No One-Size-Fits-All Tale:
The Diversity and Complexity in Asset Pricing across Global Markets

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Abstract

We utilize a Bayesian approach developed by Chib, Zeng, and Zhao (2020) and Chib and Zeng (2020) to identify the best asset pricing models for international stock markets. Our findings reveal that models with Student-t distribution outperform models with Gaussian distribution in all markets. However, the best models vary depending on the specific market, and the factor strength fluctuates over time, highlighting the diversity and complexity of asset pricing in different markets. Although currency risk factors are crucial in international asset pricing, they were weakened during the global financial crisis in 2008. Additionally, we evaluate the efficiency of our local, regional, and global models in explaining various cross-sectional anomalies. Our research indicates that local factor models are the most successful, while regional and global models have similar outcomes.

Keywords: Bayesian analysis, Model comparison, Fat tails, Currency risk, Factor strength, International asset pricing

JEL classification: G12, G15

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1. Introduction

Financial economists have been studying why expected stock returns differ using asset pricing models with a few factors for years. The most famous factors were suggested by Fama and French (1993). Since then, many more factors have been proposed, creating a "factor zoo," as mentioned by Cochrane (2011). However, it's uncertain if these factors are useful in asset pricing. Harvey, Liu, and Zhu (2016) list 316 factors in the literature and suggested that many of these may have been found through extensive data mining. With so many new pricing factors emerging in recent literature, it has become difficult for researchers to compare the various models constructed using this "zoo" of factors.

To identify factors, researchers have proposed two technical approaches in the literature. Some use the frequentist statistics method to compare models, while others use the Bayesian statistics method. The GRS F-test of Gibbons, Ross, and Shanken (1989), one of the frequentist statistics approaches, is a famous test used to evaluate asset pricing models. It tests the goodness of a factor model by examining whether all intercepts in the time-series regressions of the model are jointly equal to zero. However, this method only works for comparing two nested asset pricing models. Barillas and Shanken (2017) develop another model comparison method that measures the extent of model mispricing by improving the squared Sharpe ratio. Barillas et al. (2020) explain how to properly compare non-nested models using valid asymptotic tests based on the framework developed by Barillas and Shanken (2017). Other methods for comparing models include the Hansen-Jagannathan distance by Hansen and Jagannathan (1997) (discussed in Kan and Robotti, 2009; Gospodinov, Kan, and Robotti, 2013) and the cross-sectional R^2 by Kan, Robotti, and Shanken (2013).

We adopt the Bayesian approach to select the best asset pricing model in this study due to multiple reasons. Bayesian solves the issue of the factor zoos as it can handle a large pool of candidate factors (Harvey, 2017). Recently, researchers have come up with new model comparison methods that are based on this approach. In contrast to traditional statistics, the Bayesian approach incorporates priors that provide information from previous data. The Bayesian approach is advantageous over the frequentist methods because it simultaneously compares many nested and non-nested models, which frequentist methods cannot do. Barillas and Shanken (2018) propose a Bayesian method to compare all possible pricing models based on subsets of the given factor space.

Chib, Zeng, and Zhao (2020) find that the original prior specification of Barillas and Shanken (2018) is unsuitable for model comparisons. To address this issue, Chib, Zeng, and Zhao (2020) develop a new set of priors that leads to valid comparisons for asset pricing factor models and demonstrate that their new method has significantly superior performance.[1] Their approach also determines the SDF factors, the underlying principle of genuine risk factors according to Pukthuanthong, Roll and Subrahmanyam (2019), while some frequentist approaches, such as the GRS test, focus on the zero alpha condition.

In addition, Barillas and Shanken (2018) and Chib, Zeng, and Zhao (2020) assume that risk factors follow a Gaussian distribution. However, the actual factor data often displays fat tails (Fama, 1965; Affleck-Graves and McDonald, 1989; Zhou, 1993), which can be problematic. Chib and Zeng (2020) develop a Bayesian model scan strategy to estimate and compare Student-t distributed factor models with different degrees of freedom to

[1] Another limitation of Barillas and Shanken (2018) is that the market (MKT) factor is prejudged as a risk factor in all models, whereas Chib, Zeng, and Zhao (2020) are agnostic about the status of the MKT factor.

address this issue. They find that the Student-t distributed factor model outperforms the Gaussian distributed model in the US stock market. [2] Our adopted approaches allow us to compare the models with Student-t distribution and Gaussian distribution in all markets.

Due to their limitations, we do not adopt other approaches in selecting the best asset models. The factor identification protocol proposed by Pukthuanthong, Roll and Subrahmanyam (2019) effectively determines genuine risk factors. However, it becomes inadequate when dealing with many factor candidates, resulting in an unstable covariance matrix. As a result, this study cannot use their protocol. Feng, Giglio, and Xiu (2020) utilize Lasso to identify factors from the factor zoo. However, their method requires knowledge of the actual risk factors we do not possess. Hence, we cannot apply their approach. The Bayesian approach that we adopt has limitations as it depends on prior and requires a large amount of computing power, which also limits the set of factor candidates.

To our knowledge, this paper is the first to consider the most comprehensive set of factors, including the local, regional, and global stock market factors and currency risk factors, and select the best factor model in international stock markets. We provide a new economic insight that no standard asset pricing model applies to all stock markets, revealing the diversity and complexity of asset pricing across different stock markets. We further estimate the strengths of factors presented in the best models and find that their strengths vary across markets over time. These findings further disclose the complexity and variability in asset pricing across international markets.

Specifically, we utilize Bayesian methods developed by Chib, Zeng, and Zhao (2020)

[2] Bryzgalova, Huang, and Julliard (2022) develop a new Bayesian method for analyzing linear asset pricing factor models. Their approach can estimate and compare many models generated by both traded and non-traded factors, and it delivers robust inference to standard identification failures caused by weak and level factors. However, their method does not handle the fat tail of factor data.

and Chib and Zeng (2020) to estimate and compare multiple-factor pricing models that follow Gaussian and Student-t distributions in 22 local stock markets, three regional stock markets (Europe, Asia-Pacific, and North America), and the global stock market.[3] Our pool of factor candidates comprises the factor from seminal models, including Fama-French six-factor models (MKT, SMB, HML, RMW, CMA, and the momentum factor (WML)) and Stambaugh and Yuan's (2017) two mispricing factors (MGMT and PERF). Additionally, we examine the role played by two currency risk factors, CARRY and DOLLAR, in asset pricing.

Our findings suggest that the factor data exhibit fat tails, and Student-t distributed models perform better than Gaussian distributed models in all markets. Notably, we show that no one-size-fits-all asset pricing model applies to all stock markets, highlighting the diversity and intricacy of asset pricing across different markets. Understanding the significance of a factor in pricing stock returns carries critical implications for investors as they craft their investment strategies. By applying the recent methodology pioneered by Bailey, Kapetanios, and Pesaran (2021), we estimate the strength of the factors presented in the top models and find that it varies across markets and over time, underscoring the variability in asset pricing across international markets.

We also show that currency risk factors are essential in determining the prices of international assets. CARRY is the only factor in the best model in all markets, whereas DOLLAR constitutes the best factor model for fourteen markets. However, their strength in pricing international stock returns was weakened by the 2008 global financial crisis. In

[3] 22 stock markets include three regions: 13 markets in Europe, 7 in Asia-Pacific, and two in North America, respectively. These markets are Austria (AUT), Switzerland (CHE), Germany (DEU), Denmark (DNK), Spain(ESP), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Italy (ITA), Norway (NOR), Netherland (NLD), Sweden(SWE), Australia(AUS), Hong Kong (HKG), Japan (JPN), Korea (KOR), Malaysia (MYS), Singapore (SGP), Thailand (THA), Canada (CAN) and the United States (US).

addition, our study tests the ability of our best models (local, regional, and global) to explain a range of cross-sectional anomalies. Our crucial finding is that local factor models generally have lower average alphas than regional and global models, while the latter models perform similarly.

Our research enhances the existing body of literature in three ways. Firstly, we advance the empirical investigation of asset pricing model evaluation and comparison, emphasizing the Bayesian approach within an international purview. Previous studies test whether those well-known models found by using the US market data (such as Fama-French three factor model (FF3), Fama-French five factor model (FF5)) also apply for other stock markets. Our paper is the first to look for the best models in international stock markets.

Our approach considers the significance of the fat tails issue linked to factor data. Additionally, our research reveals a notable discrepancy in the best asset pricing model across various markets. Recognizing the importance of a factor in pricing stock returns is crucial for investors in developing their investment strategies. Our study examines the factor strength of the best asset pricing models, and we observe that the strength of these factors can vary over time. This implies that investors must exercise caution in applying any asset pricing model, given the dynamic and intricate nature of the real world.

Second, we present further insights into the ongoing discussion regarding the pricing of currency risk in stock returns. Several studies have tested whether currency risk is priced in stock returns, but their empirical evidence is inconclusive (Dumas and Solnik, 1995; De Santis and Gerard, 1998; He and Ng, 1998; Griffin and Stulz, 2001; Karolyi and Wu, 2021). We argue that it is important to include currency risk factors in estimating and comparing international asset pricing models (see the literature review section for a detailed discussion on the limitations of previous research work).[4]

Finally, our study contributes to the discourse on the relative utility of global, regional, or local models in international asset pricing. The academic community has long debated whether stocks are priced locally in segmented markets or globally within a unified stock market (Karolyi and Stulz, 2003). Determining the primary influencers of expected stock returns is crucial for understanding the market structure and developing investment strategies (Chaieb, Langlois, and Scaillet, 2021). Though many theoretical studies examine global asset pricing models, the empirical findings are inconsistent. Some researchers find that stocks are priced globally rather than locally (e.g., Fama and French, 1998; Hau, 2011), while others document opposite findings (e.g., Griffin, 2002; Hou, Karolyi, and Kho, 2011; Chaieb, Langlois, and Scaillet, 2021; Hollstein, 2022). However, the conclusions made by these studies rely on the assumptions that the seminal factor models they used are true risk factor models and currency risk factors are not priced, while we do not make any of these assumptions and apply our top-performing asset pricing models, derived from the Bayesian approach. The evidence we glean from such an approach is particularly persuasive.

The rest of the paper is organized as follows. We review relevant literature in Section 2, introduce our methodology in Section 3, describe our data in Section 4, present our empirical results in Section 5, and conclude in Section 6.

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[4] Ignoring currency risk implicitly assumes either complete purchasing power parity (relative prices of goods are the same everywhere and an exchange rate is just the ratio of the nominal prices of any good in two countries) or the assets in analysis cannot be used to hedge exchange risk (Fama and Farber, 1979; Adler and Dumas, 1983; Dumas and Solnik, 1995; Fama and French, 2012); therefore, ignoring this risk in testing international asset pricing models may lead to biased empirical findings and wrong inferences (Fama and French, 2012).

2. Literature review

In this section, we review some studies about our study. Starting from the currency risk, theoretical frameworks suggest that currency risk could be, and indeed should be, priced in scenarios where consumption opportunities vary across nations (Solnik, 1974; Stulz, 1981; Adler and Dumas, 1984; Black, 1990; Karolyi and Wu, 2021). Despite this, empirical evidence on the matter remains inconclusive. By applying and scrutinizing both the Asset Pricing Model (APM) and the International Capital Asset Pricing Model (ICAPM), Dumas and Solnik (1995), as well as De Santis and Gerard (1998), indicate that currency risk is priced in stock returns. On the other hand, Griffin and Stulz (2001) and He and Ng (1998) report contradicting findings.

Recently, Karolyi and Wu (2021) expand on this body of work, driven by the increasing evidence that stock returns correlate with factors grounded in firm-level attributes, such as market capitalization, book-to-market (B/M) ratios, profitability, and investment levels. They explore whether two widely recognized currency risk factors, CARRY and DOLLAR (as defined by Lustig, Roussanov, and Verdelhan, 2011, 2014; Verdelhan, 2018), are priced within international stock markets. Specifically, they utilize the model comparison method that Kan, Robotti, and Shanken (2013) develop, leveraging cross-sectional R^2 as the testing criteria, to evaluate three benchmark models. These include the three-factor model (FF3) by Fama and French (1993), a four-factor model (FF4) integrating the three factors of Fama and French (1993) with the WML factor of Carhart (1997), and a five-factor model (FF5) proposed by Fama and French (2015). They compare these models with their counterparts, each augmented with the CARRY and DOLLAR factors. Their research provides evidence for the pricing of the CARRY factor in international stock markets. However, the pricing of the DOLLAR factor is less reliable. While Karolyi and Wu (2021) meticulously design and execute the tests, they operate under the critical assumption that FF3, FF4, and FF5, all well-regarded models within the US stock market, are universally applicable to all other stock markets, which might not be accurate.

Our research methodology is agnostic about the actual risk factor models from the outset. Instead, we amalgamate eight stock market factors with two currency risk factors and utilize a Bayesian approach to estimate and pinpoint the optimal model that constitutes factors in the SDF from all potential models built upon subsets of this factor pool. The comparison of our models unequivocally indicates that currency risk factor(s) feature in the best models of our selected markets.

Another branch of the literature determines the global, regional, or local models in international asset pricing. Although theoretical literature predominantly focuses on global asset pricing models (Solnik, 1974; Grauer, Litzenberger, and Stehle, 1976; Stulz, 1981; Adler and Dumas, 1983), empirical findings remain inconclusive, despite financial markets becoming increasingly globalized over recent decades. For instance, Fama and French (1998) and Hau (2011) suggest that stocks in developed markets are priced globally rather than locally, indicating a trend toward greater global integration of financial markets.

Contrarily, Griffin (2002) and Hou, Karolyi, and Kho (2011), in testing local versus global versions of the Fama-French three-factor model (FF3), find that local models exceed global ones in terms of performance within international stock markets.[5] Fama

[5] In addition to standard FF3 model, Hou, Karolyi, and Kho (2011) also test local vs. global versions of CAPM and a three-factor model including market, momentum, and value factors and they also find local models outperform global models.

and French (2012) expand upon Griffin's results, comparing the regional Fama-French four-factor (FF4) and global FF4 models, and discover that regional models tend to outperform their global counterparts. Additionally, Chaieb, Langlois, and Scaillet (2021), after estimating 13 benchmark models, each incorporating a unique combination of six factors (market, size, value, momentum, profitability, and investment), conclude that the local market is crucial for capturing the factor structure in international stock markets.[6]

In a study similar to ours, Hollstein (2022) analyzes the top asset pricing models considering local, regional, and global factors. However, unlike our study, Hollstein focuses on the 14 most influential factor models constructed from the US equity data. These models include CAPM, FF3, FF4, FF5, and 4-factor models from Hou, Xue, and Zhang (2015) and Stambaugh and Yuan (2017), as well as the 5-factor model by Hou et al. (2021) to explain 134 anomalies observed in international stock markets. Hollstein shows that local factor models outperform both regional and global factor models.[7] We find similar evidence.

Chib and Zeng (2020) and Qiao, Wang, and Lam (2022) are the studies closest to ours. Chib and Zeng (2020) and Qiao, Wang, and Lam (2022) employ the Bayesian methods of Chib, Zeng, and Zhao (2020) and Chib and Zeng (2020) to evaluate and compare a range of Gaussian and Student-t distributed global factor pricing models in the US stock market

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[6] Specifically, they propose an estimation methodology tailored for large, unbalanced panels of individual stock returns to study the factor structure in international stock markets. By apply a new diagnostic criterion proposed in Gagliardini, Ossola, and Scaillet (2019), they find omitted factors in the errors for models with world factors for both developed markets (DMs) and emerging markets (EMs). Their results indicate that adding the excess country market factor is sufficient to capture the factor structure in the large cross-section of individual stock returns of almost all DMs and most EMs.

[7] Political risk and differences in information quality, legal protection for private investors, and market regulations, may inhibit full market integration and explain why stocks are better priced locally (Hou, Karolyi, and Kho, 2011).

and aggregate global stock market, respectively. Similar to ours, they find that the Student-t distributed factor models outperform the Gaussian distributed models. However, our study is distinct from theirs in two key respects. For one, we consider the potential influence of currency risk on stock returns, which their analyses disregard entirely. As mentioned, disregarding this risk could lead to biased empirical results and incorrect conclusions. Additionally, Chib and Zeng (2020) explore the US market only and Qiao, Wang, and Lam (2022) explore the global stock market only. In contrast, our study is the first to investigate the best factor model using local, regional, and global markets, including 22 local markets (the US and 21 non-US) and three regional and global stock markets. Our finding concludes that no one-size-fits-all model exists across markets.

