Exploring Risk Premium Factors for Country Equity Returns

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Abstract

In this paper, we study a comprehensive set of risk premia of country equity returns for 45 countries over the sample period 2002 to 2018 in both a single and a multiple factor setting. Using a new three-pass estimation method for factor risk premia by Giglio and Xiu (2021), we find that several factors, including default risk, are also priced in country equity excess returns, controlled by the Fama-French 5-factor and Carhart model. Moreover, we apply a novel approach to investigate the multi-factor impact on country equity returns. We find that the multi-factor information, constructed from the first principal component of the statistically significant single factors, provides a consistent and stronger prediction of anomalies in country equity returns.

Keywords: Country Equity Return, Country-based Portfolio, Country Risk Premium, Country Equity Asset Pricing Model

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1 Introduction

Country equity allocation has become increasingly important for investors with the rise of globalization and the interconnectedness of financial markets. In general, market practitioners regard local equity markets to be less efficient and less diversifiable on a global scale.[1] A recent report notes that country selection accounts for 24% of equity returns over the past decade.[2] However, the launch of new financial products, e.g., global ETF (Exchange-Traded Fund) or tradable country-related index, has made country equity investments widely popular in financial markets.

There is a long-established literature on equity risk premia for individual stocks (see, e.g., Fama and French, 1993; Carhart, 1997; Fama and French, 2015; Hou et al., 2015). Yet, asset pricing research on country equity returns is still relatively scarce. In this paper we aim to bridge this gap in the literature by investigating risk premia factors that could explain country equity returns. Therefore, this paper adds to the strand of the literature focused on factor investing based on stocks, and also provides useful insights to asset managers that specialize in global asset allocation strategies.

Understanding financial anomalies is important and has been a central question in the extant financial economics literature. In a cross-country investment perspective, market anomalies are key to investors because investors need to manage the risk-return profile of their investments. It is also potentially relevant for policy makers and global financial regulators, because equity markets have become in recent years more interconnected. Consequently, regulators might need to look closely at the main drivers that influence cross-country equity investments.

The aim of this paper is to provide a comprehensive analysis of risk premia for country equities. Most of the studies on the pricing factors for the equity market are only conducted at domestic (primarily U.S) stock market level. Furthermore, these studies centre on the predictability of the individual factor, while we also study the multi-factor information. An established fact from these prior studies is that individual factors do not actually convey stable return predictability.[3] Such instability possibly originates from the evidence that asset prices are so noisy that single factors fail to provide stable and consistent information (Asparouhova et al, 2013). Though we do not understate the importance of single factors; we argue that the multi-factor approach that combine multiple single factor information can provide stable and stronger prediction on country equity returns.

[1] Vangard, "Considerations for global equities: A UK investor's perspective", January 2014 (https://www.vanguard.co.uk/documents/adv/literature/case-for-global-equities-tlisg.pdf).
[2] LAPF Investments, "Why country allocation matters", August 2015 (https://www.lapfinvestments.com/2015/08/why-country-allocation-matters-2/).
[3] In recent years, studies started examining if single pricing factors identified in the literature actually carry predictability, but they found most of them do not. e.g. Green et al. (2017) study 94 firm-specific factors and find only 12 of them can predict the monthly stock return.

Our study contributes to the growing empirical literature on country equity risk premia. Prior research on country equity returns only focuses on classical pricing factors, e.g. Fama-French related factors, momentum, etc. Using a unique and rich proprietary database, we are able to explore a range of country-specific factors that can potentially explain country risk premia. Hence, we contribute to this strand of the literature in two main ways. First, our dataset enables us to identify a richer set of driven factors for global investment strategies. Second, we identify the factors that provide independent, non-redundant information for country equity returns. Therefore, future research on country equity returns should include these factors as control variables, given the statistically significant inference of the factors, to avoid omitted variable bias.

We provide the first broad empirical evidence of the factors that can predict country equity returns by investigating a broad range of country-specific factors. Our major finding is that, in addition to existing factors identified in prior asset pricing research, default risk is also priced in country equity returns. More importantly, our study sheds light on how multi-variate information explains country equity risk premia. These findings distinguish our analysis from alternative previous theories and empirical investigations. Therefore, our paper fills an important gap in the asset pricing literature as the mainstream country equity studies are based solely on single-variable predictors (e.g. Asness et al., 1997; Desrosiers et al., 2004).

Empirically, we examine a comprehensive dataset of 90 country-specific variables for 45 countries over the 2002–2018 period and explore the predictability power of these factors for country equity returns. We use the MSCI country index as a proxy of country equity return and the single-sorted tritile portfolio to examine the excess return (defined as the MSCI country index return controlled by the Fama-French 5-factor and Carhart factor model) to identify country factors that explain significant abnormal returns.

In this paper, we use two methods to estimate the factor risk premia. We first use the Fama-MacBeth two-pass estimation approach. Although the Fama-MacBeth two-stage procedure yields insights on the factor risk premia in a time-varying context, the estimation, however, raise two major concerns in a country-specific factor case. First, we are unable to include all the country-specific factors because the number of countries is smaller than that of factors, and this leads to potential bias caused by omitted variables. Another concern is the measurement error of the factor. Hence, to obtain the factor risk premia adjusted by the omitted variable bias and the measurement error, we turn to a novel three-pass estimation methodology proposed recently by Giglio and Xiu (2021), which can be viewed as a PC-augmented two-pass regression.

The risk premia estimates can be obtained via a three-stage procedure, and the risk premia for the observed factors are adjusted by the omitted variable bias and measurement error in the factor. The factor risk premia using the three-pass estimation are still valid when not all the factors in the regression model are included, even when a subset of the country-specific factors is used for risk premia estimation. This implies that the risk premia estimates and their statistical inference are statistically unaffected when some country-specific factors are omitted.

Notably, we find that approximately one-fifth of the country-specific variables can generate abnormal returns, and the results are robust to using different methods of portfolio constructions (i.e. equal weight, market-cap weight, and volatility weight), as well as in the regression analysis.

Moreover, when we break down these pronounced country-specific variables, we identify a new type of factor which also contributes to the abnormal return: default risk (i.e. DEBT_CAPITAL and DEBT_EQUITY), along with value, size, and momentum factors, as uncovered in prior academic research. It is important to note that the default risk premium is a component still under-explored in the strand of the literature on country equity risk premia.

Furthermore, in the second part of our analysis, we go one step further and study also the multi-factor information. To this end, we closely follow the portfolio construction approach proposed in a recent contribution by Angelidis and Tessaromatis (2017).

Three main findings emerge from our analysis. First, we find that there are substantial abnormal returns from the multi-factor portfolio, a portfolio constructed based on statistically significant single-factor portfolios. Second, and more importantly, when comparing single-factor and multi-factor information, we find the latter to provide a more consistent and significant predictability of the MSCI country index return. Third, we demonstrate that the multi-factor information not only provides a strong in-sample predictability but also a statistically significant out-of-sample predictability. Indeed, the out-of-sample R-square results show that the multi-factor prediction can outperform the benchmark historical country equity return. We also find that the multi-factor prediction on average outperforms the out-of-sample R-square than that of single-factor prediction, implying that multi-factor information dominates single factor models. Overall, our results indicate that multi-factor information is non-trivial and superior to the single factor.

Thus, our analysis contributes to the broader literature on equity risk premia in a multi-dimensional investment setting. Our study is related to several strands of academic research which documents the existence of equity market anomalies. A strand of this literature empirically explores the equity anomalies of individual stocks. After the seminal paper of Fama and French (1993), which shows that there are other stock return anomalies that cannot be solely captured by the classical CAPM model, there has been an extraordinaryrenewed interest in academic research attempting to identifying the set of potential candidate risk factors embedded in individual stock returns. Important papers in this strand of the finance literature are, among others, Carhart (1997) (momentum), Fama and French (2015) (5-factor model), and Hou et al. (2015) (investment-based q-model). Other asset pricing studies also consider firm-specific characteristics to explain stock return anomalies. For instance, Ang et al.

(2006) document a negative relationship between aggregated volatility risk and stock return. Frazzini and Pedersen (2014) argue that, in an investment environment allowing for leverage and margin constraint, the stock abnormal return (α) is also affected by the beta risk exposure to systematic risk. Hence, a strategy of a long position in a a low-beta stock and shorting a high-beta stock at the same time can generate abnormal returns. Neely et al. (2014) examine both technical indicators (e.g. stock return moving average) and macroeconomic variables and find that both types of variables can predict individual stock returns. Novy-Marx (2014) finds strong performance tilts for defensive stocks (i.e. low volatility and low beta) and that their returns cannot be explained by traditional value and profitability pricing factors. However, Green et al. (2017) examine 94 firm-specific characteristics and document that only a few factors can actually predict the U.S. monthly stock returns after controlling for conventional systematic risks components.

Despite a large literature on individual stock returns, there exists relatively little empirical work on country-based equity markets. It is also important to note that the size of the country-based equity market is still relatively small because of the scope of the global investment strategies. In this context, Angelidis and Tessaromatis (2014) show that country-based and stock-based global investments are similar in terms of performance and risk characteristics. Furthermore, they find that country-based portfolios (e.g. constructed by ETFs or tradable stock index) have slightly higher returns and lower risk than stock-based portfolios. Johnson et al. (2016) argue that country-based ETFs are less costly than index-linked ETFs and provide direct strong evidence for investing in country-based portfolios.

There are several studies that investigate country-based portfolios, and in particular their risk characteristics. Asness et al. (1997), Asness et al. (2013), and Asness et al. (2015) study the MSCI value-weighted country-index return and find that the factors in traditional asset pricing model–value (measured by book-to-market), size (measured by market capitalization), and momentum (past one-year return)–can capture the future country index return. They also show that a country-based portfolio of MSCI country indices with high value, small size, and upward momentum yields a higher future portfolio return. On the other hand, Desrosiers et al. (2004) examine the value and momentum factor impacts on the unhedged MSCI country index return and find that the momentum factor is stronger than the value factor in predicting the country index return. Ang et al. (2009) further document the negative relationship between aggregated volatility risk and country index return. Brusa et al. (2014) propose a new three-factor asset pricing model for international equity, comprising a global equity factor and two currency dollar and carry factors. Bekaert et al. (2009) show that international stock returns comove and the arbitrage pricing theory (APT) model and the Fama-French model with global and regional factors fit the data particularly well. Interestingly, the majority of the studies on country-based investments usually focus on single-factor portfolio but they are mostly silent about the multi-factor impact. Angelidis and Tessaromatis (2017) apply the Fama-French-Carhart four factor model for country-based case and find that a combination of high value, small-cap, high-momentum, and low-beta portfolios exhibit return anomaly in country equity investment. Naturally, our work is related to these studies but we go beyond by providing also a broader perspective on country-specific factors. Moreover, we compare the performance of the single-factor and the multi-factor portfolio. A paper closely related to our is Jensen et al. (2021) who also explore global stock returns with a large set of factors. Different from this paper which study, at global level, the firm-factor replicability and focus mainly on factor replication methods, we approach this important question in a new way, namely through the lens of a cross-country asset pricing model. Hence, our study is more closely related to the academic body of research on global equity country allocation using factor investing. Furthermore, we assume in our framework that the factors exhibit the omitted variable bias and the measurement error, which instead Jensen et al. (2021) do not consider. Likewise, our findings also show that asset pricing predictability is stronger when using a large number of observed factors.

Finally, our study is also closely related to portfolios construction methods. In this respect, a variety of portfolios construction methods have been proposed in the literature. Clarke et al. (2006) propose the minimum-variance portfolio. Choueifaty and Coignard (2008) use a diversity ratio, a weighted average of volatility divided by the portfolio volatility, and document that a portfolio with the maximum diversity ratio outperforms other portfolios with traditional market-cap, minimum-variance, and equal weight methods. DeMiguel et al. (2007, 2009) examine the mainstream methods of portfolio construction against the naive 1/N portfolio and document that none of the models persistently outperforms the benchmark 1/N equal-weighted portfolio. They advocate that these models are weakened by model estimation error, although Kirby and Ostdiek (2012) disagrees with DeMiguel et al. (2007, 2009) suggesting that such results are mainly driven by the formulation of the research design. Hence, we further examine whether the reliability of the multi-factor asset predictability tests depends on the employed portfolio construction method. We use the three most traditional methods—equal, value, and volatility weights—to form country equity portfolios, based on country-specific factors. Consistent with DeMiguel et al. (2007, 2009), our main findings suggest that portfolio construction does not seem to alter portfolio returns nor their statistical significance.

Our paper is organized as follows. Section 2 describes the data. Section 3 presents our methodology. Section 4 discusses the main results from the single- and multi-factor settings. Section 5 presents the results of the out-of-sample analysis. Section 6 provides robustness exercises by regional/countries areas. Finally, Section 7 concludes.

2 Data

We obtain our main dataset from various sources. The country-level return is calculated from the MSCI country index. We use the USD total return of the index. The country-level factors are obtained from two sources: (i) equity factors are collected from a proprietary database[4] where the factors are constructed for in-house trading and analyses purposes, and (ii) sovereign credit default swap (CDS) data are collected from Markit. All the data are at monthly (month-end) frequency, except sovereign CDS, which are daily data. We merge these datasets by country and by the end of each month's observations.

In the final dataset, we have monthly observations for 45 countries with the sample period spanning from January 2002 to April 2018, while the sovereign CDS data is from 2002 to 2018.

Table 1 reports the descriptive statistics of the monthly MSCI country-index return for our 45 countries. The sample period comprises all the countries from 2002 to 2018, except for United Arab Emirates (UAE) and Qatar with starting year being 2005 and 2006, respectively. Peru has the highest average monthly return (1.936%) over the sample period, while Greece has the lowest (-0.300%). The low returns reflect the country's economic conditions; e.g., Greece's low equity performance may be due to their debt crisis during 2007–2009. In addition, Turkey has the highest return volatility (11.463%) while U.S. has the lowest return volatility (4.048%). Interestingly, the average return across all the countries is 1.001%, much higher than the average return of MSCI all-country index (0.512%, last row in Table 1).

[Table 1 is about here.]

Table 2 reports the descriptive statistics including start month, sample average, sample standard deviation, sample maximum and sample minimum. In total, we obtain 115 country-specific variables for our 45 countries, 106 of which are obtained from a unique proprietary dataset and 9 of which are sovereign CDS spreads with tenors from 1 year to 30 years. The average number of country-month observations is approximately 8100. The definition for each variable is provided in Table A.1. In addition, the average number of observations by country and by variable (not presented) is 181.

4 We would like to assure about the reliability of the country-specific variables. We obtain the data from a commercial private company that offers investment advice services for global investors. Although these variables are constructed with the company's in-house data and methodology, researchers or practitioners can still construct similar measures based on the variable definition provided in Table A.1 in the Appendix. Indeed, we do not construct these variables by ourselves because it requires comprehensive global databases. Also, the variable construction may not be precise if insufficient data is used. Therefore, it is more efficient and accurate to use the proprietary data sources.

[Table 2 is about here.]

Given the large number of country-specific variables, two issues may potentially affect our analysis: missing values and multicollinearity. In fact, a complete dataset would provide 8820 country-month observations (196 months for 45 countries). As shown in Table 2, the actual number of observations range from 5120 (SCDS_30Y) to 8447 (e.g. CURRENT_R), indicating that the missing rate is between 42% and 4%. If we remove the missing values directly, it may result in an insufficient sample due to the wide range of missing values. Therefore, in order to utilize all the available observations, we standardize each variable by subtracting their pooled sample means and divide by their pooled sample standard deviations. After standardization, we fill the missing values with zeros. This procedure, zero-order regressions, is statistically unbiased in regression-type analysis (Afifi and Elashoff, 1966; Wilks, 1932).

Another potential concern is multicollinearity when a large set of variables is used. For example, we include sovereign CDS with tenors of 1, 2, 3, 5, 7, 10, 15, 20, and 30 years. Although different tenors represent investor's liquidity preference and investment horizon, it may be less meaningful to include all the variables for country-specific investment. To reduce the multicollinearity concern, we perform Variance Inflation Factor (VIF) analysis for our 115 country-specific variables. Specifically, we calculate the VIFs for all the country-specific variables, and we drop one variable with the highest VIF at a time. We repeat the procedure until all the VIFs of the short-listed country-specific variables are less than 7. At the end, we short-list 90 country-specific variables with the VIF from 1.071 to 6.903. Table 3 reports the summary statistics and the distributions of the variable VIFs.

[Table 3 is about here.]

Next, we provide further preliminary analyses for our observations. For the ease of the analysis, we use standardized observations and country equity FF5C excess returns of the next period, as they are applied in the main estimations. We find that our preliminary analyses from standardized variables still produce significant results which are consistent with those from the original variables.

The first statistic is the correlation coefficient. Since we have a large number of variables under investigation (i.e. 90 country-specific variables plus country equity return), we present the histogram of the correlation coefficients. Table 4 reports the pooled correlation coefficients for the nonoverlapped pairs of the variables[5] The mean of the correlation coefficients is 0.026 with the standard deviation equal to 0.149. The largest correlation coefficient appears at RTN1PEQ-RTN1PCAP pair (corr. coef. = 0.902), while the lowest correlation coefficient appears at PE_LTM_B-DIV_PAYOUT pair (corr. coef. = -0.877). In addition, the histogram shows the correlation coefficients to be rather centered and symmetric around the [-0.2, +0.2] range, indicating that there is a rather diversified set of country-specific variables, and that they capture versatile aspects of country-specific information.

[Table 4 is about here.]

We are particularly interested in the relationship of country-specific variables with country returns. Hence, we single out the correlation coefficients related to the country equity return, reported in Panel B. The averaged correlation coefficient is 0.018, similar to the overall average. In addition, the top five variables with the strongest correlation coefficients, in terms of the absolute values, are EBITDA_EV, EBIT_EV, RNOA, EPSYLD_LTM_B, and GR_INTR_SALE, indicating that profitability-related variables are more likely to have a stronger link to country equity returns.

Next, we provide time-series trend for our observations. To elucidate better this analysis, each year, we take the cross-sectional average of the variables and observe the annual trend of the cross-sectional averages. Again, due to the large number of variables, we choose to use heatmap to illustrate the trend. The visualization feature of data with a system of color-coding to represent different values allows to easily spot the high and low trends. In addition, recall that we use standardized country-specific variables. Standardization is convenient for cross-variable comparison.

[Figure 1 is about here.]

Figure 1 plots the time-series trend, in the heatmap format, for all the variables. In general, we observe higher values in the first-half sample period, while most variables have lower values in the second-half sample period. Interestingly, extreme values appear in the 2007—2010 period, when the global financial crisis occurred. This suggests that the countries were severely affected by the 2008 and 2009 financial crisis. In the same spirit, we plot the cross-sectional standard deviations of our variables in each year. We observe greater cross-sectional volatility in the earlier sample period, while the volatility is lower towards the end of the sample period.

[5] We have 4095 pairs (i.e. (91×90)/2) of variables.

3 Single-factor Analyses

In this section, we attempt to identify which factors can predict country equity returns. In the factor pricing model, a country's expected excess return is modelled by $E(exr_i) = \beta_{i,1}\,\lambda_1 + \cdots + \beta_{i,m}\,\lambda_m = \boldsymbol{\beta_i}'\boldsymbol{\lambda}$, where $\boldsymbol{\lambda}$ is a vector of factor risk premia and $\boldsymbol{\beta_i}'$ is a vector of factor loadings. Empirically, the factors are time varying. The excess return is determined by $exr_{i,t} = \alpha_i + \beta_{i,1}\,f_{1,t} + \cdots + \beta_{i,m}\,f_{m,t} + \varepsilon_{i,t} = \boldsymbol{\beta}_i'\boldsymbol{f} + \alpha_i + \varepsilon_{i,t}$, where $\boldsymbol{f}$ is a vector of factors at time t and $\alpha_i + \varepsilon_{i,t}$ is the unexplained part of the factors. Note that, under factor pricing model, λ and f_t are common across assets. Several methods have been proposed in the finance literature to obtain the factor risk premia λ in the time-varying context. For example, Fama and MacBeth (1973) suggest a two-pass procedure to estimate the factor risk premia. However, since the number of factors exceeds the number of countries, traditional asset pricing analysis does not allow us to deal with all the factors at once. Hence, we focus on one factor at a time, and use portfolio sorting and regression to narrow down the important single factors. In the next section, we explain the construction and the validation of factors.

