated by data availability for the portfolio construction and our empirical results are not sensitive to our selection of countries. We also construct $\Delta Corr$ using MSCI equity indices in local currencies in Section 5. We show that the equity correlation innovation is not largely affected by currency correlation.

[13] First, for a stock to be included in our data set, at least one of the six financial variables must be available for a minimum of one year. Second, we only select common stocks that are traded on the country's major exchange(s), excluding preferred stocks, Real Estate Investment Trust (REIT), depositary receipts, warrants, and closed-end funds. Third, we set both R_t and R_{t+1} to missing if R_t or R_{t+1} is greater than 300% and $(1 + R_t)(1 + R_{t+1}) - 1 \leq 50\%$. Fourth, we drop observations with previous month price less than $1.00 to reduce errors in Datastream. Fifth, firms are required to have at least 12 monthly returns. To limit the survivorship bias, we include dead stocks in the sample.

[14] See www.globalfinancialdata.com.

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

[16] For robustness, we consider other model-free measures of our correlation factor weighted by GDP and market capitalization of countries. We also consider a model-based correlation measure that relies on the DECO model of Engle and Kelly (2012). We report the details of alternative models for measuring the correlation factor in Section 5.5.

[17] Based on an augmented Dicky-Fuller stationary test and Breusch-Godfrey serial dependence tests (untabulated), $\Delta Corr$ is stationary. Therefore, it is a statistically valid factor under an unconditional CSR framework. Furthermore, given that we rely on the unconditional cross-sectional regression as our main test, the existence of autocorrelation should not affect the validity of our test.

[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 are from Option Metrics.

[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. Market microstructure issues such as different time zones and stale prices of smaller countries can be mitigated for the internal correlation measure.

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

[22] Panel A of Figure A1 in the online appendix compares $\Delta Corr$ 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 in the online appendix 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.

[23] Kan et al. (2013) emphasize that statistical significance of the price of covariance risk is an important consideration if we want to answer the question of whether an extra factor improves the cross-sectional R^2. They also show how to use the asymptotic distribution of the sample R^2 in the second-pass CSR as the basis for a specification test.

[24] We describe the details of portfolio construction methodologies for the FX carry and momentum in Section 5.6 as a special case.

[25] Kan et al. (2013) show empirically that misspecification-robust standard errors are substantially higher when a factor is a nontraded factor. That is because the effect of misspecification adjustment on the asymptotic variance of beta risk is potentially large because of the variance of residuals generated from projecting the nontraded factor on the returns. It is thus important to note that our correlation factor, although not being traded, has a highly significant t ratio.

[26] None of the intercepts of the extended two-factor models (model 2) are statistically significant. We present intercepts of those regression models in Table A2 of the online appendix.

[27] We thank an anonymous referee for this suggestion.

[28] The 104 portfolios include Fama-French 25 size-value sorted portfolios, 10 maturity sorted U.S. government bonds, 10 yield spread sorted U.S. corporate bonds, 6 sovereign bonds, 18 moneyness and maturity sorted S&P 500 index options, 23 commodities, and 12 carry and momentum sorted foreign exchange rates. We exclude Credit Default Swap (CDS) portfolios because of short sample periods.

[29] The 48 portfolios include 6 value and momentum portfolios constructed from the U.S. stock market, the U.K. stock market, European stock market, Japanese stock market, international equity indices, foreign exchange rates, fixed income securities, and commodities.

[30] We find that the portfolios of He et al. (2017) and Asness et al. (2013) are U.S.- and equity-centric, respectively. Our factor generally has higher estimated prices of risk using global-centric multiasset portfolios.

[31] The R^2s of two nested models are statistically different from each other if and only if the covariance risk (λ) of the additional factor is statistically different from zero with misspecification robust errors. Therefore, we perform a statistical test on the price of covariance risk of our correlation factor under the null hypothesis of zero price (Hypothesis 0: $\lambda_{\Delta Corr} = 0$). Although we only show the case for the price of covariance risk, similar results can be obtained from the tests of the price of beta risk.

[32] An implicit assumption behind our realized correlation measures is that all parts of returns are perceived as shocks by investors. To mitigate this issue, we implement the DECO model and describe the details of the model in the online appendix (Section C). Although the model is implemented in an out-of-sample manner, it is still not a fully conditional model because the standardization process involves estimating an unconditional mean at each time t. We perform an additional robustness check with a conditional mean assumption and confirm that the pricing results are similar to empirical results reported in this section.

[33] CSR-GLS is a different way of measuring and aggregating sampling deviations. Although GLS may be of greater interest from an investment perspective, we use OLS in our main analysis and GLS as robustness check because our focus is on the expected returns for a particular set of test portfolios.

[34] Following the tradition in the literature, we use a rolling 60-month window for the estimation of time-varying portfolio beta. We correct for heteroskedasticity and autocorrelation in errors by using the standard errors of Newey and West (1987) computed with optimal number of lags according to Newey and West (1994).

[35] We report the details of the GMM methodology and underlying assumptions in the online appendix (Section D). The basic assumption is that stochastic discount factor (SDF) is linear in our factors ($m_{t+1} = 1 - \lambda_{DOL}(DOL_{t+1} - \mu_{DOL}) - \lambda_{Corr}(\Delta Corr_{t+1} - \mu_{\Delta Corr})$). Standard errors are also corrected for heteroskedasticity and autocorrelation with optimal number of lags using Newey and West (1994).

[36] To detrend the level of correlation, in panel A, we run the following time-series regression, $Corr_t = \alpha + \beta \cdot t + \epsilon_t$, and we define the residual of the regression (ϵ_t) as a detrended level of the global equity correlation ($Corr_{detrended,\,t}$). In panel B, we subtract 12-month exponential moving average (EMA) from the level of correlation.

[37] The price of the covariance risk, λ_{norm} in Table 9, is also economically significant, because one standard deviation of cross-sectional differences in covariance exposure can explain about 2.39% per annum in the cross-sectional differences in mean returns across *FX 10* portfolios.

[38] Regarding alternative downside market risk explanations, Jurek (2014) demonstrates that crash risk premia account for around 10% of the excess returns of the carry trade. We also control for downside beta with respect to the world equity market risk factor as in Lettau et al. (2014) and find our results are robust.

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

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