Besides, the studies mentioned above all share a notable limitation: they all use existing published models for the US stock market in their investigations of other markets. Furthermore, their analyses overlook the consideration of currency risk factors, a significant concern underscored by Fama and French (2012) in their exploration of this research area.[8]

Our study addresses this gap in the literature by applying our top-performing asset pricing models, derived using the Bayesian approach, to reevaluate this crucial research question in the context of international stock markets. Additionally, we use a more extensive set of anomalies (153) compared to Hollstein's (2022) 134 anomalies in our analysis.

[8] Chaieb, Langlois, and Scaillet (2021) find that excess market factors, defined as the spread between the country market factor and the world (or regional) market factor, capture currency risk as well as other sources of risk needed to explain stock return comovements.

3. Methodology

This section describes our empirical methodology. We first introduce the model comparison method of Chib, Zeng, and Zhao (2020) and Chib and Zeng (2020). We then introduce the approach of Bailey, Kapetanios, and Pesaran (2021) that we use to estimate the strengths of factors presented in our best models in this study.

3.1 Model Comparison

In this study, we employ the Bayesian marginal-likelihood-based model comparison approach of Chib, Zeng, and Zhao (2020) and Chib and Zeng (2020) to compare candidate factor pricing models in 22 individual stock markets, three regional stock markets, and the global stock market.[9] This approach allows us to simultaneously compare all possible models based on the subsets of the given factor space. Our model evaluation criterion is the value of its marginal likelihood, which measures how well (or likelihood) a model accommodates the data. The model with the highest marginal likelihood value is either accurate or closest to the actual model in the Kullback-Leibler information sense (Chib, Shin, and Simoni, 2018). In this model selection process, the marginal likelihoods of all candidate models are estimated simultaneously. Then we sort the estimated marginal likelihoods to select the model ranked first.

3.1.1 Model

[9] Note that the test assets are irrelevant for comparing models using their Bayesian approach. The conditional distribution of asset returns has the same restricted form regardless of what is assumed about the factors in the stochastic discount factor (SDF) so long as the factors are traded. Therefore, the distribution of asset returns is irrelevant for isolating the risk-factors (Chib and Zeng, 2020).

Suppose we have *K* risk factors (*K=10* in our study), and each can be either a risk or a non-risk factor. We denote the asset pricing model combined by these risk factors as: $\mathcal{M}_j(j = 1,\cdots,J)$. If the risk factor set cannot be empty, we therefore have $J = 2^K - 1$ candidate models in total. In a specific model j, there are risk factors $x_t: d_x \times 1$, and non-risk factors $w_t: d_w \times 1$, where $K = d_x + d_w$.[10] In this paper, we consider two different joint distributions of the global risk factors: Gaussian distributed and Student-t distributed with v_f degrees of freedom. Since our empirical results show Student-t distributed models significantly outperform Gaussian distributed ones, we only focus on introducing the Bayesian model comparison method for Student-t distributed models here to save space. Interested readers may refer to Chib, Zeng, and Zhao (2020) to discuss the Bayesian model comparison method for Gaussian distributed models.

Suppose the joint distribution of the factors $\boldsymbol{f}_t = (x_t, w_t)$ in each market that we analyze follows the Student-t distribution below:

$$\boldsymbol{f}_t \sim \mathcal{S}t_d(\mu, \Omega, v_f), t \geq 1, \tag{1}$$

where $\mu: d \times 1$ is the mean vector, $\Omega : d \times d$ is a positive definite dispersion matrix, and v_f is the degrees of freedom. Since the Student-t distribution can be expressed as a Gamma-scale mixture of normal distributions, we have:

$$\boldsymbol{f}_t | \tau_{f,t} \sim \mathcal{N}_d(\mu, \tau_{f,t}^{-1}\Omega), \tag{2}$$

$$\tau_{f,t} \sim \mathcal{G}\left(\frac{v_f}{2}, \frac{v_f}{2}\right), \tag{3}$$

where the scale $\tau_{f,t} > 0$ is latent.

The marginal and conditional distributions of the factors take the restricted form

[10] To avoid notational disorder, we do not label x_t, w_t and other parameters by model subscript j, but it should be noted that every aspect of the factor model is model-specific.

indicated below:

$$x_t = \lambda_x + \eta_{x,t}, \tag{4}$$

$$w_t = \Gamma x_t + \eta_{w\cdot x,t}, \tag{5}$$

where

$$\begin{pmatrix} \eta_{x,t} \\ \eta_{w\cdot x,t} \end{pmatrix} \Big| \tau_{f,t} \sim \mathcal{N}_d \left(0, \tau_{f,t}^{-1} \begin{pmatrix} \Omega_x & 0 \\ 0 & \Omega_{w\cdot x} \end{pmatrix} \right), \tag{6}$$

and $\Omega_{w\cdot x} = \Omega_w - \Omega_{xw}' \Omega_x^{-1} \Omega_{xw} : d_w \times d_w$. $E[x_t] = \lambda_x$, $E[w_t] = \Gamma \lambda_x$, λ_x are risk premia parameters and Γ is the matrix of regression coefficients in the regression of the w-factors on the x-factors.

3.1.2 Prior Specification

We now discuss the prior distribution of the parameters among factor models. Reasonable model-specific priors must be proper (i.e., with integral over the parameter space equal to one) and ideally require no user intervention. In addition, to make the differences in marginal likelihoods not only caused by prior differences, the prior distributions among different models should be comparable.

Suppose the parameters of a specific factor model $\mathcal{M}_j$ we estimate are given by:

$$\theta \triangleq \left(\lambda_x, \Omega_x, \Omega_{w\cdot x}, \gamma \right), \tag{7}$$

where $\gamma = vec(\Gamma): q \times 1$ and $q = d_w \times d_x$.

Chib, Zeng, and Zhao (2020) and Chib and Zeng (2020) set a prior construction that works very well in selecting the true underlying model. Therefore, we follow their specifications in this study.[11] To construct the model-specific prior, we use a training

[11] To save space, we do not discuss prior specification in detail here. Please refer to Chib, Zeng, and Zhao (2020) and Chib and Zeng (2020) for more information.

sample, the initial portion of our data, to locate the mean of the prior distribution of the parameters of the factor model. We then use the Markov chain Monte Carlo (MCMC) method to obtain the posterior distribution of the parameters and calculate their posterior means, with which we further calculate the marginal likelihood of the factor model.

3.1.3 Marginal Likelihood

We use the posterior odds of models given the observed data to compare different pricing models in Bayesian analysis. Let $Pr(\mathcal{M}_j)$ denote the prior probability for model $\mathcal{M}_j$. For fairness, we assign each model the same prior probability, which means for any j, $Pr(\mathcal{M}_j) = \frac{1}{J}$. In Bayesian analysis, the posterior odds reflect how well the data favor each alternative model. The posterior odds between models $\mathcal{M}_g$ and $\mathcal{M}_k$ are given by:

$$\frac{\Pr(\mathcal{M}_g|f_{1:T})}{\Pr(\mathcal{M}_k|f_{1:T})} = \frac{\Pr(\mathcal{M}_g)}{\Pr(\mathcal{M}_k)} \frac{m(f_{1:T}|\mathcal{M}_g)}{m(f_{1:T}|\mathcal{M}_k)}, \tag{8}$$

where $m(f_{1:T}|\mathcal{M}_g)$ and $m(f_{1:T}|\mathcal{M}_k)$ are the marginal likelihoods of models $\mathcal{M}_g$ and $\mathcal{M}_k$, respectively. T is the estimation period of the factor data.

Based on our assumption that the prior odds equal one, the posterior odds equal the ratio of marginal likelihoods. Therefore, we can use the estimated marginal likelihoods to compare factor pricing models.[12]

Under the assumption of Student-t distribution, the marginal likelihood is:

$$m(f_{1:T}|\mathcal{M}_j) = \int_{\Theta_j} p(f_{1:T}|\theta, \mathcal{M}_j)\pi(\theta|\mathcal{M}_j)d\theta\,, \tag{9}$$

and the integration is over the parameter space:

[12] To obtain the posterior mean of the parameter $\theta^* = (\lambda_x^*, \Omega_x^*, \Omega_{w\cdot x}^*, \gamma^*)$, we sample its distribution using the MCMC method. For detailed information on sampling of the posterior distribution, please refer to Chib and Zeng (2020), equations (3.27) to (3.49).

$$\Theta = \mathbb{R}^{d_x} \times \mathbb{R}^{q} \times \{set\ of\ d_x \times d_x\ pd\ matrices\ \} \times \{set\ of\ d_w \times d_w\ pd\ matrices\}$$

where *"pd"* denotes the positive-definite.

We employ the approach of Chib (1995) to estimate the following log-marginal likelihood of each model:

$$ln\, m\big(f_{1:T}\big|\mathcal{M}_j\big) = ln\, \pi\big(\theta^*\big|\mathcal{M}_j\big) + ln\, p\big(f_{1:T}\big|\mathcal{M}_j, \theta^*\big) - ln\, \pi\big(\theta^*\big|\mathcal{M}_j, f_{1:T}\big). \qquad (10)$$

Interested readers could refer to Chib and Zeng (2020) equations (3.53) to (3.59) for a detailed calculation of the log-marginal likelihood.

3.2 Factor Strength Estimation

We adopt Bailey, Kapetanios, and Pesaran's (2021) approach to estimate the strengths of factors presented in our identified best models. They measure the strength (α) of a factor by the degree of its pervasiveness identified by the number of its associated nonzero factor loadings.

Let *T* denote the number of observations in our sample period, and *n* denotes the unit number of cross sections. We consider the following factor model, which is the best asset pricing model we identify for each market by using the Bayesian approach we introduced above:

$$R_{it} = c_i + \sum_{l=1}^{m} \beta_{il} F_{lt} + \epsilon_{it} = c_i + \boldsymbol{\beta}_i' \mathbf{F_t} + \epsilon_{it}, \qquad \text{for } i = 1,2,\cdots,n\ and\ t = 1,2,\cdots,T \quad (11)$$

where $\{R_{it}, i = 1,2,\cdots,n,\ t = 1,2,\cdots,T\}$ is the excess returns of the stock i at time t, $\mathbf{F_t} = (F_{1t}, F_{2t}, \cdots, F_{mt})'$ is a vector of asset pricing factors, c_i is the unit-specific effect, $\boldsymbol{\beta}_i = (\beta_{i1}, \beta_{i2}, \dots, \beta_{im})'$ is a vector of factor loadings for stock i, and $\epsilon_{it} \sim IID(0, \sigma_i^2)$ is an idiosyncratic error. Assume that for some unknown unit ordering on i, for the first $[n^{\alpha_{l0}}]$

stocks, the factor loadings β_{il} are set to be nonzero; for the rest, they are set to zero.[13] $[\cdot]$ denotes the integer part function. That is, for some $s > 0$, we have:

$$|\beta_{il}| > s > 0 \; a.s. \text{for } i = 1,2,\cdots,[n^{\alpha_{l0}}], \tag{12}$$

$$|\beta_{il}| = 0 \; a.s. \text{for } i = [n^{\alpha_{l0}}]+1, [n^{\alpha_{l0}}]+2,\cdots,n. \tag{13}$$

The inference on factor l's strength α_{l0} $(l = 1,2,\cdots,m)$ can be obtained using the following steps. For a given unit i, run the least squares regression of $\{R_{it}\}_{t=1}^{T}$ on the intercept and $\mathbf{F}_t$. $\hat{c}_{iT}$ and $\hat{\beta}_{iT}$ are OLS estimates. The *t* statistic of β_{il} is given by:

$$t_{ilT} = \frac{\left(\mathbf{F}'_{lo}\mathbf{H}_{F_{-l}}\mathbf{F}_{lo}\right)^{-\frac{1}{2}}\left(\mathbf{F}'_{lo}\mathbf{H}_{F_{-l}}\mathbf{R}_i\right)}{\hat{\sigma}_{iT}}, l = 1,2,\cdots,m; i = 1,2,\cdots,n \tag{14}$$

where $\mathbf{F}_{lo} = (F_{l1}, F_{l2},\cdots,F_{lT})'$, $\mathbf{R}_i = (R_{i1}, R_{i2},\cdots,R_{iT})'$, $\mathbb{F}_l = (\boldsymbol{\tau}_T, \mathbf{F}_{1o},\cdots,\mathbf{F}_{l-1o},\mathbf{F}_{l+1o},\cdots,\mathbf{F}_{mo})'$, $\mathbf{H}_{F_{-l}} = \mathbf{I}_T - \mathbb{F}_{-l}(\mathbb{F}'_{-l}\mathbb{F}_{-l})^{-1}\mathbb{F}'_{-l}$, $\hat{\sigma}_{iT}^2 = T^{-1}\sum_{t=1}^{T}\hat{\epsilon}_{it}^2$, and $\hat{\epsilon}_{it} = R_{it} - \hat{c}_{iT} - \widehat{\boldsymbol{\beta}}'_{iT}\mathbf{F}_t$. Count the total number of statistically significant factor loadings β_{il}:

$$\widehat{D}_{nT,l} = \sum_{i=1}^{n}\hat{b}_{il,nT} = \sum_{i=1}^{n}\mathbf{1}\left[|t_{ilT}| > c_p(n)\right], \tag{15}$$

where $\hat{b}_{il,nT} = \mathbf{1}\left[|t_{iT}| > c_p(n)\right]$, $\mathbf{1}(\mathrm{A}) = 1$, if $A > 0$, and $\mathbf{1}(\mathrm{A}) = 0$ if $A < 0$. $c_p(n)$ is the critical value function, which is given by:

$$c_p(n) = \phi^{-1}\left(1 - \frac{p}{2n^{\delta}}\right), \tag{16}$$

where $\phi^{-1}(\cdot)$ is the inverse cumulative distribution function of the standard normal distribution, p is the nominal size of the individual tests. $\delta > 0$ is the critical value exponent. Let $\hat{\pi}_{nT,l}$ be the fraction of significant loadings of factor l, and note that $\hat{\pi}_{nT,l} =$

[13] α is factor strength. See Bailey, Kapetanios, and Pesaran (2021) for the detail explanation.

$\widehat{D}_{nT,l}/n$. Then we apply the estimator of α_{lo}, for $l = 1,2,\cdots,m$ below to factor loadings and obtain estimates of factor strength:

$$\hat{\alpha}_l = \begin{cases} 1 + \dfrac{ln\hat{\pi}_{nT,l}}{\ln n}, \text{if } \hat{\pi}_{nT,l} > 0, \\ 0, \qquad\qquad\quad \text{if } \hat{\pi}_{nT,l} = 0. \end{cases} \tag{17}$$

4. Data and Summary Statistics

4.1 Candidate Factors and Sample Markets

Our set of candidate factors consists of 10 factors, including eight stock market factors and two currency risk factors that are well documented in the literature. In addition to the Fama and French five factors (i.e., MKT, SMB, HML, RMW, and CMA) (Fama and French, 1993, 2012, 2015, 2017), we also consider the well-known momentum (WML) factor (Jegadeesh and Titman, 1993; Carhart, 1997) and two mispricing factors, i.e., the management factor (MGMT) and performance (PERF) factor developed by Stambaugh and Yuan (2017). These two factors are established based on documented anomalies, which in part reflect mispricing and possess common sentiment effects (Stambaugh and Yuan, 2017). The MGMT is computed as the average percentile of asset growth, composite equity issues, investment-to-assets, net stock issues, net operating assets, and operating accruals. The PERF is computed as the average percentile of gross profitability, six-month momentum, and return on assets. As for currency risk factors, we use the CARRY and DOLLAR factors developed by Lustig, Roussanov, and Verdelhan (2011). These two factors effectively capture variation in a broad cross-section of bilateral exchange rates and explain currency market risk well. The CARRY factor is the return on a zero-cost strategy that goes long (short) on high (low) interest-rate currency portfolios. The DOLLAR factor is an equally weighted average of excess returns on all non-US dollar currencies in the forward market.

The factor data used in this paper is extracted from several sources. The data of Fama and French's five factors, WML factor, and data of MGMT and PERF factors for the US stock market are provided by Kenneth French and Robert Stambaugh, respectively. The risk-free rate we used is a one-month Treasury bill rate, also collected from Kenneth French’s website. The data for these eight factors for the non-US stock market are collected from the data library of Matthias Hanauer (2020).[14] Hanno Lustig provides the data for CARRY and DOLLAR factors.[15] Our sample period is from July 1995 to October 2017 (268 months). We choose July 1995 as the starting date of our sample because it allows us to include as many markets as possible for cross-market analysis. Our sample period ends in October 2017, when all factor data are available.