3.1 Single-factor Portfolio Construction

To begin with, we analyze the country portfolio performance, which is sorted by a particular country factor. Portfolio sorting analysis is commonly used to identify the factor risk premia priced in a certain asset class in the literature (e.g. Fama and French, 1993; Carhart, 1997), because it can reduce the amount of idiosyncratic volatility and hence allows more precise estimates of the factors impact (Blume, 1970).

Each month, we sort the 45 countries into three groups (Low/Medium/High) by one of the 90 country-specific variables. For each group, we form each individual portfolio and calculate the portfolio return for the following month:

$$exr_{p,t+1} = \sum_{i=1}^{N_{p,t}} [\omega_{i,t} \times exr_{i,t+1} | \{i(t) \in p(t)\}]\,, \tag{1}$$

where ω is the portfolio element weight and exr_i is monthly country-index excess return for country i. $\{i(t)\ \in\ p(t)\}$ means that, in month t, country i is grouped into one of the three Low/Medium/High portfolios p based on the sorting variable. The excess return is the unexplained part of the Fama-French (2015) 5-factor and Carhart (1997) model (FF5C model).[6] We use three weights to form each

[6] The monthly factors for international finance are obtained on Kenneth French's website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We are grateful to the author to make the data publicly available. Note that the original FF5C factors are provided for developed and developing markets separately. Thus, we take the value-weighted average of the developed and developing market factors as the global FF5C factors.

portfolio: equal weight, value weight, and inverse-volatility (IVOL) weight. There exists a vast academic debate on whether portfolio weights matter for portfolio performance. A number of scholars argue that the choice of weight affects portfolio performance (e.g. Clarke et al., 2006; Kirby and Ostdiek, 2012), while others disagree (e.g. DeMiguel et al., 2007). For robustness checks, we choose the most popular three weighting methods to form our single factor portfolios. For the equal weight, $\omega_{i,t} = \frac{1}{N_{p,t}}$, where $N_{p,t}$ is the number of countries included in the portfolio p at month t. For the value weight, we use the logarithm of the market capitalization (LOG_MKTCAP) as the total value of the country index, and the corresponding weight is equal to $\omega_{i,t} = \frac{LOG\_MKTCAP_{i,t}}{\sum_{i=1}^{N_{p,t}}[LOG\_MKTCAP_{i,t}|\{i(t) \in p(t)]}$. Finally, the weight in IVOL case is equal to $\omega_{i,t} = \frac{(VOL\_12M_{i,t})^{-1}}{\sum_{i=1}^{N_{p,t}}[(VOL\_12M_{i,t})^{-1}|i(t) \in p(t)]}$, where VOL_12M is the volatility of the MSCI country-index return over the past 12 months. Therefore, for each country-specific variable, we are able to calculate the monthly return for the three portfolios (p = Low, Medium, or High) with the three different weights (ω = Equal-, Value-, or IVOL-weighted). Note that our approach for sorting portfolios is in line with prior papers such as Asness et al. (1997) and Angelidis and Tessaromatis (2017).

Single-factor Long-Short Portfolio

To examine whether the variable is an investment factor at the country level, we form the long-short portfolio by taking a long position on the High and a short position on the Low portfolios at the same time $\left(exr_{LS,t} = exr_{High,t} - exr_{Low,t}\right)$, and test the statistical significance of the long-short portfolios. Note that we do not test the individual portfolio return against the MSCI all-country index return because, from our summary statistics for the MSCI country-index return (Table 1), the averaged country-index return is higher than the all-country index return. Hence, portfolio returns are likely to outperform the all-country index returns, irrespective of the sorting on a specific country-specific variable, resulting in a less meaningful comparison between the individual portfolio and the all-country index.

To further control for the systematic factor, we perform a time-series regression for the long-short portfolio by using:

$$exr_{LS,t} = \alpha_{LS} + \beta_{AC}\, exr_{AC,t} + \varepsilon_t, \tag{2}$$

where exr_{AC} is the monthly excess return of the MSCI all-country index. We also evaluate the statistical significance of the intercept α_{LS}. A statistically significant α_{LS} means that the country-specific variable can earn abnormal returns, controlled by the systematic factor. Economically speaking, the identified factor contributes to the equity return difference across counties. Hence, an important investment management implication is that investors may construct a “styled” investment based on the factors. Note that we use the Newey-West standard errors for regression significance.

Single-factor Portfolio Performance

Table 5 shows the performance analyses for our 90 single-factor portfolios. For each single-factor portfolio, we report the monthly returns on the long-short strategy and the abnormal return with the model specification Equation (2). In summary, we can see that 25 (or 6) country-specific variables are positively (or negatively) statistically significant in predicting long-short portfolio returns at the 5% level. Among these variables, 13 (or 4) are positively (or negatively) statistically significant at the 1% level. When we turn to the results for abnormal returns, we find that the statistical significance is qualitatively the same; one variable, SALE_ASSET_CHG, becomes insignificant at 5% level.

[Table 5 is about here.]

Several notable findings emerge from the single-factor portfolio analysis. First, the single-factor portfolio is constructed one-month ahead, indicating that some of the country-specific variables provide strong predictive power for MSCI country indices, and hence one can use this information to earn abnormal returns. Second, those significant country-specific variables can be broadly grouped into four types: (i) size related (e.g. ASSET_PS_GR), (ii) profit related (e.g. EBIT_EV, EPSYLD_LTM_B), (iii) momentum (e.g. RTN1D), and (iv) default risk related (e.g. DEBT_CAPITAL). Those variables, except the default risk, are rather traditional variables in seminal corporate asset pricing studies (see, e.g., Carhart, 1997; Fama and French, 2015). Here, we add a new dimension to this strand of the literature by showing that those variables can be used also at country level.

Table 6 reports the results for the value- and IVOL-weighted single-factor portfolio analyses. To save space, we include only the 20 statistically significant country-specific variables at the 5% level found in the all analyses so far. Overall, our results are again quantitatively similar in value- and IVOL-weighted portfolios. Note that in only few cases some of the variables become less significant. Therefore, this suggests that these country-specific variables indeed display strong predictive power for portfolio returns. Our results, in comparison to different weighting methods, imply that no particular portfolio weighting yields superior returns to others. It is important to note that in the empirical finance literature, there is no clear-cut consensus on the choice of an optimal portfolio construction method. Our results show that, in the country investment case, there is no obvious optimal diversification method, confirming the findings in DeMiguel et al. (2007).

[Table 6 is about here.]

3.2 Factor Risk Premia Estimation

Once the time-varying long-short portfolio returns for each factor are estimated, we then use them as pricing factors (i.e. f_t, mentioned at the beginning of Section 3). Recall that the time-varying factor is common across all assets. The factor constructed by portfolio sorting analysis is generally applied in the literature.

Here, we use two methods to estimate the factor risk premia, λ, and the statistical significance on λ indicates the importance of the factor. We first use the Fama-MacBeth two-pass estimation approach. In the first stage, we obtain the beta estimates by performing a time-series regression for individual countries, i.e. in total, 39 regressions of country's excess return on the chosen factors. Then, in the second stage, we perform, for each month, a cross-sectional regression of excess return on the beta estimates obtained from the first stage. The factor risk premia, λ, are the time-averaged λ_t from the second stage.[7] Due to the limitation in the number of explanatory variables in econometric testing, we are unable to include all the 90 factors in the two-pass estimation; instead, we use the 20 factors identified in Section 3.1. Since these factors can produce abnormal returns in the single factor analysis, we then investigate the existence of factor risk premia within a multivariate framework.

The Fama-MacBeth two-stage procedure is very popular in the empirical finance literature, and provides the insights of the factor risk premia in a time-varying context. The estimation, however, raises two major concerns in our country-specific factor case. First, as mentioned, we are unable to include all the country-specific factors, which leads to a potential bias due to omitted variables. Another concern is the measurement error on the factor. Recall that since we have a relatively narrow spread of the portfolio (i.e. we only sort the countries into three groups), the factor may actually contain a higher level of measurement error.

To obtain the factor risk premia adjusted by the omitted variable bias and the measurement error, we apply a novel three-pass estimation recently proposed by Giglio and Xiu (2021). Recall from Section 3 that an asset's excess return is equal to $exr_t = \boldsymbol{\beta\lambda} + u_t$, with $\boldsymbol{\beta}$ (or $\boldsymbol{\lambda}$) being a vector of factor loadings (or factor risk premia). In Giglio and Xiu (2021), the excess return is denoted as

$$exr_t = \boldsymbol{\beta}\,\boldsymbol{\lambda} + \boldsymbol{\beta}\,\boldsymbol{v_t} + u_t, E(v_t) = E(u_t) = 0, \text{and } Cov(u_t, v_t) = 0, \tag{3}$$

where $\boldsymbol{\beta}$ (or $\boldsymbol{\lambda}$) is a vector of factor loadings (or factor risk premia); $\boldsymbol{v_t}$ is the time-varying innovations of the factors; and u_t is the idiosyncratic pricing error. $\boldsymbol{v_t}$ are the true factors that are however, unobservable but are related to some observable factors, g_t, in the form of:

$$g_t = \delta + \boldsymbol{\eta}\,\boldsymbol{v_t} + z_t, E(z_t) = 0, \text{and } Cov(z_t, v_t) = 0, \tag{4}$$

[7] Since the Fama-MacBeth two-pass estimation is pretty widely used, here we provide brief explanation. One can refer to, e.g., Cochrane (2009), for further detail.

where $\boldsymbol{\eta}$ is a vector of loadings on the time-varying innovations of the factors and z_t is the measurement error of the observed factor. Note that the observable factors g_t can be related just to part of the true factors v_t; hence, if one directly uses the observable factors, instead of the true factors, to estimate risk premia, the risk premia estimates will contain both the omitted variable bias and the measurement bias. Following Giglio and Xiu (2021), the risk premia of the observed factor g_t are $\boldsymbol{\eta\lambda}$, where the risk premia are adjusted for the omitted variable and measurement error biases.

The risk premia estimation can be obtained via a three-stage procedure[8]: (1) The first step is to construct the principal components (PCs) of the asset return. The aim is to extract the latent innovations of the true factors and the estimated factor loadings $\hat{\boldsymbol{\beta}}$. (2) The second step is to run a cross-sectional regression of the average return on the estimated factor loadings, to determine the factor risk premia $\hat{\boldsymbol{\lambda}}$. (3) The third step is to run a time-series regression of observed factor g_t on the PCs from the first step, to obtain $\hat{\boldsymbol{\eta}}$. Then the risk premia for the observed factors are $\hat{\boldsymbol{\eta}}\hat{\boldsymbol{\lambda}}$. It is worth noting that there are several key benefits of using this three-pass estimation method. First, since risk premia estimates $\hat{\boldsymbol{\eta}}\hat{\boldsymbol{\lambda}}$ are adjusted for the omitted variable bias, the estimates are still valid when not all the factors in the regression model are considered. Recall that we can only include a subset of the country-specific factors. Therefore, the risk premia estimates and their statistical inference are not affected when some country-specific factors are omitted. Another benefit of the three-stage procedure is that the information on the unobserved factors v_t is redundant. Instead, the unobserved factors are assumed to be latent variables and are estimated by the principal component analysis. Thus, to conduct the three-pass estimation, we follow the authors' suggestion to set the number of latent factors as 7. In addition, we plot (Figure A.1 in the Appendix) the first 20 eigenvalues of the country equity excess return. The Figure shows that the first six eigenvalues drop quickly, and that the seventh to the twentieth eigenvalues are relatively stable.[9] Therefore, we choose 7 as representative of the number of latent factors.

Table 7 reports the risk premia estimates using the two-pass and three-pass procedures. We test all the three (i.e. equal weighted, value weighted, and IVOL weighted) factors models. Overall, we do not find substantial differences among the methods. The results for the two-pass estimates show that the statistical significance is affected, and only four country-specific variables can explain the country equity excess return at 5% level: DEBT_CAPITAL, EBIT_EV, NET_MARGIN, and SALE_EMPL, while three variables—DEBT_EQUITY, RNOA, and ROA_CHG—marginally explain the excess return at 10% level. Moreover, the factors perform slightly better when they are constructed by using the IVOL weighted model, in which DEBT_EQUITY is negatively related to the country equity excess return at 5% level. By contrast, value-weighted factors perform worse.

[8] Here we only briefly explain the steps intuitively without heavy technical detail. For further technical detail can be referred to Giglio and Xiu (2021).

[9] We also test the number of latent factors, following Giglio and Xiu (2021, Internet Appendix I.1). Our results indicate to set the number of factors as 3.

[Table 7 is about here.]

We then turn to the risk premia estimates using the three-pass method. It turns out that, after adjusting for the omitted variable bias and the measurement error, 70% (or 14) of the shortlisted factors are related to the country equity excess return at 5% level in the equal weighted case. Specifically, we find that 6 factors—AC_5Y_DPS, CFRNOA, CFROA, EBITDA_EV, ES_RECOMM_AVG, and OP_MARGIN_CHG—become insignificant at 5% level in the multivariate analysis. The difference in statistical inference between the two-pass and the three-pass estimation methods indicate that some factor risk premia and statistical inferences are affected by the underlying omitted variable bias and measurement error. However, the overall statistical significance on the country-specific factors implies that the existing approaches in the literature have not yet captured some country-specific pricing factors. In particular, we show that default risk related factors (i.e. DEBT_CAPITAL and DEBT_EQUITY) are rather pronounced in explaining country equity returns. Hence, the results imply that styled investment based on these factors is possible. We find that the weighting method does not alter much of the factor risk premia as well as the corresponding statistical inference, although the significance of IVOL weighted factor seems to be affected: ES_RECOMM_AVG, INVENTO, and ROE_CHG become insignificant at 5% level.

We also report the goodness of fit (denoted as R_f) of each observed factor on the latent factors. The R_f tell us how well the observed factors are related to the true factors. If the measurement error is present, then the R_f is expectedly lower than 100%; the lower the R_f, the worse the measurement error. We observe heterogeneous R_f 's across the observable factors. SALE_EMPL contains the least measurement error with the R_f between 76% and 79%, while AC_5Y_DPS, OP_MARGIN_CHG, and RTN1D contain a substantial measurement error with the R_f less than 10%, indicating that these factors are dominated by noise. For the other factors, the R_f's ranges between 10% and 65%. Although not a general rule, if an observed factor has a lower measurement error, the statistical significance is likely higher in the two-pass estimation, as our evidence illustrates that the statistical factors in the two-pass estimation usually have higher R_f (i.e. lower measurement error). Therefore, the two-pass method estimates suffer from measurement error. Additionally, we conduct a further test on R_f to verify whether the observable factor is weak. We find that the majority of the observed factors reject the null hypothesis, revealing that they are strong factors for the cross-section of test portfolios. We can see that only OP_MARGIN_CHG and RTN1D are weak factors.

We further plot the time-series of the 10 identified factor risk premia. Recall that the factor risk premia are constructed by the portfolio excess return difference between the prior one month highest and the lowest country factor. We are intrigued by how these factor risk premia evolve over time. To obtain a clear trend, we plot the time-averaged values for each year. Figure 2 provides the time-series of the factor risk premia. The Figure shows that the factor risk premia are comparable with the risk premia estimates in Table 7. In particular, we expect negative risk premia for DEBT_CAPITAL and DEBT_EQUITY, because of the negative relationship between the default probability and the equity value. Additionally, the other factors are expected to show a positive relationship with the equity value. Interestingly, we find that DEBT_CAPITAL and DEBT_EQUITY are increasingly negative in the early years of the financial crisis, indicating that the risk premia are larger; NET_MARGIN and RNOA become slightly weaker (close to zero) in the last three years of the sample.

[Figure 2 is about here.]

We also study how these factor risk premia relate to global business cycles conditions. Thus, we use Fama-French market excess return as a proxy for global economic conditions. Note that a higher excess return implies a boost in economic activity. As shown in Panel B, most of the risk factors are positively related to market excess return; the coefficient correlations range from 0.242 to -0.160. NET_MARGIN has the strongest correlation with market excess return (0.242), while GR_INTR_SALE has the lowest value (0.033). This indicates that during periods of economic expansion, the factor risk premia are likely to be larger.

4 Multi-factor Analyses

In this section, we conduct several tests on multi-factor analyses. Similar to single-factor analyses, we use portfolio sorting and regression methods to investigate the multi-factor predictability. In addition, the construction of the multi-factor is based on statistically significant single factors identified in Section 3.

4.1 Multi-factor Portfolio Construction

We further explore the usefulness of multi-factor information for explaining country equity returns. It is important to point out that with such a large number of country-specific variables, it is unfeasible to form directly a multi-factor portfolio, given that each month we can only rely on a group of 45 countries. Therefore, following Angelidis and Tessaromatis (2017), we form our multi-factor portfolio from the single-factor portfolios. Specifically, $exr_{High,t}^{Multi}$ is the monthly excess return of a multi-factor portfolio where a set of single-factor portfolios are included. The criteria of inclusion are as follows: (i) if the country-specific variable is statistically positively significant, then the corresponding $exr_{High,t}^{Single}$ is included; (ii) if the country-specific variable is statistically negatively significant, then the corresponding $exr_{Low,t}^{Single}$ is included. On the other hand, $exr_{Low,t}^{Multi}$ is the monthly return of a multi-factor portfolio consisting of $exr_{Low,t}^{Single}$, for the country-specific variable being statistically positively significant, and $exr_{High,t}^{Single}$, for the country-specific variables being statistically negatively significant. We, again, use equal, value, or IVOL weights to form multi-factor portfolio. Similarly, we test the multi-factor long-short portfolio, defined as $exr_{LS,t}^{Multi} = exr_{High,t}^{Multi} - exr_{Low,t}^{Multi}$ by repeating the performance analyses for single-factor portfolio.

To construct the multi-factor portfolios, we use the country factors with at least 5% significance level in the single-factor analysis. Based on our previous analyses, there are 20 country-specific variables which can produce statistically significant long-short portfolio returns. Moreover, following the three-pass estimation, we eliminate some of the variables. Hence, we restrict our sample to a multi-factor portfolio with 10 variables. In the same spirit, we also construct a multi-factor portfolio with statistical insignificance, where a factor is insignificant at 10% level in all scenarios. We use this multi-factor portfolio as a placebo. The detailed lists of these variables are provided in Table A.2 in the Appendix. Table 8 provides the results of the multi-factor portfolio returns for three different weighting construction. Strikingly, our major finding is that multi-factor portfolios can produce positive returns based on a long-short strategy. The long-short strategy returns are roughly 0.50% in terms of monthly returns, suggesting that an optimizing investor can earn positive returns using the combined country-factor single-factor portfolios. In addition, we find that all three weights produce similar positive returns, but the equal-weighted portfolio generates slightly higher monthly returns.

Again, when we control for the benchmark MSCI all-country index, we find statistically significant abnormal returns. This highlights the effectiveness of the multi-factor portfolio.

[Table 8 is about here.]

The results of the two multi-factor portfolios are reported in Table 8 (see rows *Multi-ft. (1%)* and *Multi-ft. (5%)*). As expected, both portfolios produce positive long-short strategy returns in all cases and the returns are still statistically significant after controlling for the systematic factor. Furthermore, we find small return difference between $exr_{LS,t}^{Multi,1\%}$ (around 0.45%-0.49% in terms of monthly return) and $exr_{LS,t}^{Multi,5\%}$ (around 0.47%-0.52% in terms of monthly return), while $exr_{LS,t}^{Multi,5\%}$ has slightly larger range among different construction methods than $exr_{LS,t}^{Multi,1\%}$.