Our sample comprises 22 stock markets in three regions, including 13 markets in Europe, 7 in Asia-Pacific, and two in North America, respectively. These markets are Austria (AUT), Switzerland (CHE), Germany (DEU), Denmark (DNK), Spain(ESP), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Italy (ITA), Norway (NOR), Netherland (NLD), Sweden(SWE), Australia(AUS), Hong Kong (HKG), Japan (JPN), Korea (KOR), Malaysia (MYS), Singapore (SGP), Thailand (THA), Canada (CAN) and the United States (US). Following Hou, Karolyi, and Kho (2011), Griffin (2002), and Hollstein (2022), we

[14] Following the literature, Matthias Hanauer construct these factors carefully. Please refer to Hanauer (2020) for detailed information on these factors.

[15] We are very grateful to Kenneth French, Robert Stambaugh, Matthias Hanauer and Hanno Lustig for sharing their factor data.

construct regional stock market factors for Europe, Asia-Pacific, and North American regions and the global market using a value-weighted market capitalization approach, respectively.

4.2 Summary Statistics

Table 1 provides summary statistics for the monthly factor returns between July 1995 and October 2017, including mean, standard deviation, skewness, kurtosis, and test statistics for univariate and multivariate normality for the global stock market.[16] The stock market factor with the highest average return is PERF (0.635%), followed by MKT (0.612%) and WML (0.563%), while the SMB has the lowest average return (0.137%). The two currency risk factors are also positive, with the CARRY factor having the highest return (0.676%) and the DOLLAR factor the lowest (0.045%). Factor returns of MKT, RMW, WML, PERF, CARRY, and DOLLAR are skewed to the left, whereas the rest are skewed to the right. The kurtosis measures exceed 3 for all factor returns, implying that the distribution of the factor returns has fat tails. The joint normality test statistic based on skewness and kurtosis follows a chi-squared distribution with two degrees of freedom (D'agostino, Belanger, and D'Agostino, 1990). Its values suggest that all factors return time series are rejected as normally distributed, which is typically accurate for most financial time series.[17] We also adopt Doornik-Hansen's (2008) method for the multivariate normality tests. We find their test statistic is 274.166, which is highly significant. Hence, we strongly reject the null

[16] Table A1 in Appendix provides the summary statistics of these factors for twenty-two individual stock markets and three regional stock markets.

[17] We also perform the Jarque-Bera (JB) normality test and the test results are qualitatively unchanged. These results are available upon request.

hypothesis that our factor data follow a multivariate normal distribution. This finding supports the importance of using the Chib and Zeng (2020) approach to model our study's fat tails of risk factor data.

< Table 1 here >

5. Empirical Results

This section contains our main empirical results. We start by estimating and selecting each market's best asset pricing model. Then we estimate and analyze the strengths of CARRY and DOLLAR factors in international asset pricing.[18] Finally, we discuss our findings on whether global, regional, or local factor models are more useful in international asset pricing.

5.1 Selection of the best asset pricing models

We begin by estimating and comparing factor pricing models in the 22 individual stock markets, three regional stock markets, and the global stock market.[19] We employ the aforementioned Bayesian approach to estimate and compare many factor pricing models formed from the set of our ten candidate factors. Their joint distribution is Student-t with unknown degrees of freedom v_f. In literature, the suitable number of factors included in an excellent asset pricing model is an empirical issue. A model with too few factors (e.g., CAPM) may miss essential factors that can explain stock returns well, while a model with

[18] We also estimate the strengths of other factors presents in our best models for each market. Due to limited space, we report the results in the Appendix Table A3.

[19] We are grateful to Siddhartha Chib for providing the code for conducting the model comparison tests.

too many factors may lead to overfitting problems. The literature supports a parsimonious model (Fama and French, 1992; Daniel, Hirshleifer, and Sun, 2020) as it is more appealing to practitioners.

Chib, Zhao, and Zhou (2023) report that the best asset pricing model usually contains five to seven factors. We, therefore, set the maximum number of factors in our model to be seven, which means that we estimate $C_{10}^{1} + C_{10}^{2} + \cdots + C_{10}^{7} = 967$ factor models for each degree of freedom. In fitting the different Student-t models, we try a grid of 55 values of v_f, from 3 to 30, in increments of 0.5. Under this collection of factors and a grid of 55 degrees of freedom, our universe of models comprises 967×55 = 53,185 possible Student-t distributed factor models.[20] In our analysis, we use 10% of the 268 observations for our entire sample (i.e., 27 observations from July 1995 to September 1997) as a training sample to form our prior distribution, leaving a sample size of 241 observations from October 1997 to October 2017 as our estimation sample.

Panel A of Table 2 presents the best models as well as their estimated log-marginal likelihoods, $ln\, m(f_{1:T}|M_j)$, for 22 local stock markets (we name the model comprising local factors as Model 1 in this study).[21] We find these selected best models are market specific, and no standard asset pricing model applies for all stock markets. This can be attributed

[20] Because of the Cholesky decomposition problem, we did not obtain the estimated results when the degrees of freedom are fewer than three.

[21] For comparison purpose, we also consider a set of 957 Gaussian distributed factor pricing models for each stock market. Appendix Table A2 presents the best Gaussian distributed model selected from the 957 candidate factor models for each market. A comparison between Table 2 and Table A2 shows that the log-marginal likelihood of best Gaussian distributed factor model is significantly lower than that of the best Student-t distributed factor model reported in Table 2 for all markets, indicating Student-t distributed factor model is a better model than the Gaussian distributed factor model. This finding demonstrates the importance of using multivariate Student-t distribution to model the fat tails in factor data.

to the differing economic characteristics, market dynamics, and regulatory environments across different regions or countries. Factors such as the level of economic development, financial market maturity, the presence of foreign investors, tax policies, corporate governance, transparency, and investor protection can all impact the asset pricing dynamics within a specific market. A closer examination of our selected models reveals that different factors have different market pricing performances. For example, the Fama and French five factors have impressive pricing abilities in international stock markets. Specifically, the best models of three stock markets, Canada (CAN), Switzerland (CHE), and Greece (GRC), select all five factors of FF5, while the best models of ten (nine) stock markets select four (three) factors. Among these five pricing factors, SMB is favored by all markets except Austria (AUT). RMW, HML, CMA, and MKT factors appear in the best 20, 18, 13, and 9 stock markets models, respectively.

In addition, we also notice that the momentum WML factor is another excellent pricing factor in international stock markets, evidenced by the fact that 20 out of 22 markets select it for their best pricing models. As for the two mispricing factors, MGMT and PERF, we find that the MGMT factor appears in the best pricing models of 13 markets. In contrast, the PERF factor only appears in the best pricing models of the four markets, suggesting the MGMT factor plays a more critical role in pricing stock returns in international stock markets.

One noteworthy finding is that currency risk factors are well-priced in global stock markets. Panel A of Table 2 shows that 14 stock markets select the DOLLAR factor as a critical pricing factor, while all markets select the CARRY factor for their best pricing models. In Panel B of Table 2, we present the best models for three regional stock markets

(Model 2 in this study) and the best model for the global market (Model 3). We discover that all of these models include currency risk factors.[22] Overall, we conclude that currency risk factors are vital pricing factors. Our research findings differ from those of He and Ng (1998) and Griffin and Stulz (2001) but align with those of Dumas and Solnik (1995), De Santis and Gerard (1998), and Karolyi and Wu (2021).[23] Based on this finding, we will estimate and analyze their strengths in international stock markets.

< Table 2 here >

5.2 Analysis of strengths of currency risk factors

We consider monthly excess returns of the stocks in the 22 stock markets over our estimation sample period from October 1997 to October 2017 (241 months). To account for possible time variations in factor strength, we use rolling samples (241), and our rolling window size is 24 months (2 years) each. We apply the method of Bailey, Kapetanios, and Pesaran (2021) to estimate the strengths of two currency risk factors in 22 stock markets.[24] We also calculate their power in 3 regional and global stock markets by taking the average factor strengths in corresponding markets.

[22] This finding contrasts with the findings of Karolyi and Wu (2021). They report that currency risk factors are more likely to be priced globally than locally.

[23] As for why CARRY factor is more popular than DOLLAR factor, this could be because DOLLAR is unique to the US currency, while CARRY is more closely related to global liquidity and financial conditions.

[24] We appreciate M. Hashem Pesaran for providing the code for estimating the factor strength.

In Appendix Table A3, we report the descriptive statistics of our estimated strength of the CARRY and DOLLAR factors and find their factor strengths vary across markets.[25] Panel A of Table A3 shows that the power of the CARRY factor is the greatest in the US stock market, followed by the UK and Canada, while its strength is the smallest in the Austria stock market. Its strength in Europe, Asia-Pacific, North America, and the global stock market is 0.439, 0.520, 0.573, and 0.477, respectively.

Carry trade strategies can be very effective in countries with strong economies and high-interest rates (like the US, UK, and Canada). Investors borrow in low-interest rate currencies and invest in high-interest rate currencies, thus capturing the difference in interest rates. In contrast, in countries with lower interest rates (like Austria), the effectiveness of carry trade strategies may be limited. For instance, the US, UK, and Canada tend to have more aggressive monetary policies, and their central banks are more likely to adjust interest rates to manage the economy. This can create greater opportunities for carry trade strategies, thus strengthening the CARRY factor. Lastly, The US, UK, and Canada have very mature and developed financial markets with high levels of liquidity. This can facilitate the execution of carry trade strategies and increase the strength of the CARRY factor.

Panel B shows that the strength of the DOLLAR factor is the greatest in the German stock market, followed by the UK and Finland, while it has little strength in Malaysia. Its strength in Europe, Asia-Pacific, North America, and the global stock market are 0.643, 0.583 and 0.618, and 0.620, respectively. Germany, the UK, and Finland have significant

[25] We also estimate the strengths of other factors presented in the best models of our sample markets. We find their powers are also different across markets and vary over time. We report their descriptive statistics In Table A4.

trade and investment relationships with the US, making their stock markets more sensitive to movements in the US dollar. For these countries, a stronger US dollar could increase the cost of imports from the US and affect companies with substantial US-dollar-denominated debt, thereby influencing stock prices. Furthermore, countries with more robust economic ties to the US may experience greater sensitivity to changes in the US dollar. This could explain why Germany and the UK, two of the largest economies in Europe with robust ties to the US, show a high DOLLAR factor strength. Finally, countries whose central banks closely align their policies with the US Federal Reserve or whose currencies move in tandem with the US dollar might exhibit a higher DOLLAR factor strength.

Further, we analyze the fluctuation of factor strength over time. Figure 1 displays the factor strength of CARRY and DOLLAR changes significantly over time. This suggests that global stock markets respond differently to CARRY and DOLLAR factors at different times. During the 2008 global financial crisis, there was a sharp drop in factor strength. However, we do not notice any significant shift in factor strengths during the dot-com bubble. This could be because the dot-com bubble was confined to high-tech stocks, while the latter had a more widespread impact. Additionally, in the Appendix Table A4, we present the strengths of other factors, and all of them show high volatility between 14% to 18%, which is comparable to the volatility of CARRY and DOLLAR, which is 15% and 17%, respectively. These varying factor strengths suggest the variability in asset pricing across international markets.

< Figure 1 here >

Considering this observation, we examine the time-varying factor strength in response to the 2008 financial crisis. We run OLS regressions of these two currency risk factor strengths on a crisis dummy, $crisis_t$, respectively. We set this dummy variable to one from December 2007 to June 2009 to indicate the presence of the crisis and zero otherwise. The estimated coefficients are reported in Table 3. The evidence shows that most coefficients are negative and significant, implying that the two currency risk factors' ability to explain stock returns worsens during the global financial crisis. The reduced ability of CARRY factor to explain stock returns during the global financial crisis can be attributed to depreciation of high-interest-rate currencies and appreciation of low-interest-rate currencies resulting in a collapse of currency carry trades in bad times when consumption, global trade and investment activity decrease (Lustig and Verdelhan, 2011). As a result, the CARRY factor becomes less significant in explaining stock returns. As for the reduced ability of DOLLAR factor, one possible explanation is that the subprime mortgage crisis led to a decrease in investor confidence, which could have affected the relationship between the dollar and other currencies. As a result, DOLLAR factor becomes less powerful to explain bilateral exchange rate changes, leading to a poorer ability of DOLLAR factor in explaining stock returns. We leave it for other researchers to examine this issue.

< Table 3 here >

5.3 Explaining anomalies using different models

Next, we examine another critical question: whether there are systematic differences between the alphas for the best model in each class (i.e., Model 1, Model 2, and Model 3) that we select using the Bayesian approach in Section 5.1. Specifically, for each of the 22 stock markets, we compare the ability of these models to explain 153 cross-sectional anomalies. This large set of anomaly portfolios corresponds to what investors in different countries could invest in. Our analysis uses the dataset developed by Jensen, Kelly, and Pedersen (2021).[26] Jensen, Kelly, and Pedersen (2021) study a set of 153 characteristic anomaly variables and build 153 anomalies across 93 countries. They build the 1-month holding period factor return for a given characteristic as follows. In each market and month, they first sort stocks into characteristic terciles (top/middle/bottom third) with breakpoints based on large stocks in that country. This study designs to mitigate the impact of small stocks, which are difficult to trade. Then, for each tercile, they compute its value-weighted portfolios. The anomaly is then defined as the high-tercile return minus the low-tercile return, corresponding to the excess return of a long–short zero-net-investment strategy.[27]

To assess the ability of these three classes of models in pricing the return anomalies for each of the 22 stock markets, we regress the time series of each of the 153 anomaly returns on the factors included in the best local, regional, and global models that we reported in Table 2 to obtain the corresponding absolute alphas, respectively.[28] Then, for each model, we compute its average absolute alpha, $\overline{|\alpha|}$, which is the average absolute annualized alpha (in percentage points) of the long–short portfolios, averaged over all

[26] The data is available at https://github.com/bkelly-lab/GlobalFactor. We appreciate Bryan and Theis for their kind help on their data.

[27] Please refer to Jensen, Kelly, and Pedersen (2021) for more detailed information on how they construct their dataset. Hollstein (2022) uses a similar approach to construct his dataset for 134 anomalies. Different from Jensen, Kelly, and Pedersen (2021), he sorts stocks into characteristic quartiles instead of terciles for most anomaly variables.

[28] We look at the absolute alphas because it is at the investors' discretion whether to go long or short in their investment.

153 anomalies in the market. We also calculate the average annualized absolute alphas for three aggregate markets (i.e., developed market (DM) and emerging market (EM); global stock market) by averaging the absolute annualized alphas of the long–short portfolios in the relevant markets covered by the three aggregate markets, respectively. The average absolute alpha, $\overline{|\alpha|}$, measures the performance of our models. The lower $\overline{|\alpha|}$, the better the model can explain the returns of anomalies. To compare the pricing performance of different models, we calculate the $\Delta\overline{|\alpha|}$, which is the difference in the average absolute alphas for different factor model specifications (i.e., Model 1, Model 2, and Model 3). We conduct a t-test to investigate whether the difference is statistically significant.

We visualize our main findings in Figure 2 and present the corresponding numbers and significance tests in Table 4. We first examine the aggregate results. Figure 2 indicates that the average absolute alpha of Model 1 is significantly lower than that of Model 2 and Model 3 in emerging markets, developed markets, and all sample markets. For example, all over the 22 markets, the average absolute annualized alpha of Model 1 is 0.5119 (0.3648), percentage points lower than that for Model 2 (Model 3). This finding is in line with those reported by Griffin (2002), Hou, Karolyi, and Kho (2011), and Hollstein (2022) but against Fama and French (1998) and Hau (2011). We also compare the performance of the regional model (Model 2) and the global model (Model 3), but do not find significant differences in their pricing ability. This finding contradicts what Fama and French (2012) reported, which shows regional model performs better than a global model, and partially supports Hollstein (2022). He provides evidence that the regional model performs better than the global model in developed markets, but there is no significant difference in their pricing ability in emerging markets.

One interesting finding is that the differences in average absolute alphas, $\Delta\overline{|\alpha|}$, between Model 1 and Model 2 and between Model 1 and Model 3 for emerging stock markets are larger than for developed markets. For example, $\Delta\overline{|\alpha|}$ between Model 1 and Model 2 is -0.9923% for emerging markets, but -0.4062% for developed markets; $\Delta\overline{|\alpha|}$ between Model 1 and Model 3 is -0.7867% for emerging markets, while -0.2719% for developed markets. This finding is consistent with what is documented by Hollstein (2022). This is a reasonable finding. Due to regulatory restrictions of cross-market capital flows investor protections as well as differences in accounting standards, information environments, information quality, and so on, market liberalization of emerging stock markets lags that of developed markets, leading to more significant gaps between the performance of local models and regional (global) models. [29]

We further examine the performance of Model 1, Model 2, and Model 3 for each of the 22 stock markets. Though heterogeneity in their relative performance exists across markets,[30] we find overall, Model 1 creates smaller $\overline{|\alpha|}$ than Model 2 (Model 3) in most markets. This finding generally is consistent with Hollstein (2022). Lastly, we compare the performance of Model 2 and Model 3 in each of the 22 stock markets. Similarly to what we find from 3 aggregate market samples, we do not see much performance difference in these two models for all markets except Korea, Sweden, and the US.