On the other hand, the multi-factor portfolio constructed by the insignificant factors does not produce any abnormal return in all cases, with the excess return ranging between 0.02% and 0.04%. When we test the difference between $exr_{LS,t}^{Multi,1\%+5\%}$ and $exr_{LS,t}^{Multi,Insig}$, we find strong evidence that indeed $exr_{LS,t}^{Multi,1\%+5\%}$ outperforms $exr_{LS,t}^{Multi,Insig}$ by around 0.4% in terms of monthly excess returns. Importantly, the results still hold, when we control for the systematic factor. Overall, our findings suggest that multi-factor portfolio performance can be improved by combining different country-specific variables. A further noteworthy implication of our results is that investors can construct a multi-factor portfolio more efficiently than using single-factor portfolios.

4.2 Multi-factor Risk Premia

Similarly, we next explore the multi-factor risk premia with the two-pass and three-pass procedures. We perform two models:

$$E(exr_i) = \beta_{i,1}\,\lambda^{multi,1\%+5\%} + \beta_{i,2}\,\lambda^{multi,Insig}, \text{and} \quad (5)$$

$$E(exr_i) = \beta_{i,1}\,\lambda^{multi,1\%} + \beta_{i,2}\,\lambda^{multi,5\%} + \beta_{i,3}\,\lambda^{multi,Insig}, \quad (6)$$

where $\lambda^{multi,1\%+5\%}$, $\lambda^{multi,1\%}$, $\lambda^{multi,5\%}$, and $\lambda^{multi,1\%+5\%}$ are the risk premia—which are our objectives of the estimation—for the abovementioned multi-factor portfolios. Since $\lambda^{multi,1\%}$ and $\lambda^{multi,5\%}$ are the subset of $\lambda^{multi,1\%+5\%}$, we do not combine these three variables together. Instead, we use Equation (6) to investigate the effectiveness of the multi-factors separately. In both models, we include $\lambda^{multi,Insig}$ as a placebo variable. We expect positive factor risk premia for all variables except $\lambda^{multi,Insig}$. Positive factor risk premia indicate that the multi-factor model is indeed important to cross-country investments.

Table 9 presents the multi-factor risk premia estimates. The upper panel reports the results for Equation (5). We obtain positive risk premia for *Multi-ft. (1%+5%)* at 1% significance level for both estimation methods and across three weighting methods, while the risk premia for *Multi-ft. (Insig)* are rather small, around 0% and insignificant at 10% level in all cases. Hence, the findings provide strong support for our predictions. In terms of measurement error, all the multi-factors constructed by significant single factors apparently have very high R_f^2, indicating that the factor is measured essentially without error, while the multi-factor constructed by insignificant single factors is dominated by noise. However, both multi-factors are not weak factors.

[Table 9 is about here.]

The bottom panel reports the results for Equation (6), where individual multi-factors are examined. Similar to the upper panel, we obtain significantly positive risk premia for those multi-factors constructed by significant single factors, while insignificant risk premia for the multi-factor constructed by insignificant single factors. Interestingly, we find that the risk premia are larger for *Multi-ft. (1%)* than those for *Multi-ft. (5%)*. This suggests that factor risk premia are related to the constituents of the single factors, holding other factors constant. Similarly, the R_f^2 is higher for *Multi-ft. (1%)* than for *Multi-ft. (5%)*, indicating that a larger statistical significance has a lower measurement error in factors.

Similarly to the single-factor analysis, we plot the time-series of the multi-factor risk premia. We can observe from Figure 3, positive risk premia over time for the multi-factors constructed by the identified significant country-specific variables. On the other hand, the *multi-ft. (Insig)* is pretty small and revolves around zero, suggesting no risk premia from *multi-ft. (Insig)*. Thus, the time-series plot confirms the importance of multi-factors in country equity asset pricing.

[Figure 3 is about here.]

5 Country-specific Characteristics Prediction

5.1 In-sample Prediction

So far, we have identified the factors that can yield risk premia in the country equity returns. In this section, we aim to study factor's predictability. Unlike prior studies, in our setting we use country-specific characteristics directly. The main purpose of this analysis is to understand whether these characteristics convey key information for returns predictability. We run the Fama-MacBeth regression by using:

$$exr_{it+1} = \alpha + \beta\, F_{it} + \gamma\, Controls_{it} + \varepsilon_{it}, \tag{7}$$

where F_{it} is the country-specific characteristics for country i at month t, and $Controls$ is a vector of control variables. We construct principal components based on different groups of country-specific variables. $PC^{1\%+5\%}$ is the principal component constructed using the statistically significant country-specific variables identified in the portfolio analyses in Section 3, excluding the factor F. PC^{Insig}, on the contrary, is the principal component from the insignificant country-specific variables. We use the first three PCs for each group as controls.

The regression results are presented in Table 10. Panel A reports the statistical significance when PC^{Insig} are included as control variables. We find that these factors can predict individually the country excess return one month ahead, while we find no evidence of statistical significance for in PC^{Insig}. When we include the $PC^{1\%+5\%}$ in the regression, the individual country's characteristics are mostly insignificant at 10% level. Only SALE_EMPL and EBIT_EV maintain statistical significance at 10% level, where the first PC (i.e. $PC1^{1\%+5\%}$) is significantly positive at 5% level for all cases, indicating that the aggregate information outperforms the single factor information.

[Table 10 is about here.]

We further test for the predictability between the PCs. We additionally construct the PCs based on different significance groups, i.e. $PC^{1\%}$ (or $PC^{5\%}$) is the PC of the country-specific variables with only 1% (or 5%) significant level. We repeat the regression specification in Equation (7) but just focus on the PCs of the four groups. The results are reported in Table 11.

[Table 11 is about here.]

We find that overall the PCs constructed by the country-specific variables identified as significant factors can predict the country return one month ahead, while, again, PC^{Insig} is statistically insignificant .We also document evidence of predictability at the first PCs: $PC1^{1\%+5\%}$ (in Model 1), $PC1^{1\%}$ (in Model 1), and $PC1^{5\%}$ (in Model 3) are un fact all statistically positive at the 1% level. Hence, this underscores the importance and effectiveness of information at the aggregate level in country equity return predictability. In Model 4, we combine the PCs of 1%- and 5%-significance factors and find that $PC1^{5\%}$ shows stronger significance while $PC1^{1\%}$ and $PC2^{1\%}$ are just marginally significant. A possible explanation is that since $PC^{1\%}$ includes more factors than $PC^{5\%}$, the PCs (1%) are more noisy than PCs (5%).

5.2 Out-of-sample Prediction

We next study the out-of-sample performance as a robustness check of our major findings. We first consider the prediction error for our factors. The most commonly used measure for prediction error is the Rooted Mean Square Error (RMSE):

$$RMSE_{t+1} = \sqrt{\frac{1}{N_{t+1}} \sum_{i=1}^{N_{t+1}} \left(exr_{i,t+1} - \widehat{exr}_{i,t+1}\right)^2} \tag{8}$$

where $exr_{i,t+1}$ is the excess return of country i in month $t+1$, and $\widehat{exr}_{i,t+1}$ is the *predicted* value from the training regression. In the training regression, we include prior 5-year data to determine the Fama-MacBeth regression parameters: $exr_{i,s} = \hat{\alpha}_t + \hat{\beta}_t F_{i,s-1} + \varepsilon_{i,s-1}$, with the excess return $\{exr_{i,s}\}_{s=t-5y}^{s=t}$ and country-specific factor $\{F_{i,s}\}_{s=t-1-5y}^{s=t-1}$. Then we calculate the predicted value $\widehat{exr}_{i,t+1}$ by $\hat{\alpha}_t + \hat{\beta}_t F_{i,t}$. Therefore, the out-of-sample period starts in January 2007, and then it rolls over by each month until April 2018. As such, we have in total 136 months. In addition, given the large number of single factors, we restrict our focus only on the 30 statistically significant factors identified in our prior analysis. Furthermore, we run a battery of regressions for our multi-factors $PC_t^{1\%+5\%}$, $PC_t^{1\%}$, $PC_t^{5\%}$, and PC_t^{Insig}, to assess their predictability. Empirically, we use PC_t^{Insig} to test for the predictability of the remaining insignificant factors.

The monthly RMSE allows us to shed light on the predictability along the time series dimension. We first study the predictive error for $PC^{1\%+5\%}$, because it proves elusive to analyse the time-series RMSE for each factor, given their sheer amount. Figure 4 plots the time-series RMSE for $PC^{1\%+5\%}$, the first principal component constructed by all identified significant factors. We also highlight in the shaded area of the figure the recession periods during the business cycle[10], to highlight the dynamic variation in predictability over stable and turbulent times. Although the recession/expansion periods as defined by the National Bureau of Economic Research (NBER) are U.S. country-specific, we use the U.S. economy as a proxy for the global business cycle. According to the NBER, the only recession period identified in our sample spans from December 2007 to June 2009 and this broadly coincides with the global financial crisis of 2008 and 2009. In Figure 4 (dash line), we observe that for most of our sample period the prediction error is rather stable. However, the predictability is apparently affected between late 2007 and early 2009 (in the shaded area), as we observe large prediction errors during that time. This means that the predictive power of the multi-factor model considerably drops during times of financial turmoil. This also suggests that the single factor's predictability is also weaker during epochs of economic recessions, as our empirical evidence clearly indicates (comparing the single and multi-factors shown in Table 10) that the in-sample country equity returns predictability for the multi-factor model has a stronger statistical significance.

[Figure 4 is about here.]

Nevertheless, note that the RMSE model does not tell us about the effectiveness of the factors from the computed prediction errors. We next attempt to investigate the factor's predictability effectiveness. Methodologically, there are several methods to measure the model's prediction accuracy, e.g. scale-dependent measures such as RMSE (Rooted Mean Squared Error) and MAE (Mean Absolute Error), measures based on relative errors such as MRAE (Mean Relative Absolute Error), and scaled error measures such as MASE (Mean Absolute Scaled Error).[11] Here, we closely follow Hyndman and Koehler (2006) who propose the use of MASE (Mean Absolute Scaled Error) to gauge the factor model prediction accuracy. Specifically, MASE is the Mean Absolute Error (MAE) scaled by the error based on the MAE from the naïve random walk. The purpose is to compare the model prediction error and the prediction error estimated by the random walk. Hyndman and Koehler (2006) show that MASE is less sensitive to outliers and of straightforward interpretation among these measures. We calculate our monthly MASE by using:

$$MASE_{t+1} = \frac{1}{N_t} \sum_{i=1}^{N_{t+1}} q_{i,t+1}\,, \tag{9}$$

[10] The periods of business cycle expansion and contraction can be found in the NBER website https://www.nber.org/cycles.html.

[11] See Hyndman and Koehler (2006) for detailed discussion and comparison for the model prediction accuracy.

$$\text{where } q_{i,t+1} = \frac{\left|exr_{i,t+1} - \widehat{exr}_{i,t+1}\right|}{mean\left(\left|exr_{i,s} - exr_{i,s-1}\right|\right)} \text{ with } \{exr_{i,s}\}_{s=t-5y}^{s=t}. \tag{10}$$

In Equation (10), $q_{i,t+1}$ represents the absolute error between the actual and predicted values, scaled by the mean absolute error of the naïve forecast method, i.e. using the most recent value as predicted value. Note that $exr_{i,s}$ in the denominator is our all in-sample observations of country excess returns, and that, since we employ panel data, we simply use pool average of $\left|exr_{i,s} - exr_{i,s-1}\right|$ to calculate the mean absolute error for the naïve model. Similarly to the RMSE estimation setting, we use past 5-year data to determine the regression parameters $\hat{\alpha}_t$ and $\hat{\beta}_t$ and the one-month ahead country equity return is calculated by $\widehat{exr}_{i,t+1} = \hat{\alpha}_t + \hat{\beta}_t\, F_{i,t}$ for a single-factor case or $\widehat{exr}_{i,t+1} = \hat{\alpha}_t + \hat{\beta}_t\, PC_{i,t}$ for a multi-factor case.

Since the objective of the MASE is to compare the prediction error in the proposed model against that of the naïve method, $MASE < 1$ indicates the proposed model is effective because it generates a smaller error versus the naïve method.

Figure 4 (solid line) plots the monthly MASE for $PC1^{1\%+5\%}$, the first principal component constructed by all the identified significant factors. We can observe that the MASE is proportional to the RMSE. Again, $PC1^{1\%+5\%}$ is not an effective out-of-sample predictor during the financial crisis period because MASE is above 1. Yet, during the non-financial crisis period, $PC1^{1\%+5\%}$ is effective because for the majority of time MASE is below 1. Hence, Figure 1 in general shows that country-specific factors can provide accurate estimates of country equity returns predictability.

Essentially, the RMSE and MASE methods uncover whether the country-specific factors can provide additional meaningful information than the random walk. Consequently, we are interested in assessing whether these factors are able to outperform commonly recognized benchmark predictors. Two benchmark predictors are commonly used—the historical average (Welch and Goyal, 2007) and the constant term plus the unpredicted residual, $\hat{\alpha}_t + \varepsilon_{i,t+1}$, (Welch and Goyal, 2007; Campbell and Thompson, 2008). Here we simply use the historical average, calculated by the pooled average of the country equity return from the last 5 years of our sample. Studies, e.g. Welch and Goyal (2007), show that the historical average is a robust benchmark to test the out-of-sample performance. Following Welch and Goyal (2007) and Campbell and Thompson (2008), the statistics for testing the predictive performance against the historical average is:

$$R_{OOS,t+1}^2 = 1 - \frac{\sum_{i=1}^{N_{t+1}}\left(exr_{i,t+1} - \widehat{exr}_{i,t+1}\right)^2}{\sum_{i=1}^{N_{t+1}}\left(exr_{i,t+1} - \overline{exr}_{i,t+1}\right)^2}, \tag{11}$$

where $\widehat{exr}_{i,t+1}$ is the one-month ahead prediction from the country factor model, $\overline{exr}_{i,t+1}$ is the historical pooled average of the country equity return, and $exr_{i,t+1}$ is the actual country equity return at time $t+1$. As such, we are able to obtain the monthly estimates of $R^2_{oos,t}$. If $R^2_{OOS} > 0$, then the predicted model estimates $\widehat{exr}_{i,t+1}$ have a smaller prediction error than the benchmark $\overline{exr}_{i,t+1}$, indicating a more powerful alternative predictor than the benchmark.

5.3 Single-Factor Out-of-Sample Performance

For individual single factors, we simply average their monthly $RMSE_t$ or $MASE_t$ time-series. If the averaged MASE is below 1, then the single factor is a more effective predictor than the naïve random walk method. Table 12 shows that each factor, over time, can beat the naïve method, revealing that they are all robust predictors. The MASE ranges from 0.688 to 0.690, where CA_PS_GR, GR_INTR_SALE and RNOA have the least mean prediction error while SALE_EMPL has the largest mean prediction error. However, we find the MASE is rather similar across single factors. Therefore, we are unable to conclude which factor is a better predictor than the others.

Since the MASE method is benchmarked only against the random walk, we further compare the factor model prediction with the historical average. Again, we average the monthly $R^2_{OOS,t}$ over the prediction period to study the out-of-sample performance over time. The last column of Table 10 reports the averaged R^2_{OOS} for single factors. We can see that, although all the single factors provide effective information (from MASE results), not all of them outperform the historical average. We find that most of the single factors, identified in the previous sections, still beat the historical average out-of-the-sample. In particular, our estimates clearly show that size-relevant factors, e.g. CA_GR, and CA_PS_GR provide statistically significant out-of-sample performance. Those factors are conventional asset pricing model factors well known in individual stock asset pricing models. Furthermore, factors related to default risk, i.e. Debt_Capital, and Debt_Equity also outperform out-of-sample. To the best of our knowledge, this is the first empirical evidence on these factors in the relatively small strand of work on country equity returns. Hence, our findings provide strong support for the in-sample predictability of the default risk premium. Additionally, we complement this analysis by showing out-of-sample predictability from the default risk premium.

[Table 12 is about here.]

Of these single factors statistically significant in-sample prediction, only one factor, SALE_EMPL, is irrelevant for the out-of-sample performance. Hence, the in-sample performance to some extent relates to the out-of-sample performance. Finally, RNOA has the highest R^2_{OOS} (0.344%) while SALE_EMPL displays the lower R^2_{OOS} (-0.593%), among all factors.

5.4 Multi-factor Out-of-sample Performance

Next, we turn to the out-of-sample results for the four groups of principal components, $PC^{1\%+5\%}$ (with $PC^{1\%}$ and $PC^{5\%}$, separately) and PC^{Insig}, constructed from the significant and insignificant factors, respectively. The RMSE and MASE for prediction errors are reported in Table 13. We can observe that all the principal components, including PC^{Insig}, have a MASE below 1. This indicates that those insignificant factors somewhat still provide some meaningful information in explaining country equity return, although they do not provide statistically significant in-sample prediction. However, the evidence from the RMSE and MASE analysis demonstrates that the country factors indeed provide non-negligible information for explaining country equity returns. Overall, we do find that $PC^{1\%+5\%}$ has a smaller prediction error than PC^{Insig}, indicating a better prediction performance in $PC^{1\%+5\%}$.

[Table 13 is about here.]

The multi-factor R^2_{OOS}s are reported in the last column of Table 13. The table shows that all three PCs of PC^{Insig} do not outperform the benchmark predictor, the historical average with the $R^2_{OOS}(PC^{Insig})$ between -0.643% and -0.005%. On other hand, $R^2_{OOS}(PC1^{1\%+5\%})$ is 0.418%, meaning that $PC1^{1\%+5\%}$ is a superior predictor than the historical average. More importantly, $PC1^{Sig}$ has the higher R^2_{OOS} than the single factor R^2_{OOS}, meaning that the multi-factor is a stronger out-of-sample predictor than the single-factor predictor. We do not find positive R^2_{OOS} for the second and third PCs for $PC^{1\%+5\%}$; which lends support to our previous in-sample analysis that the first PC leads the predictability in country equity excess returns.

We further study the out-of-sample performance R^2_{OOS} for $PC^{1\%}$ and $PC^{5\%}$. We find that both $PC1^{1\%}$ and $PC1^{5\%}$ have positive out-of-sample R-squares. Similar to the in-sample analysis, R^2_{OOS} of $PC1^{5\%}$ is slightly higher (0.412%) than R^2_{OOS} of $PC1^{1\%}$ (0.302%). A plausible explanation for the underperforming $PC1^{1\%}$ is that $PC^{5\%}$ includes more variables and hence may be more informative. Again, our results show out-of-sample prediction only in the first PCs.

6 Regional Analyses

Our results so far suggest that our multi-factors, constructed by applying the principal component method, are an effective country return predictor in both in-sample and out-of-sample cases. We further conduct a robustness test to assess its effectiveness at regional level.

We group our sample of countries according to their levels of development—developed countries versus developing countries--and geographical location—America, Asia, Europe, and the rest of the countries (ROTC). Note that in our sample, 12 countries are classified as developing countries and 33 countries are classified as developed countries.[12] We rerun the three-pass estimation procedure, including single factors and multi-factors, for different regions.

Table 14 reports the factor risk premia by countries classified by level of economic development. We find that most of the factors produce statistically significant risk premia at 10% level. It is important to note that there are less significant factor risk premia (11 out of 20 factors significantly at 10% level in the equal-weight case) in developed countries than in developing countries (16 out of 20 factors significantly at 10% level in the equal-weight case). This suggests that the equity markets in developed countries are more efficient. Hence, country-specific factors are less likely to produce abnormal returns. On the other hand, since the equity markets in developing countries are less efficient, investors are more likely to earn abnormal returns from the styled country characteristics investments.

[Table 14 is about here.]

There are some common factors that affect both developed and developing countries. The default risk related factor—DEBT_CAPITAL—is negatively significant at 5% level in all cases. Other factors, namely DEBT_EQUITY, TY, EBIT_EV, GR_INTR_SALE, LT_DT_EQUITY, RECEIVA_TO, RNOA, ROA_CHG, and SALE_EMPL, are weak common factors for both developed and developing countries, although they are still statistically significant at 10% level in all cases. In addition, most of these factors are also the ones we identified in the complete sample analysis, implying that they also work at the level of development when predicting country equity returns.

We next turn to the single factor analysis by geographical location. The results are reported in Table 15. Interestingly, we find substantial heteroskedasticity of the factor risk premia in different

[12] We use the Human Development Index (HDI) published by United Nations to decide country development. Although there is no strict definition for developed countries, conventionally a developed country has a HDI more than or equal to 0.8, while a developing country has a HDI less than 0.8. The list of developing counties in our sample is Brazil, China, Colombia, Egypt, Indonesia, India, Mexico, Peru, Philippines, Thailand, Turkey, and South Africa. The rest are developed countries.

regions. We can see that only DEBT_CAPITAL and EBIT_EV can price the equity returns of the American countries with marginal significance; similarly, few factors can price ROTC region. On the other hand, country-specific factors in Asian and European countries appear as key determinants of country equity returns, implying that the factors are more efficient in these two regions. Strikingly, we find that DEBT_CAPITAL is statistically significant in all four regions at 10% level.

[Table 15 is about here.]

Finally, we study multi-factor risk premia for different regions, and report the main results in Table 16. Consistent with our previous analysis, we find that the risk premia of the multi-factors, constructed by the significant factors, are pronounced in both developed and developing countries, although the statistical significance is slightly weaker among developed countries. In terms of geographical location, we can observe multi-factor risk premia in Asian and European regions, while no (weak) multi-factor risk premia in American countries and ROTC.

[Table 16 is about here.]

7 Conclusion

In this study, we empirically examine the risk premium for country equity returns. Using a set of country-specific characteristics for 45 countries over the sample period from 2002 to 2018, we find that approximately one-fifth of the variables can explain the abnormal returns of the monthly MSCI country index. Notably, the results remain also quantitatively unchanged when using different portfolio construction methods as well as regression analysis.

Since there are many country-specific factors that can predict one-month ahead country-equity returns, the results imply that the country equity market is not as efficient as the domestic stock market. Some existing studies on domestic, especially U.S. stock markets, show that only few firm-specific factors can predict stock market returns. In addition, the single-factor results are consistent with the three portfolio construction methods, indicating that there is no optimal portfolio diversification, as emphasized by DeMiguel et al. (2007). Our findings on the single-factor analysis enable global investors to gain a better understanding of the risk premia priced in cross-country asset allocation.

We further study multi-factor information. The collection of the multi-factor information is based on the statistically significance in the single-factor analyses. We find that on average multi-factor portfolios can produce even higher abnormal returns of the MSCI country index. Furthermore, when we compare single- and multi-factor information, the latter provides stronger and more persistent statistical evidence in explaining abnormal returns. Our results indicate that the multi-factor is non-negligible and superior to the single factor. Thus, our paper helps shed new light on risk premia in a multi-dimensional investment setting and extend the asset pricing literature on cross-country equity by providing a comprehensive investigation on the country equity pricing factors.

Finally, we show that multi-factors not only provide in-sample prediction but also out-of-sample. Indeed, we provide evidence that the multi-factor prediction can outperform the benchmark historical country equity returns, although we find that the prediction error becomes larger during periods of financial stress. We also find that the multi-factor setting produces better out-of-sample R-square than the single-factor prediction, implying the statistical superiority of using multi-factor information.

Our results have important implications for market practitioners. First, investors can deploy their global investment strategies based on the set of identified 10 asset pricing factors, or, alternatively, conduct multi-factor asset allocation, given that the multi-factor is a stronger predictor of country equity returns. Therefore, an average investor who is long in countries with the most negative exposure to the multi-factor and at the same time short in countries with the most positive exposure to the multi-factor, is expected to earn average monthly return of 0.507%, or equivalently 6.08% in term of annualized return, according to our multi-factor long-short portfolio results.

Second, our results indicate that global equity returns may expose to different risk categories. Therefore, an important practical implication is that a multi-factor setting should convey higher dimensional risk information, not just a single factor risk exposure. Notably, such information is important for risk management practitioners. For example, financial risk managers may consider the multi-factor beta to exhibit a more comprehensive view on risk exposure. More precisely, portfolio managers, can regress one country's return on the multi-factor to obtain the beta risk exposure. Since the calculated beta represents the exposure of the investment in a specific country to higher dimensional risk, assets managers may impose a threshold value on beta for investment risk management purposes.

Similarly, policymakers may use the multi-factor information to assess and monitor key trends of global equity markets. As shown in the out-of-sample results, the multi-factor prediction error is larger at times of financial distress. Hence, the difference between the observed and factor-predicted returns could be used as a signal to capture the unexpected impact on global financial markets, in the same spirit as of Hu et al. (2013) who use observed bond returns and model prices to measure U.S. systematic risk.

Overall, our study elucidates on the factors that may drive equity return anomalies within a cross-country investment perspective. Market anomalies are critical to investors for an effective risk management of their asset portfolios and are also important for policymakers and global financial regulatory bodies, in order to effectively and timely identify the key drivers that influence cross-country equity investments within more interconnected equity markets.

Our study is limited to the country-specific factors' prediction on country equity returns, specifically highlighting multi-factor predictability. As mentioned above, the multi-factor analysis should contain high-dimension risk information. However, we do not examine this aspect as it goes beyond the scope of our paper. Therefore, future research should also investigate this issue. Additionally, future research could extend the analysis of this paper to other financial markets, e.g. the foreign exchange market, as the foreign exchange market is the largest and most dynamic market for global investors.

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Table 1: MSCI Country-Index and All-Country Index Descriptive Statistics

This table reports the descriptive statistics of the 45 MSCI country-index return and all-country index return (MSCI AC). The sample period is from January 2002 to April 2018. The data frequency is in month, and the descriptive statistics, including sample mean, median, standard deviation, maximum, and minimum, are presented in percentage.

Country	Mean (%)	Median (%)	Std (%)	Max (%)	Min (%)	N	Period
Australia	1.039	1.568	6.120	17.795	-25.510	196	200201–201804
Belgium	0.761	1.612	6.430	18.190	-36.555	196	200201–201804
Brazil	1.506	1.307	10.196	30.531	-32.047	196	200201–201804
Canada	0.848	1.022	5.516	21.263	-26.943	196	200201–201804
Chile	1.080	0.955	6.266	20.131	-25.615	196	200201–201804
China	1.351	1.892	7.236	19.939	-22.743	196	200201–201804
Colombia	1.917	2.562	8.350	23.477	-28.163	196	200201–201804
Czech	1.475	1.632	7.278	19.882	-29.445	196	200201–201804
Denmark	1.189	1.951	5.861	18.342	-25.672	196	200201–201804
Egypt	1.839	1.126	9.779	42.709	-33.518	196	200201–201804
Finland	0.652	0.815	7.648	28.299	-24.015	196	200201–201804
France	0.732	0.843	5.959	15.743	-22.414	196	200201–201804
Germany	0.856	1.172	6.779	23.693	-24.351	196	200201–201804
Greece	-0.300	0.237	11.027	30.705	-36.703	196	200201–201804
Hong Kong	0.970	1.062	5.686	18.093	-21.275	196	200201–201804
Hungary	1.348	1.425	9.643	27.302	-43.349	196	200201–201804
India	1.413	1.612	8.029	36.677	-28.475	196	200201–201804
Indonesia	1.891	1.896	8.688	30.544	-39.476	196	200201–201804
Ireland	0.251	1.112	6.790	19.219	-26.044	196	200201–201804
Israel	0.524	0.557	5.682	14.864	-17.790	196	200201–201804
Italy	0.564	0.720	6.859	19.157	-23.601	196	200201–201804
Japan	0.585	0.701	4.480	13.463	-14.782	196	200201–201804
Malaysia	0.845	1.151	4.858	16.089	-17.469	196	200201–201804
Mexico	0.973	1.174	6.378	17.233	-30.675	196	200201–201804
N. Zealand	1.075	1.329	5.978	18.034	-22.437	196	200201–201804
Netherlands	0.792	1.245	6.021	14.387	-25.111	196	200201–201804
Norway	1.149	1.513	7.832	21.469	-33.360	196	200201–201804
Peru	1.936	1.812	8.372	27.055	-36.043	196	200201–201804
Philippines	1.203	1.295	6.458	19.262	-24.330	196	200201–201804
Poland	1.067	1.210	9.009	28.597	-33.850	196	200201–201804
Portugal	0.397	0.466	6.548	15.770	-26.250	196	200201–201804
Qatar	0.517	0.465	7.743	23.374	-26.484	147	200602–201804
Russia	1.171	1.768	9.344	31.922	-35.276	196	200201–201804
S. Africa	1.301	1.643	7.199	17.981	-26.182	196	200201–201804
S. Korea	1.240	1.212	7.467	26.376	-26.122	196	200201–201804
Singapore	1.010	0.995	5.996	24.857	-28.993	196	200201–201804
Spain	0.826	1.329	7.162	22.093	-25.268	196	200201–201804
Sweden	0.973	0.848	6.833	25.489	-26.656	196	200201–201804
Switzerland	0.785	1.420	4.517	11.803	-12.267	196	200201–201804
Taiwan	0.783	1.199	6.297	17.404	-18.907	196	200201–201804
Thailand	1.648	1.830	7.197	31.026	-33.009	196	200201–201804
Turkey	1.274	1.764	11.463	40.928	-34.274	196	200201–201804
UAE	0.355	0.120	9.919	36.250	-33.363	155	200506–201804
UK	0.563	0.630	4.764	13.871	-18.961	196	200201–201804
US	0.682	1.156	4.048	10.987	-17.102	196	200201–201804
MSCI AC	0.512	0.973	4.374	11.618	-18.972	196	200201–201804

Table 2: Country-Specific Variable Descriptive Statistics

This table reports the descriptive statistics of the 115 country-specific variables including sample mean, median, standard deviation, maximum, and minimum. The sample period is from January 2002 to April 2018. The data frequency is in month.

Country Variable	Mean	Median	Std	Max	Min	Obs
AC_5Y_CFPS	0.000	0.000	0.001	0.015	-0.028	8288
AC_5Y_DPS	0.000	0.000	0.001	0.020	-0.002	8070
AC_5Y_EPS	0.000	0.000	0.000	0.004	-0.005	8241
AC_5Y_OEPS	0.000	0.000	0.000	0.004	-0.007	8241
AC_5Y_SALE	0.001	0.000	0.006	0.078	-0.219	8410
ACCRUALS	0.023	0.015	0.033	0.258	-0.082	8444
ASSET_GR	0.076	0.063	0.072	0.493	-0.147	8444
ASSET_PS_GR	0.065	0.054	0.075	0.688	-0.509	8355
BOOKP	0.620	0.571	0.269	3.571	0.050	8447
CA_GR	0.077	0.062	0.107	1.046	-0.586	8436
CA_PS_GR	0.064	0.049	0.114	1.131	-0.583	8355
CFO_CURR_LIAB	0.213	0.173	0.171	1.441	-0.244	8419
CFOYLD	0.110	0.100	0.071	0.570	-0.238	8431
CFPS_SUR	0.211	0.139	0.410	3.796	-1.742	7974
CFRNOA	0.154	0.150	0.077	0.704	-0.288	8415
CFROA	0.051	0.046	0.033	0.234	-0.094	8430
CFROE	0.183	0.182	0.097	0.645	-0.499	8409
CL_GR	0.070	0.058	0.090	0.555	-0.520	8441
CL_PS_GR	0.069	0.061	0.122	1.555	-0.571	8338
CURRENT_R	0.693	0.592	0.363	3.003	0.084	8447
DEBT_CAPITAL	0.516	0.483	0.159	1.396	0.080	8402
DEBT_CHG	0.072	0.047	0.149	1.450	-0.529	8402
DEBT_EQUITY	1.028	0.853	0.642	6.005	0.116	8431
DEBT_MKTCAPITAL	0.313	0.295	0.119	0.700	0.016	8444
DIV_PAYOUT	0.449	0.441	6.807	245.665	-543.777	8199
DIVYLD_EXP	0.150	0.100	0.147	0.888	0.000	8226
DIVYLD_SH	0.620	0.571	0.269	3.571	0.050	8447
DIVYLD_TRL	0.030	0.029	0.014	0.129	0.000	8447
DPS_SUR	0.171	0.054	0.485	6.554	-0.478	7802
EBIT_EV	0.076	0.072	0.029	0.267	-0.048	8443
EBITDA_EV	0.114	0.108	0.039	0.390	0.007	8438
EPS_STAB	0.873	0.779	0.436	5.531	0.231	8258
EPSYLD_LTM_B	0.071	0.066	0.038	0.785	-0.274	8444
EPSYLD_LTM_D	0.070	0.066	0.032	0.529	-0.274	8392
ES_REC_D1M	-0.004	-0.002	0.028	0.400	-0.250	8252
ES_REC_D3M	-0.011	-0.008	0.055	0.375	-0.500	8248
ES_REC_R1M	0.002	0.001	0.024	0.273	-0.267	7052
ES_REC_R3M	0.006	0.004	0.044	0.385	-0.302	7050
ES_RECOMM_AVG	2.478	2.483	0.242	4.500	1.000	8445
ES_TP_D1M	0.032	0.035	0.116	0.818	-0.629	7574
ES_TP_D3M	0.087	0.111	0.257	0.875	-0.866	7484
ES_TP_R1M	0.006	0.007	0.048	0.894	-0.422	7883
ES_TP_R3M	0.018	0.025	0.093	1.148	-0.689	7804
EXT_FIN_NOA	-0.031	-0.025	0.061	0.248	-0.426	8437
FCF_EV	0.025	0.026	0.025	0.152	-0.125	8433
FCFYLD	0.051	0.048	0.044	0.550	-0.348	8419
GR_5Y_CFPS	0.001	0.001	0.016	0.305	-0.201	8295
GR_5Y_DPS	0.000	0.000	0.004	0.047	-0.039	8070
GR_5Y_EPS	0.001	0.001	0.009	0.089	-0.066	8241
GR_5Y_OEPS	0.001	0.001	0.009	0.089	-0.066	8241
GR_5Y_SALE	0.010	0.010	0.030	0.119	-0.453	8351
GR_INTR_CFPS	0.048	0.058	0.391	3.201	-8.592	8412
GR_INTR_DPS	0.098	0.090	0.638	8.349	-7.815	8225
GR_INTR_EPS	0.079	0.087	3.606	140.910	-136.481	8441
GR_INTR_SALE	0.070	0.071	0.117	1.360	-2.160	8447
GRO_FL_YLD	0.075	0.071	0.032	0.298	-0.168	8444
GROSS_MARGIN	0.375	0.364	0.098	0.714	0.122	8438

INT_COVER	6.429	5.689	3.308	25.308	-0.242	8300
INVENT_TO	5.982	6.230	2.199	14.343	0.743	8366
LOG_ASSET	26.245	26.152	1.286	30.001	21.750	8299
LOG_FLOAT	24.925	24.894	1.481	29.657	20.291	8391
LOG_MKTCAP	25.626	25.618	1.324	29.754	20.381	8345
LOG_SALE	25.444	25.419	1.474	29.173	21.074	8333
LT_DT_CAPITAL	0.333	0.324	0.112	0.970	0.054	8402
LT_DT_EQUITY	0.683	0.555	0.500	4.596	0.055	8435
MARGIN_STAB	972mil	1.663	12897mil	231030mil	-707mil	8318
NET_MARGIN	0.093	0.084	0.052	0.378	-0.064	8426
OA_GR	0.043	0.024	0.122	1.951	-0.514	8420
OA_PS_GR	0.037	0.023	0.166	6.117	-0.704	8328
OEPS_STAB	0.858	0.770	0.421	5.531	0.231	7940
OEPS_SUR	0.039	0.019	0.198	2.500	-1.213	8395
OP_MARGIN	0.145	0.140	0.055	0.376	-0.026	8444
OP_MARGIN_CHG	0.028	0.017	2.004	36.208	-11.063	8428
PAYABLE_TO	3.344	3.204	2.447	11.951	0.068	8345
PE_LTM_B	48.836	14.980	2749.690	251680.541	-1139.779	8444
PE_LTM_D	14.540	15.129	58.880	711.417	-4336.232	8392
PERC_ACCRU	0.256	0.207	0.412	4.647	-4.296	8431
PPE_GR	0.058	0.046	0.073	0.595	-0.292	8444
PPE_PS_GR	0.048	0.037	0.082	0.941	-0.550	8336
PSALE	0.945	0.820	0.503	4.802	0.045	8447
QUICK_R	0.526	0.468	0.247	1.986	0.063	8447
RECEIVA_TO	2.516	2.448	1.046	6.295	0.192	8444
RNOA	0.103	0.092	0.058	0.521	-0.091	8438
ROA	0.030	0.024	0.023	0.230	-0.046	8444
ROA_CHG	0.382	0.243	1.472	15.646	-14.692	8431
ROA_STAB	5.122	4.518	2.960	27.905	-2.842	8420
ROE	0.128	0.123	0.054	0.421	-0.235	8444
ROE_CHG	0.185	0.284	4.168	29.167	-46.228	8431
ROE_STAB	13.650	12.851	5.797	43.587	-14.677	8413
ROIC	0.067	0.062	0.036	0.278	-0.153	8438
RTN1D	0.002	0.001	0.013	0.170	-0.096	8447
RTN1PCAP	0.014	0.015	0.058	0.498	-0.315	8447
RTN1PEQ	0.009	0.011	0.060	0.461	-0.395	8391
SALE_ASSET	0.312	0.271	0.165	1.330	0.070	8444
SALE_ASSET_CHG	-0.002	-0.001	0.024	0.144	-0.224	8418
SALE_EMPL	55mil	0.592mil	249mil	1927mil	4480.374	7564
SALE_EV	0.615	0.554	0.265	1.991	0.060	8447
SALE_STAB	0.274	0.244	0.641	26.179	0.083	8287
SALE_SUR	0.016	0.007	0.050	0.703	-0.336	8278
SHARE_CHG	0.005	0.001	0.024	0.910	-0.170	8447
SCDS_1Y	0.009	0.002	0.051	2.113	0.000	6079
SCDS_2Y	0.011	0.003	0.041	1.681	0.000	6073
SCDS_3Y	0.011	0.004	0.036	1.427	0.000	6295
SCDS_5Y	0.013	0.006	0.031	1.159	0.000	6535
SCDS_7Y	0.014	0.007	0.029	1.036	0.000	6350
SCDS_10Y	0.015	0.008	0.027	0.963	0.000	6369
SCDS_15Y	0.016	0.010	0.022	0.620	0.000	5443
SCDS_20Y	0.016	0.010	0.022	0.567	0.000	5435
SCDS_30Y	0.016	0.011	0.020	0.462	0.000	5120
TBP	0.553	0.487	0.316	4.320	0.055	8447
TE_GR	0.090	0.083	0.079	0.635	-0.185	8436
TE_PS_GR	0.074	0.069	0.077	0.511	-0.498	8336
TL_GR	0.072	0.055	0.082	0.555	-0.142	8437
TL_PS_GR	0.075	0.061	0.120	1.744	-0.574	8331
TP_RTN	0.137	0.108	0.164	2.611	-0.998	8172

Table 3: Country-specific Variable VIFs

This table reports the descriptive statistics, including mean, medium, standard deviation, maximum, and minimum of the 90 country-specific variables. The lower panel plots the histogram of the VIFs of the variables.