[29] As a robustness test, we use a 24-month rolling window to estimate $\overline{|\alpha|}$ for Model 1, Model 2 and Model3 over time, respectively. Our findings are qualitatively unchanged. The detailed results are available upon request.

[30] For example, we notice that difference in performance between Model 1 and Model 2 (Model 3) is relatively smaller or even insignificant for markets perceived as particularly open, such as France, Switzerland, Netherlands, Germany, Great Britain, Spain, Singapore, Hong Kong and Italy. Interestingly, the United States, which is regarded to be very well integrated into global market shows a large difference in performance between Model 1 and Model 3.

< Figure 2 and Table 4 here >

Finally, we test whether adding foreign (i.e., regional and global) stock market pricing factors into the local model (i.e., Model 1) can further improve its performance. We use Austria (AUT) below as an example to introduce our testing procedure. Table 2 shows that the best pricing model for the Austria stock market includes MKT, HML, RMW, WML, MGMT, PERF, and CARRY factors; the best pricing model for the European stock market includes MKT_*EU*, SMB_*EU*, RMW_*EU*, CMA_*EU*, WML_*EU*, MGMT_*EU* and CARRY factors; the best pricing model for global stock market includes SMB_*G*, HML_*G*, RMW_*G*, CMA_*G*, WML_*G*, DOLLAR and CARRY factors.[31]

Since the market factor MKT appears in the best factor models of Austria and European stock markets, to explicitly identify the effect of market factor MKT_*EU* of the European market on the Austria market, we follow Hou, Karolyi, and Kho (2011) and Hollstein (2022) to construct a pure European market factor MKT_*pEU* by computing value-weighted averages of MKT factors in Europe, excluding Austria.[32] We use the same method to construct RMW_*pEU*, WML_*pEU* and MGMT_*pEU* factors. Following Bekaert, Hodrick, and Zhang (2009), we do not adjust those pricing factors included only by the best pricing model for the European market (i.e., SMB_*EU* and CMA_*EU*). Then we put all pricing factors in the European stock market (i.e. MKT_*pEU*, SMB_*EU*, RMW_*pEU*, CMA_*EU*, WML_*pEU*, MGMT_*pEU* and CARRY) with Austria stock market's best pricing factors (i.e. MKT, HML, RMW, WML, MGMT, and PERF) into a pool of 13 candidate factors and employ the

[31] To distinguish different factors for local, regional and global stock markets, we use "*EU*" and "*G*" to denote for "European" and "global", respectively. Similarly, we use "*AP*" and "*NA*" to denote for "Asia Pacific" and "North America", respectively.

[32] We use "*p*" to denote for "pure" in this study.

Bayesian method we introduce in Section 3 to compare and select the best-augmented pricing model for Austria stock market, which incorporates local and regional pricing factors (Model 4 in this study). Using the same method, we identify the best-augmented pricing model, incorporating local and global pricing factors (Model 5 in this study). We report the Model 4 and Model 5 that we selected for each of the 22 stock markets in Appendix Table A5 and Table A6, respectively.

As we did above, we assess the pricing performance of Model 4 and Model 5 by calculating the $\overline{|\alpha|}$ for each model for each market. We also calculate the $\Delta\overline{|\alpha|}$ for different model specifications (i.e., Model 1, Model 4, and Model 5). If regional and global stock market factors matter for local stock returns, we expect the average absolute alphas of Model 4 and Model 5 to be significantly smaller than those for Model 1. We visualize our main findings in Figure 3 and present the corresponding numbers and significance tests in Table 5. Our test results do not provide strong evidence showing significant performance differences in pricing anomalies between Model 1 and Model 4 (Model 5). This finding is like Fama and French (2012) and Hollstein (2022), who conclude that foreign stock market factors are of little value beyond the local factor models but contrast with the findings of Hou, Karolyi, and Kho (2011) and Karolyi and Wu (2018). Table 5 also reports our test results for comparing the pricing performance of Model 4 and Model 5. We do not find much evidence showing these two models perform differently. This finding contradicts that of Hollstein (2022), which shows that the average absolute alphas are lower with local and regional stock market factors than with local and global stock market factors. The discrepancy is attributed to Hollstein (2022) relying on the assumption that the seminal factor models are true risk factor models, while we do not.

< Figure 3 and Table 5 here >

6. Conclusions

Our study is the first to use a rigorous Bayesian approach to estimate, compare and analyze many asset pricing models in international stock markets. The approach we employ not only deals with the fat tails problem displayed by the factor data well but also considers the role played by currency risk factors in pricing stock returns. Our empirical results indicate that the Student-t distributed factor models outperform the Gaussian distributed models in all markets. This finding highlights the importance of using multivariate Student-t distribution to model the fat tails in international risk factor data. A careful examination of these best Student-t distributed models shows that no standard asset pricing model applies to all stock markets, revealing the diversity and complexity in asset pricing across different markets.

However, interestingly, the currency risk factors present in the best models for all markets suggest they play a crucial role in international asset pricing. Motivated by these findings, we adopt the method Bailey, Kapetanios, and Pesaran (2021) develop to estimate the strengths of factors presented in the best models. We find that their strengths are time-varying and vary across markets. A closer investigation of currency risk factor strengths demonstrates that the 2008 global financial crisis dampens their ability to price international stock returns. Lastly, we step into the long-standing debate in the literature on whether stocks are better priced locally, regionally, or globally by using the best models we identify and an international dataset of 153 cross-sectional anomalies. We find that local models perform the best, while there is not much difference in the performance of regional and global models. Our findings reported in this paper are essential for researchers of international asset pricing and practitioners interested in cost-of-capital calculations, risk control, optimal global investment portfolio construction, and performance evaluations of global equity managers.

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Table 1

Summary Statistics Of Monthly Factor Returns For Global Stock Market

Table 1 reports summary statistics of the monthly factor returns in global stock market between July 1995 and October 2017 (268 months). MKT, SMB, HML, RMW and CMA are Fama and French five factors (Fama and French, 1993, 2012, 2015, 2017); WML is momentum factor (Jegadeesh and Titman, 1993; Carhart, 1997); MGMT is management factor and PERF is performance factor developed by Stambaugh and Yuan (2017); CARRY and DOLLAR factors are two currency risk factors developed by Lustig, Roussanov, and Verdelhan (2011). The joint normality test is a test for univariate normality based on skewness and kurtosis. It is developed by D'agostino, Belanger, and D’Agostino (1990). It follows a chi-squared distribution with two degrees of freedom. Doornik-Hansen normality test is a test for the multivariate normality, which is developed by Doornik-Hansen (2008). ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	MKT	SMB	HML	RMW	CMA	WML	MGMT	PERF	CARRY	DOLLAR
Mean	0.6123	0.1367	0.3275	0.2935	0.2310	0.5631	0.3968	0.6353	0.6763	0.0447
Std Dev.	4.3533	2.1297	2.3900	1.7469	1.6312	4.1515	2.0942	3.1575	2.4193	1.7855
Skewness	-0.7486	0.1385	0.4394	-0.1534	0.6481	-1.5142	0.5003	-0.2865	-0.1645	-0.2828
Kurtosis	4.7592	6.1829	7.5263	7.3904	5.8198	12.1603	5.7235	6.2265	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	27.98***	21.42***	33.52***	27.6***	31.06***	86.82***	25.99***	23.74***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 274.166, Prob > χ^2 = 0.0000									

Table 2

The Best Student-T Distributed Factor Pricing Models For International Stock Markets

Table 2 presents the log-marginal likelihoods of the best student-t distributed factor models for 22 individual stock markets, 3 regional stock markets and global stock market. The 22 stock markets include three regions: 13 markets in Europe, 7 in Asia-Pacific and two in North America, respectively. MKT, SMB, HML, RMW and CMA are Fama and French five factors (Fama and French, 1993, 2012, 2015, 2017); WML is momentum factor (Jegadeesh and Titman, 1993; Carhart, 1997); MGMT is management factor and PERF is performance factor developed by Stambaugh and Yuan (2017); CARRY and DOLLAR factors are two currency risk factors developed by Lustig, Roussanov, and Verdelhan (2011). "1" indicates that the factor is selected by the best model, and '0' otherwise. *Log-marg* is the estimated log-marginal likelihood and v_f is the degree of freedom. The estimation sample period is from October 1997 to October 2017 (241 observations).

	MKT	SMB	HML	RMW	CMA	WML	MGMT	PERF	CARRY	DOLLAR	v_f	*Log-marg*
Panel A												
Austria	1	0	1	1	0	1	1	1	1	0	7.5	5460.4931
Switzerland	1	1	1	1	1	1	0	0	1	0	9	5719.7505
Germany	0	1	1	1	0	1	1	0	1	1	8.5	5994.3936
Denmark	1	1	0	1	1	1	1	0	1	0	6	5287.7934
Spain	0	1	1	1	1	0	0	1	1	1	10	5437.5649
Finland	0	1	0	1	1	1	1	0	1	1	11	5191.9643
France	1	1	0	1	1	1	1	0	1	0	6.5	6214.8341
Great Britain	0	1	1	1	1	1	0	0	1	1	10.5	6139.8977
Greece	1	1	1	1	1	1	0	0	1	0	20.5	4405.1091
Italy	0	1	1	1	1	1	0	0	1	1	12.5	5542.1915
Netherland	0	1	1	0	1	0	1	1	1	1	8.5	5163.1004
Norway	0	1	1	1	0	1	1	0	1	1	8.5	5146.8108
Sweden	0	1	1	1	1	1	0	0	1	1	7	5711.8193

Australia	1	1	1	1	0	1	1	0	1	0	9	6010.4346
Hong Kong	0	1	1	1	1	1	0	0	1	1	13	5080.5121
Japan	1	1	1	1	0	1	1	0	1	0	8	6314.0699
Korea	0	1	1	1	1	1	0	0	1	1	6	5367.4092
Malaysia	1	1	0	1	0	1	1	0	1	1	11.5	6034.3421
Singapore	0	1	1	1	0	1	1	0	1	1	7	5829.0968
Thailand	0	1	1	0	0	1	1	1	1	1	16	5117.9551
Canada	1	1	1	1	1	1	0	0	1	0	7.5	6445.4105
United States	0	1	1	1	0	1	1	0	1	1	8	6543.5498
Panel B												
Europe	1	1	0	1	1	1	1	0	1	0	8.5	7028.6684
Asia Pacific	0	1	1	1	1	1	0	0	1	1	9.5	6753.0549
North America	0	1	1	1	0	1	1	0	1	1	8	6654.5620
Global	0	1	1	1	1	1	0	0	1	1	6.5	7785.0058

Table 3

Analysis of Impacts of 2008 Financial Crisis on Strengths of CARRY and DOLLAR Factors

Table 3 presents OLS regression results of CARRY and DOLLAR factor strengths on a crisis dummy, $crisis_t$, in international stock markets for period from October 1999 to October 2017. We set this dummy variable to one from December 2007 to June 2009 to indicate the presence of the crisis and zero otherwise. The international stock markets include 22 individual stock markets, 3 regional stock markets and global stock market. The 22 stock markets include three regions: 13 markets in Europe, 7 in Asia-Pacific and two in North America, respectively. These markets are Austria (AUT), Switzerland (CHE), Germany (DEU), Denmark (DNK), Spain(ESP), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Italy (ITA), Norway (NOR), Netherland (NLD), Sweden(SWE), Australia (AUS), Hong Kong (HKG), Japan (JPN), Korea (KOR), Malaysia (MYS), Singapore (SGP), Thailand (THA), Canada (CAN) and the United States (US). Standard errors in parentheses. $***$, $**$ and $*$ indicate statistical significance at the 1%, 5% and 10% level, respectively.

Panel A

	(1)	(2)	(3)	(4)
Variables	CARRY_AUT	CARRY_CHE	CARRY_DEU	CARRY_DNK
crisis	-0.0576	-0.0937**	-0.1164***	-0.0361
	(0.0445)	(0.0391)	(0.0224)	(0.0417)
Constant	0.3343***	0.4434***	0.5185***	0.3819***
	(0.0132)	(0.0116)	(0.0066)	(0.0123)
R-squared	0.0077	0.0261	0.1116	0.0035
Obs.	217	217	217	217

	(5)	(6)	(7)	(8)
Variables	CARRY_ESP	CARRY_FIN	CARRY_FRA	CARRY_GBR
crisis	-0.1801***	-0.1811***	-0.1603***	-0.0773***
	(0.0445)	(0.0455)	(0.0324)	(0.0244)
Constant	0.4226***	0.3693***	0.4936***	0.5847***
	(0.0132)	(0.0135)	(0.0096)	(0.0072)
R-squared	0.0709	0.0685	0.1021	0.0447
Obs.	217	217	217	217

Variables	(9) CARRY_GRC	(10) CARRY_ITA	(11) CARRY_NLD	(12) CARRY_NOR
crisis	0.0944*	-0.2189***	-0.1475***	-0.1438***
	(0.0522)	(0.0420)	(0.0390)	(0.0387)
Constant	0.3630***	0.4394***	0.4683***	0.5061***
	(0.0154)	(0.0124)	(0.0115)	(0.0114)
R-squared	0.0150	0.1120	0.0623	0.0603
Obs.	217	217	217	217

Variables	(13) CARRY_SWE	(14) CARRY_AUS	(15) CARRY_HKG	(16) CARRY_JPN
crisis	-0.1626***	0.0595**	-0.0191	-0.2110***
	(0.0384)	(0.0269)	(0.0279)	(0.0285)
Constant	0.5113***	0.4950***	0.4912***	0.5662***
	(0.0114)	(0.0080)	(0.0082)	(0.0084)
R-squared	0.0771	0.0223	0.0022	0.2029
Obs.	217	217	217	217

Variables	(17) CARRY_KOR	(18) CARRY_MYS	(19) CARRY_SGP	(20) CARRY_THA
crisis	-0.2156***	-0.1571***	-0.1578***	-0.2430***
	(0.0353)	(0.0304)	(0.0339)	(0.0333)
Constant	0.5508***	0.5147***	0.5355***	0.5705***
	(0.0104)	(0.0090)	(0.0100)	(0.0099)
R-squared	0.1480	0.1105	0.0917	0.1983
Obs.	217	217	217	217

Variables	(21) CARRY_CAN	(22) CARRY_US
crisis	-0.0456**	-0.1306***
	(0.0193)	(0.0240)
Constant	0.5574***	0.6036***
	(0.0057)	(0.0071)
R-squared	0.0254	0.1208
Obs.	217	217

Variables	(1) CARRY_Europe	(2) CARRY_Asia Pacific	(3) CARRY_North America	(4) CARRY_Global
crisis	-0.1139***	-0.1349***	-0.0881***	-0.1182***
	(0.0235)	(0.0185)	(0.0170)	(0.0197)
Constant	0.4489***	0.5320***	0.5805***	0.4873***
	(0.0069)	(0.0055)	(0.0050)	(0.0058)
R-squared	0.0988	0.1981	0.1107	0.1433
Obs.	217	217	217	217

Panel B

Variables	(1) DOLLAR_DEU	(2) DOLLAR_ESP	(3) DOLLAR_FIN	(4) DOLLAR_GBR
crisis	-0.1665***	-0.1782***	-0.2685***	-0.1102***
	(0.0328)	(0.0528)	(0.0567)	(0.0309)
Constant	0.6941***	0.6674***	0.6851***	0.6839***
	(0.0097)	(0.0156)	(0.0168)	(0.0092)
R-squared	0.1068	0.0503	0.0945	0.0557
Obs.	217	217	217	217

Variables	(5) DOLLAR_ITA	(6) DOLLAR_NLD	(7) DOLLAR_NOR	(8) DOLLAR_SWE
crisis	-0.2182***	-0.2242***	-0.1348***	-0.2510***
	(0.0475)	(0.0471)	(0.0421)	(0.0461)
Constant	0.6803***	0.6761***	0.5990***	0.5971***
	(0.0141)	(0.0139)	(0.0125)	(0.0136)
R-squared	0.0894	0.0953	0.0455	0.1214
Obs.	217	217	217	217

Variables	(9) DOLLAR_HKG	(10) DOLLAR_KOR	(11) DOLLAR_MYS	(12) DOLLAR_SGP
crisis	0.0215	-0.0949***	0.0283	-0.0951**
	(0.0455)	(0.0350)	(0.0341)	(0.0392)
Constant	0.5682***	0.6353***	0.5030***	0.6173***
	(0.0135)	(0.0104)	(0.0101)	(0.0116)
R-squared	0.0010	0.0330	0.0032	0.0267