	Mean	Median	Std	Max	Min	N
VIF	3.298	3.148	1.734	6.903	1.071	90

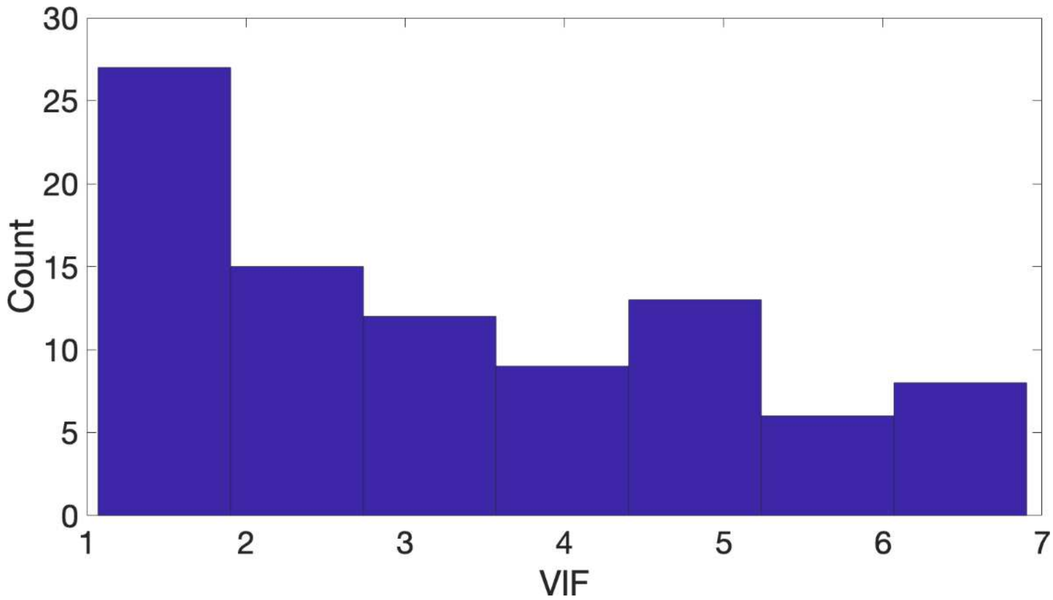
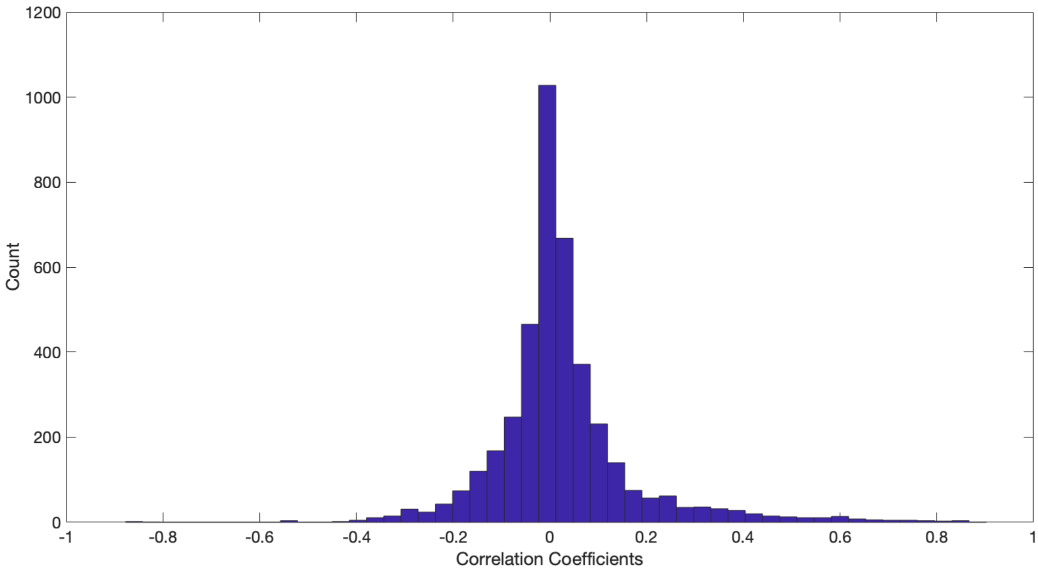


Table 4: Variable Correlation Coefficients

This table provides the variable correlation coefficients. Panel A plots the histogram of non-duplicate pairs of correlation coefficients of all variables. Panel B reports the variable correlation coefficients against country-equity excess returns.

Panel A: Correlation Coefficient Histogram

	Mean	Median	Std	Max	Min	N
Corr. Coef.	0.026	0.006	0.149	0.902	-0.877	4095



Panel B: Correlation Coefficients

	Corr. Coef.		Corr. Coef.		Corr. Coef.
AC_5Y_CFPS	-0.001	ES_REC_R1M	-0.021	PAYABLE_TO	0.048
AC_5Y_DPS	0.026	ES_REC_R3M	-0.008	PE_LTM_B	0.002
AC_5Y_SALE	0.039	ES_RECOMM_AVG	-0.028	PE_LTM_D	0.008
ACCRUALS	0.020	ES_TP_D1M	0.016	PERC_ACCRU	-0.015
ASSET_PS_GR	0.060	ES_TP_D3M	0.022	PPE_GR	0.038
CA_GR	0.061	ES_TP_R1M	0.015	PPE_PS_GR	0.030
CA_PS_GR	0.058	ES_TP_R3M	0.009	PSALE	0.002
CFO_CURR_LIAB	0.020	EXT_FIN_NOA	-0.003	QUICK_R	0.018
CFOYLD	0.010	FCF_EV	0.028	RECEIVA_TO	0.048
CFPS_SUR	-0.010	FCFYLD	0.014	RNOA	0.077
CFRNOA	0.058	GR_5Y_CFPS	0.004	ROA_CHG	0.061
CFROA	0.053	GR_5Y_DPS	-0.028	ROA_STAB	0.068
CL_GR	0.027	GR_5Y_EPS	-0.005	ROE_CHG	0.059
CL_PS_GR	0.037	GR_5Y_SALE	-0.021	RTN1D	-0.032
CURRENT_R	0.013	GR_INTR_CFPS	0.016	RTN1PCAP	-0.023
DEBT_CAPITAL	-0.036	GR_INTR_DPS	-0.008	RTN1PEQ	-0.010
DEBT_CHG	0.005	GR_INTR_EPS	-0.007	SALE_ASSET	0.037
DEBT_EQUITY	-0.028	GR_INTR_SALE	0.069	SALE_ASSET_CHG	0.052
DEBT_MKTCAPITAL	-0.036	GRO_FL_YLD	0.051	SALE_EMPL	0.004
DIV_PAYOUT	-0.018	GROSS_MARGIN	0.032	SALE_STAB	0.017
DIVYLD_EXP	-0.012	INT_COVER	0.000	SALE_SUR	0.015
DIVYLD_TRL	0.000	INVENT_TO	-0.013	SHARE_CHG	-0.015
DPS_SUR	0.036	LOG_ASSET	-0.055	SCDS_1Y	-0.016
EBIT_EV	0.085	LT_DT_EQUITY	-0.036	SCDS_15Y	0.043
EBITDA_EV	0.088	MARGIN_STAB	0.011	SCDS_30Y	0.037
EPS_STAB	0.006	NET_MARGIN	0.039	TBP	-0.007
EPSYLD_LTM_B	0.072	OA_GR	0.016	TE_GR	0.061
EPSYLD_LTM_D	0.058	OA_PS_GR	0.030	TL_GR	0.039
ES_REC_D1M	0.016	OEPS_SUR	0.008	TL_PS_GR	0.036
ES_REC_D3M	-0.002	OP_MARGIN_CHG	0.053	TP_RTN	-0.001

Table 5: Equal-Weighted Single-factor Portfolios

This table reports performance analysis for the equal-weighted single-factor portfolios over the sample period from January 2002 to April 2018. For each country-specific portfolio, we examine their long-short portfolio excess return, denoted as exr_{LS}, and the abnormal return, denoted as α_{LS}, controlled for systematic factor proxied by MSCI all-country index return. We use Newey-West standard error to test regression coefficient significance. The corresponding t-statistics are presented in square brace. ***, **, and * denote 1%, 5%, and 10% statistical significance levels, respectively.

	exr_{LS}	α_{LS}		exr_{LS}	α_{LS}		exr_{LS}	α_{LS}
AC_5Y_CFPS	0.182	0.184	ES_REC_R1M	-0.098	-0.060	PAYABLE_TO	0.174	0.163
	[1.38]	[1.38]		[-0.70]	[-0.43]		[1.24]	[1.21]
AC_5Y_DPS	0.484***	0.479***	ES_REC_R3M	-0.021	0.012	PE_LTM_B	-0.154	-0.164
	[3.16]	[3.20]		[-0.14]	[0.09]		[-0.92]	[-0.90]
AC_5Y_SALE	0.446***	0.472***	ES_RECOMM_AVG	-0.367**	-0.390***	PE_LTM_D	-0.193	-0.200
	[3.14]	[3.36]		[-2.26]	[-2.63]		[-1.22]	[-1.21]
ACCRUALS	0.173	0.205	ES_TP_D1M	0.239	0.257	PERC_ACCRU	0.082	0.100
	[0.95]	[1.12]		[1.42]	[1.48]		[0.51]	[0.61]
ASSET_PS_GR	0.453**	0.478**	ES_TP_D3M	0.180	0.179	PPE_GR	0.229	0.247
	[2.54]	[2.56]		[1.01]	[0.99]		[1.35]	[1.45]
CA_GR	0.400**	0.418***	ES_TP_R1M	0.285*	0.298*	PPE_PS_GR	0.289*	0.315*
	[2.50]	[2.62]		[1.72]	[1.73]		[1.70]	[1.84]
CA_PS_GR	0.457***	0.479***	ES_TP_R3M	0.254	0.270	PSALE	-0.103	-0.113
	[2.88]	[3.12]		[1.38]	[1.47]		[-0.63]	[-0.72]
CFO_CURR_LIAB	0.052	0.022	EXT_FIN_NOA	0.077	0.069	QUICK_R	0.059	0.070
	[0.32]	[0.14]		[0.53]	[0.48]		[0.42]	[0.50]
CFOYLD	0.066	0.061	FCF_EV	0.160	0.148	RECEIVA_TO	0.477***	0.474***
	[0.37]	[0.33]		[1.14]	[1.06]		[3.49]	[3.42]
CFPS_SUR	-0.003	-0.014	FCFYLD	0.043	0.028	RNOA	0.501**	0.541***
	[-0.02]	[-0.10]		[0.27]	[0.18]		[2.56]	[2.91]
CFRNOA	0.361**	0.370**	GR_5Y_CFPS	-0.021	-0.015	ROA_CHG	0.455**	0.496***
	[2.37]	[2.56]		[-0.15]	[-0.11]		[2.42]	[2.67]
CFROA	0.336**	0.347***	GR_5Y_DPS	-0.287*	-0.274*	ROA_STAB	0.505***	0.546***
	[2.55]	[2.70]		[-1.91]	[-1.88]		[2.60]	[2.90]
CL_GR	0.248*	0.265*	GR_5Y_EPS	-0.274*	-0.264*	ROE_CHG	0.398**	0.418***
	[1.62]	[1.73]		[-1.73]	[-1.73]		[2.50]	[2.84]
CL_PS_GR	0.431***	0.455***	GR_5Y_SALE	-0.250*	-0.273*	RTN1D	-0.491***	-0.483***
	[2.95]	[3.06]		[-1.66]	[-1.83]		[-3.26]	[-3.23]
CURRENT_R	0.162	0.168	GR_INTR_CFPS	0.054	0.064	RTN1PCAP	-0.305*	-0.270
	[1.13]	[1.15]		[0.42]	[0.49]		[-1.74]	[-1.54]
DEBT_CAPITAL	-0.535***	-0.534***	GR_INTR_DPS	-0.022	-0.003	RTN1PEQ	-0.109	-0.081
	[-3.67]	[-3.68]		[-0.17]	[-0.02]		[-0.62]	[-0.46]
DEBT_CHG	-0.159	-0.133	GR_INTR_EPS	0.273*	0.273*	SALE_ASSET	0.313*	0.331**
	[-0.97]	[-0.81]		[1.77]	[1.84]		[1.93]	[2.08]
DEBT_EQUITY	-0.446***	-0.446***	GR_INTR_SALE	0.479***	0.503***	SALE_ASSET_CHG	0.331**	0.338*
	[-3.04]	[-3.17]		[2.88]	[3.11]		[1.96]	[1.94]
DEBT_MKTCAPITAL	-0.277	-0.274*	GRO_FL_YLD	0.351**	0.360**	SALE_EMPL	0.588***	0.623***
	[-1.60]	[-1.67]		[2.33]	[2.46]		[3.06]	[3.22]
DIV_PAYOUT	-0.118	-0.131	GROSS_MARGIN	0.214	0.201	SALE_STAB	0.236	0.248
	[-0.82]	[-0.93]		[1.59]	[1.44]		[1.34]	[1.37]
DIVYLD_EXP	-0.262*	-0.273**	INT_COVER	0.057	0.072	SALE_SUR	0.138	0.124
	[-1.87]	[-2.04]		[0.38]	[0.50]		[0.98]	[0.86]
DIVYLD_TRL	-0.061	-0.075	INVENT_TO	-0.418***	-0.439***	SHARE_CHG	-0.222	-0.254*
	[-0.42]	[-0.51]		[-2.84]	[-3.12]		[-1.58]	[-1.81]
DPS_SUR	0.451***	0.467***	LOG_ASSET	-0.151	-0.143	SCDS_1Y	-0.261	-0.333
	[3.14]	[3.12]		[-1.02]	[-0.90]		[-0.94]	[-1.23]
EBIT_EV	0.729***	0.775***	LT_DT_EQUITY	-0.401**	-0.417**	SCDS_15Y	0.205	0.166
	[4.23]	[4.61]		[-2.36]	[-2.54]		[0.91]	[0.72]
EBITDA_EV	0.681***	0.705***	MARGIN_STAB	0.148	0.171	SCDS_30Y	0.130	0.085
	[4.23]	[4.40]		[1.00]	[1.08]		[0.55]	[0.34]
EPS_STAB	0.056	0.048	NET_MARGIN	0.406**	0.436**	TBP	0.080	0.076
	[0.36]	[0.33]		[2.04]	[2.23]		[0.48]	[0.45]
EPSYLD_LTM_B	0.329**	0.350**	OA_GR	0.192	0.216	TE_GR	0.419**	0.424**
	[2.06]	[2.14]		[1.17]	[1.36]		[2.53]	[2.54]
EPSYLD_LTM_D	0.257	0.276*	OA_PS_GR	0.322**	0.336**	TL_GR	0.297*	0.319*
	[1.63]	[1.73]		[2.12]	[2.16]		[1.72]	[1.77]
ES_REC_D1M	0.185	0.180	OEPS_SUR	0.183	0.182	TL_PS_GR	0.207	0.226
	[1.40]	[1.43]		[1.26]	[1.17]		[1.28]	[1.33]
ES_REC_D3M	0.249*	0.237*	OP_MARGIN_CHG	0.404***	0.420***	TP_RTN	-0.058	-0.080
	[1.66]	[1.65]		[2.74]	[2.75]		[-0.34]	[-0.46]

Table 6: Value- & IVOL-Weighted Single-factor Portfolios

This table reports performance analysis for the value- and IVOL-weighted single-factor portfolios over the sample period from January 2002 to April 2018. For each country-specific portfolio, we examine their long-short portfolio excess return, denoted as exr_{LS}, and the abnormal return, denoted as α_{LS}, controlled for systematic factor proxied by MSCI all-country index return. We use Newey-West standard error to test regression coefficient significance. The corresponding t-statistics are presented in square brace. ***, **, and * denote 1%, 5%, and 10% statistical significance levels, respectively.

	Value Weighted		IVOL Weighted	
	exr_{LS}	α_{LS}	exr_{LS}	α_{LS}
AC_5Y_DPS	0.379***	0.376***	0.428***	0.424***
	[2.59]	[2.64]	[3.17]	[3.19]
CA_PS_GR	0.388**	0.408**	0.422***	0.444***
	[2.38]	[2.54]	[2.89]	[3.19]
CFRNOA	0.383**	0.393***	0.345**	0.351***
	[2.56]	[2.75]	[2.53]	[2.73]
CFROA	0.355***	0.366***	0.334***	0.345***
	[2.74]	[2.89]	[2.87]	[3.01]
DEBT_CAPITAL	-0.546***	-0.544***	-0.496***	-0.494***
	[-3.83]	[-3.88]	[-3.78]	[-3.76]
DEBT_EQUITY	-0.487***	-0.489***	-0.431***	-0.429***
	[-3.37]	[-3.56]	[-3.25]	[-3.32]
EBIT_EV	0.695***	0.735***	0.654***	0.688***
	[4.11]	[4.29]	[4.13]	[4.50]
EBITDA_EV	0.638***	0.661***	0.628***	0.645***
	[3.91]	[3.95]	[4.20]	[4.30]
ES_RECOMM_AVG	-0.370**	-0.392***	-0.391***	-0.414***
	[-2.27]	[-2.61]	[-2.69]	[-3.10]
GR_INTR_SALE	0.407**	0.430**	0.420***	0.438***
	[2.43]	[2.56]	[2.73]	[2.86]
INVENT_TO	-0.425***	-0.450***	-0.355***	-0.378***
	[-2.95]	[-3.30]	[-2.67]	[-3.02]
LT_DT_EQUITY	-0.420**	-0.438***	-0.356**	-0.366**
	[-2.47]	[-2.68]	[-2.34]	[-2.51]
NET_MARGIN	0.388**	0.413**	0.364**	0.386**
	[1.97]	[2.12]	[2.00]	[2.17]
OP_MARGIN_CHG	0.454***	0.470***	0.390***	0.407***
	[3.13]	[3.12]	[2.90]	[2.86]
RECEIVA_TO	0.484***	0.478***	0.408***	0.410***
	[3.61]	[3.48]	[3.18]	[3.06]
RNOA	0.493***	0.527***	0.490***	0.519***
	[2.59]	[2.85]	[2.83]	[3.15]
ROA_CHG	0.386**	0.426**	0.459***	0.489***
	[2.05]	[2.27]	[2.64]	[2.85]
ROE_CHG	0.317**	0.345**	0.363**	0.388***
	[1.97]	[2.34]	[2.45]	[2.81]
RTN1D	-0.420***	-0.415***	-0.510***	-0.501**
	[-2.81]	[-2.85]	[-3.58]	[-3.51]
SALE_EMPL	0.590***	0.618***	0.517***	0.553***
	[3.14]	[3.30]	[2.87]	[3.05]

Table 7: Single Factor Risk Premia Estimation

This table reports the factor risk premia over the sample period from January 2002 to April 2018. We report the two-pass (following the Fama-MacBeth procedure) and three-pass (following Giglio and Xiu (2021)) estimations for the country-specific factors. The corresponding Newey-West *t*-statistics are presented in square brace. ***, **, and * indicate 1%, 5%, and 10% statistical significance levels, respectively.