Obs.	217	217	217	217

	(13)	(14)
Variables	DOLLAR_THA	DOLLAR_US
crisis	-0.0988***	-0.0217
	(0.0317)	(0.0248)
Constant	0.6105***	0.6198***
	(0.0094)	(0.0073)
R-squared	0.0433	0.0036
Obs.	217	217

	(1)	(2)	(3)	(4)
Variables	DOLLAR_Europe	DOLLAR_Asia Pacific	DOLLAR_North America	DOLLAR_Global
crisis	-0.1940***	-0.0478**	-0.0217	-0.1295***
	-0.0352	-0.0238	-0.0248	-0.0277
Constant	0.6604***	0.5869***	0.6198***	0.6312***
	-0.0104	-0.007	-0.0073	-0.0082
R-squared	0.1235	0.0185	0.0036	0.0925
Obs.	217	217	217	217

Table 4

Explaining Anomalies: Local Model vs. Regional Model and Global Model

Table 4 compares the performance of local model, regional model, and global model (i.e., Model 1, Model 2, and Model 3) in explaining 153 cross-sectional anomalies in 22 individual stock markets and 3 aggregate stock markets (i.e. developed market (DM), emerging market (EM) and global stock market) for period from October 1997 to October 2017. The 22 stock markets include three regions: 13 markets in Europe, 7 in Asia-Pacific and two in North America, respectively. To assess the ability of these three classes of models in pricing the return anomalies for each of the 22 stock markets, we regress the time series of each of the 153 anomaly returns on the factors included in the best local, regional, and global models to obtain the corresponding absolute alphas, respectively. Then, for each model, we compute its average absolute alpha, $\overline{|\alpha|}$, which is the average absolute annualized alpha (in percentage points) of the long–short portfolios, averaged over all 153 anomalies in the market. We also calculate the average annualized absolute alphas for the three aggregate markets by averaging the absolute annualized alphas of the long–short portfolios in the relevant markets covered by the three aggregate markets, respectively. $*$, $**$, and $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3	Model 1 vs. Model 2	Model 1 vs. Model 3	Model 2 vs. Model 3
Austria	3.5840	4.6383	4.2278	-1.0543***	-0.6438*	0.4105
Switzerland	2.4839	2.3945	2.5709	0.0894	-0.087	-0.1764
Germany	2.4422	2.7881	2.6424	-0.3459	-0.2001	0.1457
Denmark	3.8518	4.4438	4.481	-0.5920*	-0.6293*	-0.0373
Spain	2.9606	3.3473	2.8702	-0.3867	0.0904	0.477
Finland	3.2350	4.2595	4.4389	-1.0244***	-1.2038***	-0.1794
France	2.0652	2.2466	2.1298	-0.1814	-0.0647	0.1167
Great Britain	2.3239	2.1972	2.5323	0.1267	-0.2085	-0.3352
Greece	6.7900	9.5075	9.4012	-2.7175***	-2.6112***	0.1062
Italy	2.7812	3.1176	2.8059	-0.3364	-0.0247	0.3117
Netherland	3.1582	3.0603	2.7533	0.0979	0.4049	0.307
Norway	2.9535	3.5370	3.5739	-0.5835**	-0.6204**	-0.0369
Sweden	2.5823	3.1247	2.3421	-0.5424*	0.2402	0.7826***
Australia	2.4168	3.1542	3.3442	-0.7373***	-0.9273***	-0.19
Hong Kong	4.6259	4.6211	4.8024	0.0048	-0.1766	-0.1814
Japan	2.5708	2.5316	1.9451	0.0392	0.6256	0.5864
Korea	4.6788	5.1866	4.0447	-0.5078	0.6342*	1.1419***
Malaysia	3.0665	3.4747	3.9563	-0.4082	-0.8897***	-0.4816

Singapore	3.4298	4.9180	3.6378	-1.4882	-0.208	1.2802
Thailand	3.8244	4.1815	4.1306	-0.3571	-0.3063	0.0508
Canada	1.9730	2.2735	2.4114	-0.3006*	-0.4384**	-0.1379
United States	2.0378	2.1345	2.8612	-0.0967	-0.8233***	-0.7267***
Developed Markets (DM)	2.8598	3.2660	3.1317	-0.4062***	-0.2719***	0.1343
Emerging Markets (EM)	4.5828	5.5751	5.3695	-0.9923***	-0.7867***	0.2056
All Markets	3.1705	3.6824	3.5353	-0.5119***	-0.3648***	0.1471

Table 5

Explaining Anomalies: Local Model vs. Augmented Models Incorporating Local and Foreign Factors

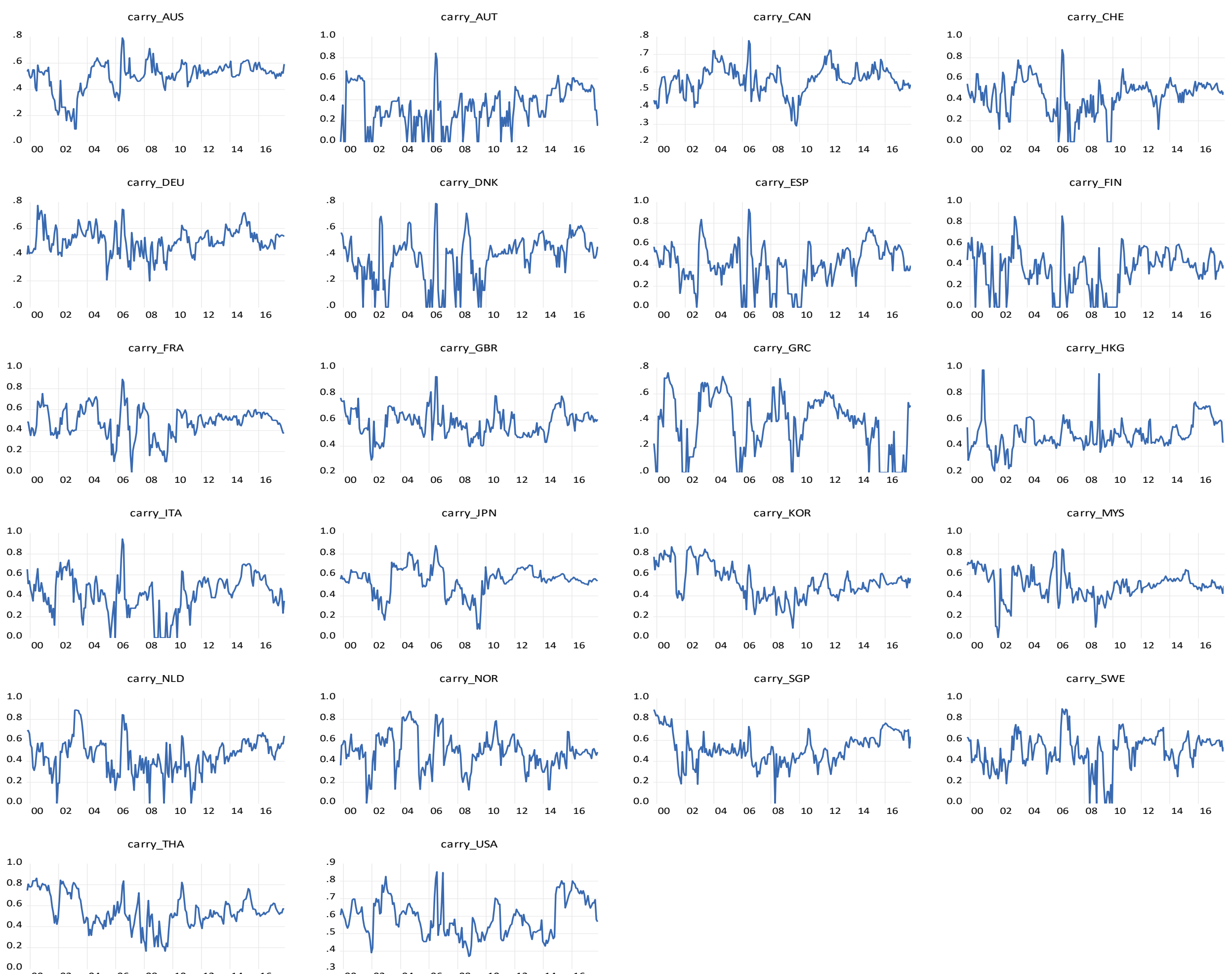
Table 5 compares the performance of the best local model, the best-augmented model incorporating local and regional factors, and the best-augmented model incorporating local and global factors (i.e., Model 1, Model 4, and Model 5) in explaining 153 cross-sectional anomalies in 22 individual stock markets and 3 aggregate stock markets (i.e. developed market (DM), emerging market (EM) and global stock market) for period from October 1997 to October 2017. The 22 stock markets include three regions: 13 markets in Europe, 7 in Asia-Pacific and two in North America, respectively. To assess the ability of these three classes of models in pricing the return anomalies for each of the 22 stock markets, we regress the time series of each of the 153 anomaly returns on the factors included in the best local model, the best-augmented model incorporating local and regional factors, and the best-augmented model incorporating local and global factors to obtain the corresponding absolute alphas, respectively. Then, for each model, we compute its average absolute alpha, $\overline{|\alpha|}$, which is the average absolute annualized alpha (in percentage points) of the long–short portfolios, averaged over all 153 anomalies in the market. We also calculate the average annualized absolute alphas for the three aggregate markets by averaging the absolute annualized alphas of the long–short portfolios in the relevant markets covered by the three aggregate markets, respectively. $*$, $**$, and $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

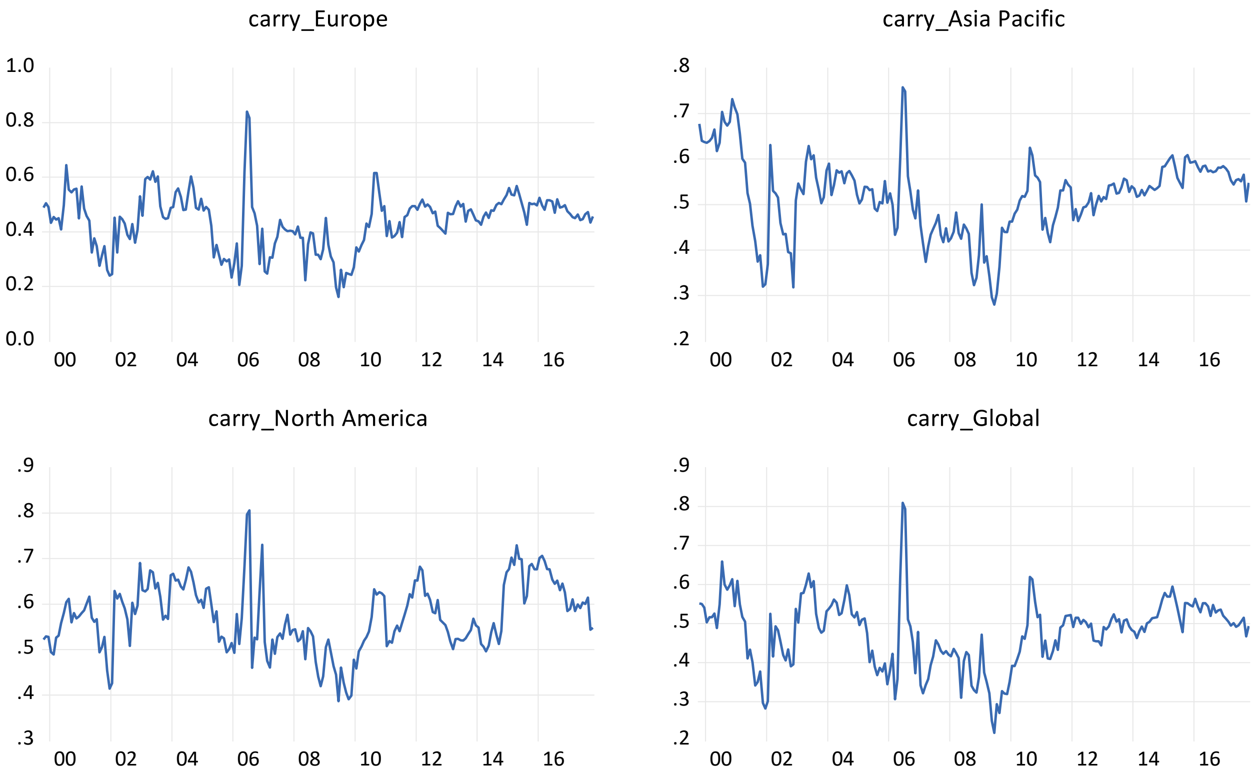
	Model 1	Model 4	Model 5	Model 1 vs. Model 4	Model 1 vs. Model 5	Model 4 vs. Model 5
Austria	3.5840	4.0107	4.0863	-0.4267	-0.5023	-0.0756
Switzerland	2.4839	2.4863	2.8577	-0.0024	-0.3737	-0.3713
Germany	2.4422	2.6876	2.7624	-0.2454	-0.3202	-0.0748
Denmark	3.8518	3.5842	4.7427	0.2676	-0.8909***	-1.1585***
Spain	2.9606	3.1101	2.8399	-0.1495	0.1207	0.2703
Finland	3.235	3.4852	3.3425	-0.2501	-0.1075	0.1426
France	2.0652	1.9644	2.13	0.1007	-0.0648	-0.1655
Great Britain	2.3239	2.4058	2.5927	-0.0819	-0.2688	-0.1869
Greece	6.7900	7.5723	6.2612	-0.7823	0.5288	1.3111**
Italy	2.7812	2.9572	2.6051	-0.176	0.1761	0.3522
Netherland	3.1582	2.8133	3.1278	0.3449	0.0304	-0.3145

Norway	2.9535	3.1518	3.5906	-0.1984	-0.6371**	-0.4387
Sweden	2.5823	2.4503	2.5697	0.132	0.0126	-0.1194
Australia	2.4168	2.5482	2.3747	-0.1314	0.0421	0.1735
Hong Kong	4.6259	4.5923	4.5474	0.0335	0.0784	0.0449
Japan	2.5708	7.2828	2.2007	-4.712	0.3701	5.0821
Korea	4.6788	4.4013	4.7729	0.2775	-0.0941	-0.3716
Malaysia	3.0665	3.0232	3.3422	0.0433	-0.2757	-0.319
Singapore	3.4298	5.9598	3.6372	-2.53	-0.2074	2.3226
Thailand	3.8244	4.2776	3.8192	-0.4532	0.0052	0.4584
Canada	1.9730	1.7189	1.8629	0.254	0.1101	-0.1439
United States	2.0378	2.5181	2.5413	-0.4803**	-0.5034**	-0.0231
Developed Markets (DM)	2.8598	3.3182	3.0229	-0.4584*	-0.1631**	0.2953
Emerging Markets (EM)	4.5828	4.8076	4.544	-0.2248	0.0388	0.2636
All Markets	3.1705	3.5868	3.2972	-0.4163*	-0.1267*	0.2896

Figure 1. Strengths of the CARRY and DOLLAR Factors

Figure 1 plots the estimated strengths of the CARRY and DOLLAR factors in 22 individual stock markets, 3 regional stock markets and global stock market from October 1999 to October 2017. The 22 stock markets include 13 markets in Europe, 7 in Asia-Pacific and 2 in North America, respectively. They are Austria (AUT), Switzerland (CHE), Germany (DEU), Denmark (DNK), Spain(ESP), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Italy (ITA), Norway (NOR), Netherland (NLD), Sweden(SWE), Australia (AUS), Hong Kong (HKG), Japan (JPN), Korea (KOR), Malaysia (MYS), Singapore (SGP), Thailand (THA), Canada (CAN) and the United States (US). The strengths of the two factors in regional stock markets and global stock market are calculated by taking the average of the estimated factor strengths in corresponding individual markets.