	Equal Weighted			Value Weighted			IVOL Weighted		
	Factor Risk Premia			Factor Risk Premia			Factor Risk Premia		
	Two-pass	Three-pass	R_f^2	Two-pass	Three-pass	R_f^2	Two-pass	Three-pass	R_f^2
AC_5Y_DPS	0.338	0.104	0.084**	0.639	0.103	0.092**	0.414	0.086	0.087**
	[0.74]	[1.51]		[1.30]	[1.49]		[1.08]	[1.51]	
CA_PS_GR	0.232	0.247**	0.396***	0.369	0.259**	0.395***	0.297	0.222**	0.34***
	[0.78]	[2.41]		[1.14]	[2.47]		[1.04]	[2.49]	
CFRNOA	0.142	0.082	0.235***	0.020	0.078	0.217***	0.101	0.028	0.211***
	[0.59]	[0.94]		[0.07]	[0.93]		[0.43]	[0.37]	
CFROA	0.085	0.079	0.235***	0.039	0.081	0.229***	0.111	0.064	0.155***
	[0.38]	[1.11]		[0.16]	[1.17]		[0.52]	[1.14]	
DEBT_CAPITAL	-0.549**	-0.318***	0.501***	-0.537**	-0.319***	0.481***	-0.577***	-0.264***	0.476***
	[-2.16]	[-3.01]		[-2.25]	[-3.09]		[-2.70]	[-2.90]	
DEBT_EQUITY	-0.438*	-0.267***	0.462***	-0.356	-0.275***	0.438***	-0.521**	-0.223**	0.481***
	[-1.72]	[-2.64]		[-1.52]	[-2.79]		[-2.25]	[-2.41]	
EBIT_EV	0.595**	0.396***	0.602***	0.479**	0.388***	0.64***	0.435**	0.305**	0.53***
	[2.42]	[2.84]		[2.14]	[2.78]		[1.99]	[2.55]	
EBITDA_EV	0.069	0.170	0.407***	0.053	0.176	0.463***	0.010	0.132	0.408***
	[0.30]	[1.43]		[0.22]	[1.41]		[0.05]	[1.24]	
ES_RECOMM_AVG	-0.169	-0.160	0.365***	-0.211	-0.168	0.394***	-0.120	-0.145*	0.336***
	[-0.53]	[-1.61]		[-0.63]	[-1.63]		[-0.43]	[-1.70]	
GR_INTR_SALE	0.655	0.290***	0.365***	0.302	0.297***	0.384***	0.372	0.230**	0.32***

	[1.50]	[2.64]		[0.77]	[2.60]		[0.98]	[2.45]	
INVENTO	-0.274	-0.228**	0.521***	-0.203	-0.216**	0.497***	-0.176	-0.157	0.517***
	[-1.58]	[-2.13]		[-1.18]	[-2.10]		[-1.14]	[-1.63]	
LT_DT_EQUITY	-0.243	-0.247**	0.536***	-0.421	-0.247**	0.502***	-0.248	-0.200*	0.531***
	[-0.90]	[-2.06]		[-1.37]	[-2.14]		[-1.01]	[-1.90]	
NET_MARGIN	0.659**	0.479***	0.653***	0.551	0.486***	0.657***	0.544**	0.406***	0.664***
	[2.39]	[2.93]		[2.25]	[2.99]		[2.29]	[2.74]	
OP_MARGIN_CHG	0.436	0.034	0.049	0.651	0.054	0.040	0.486	0.005	0.065
	[0.88]	[0.58]		[1.18]	[0.90]		[0.99]	[0.10]	
RECEIVA_TO	0.295	0.263***	0.388***	0.240	0.265***	0.386***	0.258	0.240***	0.387***
	[1.56]	[2.76]		[1.29]	[2.84]		[1.56]	[2.69]	
RNOA	0.623*	0.443***	0.613***	0.543	0.445***	0.616***	0.572*	0.358***	0.598***
	[1.74]	[2.99]		[1.55]	[3.06]		[1.81]	[2.79]	
ROA_CHG	0.549*	0.394***	0.543***	0.405	0.420***	0.567***	0.447*	0.346***	0.542***
	[1.74]	[2.82]		[1.52]	[2.96]		[1.69]	[2.71]	
ROE_CHG	0.577	0.138**	0.151***	0.445	0.147**	0.148***	0.488	0.087	0.103**
	[1.51]	[2.01]		[1.08]	[2.13]		[1.34]	[1.54]	
RTN1D	0.488	0.101**	0.044	0.414	0.099	0.048	0.337	0.114**	0.051**
	[1.15]	[2.07]		[0.94]	[1.95]		[0.86]	[2.40]	
SALE_EMPL	0.534***	0.456***	0.78***	0.608***	0.487***	0.785***	0.568***	0.421***	0.763***
	[2.64]	[2.71]		[3.05]	[2.98]		[2.95]	[2.68]	

Table 8: Multi-factor Portfolios

This table reports performance analysis for the multi-factor portfolios over the sample period from January 2002 to April 2018. We examine their long-short portfolio return, denoted as exr_{LS}^{Multi}, and the abnormal return, denoted as α_{LS}^{Multi}, controlled for systematic factor proxied by MSCI all-country index return. We form the multi-factor portfolios from single-factor portfolios in which the county-specific variable is significant at least 5% level (reported at *Multi-ft. (1%+5%)*), only at the 1% level (reported at *Multi-ft. (1%)*), only at the 5% level (reported at *Multi-ft. (5%)*), or insignificant (*Multi-ft. (Insig)*). The last row reports the multi-factor portfolios difference, $exr_{LS}^{Multi,1\%+5\%} - exr_{LS}^{Multi,Insig}$. We use Newey-West standard error to test regression coefficient significance. The corresponding *t*-statistics are presented in square brace. ***, **, and * indicate 1%, 5%, and 10% statistical significance levels, respectively.

	Equal Weighted		Value Weighted		IVOL Weighted	
	exr_{LS}^{Multi}	α_{LS}^{Multi}	exr_{LS}^{Multi}	α_{LS}^{Multi}	exr_{LS}^{Multi}	α_{LS}^{Multi}
I. Multi-ft. (1% + 5%)	0.507***	0.531***	0.484***	0.505***	0.461***	0.480***
	[3.89]	[4.11]	[3.73]	[3.84]	[3.86]	[4.02]
i. Multi-ft. (1%)	0.494***	0.517***	0.477***	0.498***	0.451***	0.471***
	[3.39]	[3.56]	[3.32]	[3.44]	[3.35]	[3.49]
ii. Multi-ft. (5%)	0.528***	0.551***	0.494***	0.516***	0.474***	0.492***
	[4.34]	[4.60]	[4.06]	[4.19]	[4.36]	[4.58]
II. Multi-ft. (Insig)	0.044	0.043	0.047	0.047	0.028	0.023
	[1.23]	[1.11]	[1.58]	[1.47]	[0.73]	[0.57]
I - II	0.463***	0.487***	0.437***	0.458***	0.433***	0.456***
	[3.68]	[3.96]	[3.53]	[3.69]	[3.60]	[3.81]

Table 9: Multi-factor Risk Premia Estimations

This table reports the multi-factor risk premia over the sample period from January 2002 to April 2018. *Multi-ft. (1%)* is the factor risk premia of the 1%-significant country variables, *Multi-ft. (5%)* is the factor risk premia of the 5%-significant country variables, and *Multi-ft. (1% + 5%)* is the factor risk premia of at least 5%-significant country variables. The corresponding Newey-West *t*-statistics are presented in square brace. ***, **, and * denote 1%, 5%, and 10% statistical significance levels, respectively.

	Equal Weighted			Value Weighted			IVOL Weighted		
	Factor Risk Premia			Factor Risk Premia			Factor Risk Premia		
	Two-pass	Three-pass	R_f^2	Two-pass	Three-pass	R_f^2	Two-pass	Three-pass	R_f^2
Model 1: Significant multi-factor vs. insignificant multi-factor									
Multi-ft. (1% + 5%)	0.454***	0.355***	0.801***	0.442***	0.363***	0.811***	0.404***	0.300***	0.781***
	[3.12]	[3.04]		[3.01]	[3.08]		[2.98]	[2.85]	
Multi-ft. (Insig)	-0.022	0.009	0.407***	0.000	0.027	0.340***	-0.071	-0.004	0.169***
	[-0.38]	[0.35]		[0.01]	[1.31]		[-0.87]	[-0.21]	
Model 2: Breakdown of significant multi-factor vs. insignificant multi-factor									
Multi-ft. (1%)	0.508***	0.392***	0.781***	0.498***	0.402***	0.796***	0.464***	0.338***	0.773***
	[3.15]	[3.06]		[3.08]	[3.14]		[3.05]	[2.88]	
Multi-ft. (5%)	0.372**	0.300***	0.697***	0.350**	0.303***	0.713***	0.303**	0.242***	0.658***
	[2.35]	[2.91]		[2.23]	[2.89]		[2.07]	[2.71]	
Multi-ft. (Insig)	-0.022	0.009	0.407***	0.002	0.027	0.340***	-0.075	-0.004	0.169***
	[-0.38]	[0.35]		[0.05]	[1.31]		[-0.91]	[-0.21]	

Table 10: Single-factor In-sample Prediction

This table reports the Fama-MacBeth regression results for the country-specific variables over the sample period from January 2002 to April 2018. The model specification is $exr_{i,t+1} = \alpha + \beta\, F_{i,t} + \gamma_1\, Controls_{it} + \varepsilon_{i,t}$, F is the country-specific variable. The corresponding Newey-West t-statistics are presented in square brace. ***, **, and * indicate 1%, 5%, and 10% statistical significance levels, respectively.

Panel A: Control for PC^{Insig}

	Intercept	F	$PC1^{Insig}$	$PC2^{Insig}$	$PC3^{Insig}$	R^2	N
CA_PS_GR	-0.006	0.033***	0.005	-0.006	-0.062	0.183	8732
	[-0.24]	[2.01]	[0.47]	[-0.40]	[-0.81]		
DEBT_CAPITAL	0.000	-0.050***	0.007	0.001	-0.007	0.176	8732
	[-0.01]	[-3.81]	[0.58]	[0.09]	[-0.09]		
DEBT_EQUITY	-0.002	-0.043***	0.011	-0.004	-0.036	0.177	8732
	[-0.09]	[-2.82]	[0.88]	[-0.25]	[-0.47]		
EBIT_EV	-0.015	0.072***	0.008	-0.028	-0.009	0.190	8732
	[-0.58]	[4.18]	[0.62]	[-1.80]	[-0.11]		
GR_INTR_SALE	-0.007	0.059***	-0.001	-0.011	-0.056	0.178	8732
	[-0.29]	[3.25]	[-0.11]	[-0.66]	[-0.67]		
NET_MARGIN	-0.001	0.033**	0.004	-0.008	-0.050	0.179	8732
	[-0.02]	[2.07]	[0.37]	[-0.52]	[-0.62]		
RECEIVA_TO	-0.003	0.030**	0.009	-0.012	-0.094	0.176	8732
	[-0.12]	[2.54]	[0.74]	[-0.76]	[-1.13]		
RNOA	-0.003	0.062***	-0.004	-0.002	-0.016	0.186	8732
	[-0.11]	[3.79]	[-0.36]	[-0.11]	[-0.20]		
ROA_CHG	-0.001	0.032*	0.006	-0.005	-0.051	0.187	8732
	[-0.04]	[1.81]	[0.48]	[-0.28]	[-0.59]		
SALE_EMPL	0.008	0.113**	0.004	-0.013	-0.065	0.176	8732
	[0.27]	[2.49]	[0.36]	[-0.83]	[-0.80]		

Panel B: Control for $PC^{1\%+5\%}$ and PC^{Insig}

	Intercept	F	$PC1^{1\%+5\%}$	$PC2^{1\%+5\%}$	$PC3^{1\%+5\%}$	$PC1^{Insig}$	$PC2^{Insig}$	$PC3^{Insig}$	R^2	N
CA_PS_GR	-0.001	0.024	0.035***	-0.007	0.023*	0.000	-0.007	-0.042	0.277	8732
	[-0.03]	[1.44]	[3.33]	[-0.52]	[1.84]	[0.04]	[-0.44]	[-0.51]		
DEBT_CAPITAL	0.001	-0.023	0.044***	-0.001	0.018	-0.007	-0.003	-0.011	0.268	8732
	[0.03]	[-1.36]	[3.37]	[-0.07]	[1.13]	[-0.59]	[-0.15]	[-0.12]		
DEBT_EQUITY	-0.004	-0.019	0.039***	-0.004	0.032**	-0.002	-0.013	-0.040	0.269	8732
	[-0.13]	[-0.98]	[3.05]	[-0.25]	[2.17]	[-0.21]	[-0.80]	[-0.49]		
EBIT_EV	-0.007	0.049***	0.035***	-0.001	0.013	-0.001	-0.018	0.000	0.274	8732
	[-0.25]	[2.80]	[2.91]	[-0.05]	[1.03]	[-0.10]	[-1.07]	[-0.00]		
GR_INTR_SALE	0.001	0.024	0.042***	0.000	0.022*	-0.006	-0.010	-0.005	0.268	8732
	[0.03]	[1.40]	[4.05]	[0.01]	[1.69]	[-0.53]	[-0.61]	[-0.05]		
NET_MARGIN	-0.006	-0.002	0.053***	0.014	0.008	-0.001	-0.012	-0.065	0.271	8732
	[-0.20]	[-0.12]	[4.53]	[1.07]	[0.51]	[-0.10]	[-0.76]	[-0.78]		
RECEIVA_TO	-0.005	0.011	0.043***	0.000	0.035**	-0.002	-0.010	0.008	0.267	8732
	[-0.18]	[0.87]	[3.96]	[-0.03]	[2.23]	[-0.15]	[-0.59]	[0.10]		
RNOA	0.003	0.013	0.050***	0.014	0.027**	-0.008	-0.011	-0.019	0.267	8732
	[0.10]	[0.72]	[3.68]	[1.08]	[2.00]	[-0.67]	[-0.68]	[-0.22]		
ROA_CHG	-0.001	-0.024	0.058***	0.014	0.002	-0.006	-0.006	0.019	0.278	8732
	[-0.03]	[-1.08]	[4.74]	[1.06]	[0.17]	[-0.55]	[-0.37]	[0.21]		
SALE_EMPL	0.009	0.085*	0.047***	0.005	0.021*	-0.007	-0.011	-0.017	0.270	8732
	[0.31]	[1.79]	[4.23]	[0.39]	[1.81]	[-0.57]	[-0.69]	[-0.20]		

Table 11: PCA-based FMB Regression

This table reports the Fama-MacBeth regression results for the country-specific variables over the sample period from January 2002 to April 2018. The model specification is $exr_{i,t+1} = \alpha + \beta\ PC_{it} + \varepsilon_{i,t}$. The corresponding Newey-West t-statistics are presented in square brace. ***, **, and * indicate 1%, 5%, and 10% statistical significance levels, respectively.

	Model 1	Model 2	Model 3	Model 4
Intercept	-0.001	0.006	-0.015	-0.002
	[-0.04]	[0.21]	[-0.56]	[-0.05]
$PC1^{1\%+5\%}$	0.047***			
	[4.39]			
$PC2^{1\%+5\%}$	0.003			
	[0.25]			
$PC3^{1\%+5\%}$	0.022*			
	[1.73]			
$PC1^{1\%}$		0.046***		0.026*
		[3.98]		[1.67]
$PC2^{1\%}$		0.031		0.042*
		[1.54]		[1.80]
$PC3^{1\%}$		0.032		0.042
		[1.01]		[1.10]
$PC1^{5\%}$			0.068***	0.056***
			[4.40]	[3.20]
$PC2^{5\%}$			-0.013	0.002
			[-0.86]	[0.09]
$PC3^{5\%}$			0.028*	0.026*
			[1.83]	[1.72]
$PC1^{Insig}$	-0.006	-0.004	0.000	-0.002
	[-0.49]	[-0.32]	[-0.02]	[-0.14]
$PC2^{Insig}$	-0.009	-0.003	-0.019	-0.021
	[-0.54]	[-0.19]	[-1.27]	[-1.21]
$PC3^{Insig}$	-0.018	-0.022	0.016	-0.028
	[-0.21]	[-0.25]	[0.21]	[-0.32]
R^2	0.244	0.240	0.244	0.327
N	8732	8732	8732	8732

Table 12: Single-factor Out-of-sample Prediction

This table reports the out-of-sample performance for the individual country-specific factors. Three measures are reported in the table: RMSE (Rooted Mean Square Error), MASE (Mean Absolute Scaled Error) and R_{OOS}^2 (Out-of-sample R-square). We first use the first 5-year data as training period and then predict the one-month ahead country equity return. We then roll to the next month and repeat the procedure to obtain the time-series prediction error of the country equity return. The numbers reported here are the time-series average of the prediction errors.

	RMSE	MASE	R_{OOS}^2
CA_PS_GR	4.683	0.688	0.203%
DEBT_CAPITAL	4.687	0.689	0.069%
DEBT_EQUITY	4.687	0.689	0.086%
EBIT_EV	4.686	0.689	0.070%
GR_INTR_SALE	4.687	0.688	0.042%
NET_MARGIN	4.687	0.689	0.122%
RECEIVA_TO	4.689	0.689	0.072%
RNOA	4.681	0.688	0.344%
ROA_CHG	4.687	0.689	0.150%
SALE_EMPL	4.703	0.690	-0.593%

Table 13: Multi-factor Out-of-sample Results

This table reports the out-of-sample performance for the multi factors. Three measures are reported in the table: RMSE (Rooted Mean Square Error), MASE (Mean Absolute Scaled Error) and R^2_{OOS} (Out-of-sample R-square). We consider three different types of PCs. $PC^{1\%}$ reports the PCs constructed by the 1%-significant country variables, $PC^{5\%}$ reports the PCs constructed by the 5%-significant country variables, $PC^{1\%+5\%}$ reports the PCs constructed by at least 5%-significant country variables, and PC^{Insig} reports the PCs constructed by insignificant country variables We first use the first 5-year data as training period and then predict the one-month ahead country equity return. We then roll to the next month and repeat the procedure to obtain the time-series prediction error of the country equity return. The numbers reported here are the time-series average of the prediction errors.

	RMSE	MASE	R^2_{OOS}
$PC1^{1\%+5\%}$	4.678	0.687	0.418%
$PC2^{1\%+5\%}$	4.690	0.689	-0.026%
$PC3^{1\%+5\%}$	4.691	0.689	-0.036%
$PC1^{1\%}$	4.682	0.688	0.302%
$PC2^{1\%}$	4.691	0.689	-0.033%
$PC3^{1\%}$	4.693	0.690	-0.110%
$PC1^{5\%}$	4.676	0.687	0.412%
$PC2^{5\%}$	4.692	0.690	-0.087%
$PC3^{5\%}$	4.691	0.689	-0.065%
$PC1^{Insig}$	4.692	0.690	-0.123%
$PC2^{Insig}$	4.689	0.690	-0.005%
$PC3^{Insig}$	4.703	0.690	-0.643%

Table 14: Factor Risk Premia by Level of Development

This table reports the factor risk premia by three-pass estimation over the sample period from January 2002 to April 2018. EW, VW, and IVOL-W means that the factor is formed by equal weight, value weight, and IVOL weight, respectively. The corresponding Newey-West *t*-statistics are presented in square brace. ***, **, and * indicate 1%, 5%, and 10% statistical significance levels, respectively.