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carry_North America
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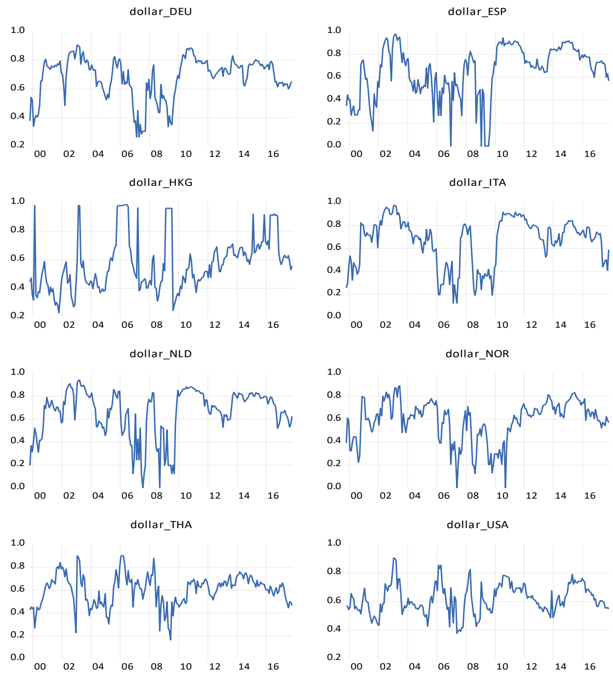
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dollar_USA

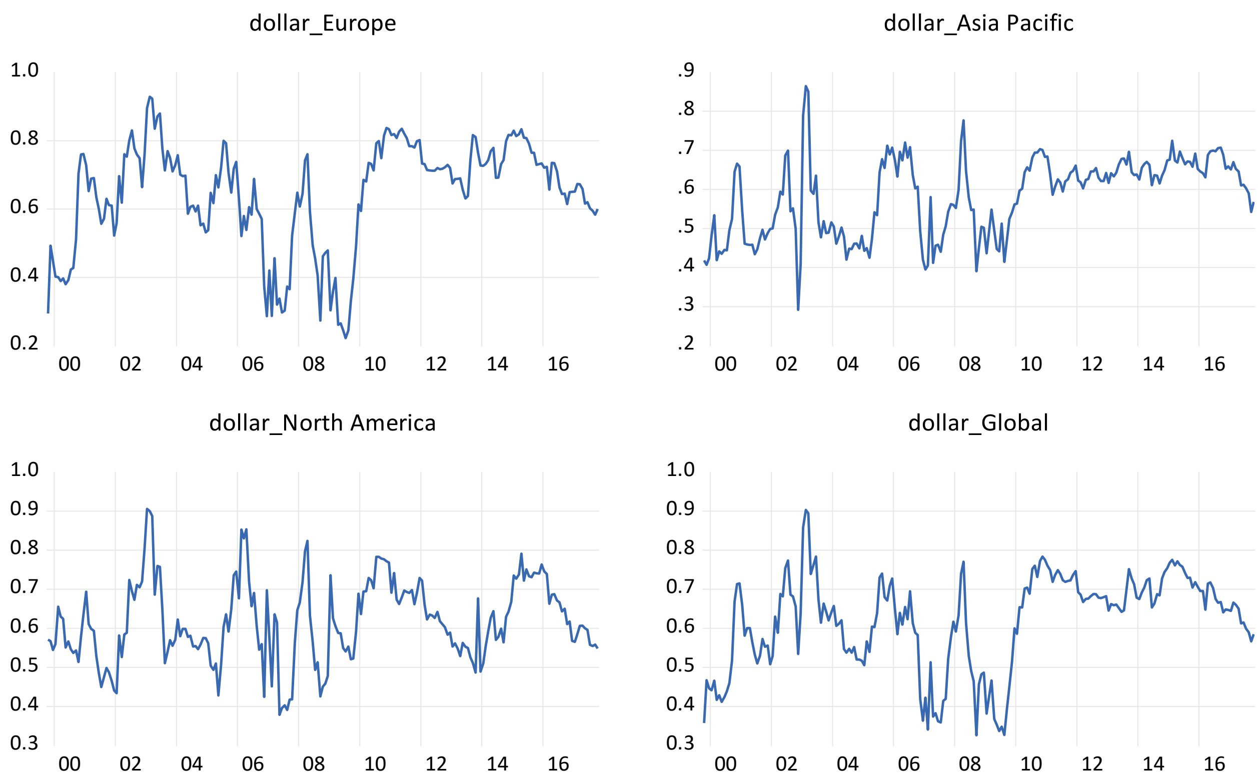
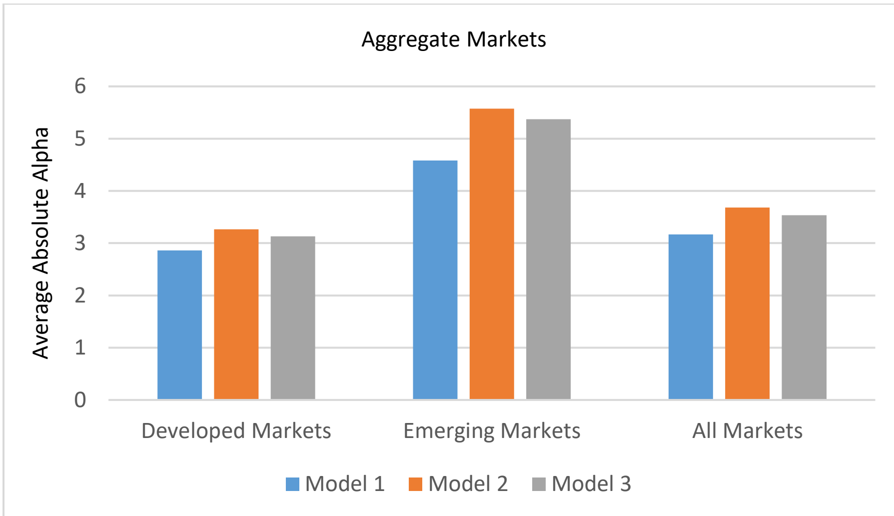

dollar_Europe
dollar_Asia Pacific
dollar_North America
dollar_Global

Figure 2. Summary of Alphas of Local, Regional and Global Models

Figure 2 plots the average absolute annualized alphas (in percentage points) of 153 cross-sectional anomalies for the best local model, regional model, and global model (i.e., Model 1, Model 2, and Model 3) in 22 individual stock markets and 3 aggregate stock markets (i.e. developed market (DM), emerging market (EM) and global stock market) for period from October 1997 to October 2017. The 22 stock markets include three regions: 13 markets in Europe, 7 in Asia-Pacific and two in North America, respectively. These markets are Austria (AUT), Switzerland (CHE), Germany (DEU), Denmark (DNK), Spain(ESP), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Italy (ITA), Norway (NOR), Netherland (NLD), Sweden(SWE), Australia (AUS), Hong Kong (HKG), Japan (JPN), Korea (KOR), Malaysia (MYS), Singapore (SGP), Thailand (THA), Canada (CAN) and the United States (US). For each of the 22 stock markets, we regress the time series of each of the 153 anomaly returns on the factors included in the best local, regional, and global models to obtain the corresponding absolute alphas, respectively. Then, for each model, we compute its average absolute alpha, $\overline{|\alpha|}$, which is the average absolute annualized alpha (in percentage points) of the long–short portfolios, averaged over all 153 anomalies in the market. The average annualized absolute alphas for three aggregate markets are calculated by averaging the absolute annualized alphas of the long–short portfolios in the relevant markets covered by the three aggregate markets, respectively. The blue bar denotes absolute alphas toward the local model. The orange and grey bars present the absolute alphas toward the regional and global models, respectively.

Panel A: Aggregate Markets



Panel B: Individual Markets

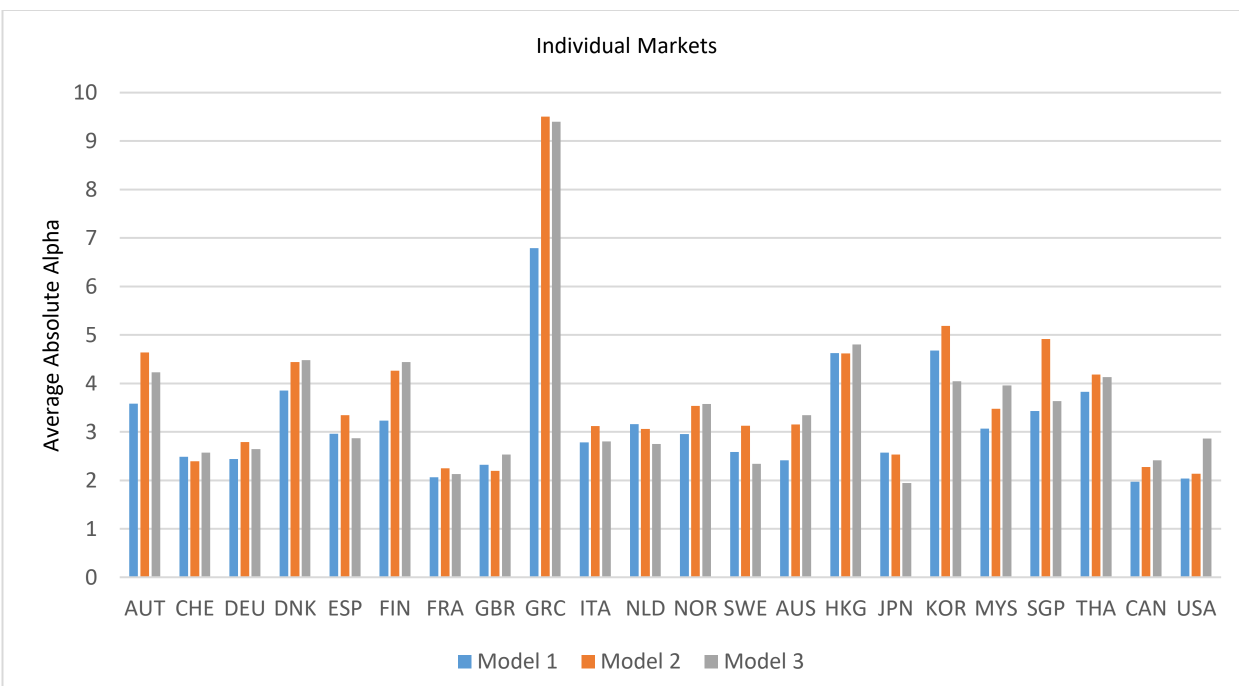
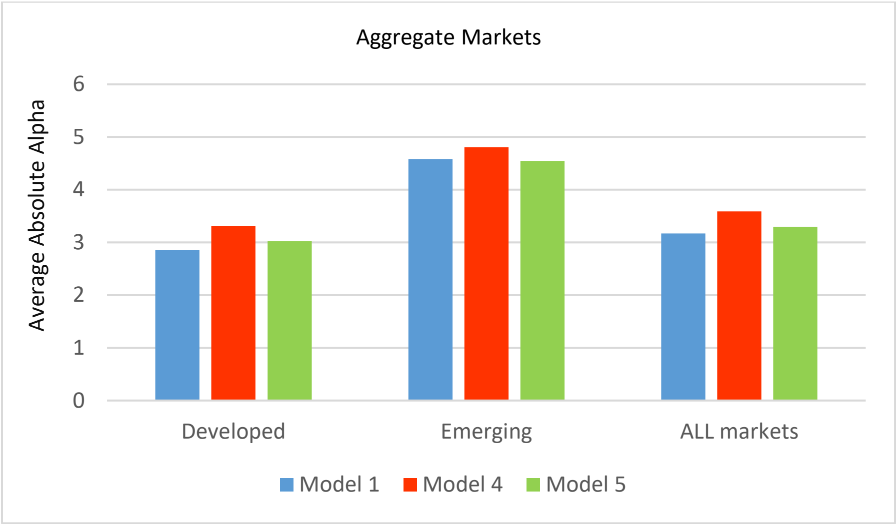


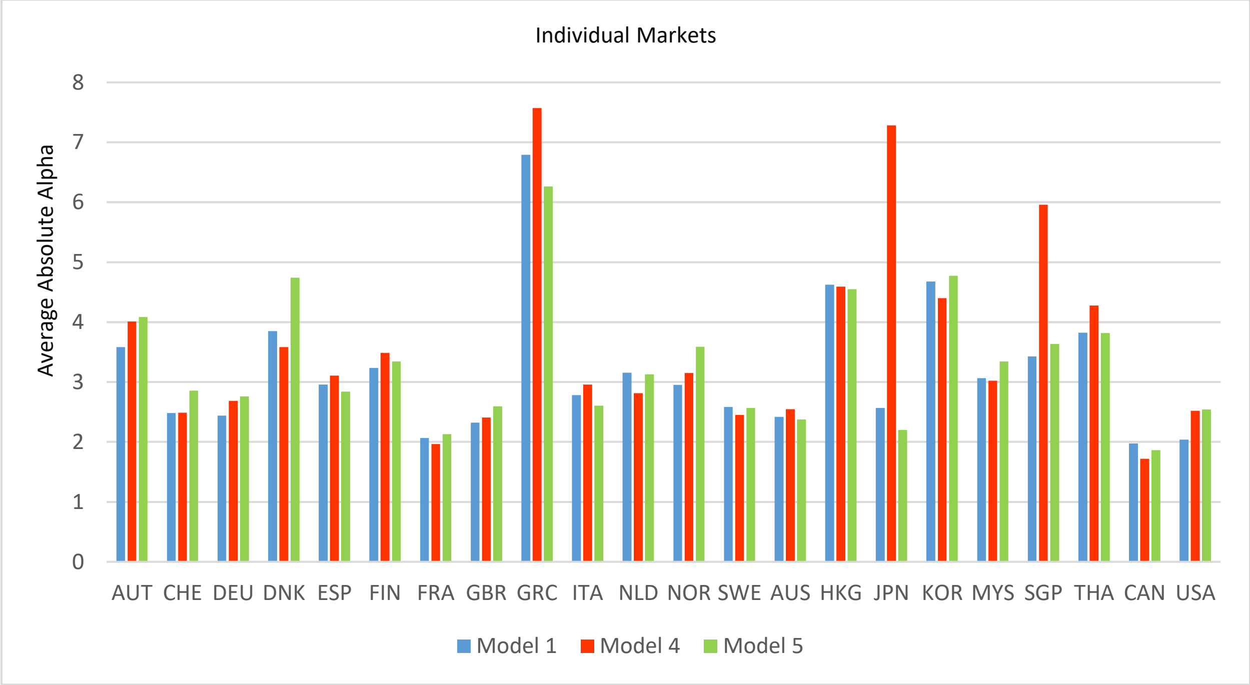
Figure 3. Summary of Alphas of Local Model and Augmented Models Incorporating Local and Foreign Factors

Figure 3 plots the average absolute annualized alphas (in percentage points) of 153 cross-sectional anomalies for the best local model, the best-augmented model incorporating local and regional factors, and the best-augmented model incorporating local and global factors (i.e., Model 1, Model 4, and Model 5) in explaining 153 cross-sectional anomalies in 22 individual stock markets and 3 aggregate stock markets (i.e. developed market (DM), emerging market (EM) and global stock market) for period from October 1997 to October 2017. The 22 stock markets include three regions: 13 markets in Europe, 7 in Asia-Pacific and two in North America, respectively. These markets are Austria (AUT), Switzerland (CHE), Germany (DEU), Denmark (DNK), Spain(ESP), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Italy (ITA), Norway (NOR), Netherland (NLD), Sweden(SWE), Australia (AUS), Hong Kong (HKG), Japan (JPN), Korea (KOR), Malaysia (MYS), Singapore (SGP), Thailand (THA), Canada (CAN) and the United States (US). For each of the 22 stock markets, we regress the time series of each of the 153 anomaly returns on the factors included in the best local model, the best-augmented model incorporating local and regional factors, and the best-augmented model incorporating local and global factors to obtain the corresponding absolute alphas, respectively. Then, for each model, we compute its average absolute alpha, $\overline{|\alpha|}$, which is the average absolute annualized alpha (in percentage points) of the long–short portfolios, averaged over all 153 anomalies in the market. We also calculate the average annualized absolute alphas for the three aggregate markets by averaging the absolute annualized alphas of the long–short portfolios in the relevant markets covered by the three aggregate markets, respectively. The blue bar denotes absolute alphas toward the local model. The red and green bars present the absolute alphas toward the best-augmented model incorporating local and regional factors, and the best-augmented model incorporating local and global factors, respectively.

Panel A: Aggregate Markets



Panel B: Individual Markets



Internet Appendix for "No One-Size-Fits-All Tale:

The Diversity and Complexity in Asset Pricing across Global Markets

Abstract

This Internet Appendix provides material that is supplemental to the paper "No One-Size-Fits-All Tale: The Diversity and Complexity in Asset Pricing across Global Markets".