	Developed Countries			Developing Countries		
	EW	AW	IVOL-W	EW	VW	IVOL-W
AC_5Y_DPS	0.072	0.073	0.071	0.117*	0.102*	0.093*
	[1.35]	[1.39]	[1.50]	[1.90]	[1.67]	[1.83]
CA_PS_GR	0.197**	0.207**	0.167**	0.139	0.136	0.134*
	[2.46]	[2.53]	[2.32]	[1.51]	[1.43]	[1.66]
CFRNOA	0.075	0.067	0.028	-0.021	-0.01	-0.029
	[0.93]	[0.86]	[0.39]	[-0.33]	[-0.16]	[-0.53]
CFROA	0.086	0.082	0.068	0.035	0.034	0.032
	[1.40]	[1.41]	[1.40]	[0.60]	[0.59]	[0.63]
DEBT_CAPITAL	-0.185**	-0.193**	-0.164**	-0.283***	-0.279***	-0.241***
	[-2.12]	[-2.31]	[-2.01]	[-3.26]	[-3.29]	[-3.21]
DEBT_EQUITY	-0.188**	-0.204**	-0.168*	-0.222***	-0.230***	-0.197***
	[-2.04]	[-2.21]	[-1.92]	[-2.90]	[-3.05]	[-2.86]
EBIT_EV	0.241**	0.231**	0.180*	0.332**	0.316**	0.299**
	[2.14]	[2.04]	[1.77]	[2.49]	[2.36]	[2.57]
EBITDA_EV	0.071	0.07	0.065	0.196*	0.202*	0.177*
	[0.75]	[0.68]	[0.71]	[1.76]	[1.72]	[1.78]
ES_RECOMM_AVG	-0.023	-0.037	-0.038	-0.182**	-0.184**	-0.146**
	[-0.26]	[-0.42]	[-0.50]	[-2.22]	[-2.20]	[-2.13]
GR_INTR_SALE	0.182**	0.194**	0.150*	0.235**	0.223**	0.216**
	[2.03]	[2.12]	[1.90]	[2.25]	[2.05]	[2.40]
INVENTO	-0.119	-0.107	-0.092	-0.164**	-0.146**	-0.108*
	[-1.22]	[-1.14]	[-0.99]	[-2.25]	[-2.11]	[-1.74]
LT_DT_EQUITY	-0.225*	-0.241**	-0.178*	-0.185**	-0.188**	-0.191**
	[-1.93]	[-2.09]	[-1.73]	[-2.11]	[-2.16]	[-2.30]
NET_MARGIN	0.229*	0.236*	0.197	0.427***	0.418***	0.397***
	[1.68]	[1.75]	[1.55]	[2.64]	[2.61]	[2.71]
OP_MARGIN_CHG	0.026	0.039	0.006	0.003	0.009	-0.022
	[0.52]	[0.79]	[0.12]	[0.05]	[0.18]	[-0.46]
RECEIVA_TO	0.178**	0.175**	0.131*	0.209**	0.208**	0.224***
	[2.16]	[2.25]	[1.78]	[2.48]	[2.49]	[2.63]
RNOA	0.256**	0.254**	0.208*	0.351**	0.334**	0.316***

	[2.01]	[2.06]	[1.82]	[2.52]	[2.47]	[2.60]
ROA_CHG	0.238**	0.248**	0.209*	0.320**	0.320**	0.310**
	[2.01]	[2.09]	[1.88]	[2.39]	[2.35]	[2.49]
ROE_CHG	0.097	0.112*	0.08	0.152**	0.150**	0.116*
	[1.50]	[1.66]	[1.35]	[2.15]	[2.10]	[1.91]
RTN1D	0.024	0.018	0.042	0.105**	0.078	0.091*
	[0.45]	[0.34]	[0.89]	[1.99]	[1.52]	[1.84]
SALE_EMPL	0.280*	0.283**	0.233*	0.442***	0.445***	0.418***
	[1.80]	[1.96]	[1.68]	[2.97]	[3.01]	[2.93]

Table 15: Factor Risk Premia by Regions

This table reports the factor risk premia by three-pass estimation over the sample period from January 2002 to April 2018. EW, VW, and IVOL-W means that the factor is formed by equal weight, value weight, and IVOL weight, respectively. The corresponding Newey-West *t*-statistics are presented in square brace. ***, **, and * indicate 1%, 5%, and 10% statistical significance levels, respectively.

Panel A: America and ROTC

	America			ROTC		
	EW	VW	IVOL-W	EW	VW	IVOL-W
AC_5Y_DPS	0.022	0.013	0.014	0.048	0.051	0.034
	[0.39]	[0.26]	[0.29]	[0.95]	[1.04]	[0.83]
CA_PS_GR	0.075	0.083	0.062	0.029	0.032	0.018
	[1.05]	[1.14]	[1.00]	[0.39]	[0.43]	[0.30]
CFRNOA	-0.128	-0.127	-0.12	-0.019	-0.017	-0.025
	[-1.52]	[-1.56]	[-1.59]	[-0.32]	[-0.30]	[-0.47]
CFROA	0.031	0.029	0.033	-0.008	-0.001	0.003
	[0.49]	[0.48]	[0.62]	[-0.16]	[-0.02]	[0.09]
DEBT_CAPITAL	-0.128*	-0.131**	-0.113*	-0.157**	-0.151**	-0.131**
	[-1.80]	[-2.03]	[-1.72]	[-2.10]	[-2.08]	[-2.01]
DEBT_EQUITY	-0.094	-0.098	-0.077	-0.126**	-0.119**	-0.113*
	[-1.40]	[-1.56]	[-1.26]	[-1.98]	[-1.99]	[-1.85]
EBIT_EV	0.210*	0.202*	0.187*	0.171*	0.169	0.152
	[1.85]	[1.79]	[1.87]	[1.65]	[1.61]	[1.64]
EBITDA_EV	0.086	0.09	0.09	0.122	0.132	0.101
	[0.91]	[0.91]	[1.06]	[1.46]	[1.51]	[1.31]
ES_RECOMM_AVG	-0.054	-0.051	-0.051	-0.072	-0.067	-0.052
	[-0.89]	[-0.89]	[-1.02]	[-1.06]	[-0.97]	[-0.85]
GR_INTR_SALE	0.089	0.084	0.073	0.083	0.071	0.066
	[1.11]	[1.05]	[1.06]	[1.14]	[0.96]	[1.07]
INVENTO	-0.067	-0.06	-0.048	-0.048	-0.047	-0.032
	[-1.21]	[-1.10]	[-0.88]	[-0.73]	[-0.71]	[-0.56]
LT_DT_EQUITY	-0.043	-0.045	-0.028	-0.111	-0.094	-0.115
	[-0.53]	[-0.57]	[-0.36]	[-1.39]	[-1.35]	[-1.61]
NET_MARGIN	0.143	0.155	0.156	0.219*	0.219*	0.185*
	[1.28]	[1.36]	[1.47]	[1.78]	[1.80]	[1.66]
OP_MARGIN_CHG	-0.054	-0.041	-0.065	0.003	0.008	-0.014
	[-1.14]	[-0.94]	[-1.50]	[0.09]	[0.25]	[-0.40]
RECEIVA_TO	0.098	0.103	0.098	0.077	0.08	0.092
	[1.34]	[1.43]	[1.29]	[1.15]	[1.22]	[1.33]

RNOA	0.075	0.065	0.077	0.163	0.162	0.14
	[0.72]	[0.67]	[0.83]	[1.61]	[1.60]	[1.56]
ROA_CHG	0.022	0.028	0.043	0.156*	0.168*	0.143*
	[0.25]	[0.31]	[0.50]	[1.68]	[1.76]	[1.67]
ROE_CHG	-0.029	-0.025	-0.036	0.079*	0.075*	0.05
	[-0.45]	[-0.40]	[-0.62]	[1.80]	[1.74]	[1.51]
RTN1D	0.083	0.027	0.06	0.026	0.029	0.024
	[1.42]	[0.47]	[1.09]	[0.65]	[0.75]	[0.69]
SALE_EMPL	0.175	0.192	0.167	0.145	0.171	0.152
	[1.51]	[1.62]	[1.52]	[1.22]	[1.58]	[1.39]

Panel B: Asia and Europe

	Asia			Europe		
	EW	VW	IVOL-W	EW	VW	IVOL-W
AC_5Y_DPS	0.025	0.02	0.012	0.072	0.079	0.076
	[0.51]	[0.45]	[0.28]	[1.34]	[1.41]	[1.60]
CA_PS_GR	0.136*	0.138*	0.126*	0.177**	0.188**	0.146**
	[1.80]	[1.75]	[1.79]	[2.22]	[2.35]	[1.97]
CFRNOA	-0.01	-0.002	-0.021	0.128*	0.125*	0.081
	[-0.22]	[-0.05]	[-0.54]	[1.69]	[1.69]	[1.24]
CFROA	0.001	-0.005	0.001	0.077	0.075	0.063
	[0.03]	[-0.11]	[0.02]	[1.11]	[1.14]	[1.13]
DEBT_CAPITAL	-0.143*	-0.139*	-0.135*	-0.161*	-0.166**	-0.129*
	[-1.76]	[-1.70]	[-1.67]	[-1.96]	[-2.11]	[-1.80]
DEBT_EQUITY	-0.091	-0.091	-0.095	-0.164*	-0.175*	-0.139*
	[-1.26]	[-1.21]	[-1.26]	[-1.80]	[-1.93]	[-1.72]
EBIT_EV	0.187**	0.181**	0.152**	0.238**	0.235**	0.170*
	[2.21]	[2.25]	[2.08]	[2.20]	[2.12]	[1.73]
EBITDA_EV	0.083	0.075	0.068	0.074	0.079	0.07
	[1.45]	[1.29]	[1.31]	[0.78]	[0.77]	[0.78]
ES_RECOMM_AVG	-0.178**	-0.181**	-0.146**	-0.027	-0.047	-0.04
	[-2.25]	[-2.20]	[-2.13]	[-0.30]	[-0.51]	[-0.50]
GR_INTR_SALE	0.201**	0.206**	0.181**	0.163*	0.184**	0.124
	[2.28]	[2.31]	[2.20]	[1.90]	[2.08]	[1.62]
INVENTO	-0.119**	-0.111*	-0.094*	-0.107	-0.095	-0.076
	[-1.96]	[-1.93]	[-1.83]	[-1.07]	[-0.98]	[-0.77]
LT_DT_EQUITY	-0.103	-0.1	-0.1	-0.187*	-0.206*	-0.141
	[-1.19]	[-1.14]	[-1.15]	[-1.71]	[-1.83]	[-1.46]
NET_MARGIN	0.320**	0.316**	0.291**	0.242*	0.246**	0.193*
	[2.26]	[2.26]	[2.20]	[1.93]	[1.96]	[1.67]

OP_MARGIN_CHG	0.049	0.051	0.023	0.029	0.047	0.015
	[1.11]	[1.16]	[0.58]	[0.60]	[0.98]	[0.34]
RECEIVA_TO	0.172**	0.171**	0.173**	0.164*	0.161**	0.118
	[2.30]	[2.30]	[2.33]	[1.95]	[1.99]	[1.54]
RNOA	0.276**	0.267**	0.236**	0.246**	0.245**	0.191*
	[2.27]	[2.28]	[2.16]	[2.00]	[2.04]	[1.76]
ROA_CHG	0.287**	0.295**	0.261**	0.202*	0.213**	0.164*
	[2.19]	[2.24]	[2.06]	[1.96]	[2.02]	[1.75]
ROE_CHG	0.132*	0.139**	0.094*	0.1	0.123*	0.084
	[1.95]	[2.02]	[1.65]	[1.61]	[1.85]	[1.44]
RTN1D	0.058	0.05	0.058	0.009	0.014	0.031
	[1.28]	[1.11]	[1.37]	[0.23]	[0.31]	[0.84]
SALE_EMPL	0.284**	0.284**	0.263**	0.305**	0.300**	0.250**
	[2.08]	[2.06]	[2.00]	[2.27]	[2.23]	[2.07]

Table 16: Multi-factor Risk Premia by Regions

This table reports the factor risk premia by three-pass estimation over the sample period from January 2002 to April 2018. EW, VW, and IVOL-W means that the factor is formed by equal weight, value weight, and IVOL weight, respectively. The corresponding Newey-West *t*-statistics are presented in square brace. ***, **, and * indicate 1%, 5%, and 10% statistical significance levels, respectively.

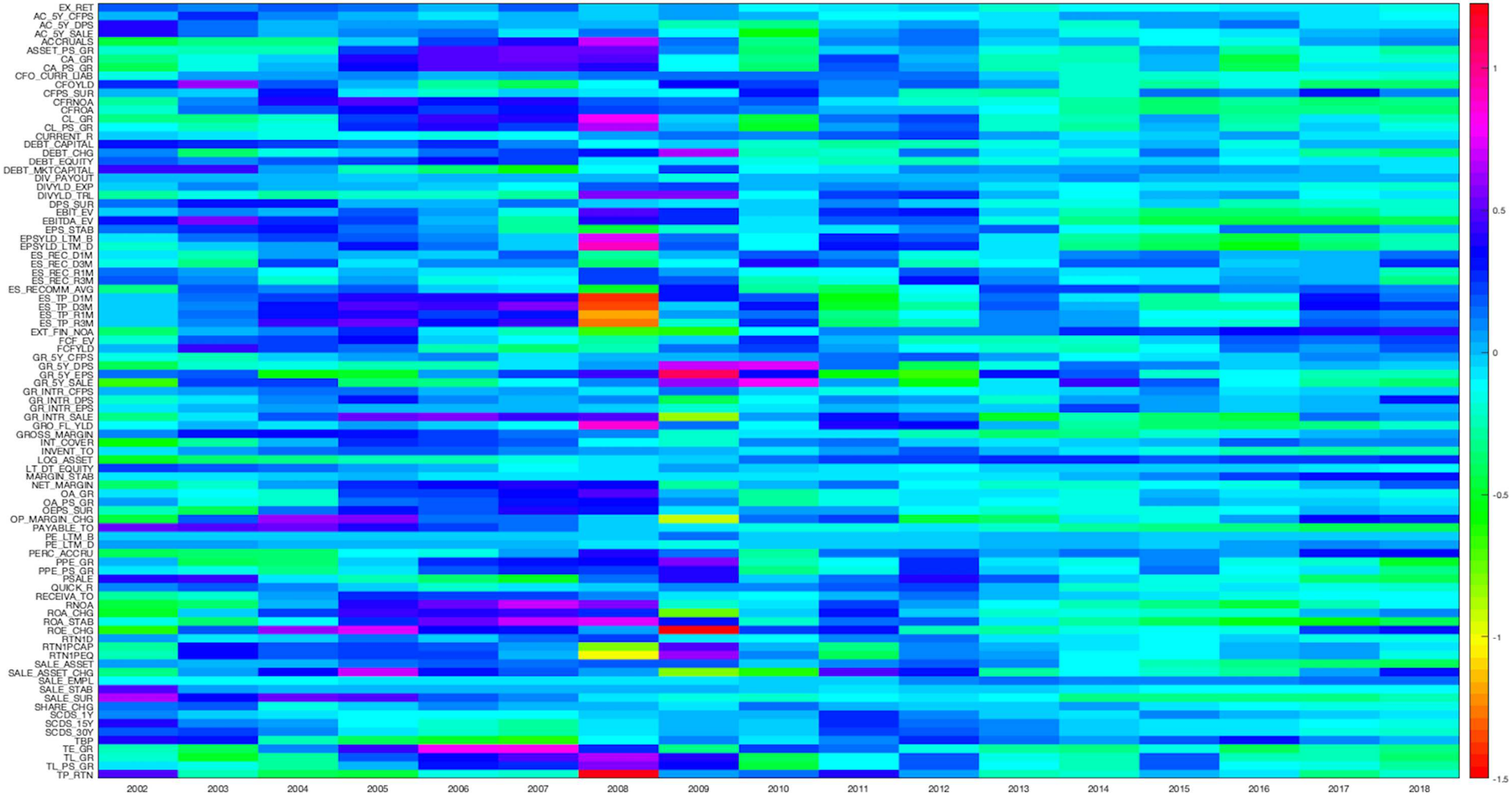
	Developed Countries			Developing Countries		
	EW	VW	IVOL-W	EW	VW	IVOL-W
Multi-ft. (1%)	0.227**	0.231**	0.191*	0.339***	0.333***	0.318***
	[2.08]	[2.16]	[1.88]	[2.87]	[2.85]	[2.90]
Multi-ft. (5%)	0.202**	0.207**	0.166**	0.232**	0.227**	0.209***
	[2.33]	[2.34]	[2.12]	[2.53]	[2.45]	[2.65]
Multi-ft. (Insig)	-0.01	0.007	-0.015	0.033	0.027	0.023
	[-0.42]	[0.42]	[-0.75]	[1.47]	[1.32]	[1.45]

	America			ROTC		
	EW	VW	IVOL-W	EW	VW	IVOL-W
Multi-ft. (1%)	0.107	0.113	0.111	0.153*	0.158*	0.140*
	[1.25]	[1.34]	[1.34]	[1.73]	[1.78]	[1.70]
Multi-ft. (5%)	0.117	0.117	0.1	0.102	0.098	0.086
	[1.58]	[1.61]	[1.57]	[1.48]	[1.40]	[1.42]
Multi-ft. (Insig)	0.025	0.021	0.02	0.005	0.008	-0.003
	[1.25]	[1.05]	[1.33]	[0.28]	[0.80]	[-0.23]

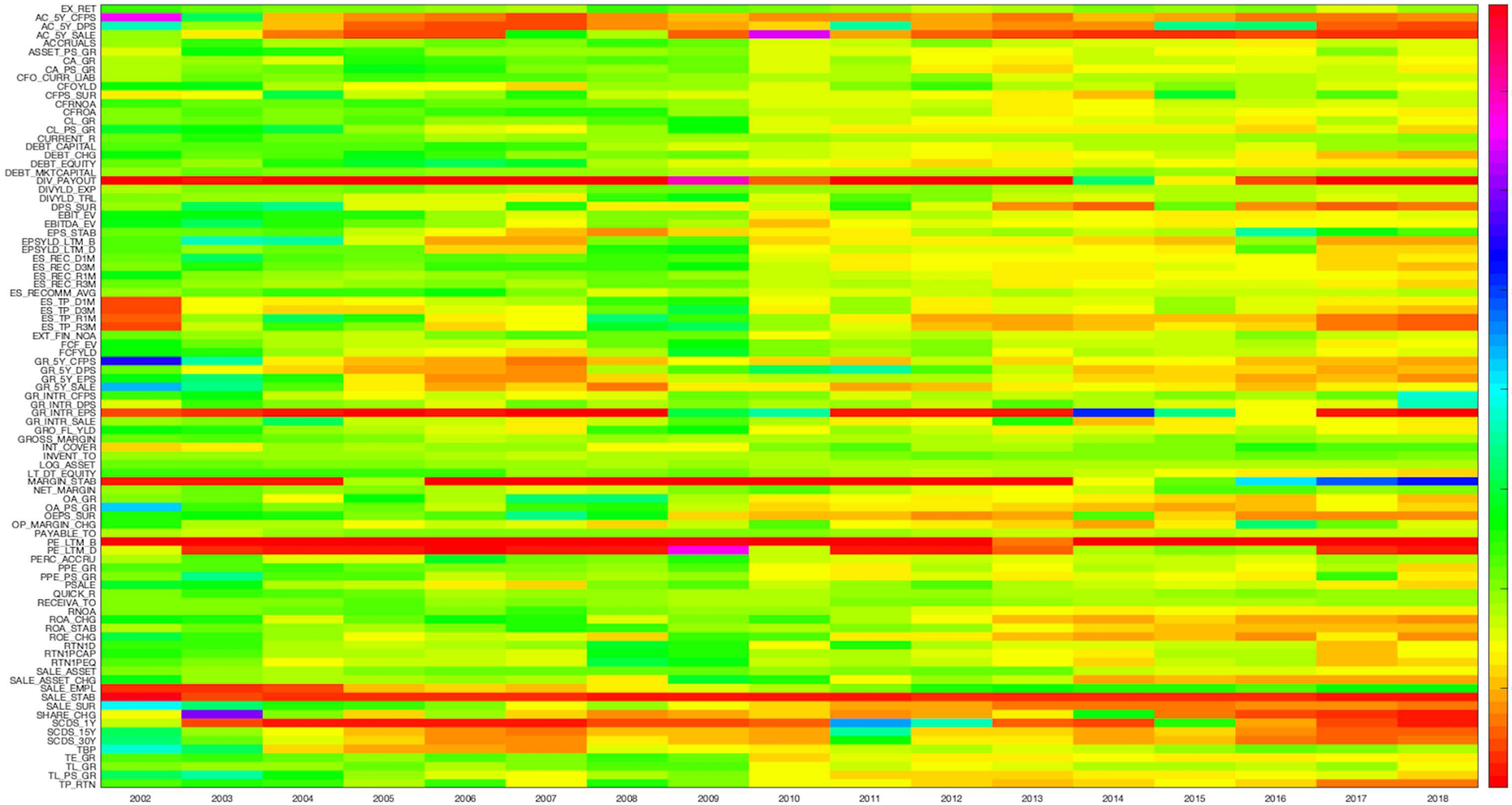
	Asia			Europe		
	EW	VW	IVOL-W	EW	VW	IVOL-W
Multi-ft. (1%)	0.247**	0.244**	0.226**	0.220**	0.221**	0.174*
	[2.30]	[2.31]	[2.22]	[2.19]	[2.22]	[1.92]
Multi-ft. (5%)	0.154**	0.154**	0.136**	0.185**	0.193**	0.143*
	[2.10]	[2.09]	[2.00]	[2.25]	[2.31]	[1.93]
Multi-ft. (Insig)	0.007	0.007	0.004	-0.013	0.002	-0.017
	[0.47]	[0.65]	[0.37]	[-0.75]	[0.16]	[-0.98]

Figure 1: Cross-sectional Average and Volatility of Variables

This figure plots the heatmaps of the cross-sectional average and volatility for the variables. Figure (i) plots the cross-sectional average and Figure (ii) plots the cross-sectional volatility.