Table A1

Summary Statistics of Monthly Factor Returns in Twenty-Two Individual Stock Markets and Three Regional Stock Markets

Table A1 reports summary statistics of the monthly factor returns in twenty-two individual stock markets and three regional stock markets between July 1995 and October 2017. 22 stock markets include three regions: 13 markets in Europe, 7 in Asia-Pacific, and two in North America, respectively. These markets are Austria (AUT), Switzerland (CHE), Germany (DEU), Denmark (DNK), Spain (ESP), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Italy (ITA), Norway (NOR), Netherland (NLD), Sweden (SWE), Australia(AUS), Hong Kong (HKG), Japan (JPN), Korea (KOR), Malaysia (MYS), Singapore (SGP), Thailand (THA), Canada (CAN) and the United States (US). MKT, SMB, HML, RMW and CMA are Fama and French five factors (Fama and French, 1993, 2012, 2015, 2017); WML is momentum factor (Jegadeesh and Titman, 1993; Carhart, 1997); MGMT is management factor and PERF is performance factor developed by Stambaugh and Yuan (2017); CARRY and DOLLAR factors are two currency risk factors developed by Lustig, Roussanov, and Verdelhan (2011). The joint normality test is a test for univariate normality based on skewness and kurtosis. It is developed by D'agostino, Belanger, and D'Agostino (1990). It follows a chi-squared distribution with two degrees of freedom. Doornik-Hansen normality test is a test for the multivariate normality, which is developed by Doornik-Hansen (2008). ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	MKT	SMB	HML	RMW	CMA	WML	MGMT	PERF	CARRY	DOLLAR
AUT										
Mean	0.5678	0.3644	0.5502	0.3556	0.5254	0.8616	0.0046	0.4316	0.6763	0.0447
Std Dev.	6.2565	3.7154	3.7369	3.3899	3.9919	4.9139	0.1390	4.1346	2.4193	1.7855
Skewness	-0.9023	0.2496	0.3782	-0.1262	-0.2678	-1.7390	-0.7411	-0.5277	-0.1645	-0.2828
Kurtosis	7.7093	4.2405	5.3031	3.3315	10.9782	15.1441	7.5782	4.6912	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	49.21***	10.6***	20.31***	2.2200	42.3***	101.86***	42.94***	20.36***	5.31*	9.87***

Doornik-Hansen normality test	χ^2 (20) = 376.205 Prob > χ^2 = 0.0000									
CHE										
Mean	0.6335	0.1743	0.1274	0.0897	0.1338	0.7705	-0.0528	0.4350	0.6763	0.0447
Std Dev.	4.8891	0.1034	3.1834	3.6782	3.2479	5.1014	2.9689	4.0419	2.4193	1.7855
Skewness	-0.4664	0.2996	-0.6072	0.1477	0.3786	-1.4263	0.9434	-0.6283	-0.1645	-0.2828
Kurtosis	4.1122	7.2203	7.1929	8.3714	4.1352	12.1811	7.0180	8.3659	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	14.67***	28.98***	36.8***	31.74***	12.54***	83.59***	47.6***	42.5***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 326.933 Prob>chi2 = 0.0000									
DEU										
Mean	0.5680	-0.0621	0.6457	0.6054	0.5029	1.0936	0.2357	0.9768	0.6763	0.0447
Std Dev.	5.8380	3.1366	3.7137	2.4377	3.3403	5.1484	3.0283	3.5897	2.4193	1.7855
Skewness	-0.4652	0.0152	0.5870	0.4226	0.8978	-0.5702	-0.0122	0.5049	-0.1645	-0.2828
Kurtosis	4.3385	3.6664	11.1441	4.9323	6.7468	8.7109	7.1949	5.2831	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	16.19***	4.0100	50.59***	19.04***	44.62***	42.04***	25.9***	23.49***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 491.232 Prob > χ^2 = 0.0000									

DNK										
Mean	0.9466	-0.3552	0.3832	0.0935	0.6930	0.9403	0.4388	0.6748	0.6763	0.0447
Std Dev.	5.3143	3.2550	4.9038	4.2194	3.3246	4.7249	3.8247	4.5010	2.4193	1.7855
Skewness	-0.7558	-0.0402	0.5037	-0.0628	0.7414	-0.9089	0.2802	-0.0394	-0.1645	-0.2828
Kurtosis	5.8749	3.4538	4.3229	3.4204	4.5682	6.7138	5.1834	3.8394	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	34.99***	2.3900	17.17***	2.2600	26.48***	44.87***	17.5***	5.52*	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 141.092 Prob > χ^2 = 0.0000									
ESP										
Mean	0.6529	0.1788	0.1595	0.5837	-0.1738	0.6769	0.0878	0.3378	0.6763	0.0447
Std Dev.	6.4215	3.4233	3.3743	3.1338	3.1469	4.9865	3.1991	3.9291	2.4193	1.7855
Skewness	-0.2894	0.0560	-0.1958	-0.0036	0.0486	-1.1192	0.2702	-0.0513	-0.1645	-0.2828
Kurtosis	3.9090	3.7217	3.4849	4.6515	4.7225	8.8782	3.4893	3.4924	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	9**	4.61*	4.3300	11.28***	11.86***	61.9***	5.82*	2.7300	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 197.886 Prob > χ^2 = 0.0000									
FIN										
Mean	0.9585	0.0400	0.6638	0.3246	0.0984	0.8946	0.3523	0.3692	0.6763	0.0447

Std Dev.	7.9595	4.2720	6.7178	4.8611	5.3872	5.9997	5.0317	5.4987	2.4193	1.7855
Skewness	0.0829	-0.0967	1.6217	0.0394	-0.2862	-0.0566	-0.1485	0.0231	-0.1645	-0.2828
Kurtosis	4.7459	5.5352	13.9217	5.0546	7.1489	6.9548	6.3667	4.0400	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	12.18***	17.35***	95***	14.05***	28.4***	24.86***	22.51***	6.94**	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 315.129 Prob > χ^2 = 0.0000									
FRA										
Mean	0.6723	0.0791	0.3669	0.1974	0.3471	0.6098	0.4662	0.5009	0.6763	0.0447
Std Dev.	5.5350	2.9441	3.8341	2.4464	2.7085	5.0558	2.7434	3.6715	2.4193	1.7855
Skewness	-0.5040	-0.0462	-2.1066	-0.1530	0.3405	-0.5513	0.4078	0.3825	-0.1645	-0.2828
Kurtosis	3.8787	4.1832	21.8939	4.3550	3.9418	7.6656	4.3021	9.7305	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	14.15***	8.04**	125.69***	10.05***	10.31***	37.23***	14.42***	40.67***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 291.185 Prob > χ^2 = 0.0000									
GBR										
Mean	0.5035	0.1915	0.1860	0.2609	0.3350	0.9562	0.2587	0.4737	0.6763	0.0447
Std Dev.	4.5069	3.2173	3.2083	2.3226	2.2327	4.5600	2.5274	2.9438	2.4193	1.7855
Skewness	-0.4732	-0.1377	0.3179	0.0281	0.7314	-1.4430	0.6239	-0.5586	-0.1645	-0.2828

Kurtosis	5.2526	5.1768	8.3335	5.4997	4.7165	9.6845	6.5538	5.6642	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	22.41***	15.45***	34.15***	16.83***	27.11***	76.9***	34.22***	27.35***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 316.937 Prob > χ^2 = 0.0000									
GRC										
Mean	0.0003	0.3523	0.4262	1.2687	-0.3999	0.9249	-0.2598	0.8966	0.6763	0.0447
Std Dev.	10.4210	6.9793	4.6634	5.1822	5.3074	8.4385	5.1094	5.7785	2.4193	1.7855
Skewness	-0.1497	0.4184	-0.0464	1.0032	-1.3019	-0.6073	-0.3676	-0.8538	-0.1645	-0.2828
Kurtosis	3.5713	5.6574	6.9662	7.6945	7.9990	6.7755	6.5834	5.1548	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	4.2700	23.42***	24.88***	52.85***	65.36***	34.81***	27.28***	34.23***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 315.834 Prob > χ^2 = 0.0000									
ITA										
Mean	0.5415	0.0733	0.2059	0.5690	-0.2346	0.8945	0.0831	0.7790	0.6763	0.0447
Std Dev.	6.6737	3.2744	3.5028	3.3812	2.9646	4.9396	3.6993	4.5992	2.4193	1.7855
Skewness	-0.1000	-0.4967	0.5418	-0.1752	0.4846	0.0384	0.0488	-0.1957	-0.1645	-0.2828
Kurtosis	3.3882	3.5844	4.5839	3.9829	4.4975	5.3615	4.7666	4.7429	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	2.3200	12.04***	20.06***	7.65**	17.81***	16***	12.16***	13.26***	5.31*	9.87***

Doornik-Hansen normality test	χ^2 (20) = 197.144 Prob > χ^2 = 0.0000									
NLD										
Mean	0.6742	-0.1137	0.3608	0.2221	0.1692	0.6891	0.0467	0.7333	0.6763	0.0447
Std Dev.	6.3997	3.4761	4.1991	3.7923	3.2690	6.3111	3.8188	4.9355	2.4193	1.7855
Skewness	-0.6952	0.1354	0.0069	-0.0761	0.2712	-0.5572	0.5016	-0.1672	-0.1645	-0.2828
Kurtosis	5.0708	4.2658	3.1025	2.8920	3.6492	8.1060	3.8723	5.3748	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	28.14***	9.23***	0.3000	0.3100	6.87**	39.26***	14.04***	17.0100	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 221.852 Prob > χ^2 = 0.0000									
NOR										
Mean	0.8327	0.2171	0.3454	0.5875	0.3728	1.2249	0.6280	0.7500	0.6763	0.0447
Std Dev.	7.0500	3.3329	4.7208	4.2794	3.8993	5.3038	4.3130	5.2483	2.4193	1.7855
Skewness	-0.7019	-0.2264	-0.1290	0.2478	0.1252	-0.1724	0.0767	0.0449	-0.1645	-0.2828
Kurtosis	5.5233	5.5848	4.2040	5.5037	3.8392	4.2275	3.8521	3.9930	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	31.12***	19.08***	8.73**	18.93***	6.06**	9.37***	5.78*	6.66**	5.31*	9.87***
Doornik-Hansen	χ^2 (20) = 157.803 Prob > χ^2 = 0.0000									

normality test										
SWE										
Mean	0.9370	0.1233	0.3328	0.3627	0.3662	0.9988	0.6374	0.9530	0.6763	0.0447
Std Dev.	6.9650	3.2778	5.1359	3.9925	3.9764	5.6526	3.5482	4.7240	2.4193	1.7855
Skewness	-0.2381	0.0833	-0.3667	-0.1979	0.6669	-0.6237	0.2875	0.1049	-0.1645	-0.2828
Kurtosis	4.4668	4.1311	10.0192	10.3838	7.6674	8.4597	5.2274	9.4774	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	12***	7.84**	41.27***	39.44***	40.84***	42.72***	17.92***	35.51***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 355.215 Prob > χ^2 = 0.0000									
AUS										
Mean	0.8100	0.0887	0.4031	0.3306	0.5046	1.4594	0.6725	0.5839	0.6763	0.0447
Std Dev.	6.0538	2.7061	2.9576	2.4217	2.5556	3.7338	3.2219	3.4959	2.4193	1.7855
Skewness	-0.6039	-0.3341	-0.1828	0.0356	0.1194	-0.4236	0.0746	-0.0700	-0.1645	-0.2828
Kurtosis	4.8653	3.8235	3.6153	4.7037	3.8186	4.8523	4.6007	4.3318	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	23.83***	9.35***	5.13*	11.69***	5.86*	18.54***	11.13***	9.21***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 160.695 Prob > χ^2 = 0.0000									
HKG										

Mean	0.7536	0.0773	0.5769	0.0928	0.3274	0.6360	0.9575	0.9930	0.6763	0.0447
Std Dev.	7.7351	5.6456	4.3631	4.4205	4.0983	5.9484	4.1945	4.9681	2.4193	1.7855
Skewness	-0.4589	0.9165	-0.7169	-0.4726	0.3286	-1.6810	0.2583	-0.7910	-0.1645	-0.2828
Kurtosis	5.9982	5.9289	8.6756	3.8071	5.3122	7.8196	6.0219	4.6204	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	26.41***	41.04***	46.6***	12.77***	19.26***	78.77***	22.12***	28.56***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 365.475 Prob > χ^2 = 0.0000									
JPN										
Mean	0.1332	0.1476	0.4926	-0.0097	0.0310	0.1787	0.0291	0.2357	0.6763	0.0447
Std Dev.	4.9244	3.2471	2.6859	1.7619	2.3143	4.6574	2.1915	3.5558	2.4193	1.7855
Skewness	0.0564	-0.1324	0.1263	-0.0568	-0.5739	-0.6084	-0.3478	0.0121	-0.1645	-0.2828
Kurtosis	3.1641	5.0228	3.2066	3.9094	6.4579	6.2433	8.2999	6.4665	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	0.7000	14.4***	1.5000	6.09**	32.17***	32.11***	34.63***	22.28***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 97.391 Prob > χ^2 = 0.0000									
KOR										
Mean	0.5718	-0.0348	1.2477	0.2050	0.5494	0.4717	0.8565	0.5871	0.6763	0.0447
Std Dev.	10.4608	6.0078	5.5392	4.3661	4.3342	7.0812	5.0841	5.5772	2.4193	1.7855
Skewness	0.7013	0.1733	1.3930	-0.4036	0.3024	-1.4552	2.0348	0.2416	-0.1645	-0.2828

Kurtosis	7.8853	11.2109	13.6298	17.8612	12.9473	11.9571	19.4096	8.2912	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	42.91***	41.63***	85.85***	60.23***	48.2***	84.09***	119.75***	32.62***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 989.353 Prob > χ^2 = 0.0000									
MYS										
Mean	0.3565	0.1403	0.4902	0.4136	0.0007	0.2319	0.2076	0.6619	0.6763	0.0447
Std Dev.	8.3365	5.0514	3.8517	3.2657	2.9601	6.9253	2.3190	6.3091	2.4193	1.7855
Skewness	0.7862	1.5672	2.4089	-1.8363	0.2990	-5.7023	-0.5664	-4.8131	-0.1645	-0.2828
Kurtosis	11.0198	15.2986	16.8820	14.7233	8.0793	53.8190	6.8207	42.4153	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	56.76***	95.87***	128.36***	104.51***	32.75***	246.08***	33.77***	220.37***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 982.293 Prob > χ^2 = 0.0000									
SGP										
Mean	0.5385	-0.0684	0.7787	0.2254	0.2075	0.0321	0.7662	0.5650	0.6763	0.0447
Std Dev.	7.0765	4.1349	3.8048	3.4395	3.3686	6.3857	3.3200	5.1985	2.4193	1.7855
Skewness	0.0062	1.0520	1.0106	-1.5005	-0.2240	-4.1020	0.5548	-2.4094	-0.1645	-0.2828
Kurtosis	6.1255	8.3446	11.9981	12.2792	9.6511	31.0314	6.0812	20.8283	3.6723	4.0514

Joint normality test (Adj χ^2 (2))	20.44***	57.35***	67.55***	86.61***	37.4***	194.84***	29.59***	134.49***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 397.554 Prob > χ^2 = 0.0000									
THA										
Mean	0.4984	0.5646	1.0780	0.4102	0.5694	0.4984	0.6962	0.5168	0.6763	0.0447
Std Dev.	9.4679	6.1973	5.1846	4.3521	3.5597	7.9611	4.1447	6.3850	2.4193	1.7855
Skewness	-0.0097	2.4874	3.2123	-1.1055	1.1347	-3.1369	1.8562	-2.2787	-0.1645	-0.2828
Kurtosis	5.3360	24.0587	32.1980	8.9868	8.2157	20.5228	13.6588	18.1655	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	15.79***	141.12***	171.36***	61.78***	59.94***	156.81***	102.93***	126.18***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 605.657 Prob > χ^2 = 0.0000									
CAN										
Mean	0.7840	0.1168	0.4721	0.7879	0.2482	1.1110	0.3352	1.0796	0.6763	0.0447
Std Dev.	5.8472	0.0949	0.2074	4.5371	3.3494	5.2917	4.3582	0.2452	2.4193	1.7855
Skewness	-0.6371	-0.1185	-0.4397	0.0741	-0.0103	-0.6877	-0.0969	-0.1232	-0.1645	-0.2828
Kurtosis	5.3807	5.6442	11.9920	3.7442	5.1194	5.8714	3.6701	6.3253	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	28.13***	18.16***	48.82***	4.91*	14.42***	32.65***	4.4700	22.05***	5.31*	9.87***

Doornik-Hansen normality test	χ^2 (20) = 446.145 Prob > χ^2 = 0.0000									
US										
Mean	0.6624	0.1918	0.2169	0.3487	0.2405	0.4299	0.4922	0.7352	0.6763	0.0447
Std Dev.	4.3869	3.1995	3.1296	2.9032	2.1741	5.1677	3.0583	4.7162	2.4193	1.7855
Skewness	-0.7295	0.4102	0.2985	-0.4378	0.6433	-1.4803	0.5051	-0.0402	-0.1645	-0.2828
Kurtosis	4.2285	7.4373	5.2407	11.9182	5.2358	12.8852	5.5534	5.8863	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	23.79***	32.39***	18.21***	48.57***	27.44***	87.37***	25.13***	19.15***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 313.863 Prob > χ^2 = 0.0000									
Europe										
Mean	0.6462	0.0806	0.3203	0.3284	0.2609	0.8740	0.2659	0.6045	0.6763	0.0447
Std Dev.	5.0521	2.1963	2.5055	1.4599	1.7252	4.1663	1.8355	2.5399	2.4193	1.7855
Skewness	-0.5556	0.0261	-0.0839	-0.2835	1.0148	-1.3127	0.5006	-0.2478	-0.1645	-0.2828
Kurtosis	4.5279	4.9691	11.5578	4.9867	6.6920	10.7834	5.3760	7.9209	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	20.1***	13.45***	41.85***	16.3***	48.67***	75.47***	23.93***	31.19***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 435.548 Prob > χ^2 = 0.0000									