(i) Cross-sectional Average

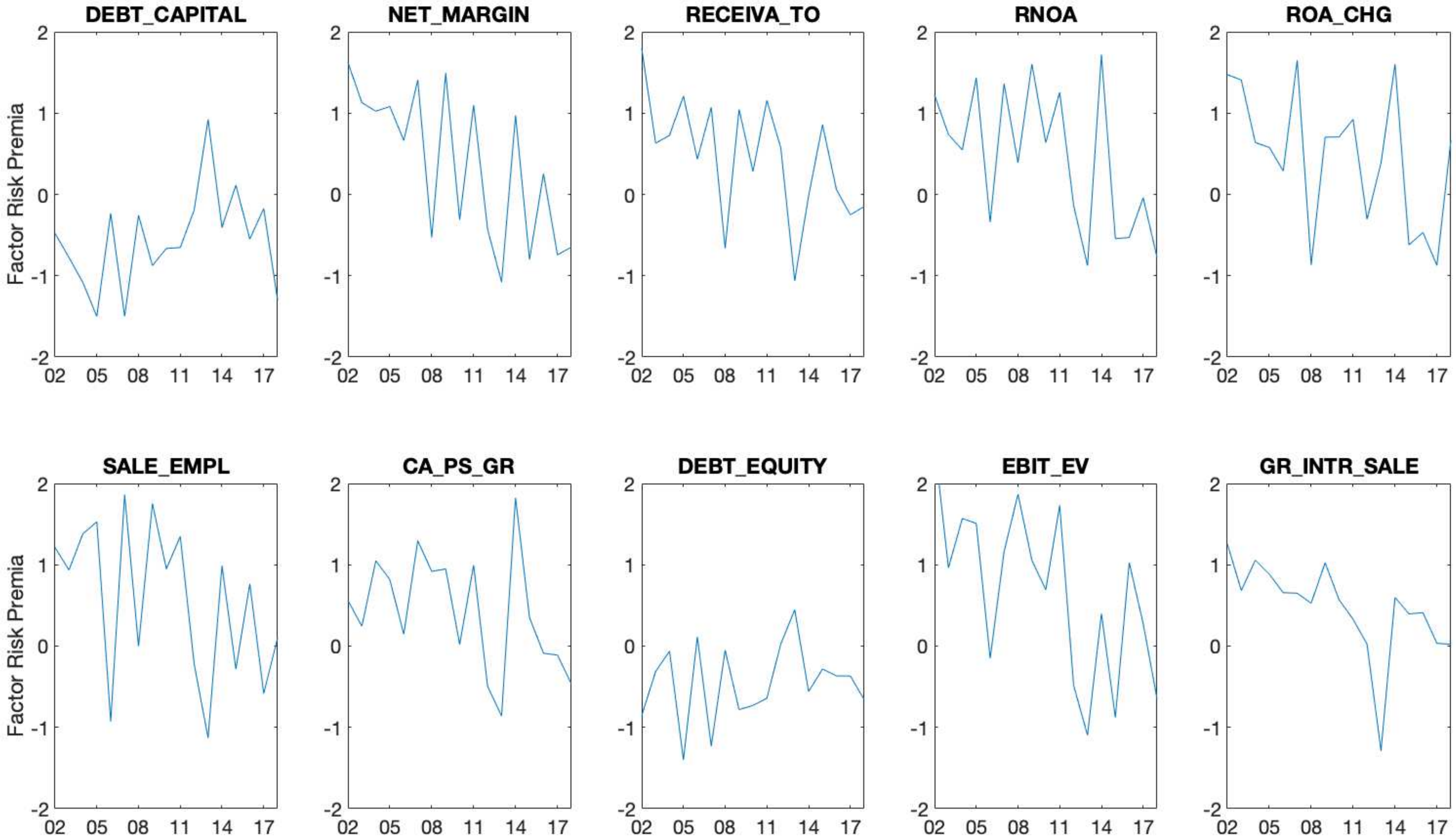


(ii) Cross-sectional Volatility

Figure 2: Factor Risk Premia

This figure plots the risk premia for the 10 factors over the sample period. Panel A plots the time-series of the factor risk premia. The vertical line represents the factor risk premia (in percentage) and the horizontal line represents the time. Panel B reports the time-series correlation of the 10 factors against Fama-French market risk premia.

Panel A: Time-series Factor Risk Premia



Panel B: Correlation Coefficient

	DEBT_CAPITAL	NET_MARGIN	RECEIVA_TO	RNOA	ROA_CHG	SALE_EMPL	CA_PS_GR	DEBT_EQUITY	EBIT_EV	GR_INTR_SALE
Corr. Coef.	-0.095	0.242	0.162	0.136	0.175	0.177	-0.144	-0.072	-0.160	0.033

Figure 3: Multi-Factor Risk Premia

This figure plots the risk premia for the four multi-factors, i.e., multi-ft. (1%+5%), multi-ft. (1%), multi-ft. (5%), and multi-ft. (Insig). The vertical line represents the factor risk premia (in percentage) and the horizontal line represents the time.

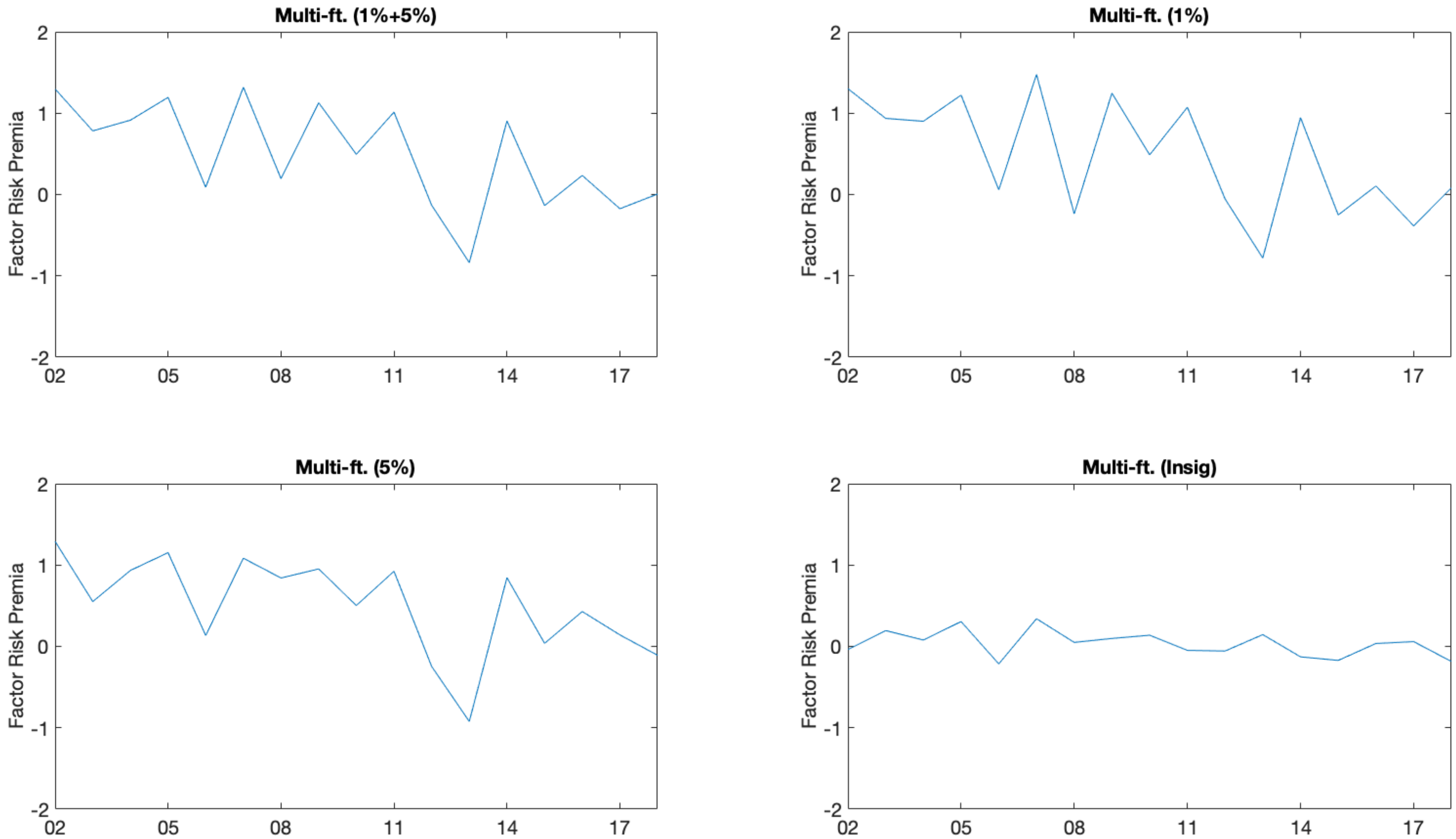
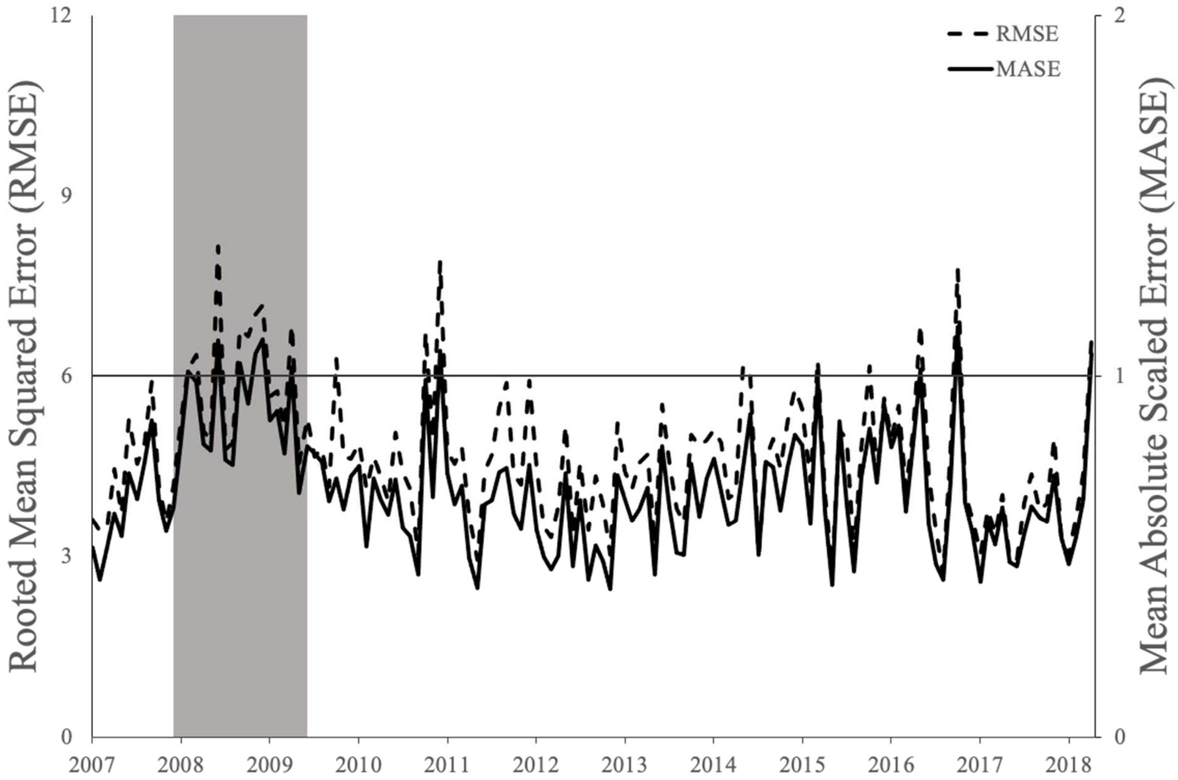


Figure 4: Monthly RMSE and MASE for PC^{Sig}

This figure plots the monthly RMSE and MASE for the PC^{Sig} over the prediction period from 2007 to 2018.



Appendix

Table A.1: Country-Specific Variable Definition

This table provides the definition of the 115 country-specific variables. The Variable column provides the variable name used in the study and the Definition column provides the explanation or definition of the corresponding variables.

Variable	Definition	Variable	Definition
AC_5Y_CFPS	Historical 5Y CFPS growth acceleration	INVENT_TO	Inventory turnover
AC_5Y_DPS	Historical 5Y DPS growth acceleration	LOG_ASSET	Log Asset USD
AC_5Y_EPS	Historical 5Y EPS growth acceleration	LOG_FLOAT	Log Float USD
AC_5Y_OEPS	Historical 5Y operating EPS growth acceleration	LOG_MKTCAP	Log Mkt Cap USD
AC_5Y_SALE	Historical 5Y revenue growth acceleration	LOG_SALE	Log Sale USD
ACCRUALS	Accruals (Sloan 1996)	LT_DT_CAPITAL	Long-term debt/total capital
ASSET_GR	Asset growth anomaly (Cooper, Gulen, Schill [2008])	LT_DT_EQUITY	Long-term debt/common equity
ASSET_PS_GR	Asset growth anomaly, per share total assets	MARGIN_STAB	Gross margin stability, 5Y
BOOKP	Book-to-market	NET_MARGIN	Net income margin
CA_GR	Growth in current assets	OA_GR	Growth in other assets
CA_PS_GR	Growth in per share current assets	OA_PS_GR	Growth in per share other assets
CFO_CURR_LIAB	Operating cash flow to current liabilities	OEPS_STAB	Historical operating EPS stability, coef of determination
CFOYLD	Operating cash flow yield	OEPS_SUR	Normalized EPS surprise (vs consensus)
CFPS_SUR	CFPS surprise (vs consensus)	OP_MARGIN	Operating profit margin (EBIT margin)
CFRNOA	Cash flow return on net operating assets (CFRNOA)	OP_MARGIN_CHG	YoY change in operating profit margin
CFROA	Cash flow return on asset (CFROA)	PAYABLE_TO	Accounts payable turnover
CFROE	Cash flow return on equity (CFROE)	PE_LTM_B	Price-to-EPS, LTM, basic
CL_GR	Growth in current liabilities	PE_LTM_D	Price-to-EPS, LTM, diluted
CL_PS_GR	Growth in per share current liabilities	PERC_ACCRU	Percent accruals
CURRENT_R	Current ratio	PPE_GR	Growth in property, plan, and equipment
DEBT_CAPITAL	Total debt/total capital	PPE_PS_GR	Growth in per share property, plan, and equipment
DEBT_CHG	YoY change in debt outstanding	PSALE	Price-to-sales
DEBT_EQUITY	Total debt/total equity	QUICK_R	Quick ratio
DEBT_MKTCAPITAL	Total debt/total capital at market value	RECEIVA_TO	Accounts receivable turnover
DIV_PAYOUT	Dividend payout ratio, trailing	RNOA	Return on net operating assets (RNOA), LTM
DIVYLD_EXP	Expected dividend yield	ROA	ROA, LTM
DIVYLD_SH	Total yield (dividend + buyback - issuance)	ROA_CHG	YoY change in ROA
DIVYLD_TRL	Trailing dividend yield	ROA_STAB	ROA stability, 5Y
DPS_SUR	DPS surprise (vs consensus)	ROE	ROE, LTM
EBIT_EV	EBIT/TEV	ROE_CHG	YoY change in ROE
EBITDA_EV	EBITDA/TEV	ROE_STAB	ROE stability, 5Y
EPS_STAB	Historical EPS stability, coef of determination	ROIC	ROIC, LTM
EPSYLD_LTM_B	Earnings yield, LTM, basic	RTN1D	Total return, past 1D
EPSYLD_LTM_D	Earnings yield, LTM, diluted	RTN1PCAP	One Month Return Cap-weighted
ES_REC_D1M	Recommendation diffusion (up/down ratio), 1M	RTN1PEQ	One Month Return Equi-weighted
ES_REC_D3M	Recommendation diffusion (up/down ratio), 3M	SALE_ASSET	Sales to total assets (asset turnover)
ES_REC_R1M	Recommendation revision, 1M	SALE_ASSET_CHG	YoY change in asset turnover
ES_REC_R3M	Recommendation revision, 3M	SALE_EMPL	Revenue per employee
ES_RECOMM_AVG	Mean recommendation	SALE_EV	Revenue/TEV
ES_TP_D1M	Target price diffusion (up/down ratio), 1M	SALE_STAB	Historical revenue stability, coef of determination
ES_TP_D3M	Target price diffusion (up/down ratio), 3M	SALE_SUR	Revenue surprise (vs consensus)

ES_TP_R1M	Target price revision, 1M	SHARE_CHG	YoY change in share count
ES_TP_R3M	Target price revision, 3M	SCDS_1Y	Sovereign CDS Spread, 1Y
EXT_FIN_NOA	Net external financing/net operating assets	SCDS_2Y	Sovereign CDS Spread, 2Y
FCF_EV	FCF (levered)/TEV	SCDS_3Y	Sovereign CDS Spread, 3Y
FCFYLD	Free cash flow (unlevered) yield	SCDS_5Y	Sovereign CDS Spread, 5Y
GR_5Y_CFPS	Historical 5Y CFPS growth trend	SCDS_7Y	Sovereign CDS Spread, 7Y
GR_5Y_DPS	Historical 5Y DPS growth trend	SCDS_10Y	Sovereign CDS Spread, 10Y
GR_5Y_EPS	Historical 5Y EPS growth trend	SCDS_15Y	Sovereign CDS Spread, 15Y
GR_5Y_OEPS	Historical 5Y operating EPS growth trend	SCDS_20Y	Sovereign CDS Spread, 20Y
GR_5Y_SALE	Historical 5Y revenue growth trend	SCDS_30Y	Sovereign CDS Spread, 30Y
GR_INTR_CFPS	Historical YoY interim CFPS growth	TBP	Tangible book-to-market
GR_INTR_DPS	Historical YoY interim DPS growth	TE_GR	Growth in total shareholders' equity
GR_INTR_EPS	Historical YoY interim EPS growth	TE_PS_GR	Growth in per share total shareholders' equity
GR_INTR_SALE	Historical YoY interim revenue growth	TL_GR	Growth in total liabilities
GRO_FL_YLD	Growth flow yield	TL_PS_GR	Growth in per share total liabilities
GROSS_MARGIN	Gross profit margin	TP_RTN	Target price implied return
INT_COVER	Interest Coverage [1968]		

Table A.2: List of Variables for Principal Components

This table lists the country-specific variables for constructing principal components. Column 1 lists the variables used for $PC_{1\%}$ and Column 2 lists the variables used for $PC_{5\%}$ Variables in Columns 1 and 2 are used for $PC_{1\%+5\%}$.

Factors included in 1%-significance group	Factors included in 5%-significance group	Factors included in insignificance group
DEBT_CAPITAL	CA_PS_GR	AC_5Y_CFPS
NET_MARGIN	DEBT_EQUITY	ACCRUALS
RECEIVA_TO	EBIT_EV	CFO_CURR_LIAB
RNOA	GR_INTR_SALE	CFOYLD
ROA_CHG		CFPS_SUR
SALE_EMPL		CURRENT_R
		DEBT_CHG
		DIV_PAYOUT
		DIVYLD_TRL
		EPS_STAB
		ES_REC_R1M
		ES_REC_R3M
		ES_TP_D3M
		EXT_FIN_NOA
		FCFYLD
		GR_5Y_CFPS
		GR_INTR_DPS
		GROSS_MARGIN
		INT_COVER
		MARGIN_STAB
		OEPS_SUR
		PE_LTM_B
		PE_LTM_D
		PERC_ACCRU
		PPE_GR
		PSALE
		QUICK_R
		RTN1PEQ
		SALE_STAB
		SALE_SUR
		SCDS_1Y
		SCDS_15Y
		SCDS_30Y
		TBP
		TL_PS_GR
		TP_RTN

Figure A.1: Eigenvalues for the Portfolio of Country Equity

This figure plots the first 20 eigenvalues for the portfolio of country equity excess return.