Asia-Pacific										
Mean	0.3887	0.0882	0.5793	0.0956	0.1172	0.4732	0.2888	0.4647	0.6763	0.0447
Std Dev.	5.0259	2.4643	2.0540	1.3563	1.8689	3.8511	1.8283	2.8861	2.4193	1.7855
Skewness	-0.2708	-0.4491	0.0682	-0.2853	-0.5194	-0.9939	-0.2860	-0.2708	-0.1645	-0.2828
Kurtosis	3.6072	5.5090	3.5038	3.6068	7.2845	6.5533	8.7357	5.8489	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	6.58**	23.33***	2.9100	6.87**	34.59***	47.2***	35.12***	21.35***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 127.873 Prob > χ^2 = 0.0000									
North America										
Mean	0.6714	0.1876	0.2349	0.3731	0.2390	0.4655	0.4892	0.7561	0.6763	0.0447
Std Dev.	4.4216	3.1031	3.0824	2.8746	2.1537	5.0908	3.0482	4.5460	2.4193	1.7855
Skewness	-0.7432	0.3919	0.3007	-0.4457	0.6213	-1.4645	0.4541	-0.0471	-0.1645	-0.2828
Kurtosis	4.3677	7.9051	5.5316	11.6376	5.0757	12.7423	5.3578	5.9941	3.6723	4.0514
Joint normality test (Adj χ^2 (2))	25.2***	34***	20.04***	48.01***	25.74***	86.43***	22.54***	19.78***	5.31*	9.87***
Doornik-Hansen normality test	χ^2 (20) = 316.861 Prob > χ^2 = 0.0000									

Table A2

Log-Marginal Likelihoods of the Best Gaussian distributed Factor Pricing Models for International Stock Markets

Table A2 presents the log-marginal likelihoods of the best Gaussian distributed factor models 22 individual stock markets, 3 regional stock markets and global stock market. The 22 stock markets include three regions: 13 markets in Europe, 7 in Asia-Pacific and two in North America, respectively. MKT, SMB, HML, RMW and CMA are Fama and French five factors (Fama and French, 1993, 2012, 2015, 2017); WML is the momentum factor (Jegadeesh and Titman, 1993; Carhart, 1997); MGMT is management factor and PERF is performance factor developed by Stambaugh and Yuan (2017); CARRY and DOLLAR factors are two currency risk factors developed by Lustig, Roussanov, and Verdelhan (2011). "1" indicates that the best model selects the factor, and '0' otherwise. *Log-marg* is the estimated log-marginal likelihood. The estimation sample period is from October 1997 to October 2017 (241 observations).

	MKT	SMB	HML	RMW	CMA	WML	MGMT	PERF	CARRY	DOLLAR	*Log-marg*
Panel A											
Austria	1	1	1	0	1	0	0	0	1	0	4612.11
Switzerland	0	0	0	0	0	1	0	0	1	0	4910.9083
Germany	0	0	1	1	0	1	0	0	1	0	4948.2217
Denmark	1	0	0	0	1	1	0	0	1	0	4491.086
Spain	0	0	0	1	0	0	0	0	1	0	4797.833
Finland	0	0	0	0	0	1	0	0	1	0	4364.6259
France	0	0	0	0	0	0	1	1	1	0	5116.671
Great Britain	0	0	0	0	1	1	0	0	1	0	5298.6842
Greece	0	1	1	1	0	0	0	1	1	0	3924.5271
Italy	0	0	1	1	1	0	0	0	1	0	4909.2133

Netherland	0	0	0	0	0	0	0	1	1	0	4498.6984
Norway	0	0	0	0	0	1	1	0	1	0	4431.9463
Sweden	0	0	0	0	0	0	1	1	1	0	4628.4294
Australia	0	1	0	1	1	1	0	0	1	0	5225.2703
Hong Kong	0	1	1	0	0	0	1	1	1	0	4450.2231
Japan	0	1	1	0	0	0	0	1	1	0	5505.6152
Korea	0	0	1	1	0	0	0	1	1	0	4065.3358
Malaysia	0	0	1	1	0	0	1	0	1	0	4896.3631
Singapore	0	0	1	0	1	0	1	1	1	0	4819.0175
Thailand	1	1	1	0	1	0	0	1	1	0	4279.3823
Canada	0	0	1	0	0	0	0	1	1	0	4831.0798
United States	1	0	0	0	0	0	1	1	1	0	5283.2293
Panel B											
Europe	1	0	1	0	0	0	0	1	1	0	5805.4877
Asia Pacific	1	1	1	0	0	0	1	1	1	0	5904.1589
North America	1	0	0	0	0	0	1	1	1	0	5338.0806
Global	1	1	0	0	0	0	1	1	1	0	5943.456

Table A3

Descriptive Statistics of Estimated Strengths of the CARRY and DOLLAR Factors in International Stock Markets

Table A3 presents descriptive statistics of estimated strengths of the CARRY and DOLLAR factors in 22 individual stock markets, 3 regional stock markets and global stock market for period from October 1999 to October 2017. The 22 stock markets include three regions: 13 markets in Europe, 7 in Asia-Pacific and two in North America, respectively. These markets are Austria (AUT), Switzerland (CHE), Germany (DEU), Denmark (DNK), Spain(ESP), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Italy (ITA), Norway (NOR), Netherland (NLD), Sweden (SWE), Australia (AUS), Hong Kong (HKG), Japan (JPN), Korea (KOR), Malaysia (MYS), Singapore (SGP), Thailand (THA), Canada (CAN) and the United States (US). The strengths of these two factors in 3 regional regionals stock markets and global stock market are calculated by taking the average of the estimated factor strengths in corresponding individual markets. Our estimation sample period is from October 1997 to October 2017 (241 months). We use rolling samples (241 months) for estimation and our rolling window size is 24 months (2 years) each.

	Mean	Median	Max.	Min.	Std. Dev.	Obs.
Panel A						
CARRY_AUT	0.3292	0.3386	0.8441	0.0000	0.1855	217
CARRY_CHE	0.4352	0.4710	0.8778	0.0000	0.1645	217
CARRY_DEU	0.5083	0.5085	0.7752	0.2007	0.0987	217
CARRY_DNK	0.3787	0.4098	0.7904	0.0000	0.1736	217
CARRY_ESP	0.4069	0.4063	0.9324	0.0000	0.1916	217
CARRY_FIN	0.3534	0.3829	0.8686	0.0000	0.1959	217
CARRY_FRA	0.4796	0.4994	0.8884	0.0000	0.1421	217
CARRY_GBR	0.5779	0.5791	0.9329	0.2939	0.1036	217
CARRY_GRC	0.3713	0.4040	0.7625	0.0000	0.2184	217
CARRY_ITA	0.4202	0.4439	0.9428	0.0000	0.1853	217
CARRY_NLD	0.4554	0.4613	0.8895	0.0000	0.1674	217
CARRY_NOR	0.4935	0.4881	0.8760	0.0000	0.1658	217
CARRY_SWE	0.4970	0.5273	0.9001	0.0000	0.1659	217
CARRY_AUS	0.5002	0.5233	0.7921	0.0978	0.1129	217
CARRY_HKG	0.4896	0.4642	0.9831	0.2115	0.1159	217
CARRY_JPN	0.5478	0.5622	0.8808	0.0835	0.1327	217
CARRY_KOR	0.5319	0.5199	0.8740	0.0925	0.1588	217

CARRY_MYS	0.5010	0.5008	0.8486	0.0000	0.1339	217
CARRY_SGP	0.5217	0.5074	0.8924	0.0000	0.1476	217
CARRY_THA	0.5492	0.5306	0.8611	0.1655	0.1546	217
CARRY_CAN	0.5534	0.5588	0.7782	0.2913	0.0811	217
CARRY_US	0.5922	0.5803	0.8538	0.3693	0.1065	217
CARRY_Europe	0.4390	0.4546	0.8402	0.1613	0.1027	217
CARRY_Asia Pacific	0.5202	0.5301	0.7574	0.2802	0.0858	217
CARRY_North America	0.5728	0.5682	0.8058	0.3865	0.0750	217
CARRY_GLOBAL	0.4770	0.4931	0.8099	0.2196	0.0885	217
Panel B						
DOLLAR_DEU	0.6795	0.7290	0.9078	0.2626	0.1444	217
DOLLAR_ESP	0.6518	0.7038	0.9797	0.0000	0.2251	217
DOLLAR_FIN	0.6616	0.7251	0.9734	0.0000	0.2475	217
DOLLAR_GBR	0.6742	0.6746	0.9263	0.3361	0.1323	217
DOLLAR_ITA	0.6612	0.7183	0.9751	0.1211	0.2068	217
DOLLAR_NLD	0.6565	0.7092	0.9422	0.0000	0.2057	217
DOLLAR_NOR	0.5872	0.6254	0.8926	0.0000	0.1791	217
DOLLAR_SWE	0.5751	0.6159	0.8997	0.0000	0.2041	217
DOLLAR_HKG	0.5701	0.5387	0.9850	0.2297	0.1890	217
DOLLAR_KOR	0.6270	0.6719	0.8788	0.1055	0.1480	217
DOLLAR_MYS	0.5055	0.5089	0.9059	0.0000	0.1418	217
DOLLAR_SGP	0.6090	0.6687	0.8699	0.1720	0.1648	217
DOLLAR_THA	0.6019	0.6295	0.9035	0.1655	0.1345	217
DOLLAR_US	0.6179	0.6056	0.9057	0.3782	0.1031	217
DOLLAR_Europe	0.6434	0.6885	0.9286	0.2221	0.1564	217
DOLLAR_Asia Pacific	0.5827	0.6100	0.8642	0.2916	0.0997	217
DOLLAR_North America	0.6179	0.6056	0.9057	0.3782	0.1031	217
DOLLAR_GLOBAL	0.6199	0.6503	0.9036	0.3258	0.1206	217

Table A4

Descriptive Statistics of Estimated Strengths of the Stock Market Factors in International Stock Markets

This table presents descriptive statistics of estimated strengths of the eight stock market factors in 22 individual stock markets, 3 regional stock markets and global stock market for period from October 1999 to October 2017. The eight factors include: Fama and French five factors (MKT, SMB, HML, RMW and CMA) (Fama and French, 1993, 2012, 2015, 2017); momentum factor (WML) (Jegadeesh and Titman, 1993; Carhart, 1997); management factor (MGMT) and performance factor (PERF) Stambaugh and Yuan (2017). The 22 stock markets include three regions: 13 markets in Europe, 7 in Asia-Pacific and two in North America, respectively. These markets are Austria (AUT), Switzerland (CHE), Germany (DEU), Denmark (DNK), Spain(ESP), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Italy (ITA), Norway (NOR), Netherland (NLD), Sweden(SWE), Australia (AUS), Hong Kong (HKG), Japan (JPN), Korea (KOR), Malaysia (MYS), Singapore (SGP), Thailand (THA), Canada (CAN) and the United States (US). The strengths of these two factors in 3 regional regionals stock markets and global stock market are calculated by taking the average of the estimated factor strengths in corresponding individual markets. Our estimation sample period is from October 1997 to October 2017 (241 months). We use rolling samples (241 months) for estimation and our rolling window size is 24 months (2 years) each.

	Mean	Median	Max.	Min.	Std. Dev.	Obs.
Panel A						
MKT_AUT	0.5064	0.5286	0.9159	0.0000	0.2260	217
MKT_CHE	0.7436	0.8603	0.9475	0.0000	0.2219	217
MKT_DNK	0.6895	0.8039	0.9374	0.0000	0.2207	217
MKT_FRA	0.7674	0.8450	0.9372	0.0000	0.1680	217
MKT_GRC	0.7259	0.8197	0.9582	0.0000	0.2405	217
MKT_AUS	0.7080	0.7528	0.8972	0.2033	0.1141	217
MKT_JPN	0.7908	0.8411	0.9531	0.0000	0.1589	217
MKT_MYS	0.7713	0.8174	0.9732	0.3053	0.1567	217
MKT_CAN	0.7099	0.7392	0.8594	0.4018	0.1108	217
MKT_Europe	0.6866	0.7188	0.9296	0.3231	0.1544	217
MKT_Asia-Pacific	0.7567	0.7884	0.9363	0.3526	0.1131	217
MKT_North America	0.7099	0.7392	0.8594	0.4018	0.1108	217
MKT_Global	0.7125	0.7522	0.8996	0.3874	0.1232	217

Panel B

SMB_CHE	0.5575	0.6418	0.9075	0.0000	0.2182	217
SMB_DEU	0.5935	0.5947	0.8793	0.3058	0.1070	217
SMB_DNK	0.6245	0.6310	0.9596	0.2144	0.1448	217
SMB_ESP	0.4338	0.4952	0.8752	0.0000	0.2069	217
SMB_FIN	0.4643	0.4760	0.8603	0.0000	0.1809	217
SMB_FRA	0.6107	0.6528	0.8599	0.2384	0.1432	217
SMB_GBR	0.6254	0.6334	0.9475	0.3056	0.1098	217
SMB_GRC	0.5412	0.5922	0.9037	0.0000	0.1859	217
SMB_ITA	0.5070	0.5394	0.9292	0.0000	0.1649	217
SMB_NLD	0.4915	0.5219	0.7887	0.0000	0.1422	217
SMB_NOR	0.4599	0.4664	0.7705	0.0000	0.1553	217
SMB_SWE	0.4691	0.5157	0.8306	0.0000	0.1694	217
SMB_AUS	0.5794	0.6090	0.8355	0.1869	0.1080	217
SMB_HKG	0.5140	0.5098	0.7760	0.2115	0.1198	217
SMB_JPN	0.7114	0.7264	0.9713	0.2180	0.1257	217
SMB_KOR	0.5967	0.6195	0.8563	0.1983	0.1239	217
SMB_MYS	0.6725	0.6930	0.9277	0.3052	0.1254	217
SMB_SGP	0.5579	0.5766	0.8382	0.0000	0.1482	217
SMB_THA	0.5860	0.6090	0.8261	0.1054	0.1281	217
SMB_CAN	0.6218	0.6113	0.8263	0.4401	0.0787	217
SMB_US	0.6193	0.6266	0.9097	0.3921	0.0954	217
SMB_Europe	0.5315	0.5418	0.6609	0.2705	0.0811	217
SMB_Asia-Pacific	0.6026	0.6180	0.7102	0.3530	0.0706	217
SMB_North America	0.6206	0.6272	0.7655	0.4321	0.0616	217
SMB_Global	0.5637	0.5866	0.6544	0.3386	0.0673	217
Panel C						
HML_AUT	0.3118	0.3392	0.7720	0.0000	0.1666	217
HML_CHE	0.3682	0.4505	0.7245	0.0000	0.1815	217
HML_DEU	0.5669	0.5664	0.8417	0.3412	0.0968	217
HML_ESP	0.4124	0.4334	0.9097	0.0000	0.2242	217
HML_GBR	0.5426	0.5517	0.7847	0.2530	0.0966	217
HML_GRC	0.4386	0.5003	0.9197	0.0000	0.2085	217
HML_ITA	0.4314	0.4418	0.9161	0.0000	0.1926	217
HML_NLD	0.4752	0.4880	0.8701	0.0000	0.1727	217
HML_NOR	0.4491	0.4635	0.7568	0.0000	0.1628	217
HML_SWE	0.4931	0.5052	0.9561	0.1136	0.1442	217
HML_AUS	0.5303	0.5304	0.8448	0.2988	0.0957	217
HML_HKG	0.5389	0.5115	0.9804	0.1900	0.1788	217
HML_JPN	0.6071	0.6431	0.8051	0.3268	0.1038	217

HML_KOR	0.5989	0.5881	0.8518	0.3313	0.0977	217
HML_SGP	0.5102	0.5206	0.8260	0.0000	0.1368	217
HML_THA	0.5901	0.5824	0.9522	0.1662	0.1633	217
HML_CAN	0.5740	0.5755	0.7318	0.3677	0.0649	217
HML_US	0.5717	0.5699	0.8574	0.3163	0.0835	217
HML_Europe	0.4622	0.4783	0.6932	0.1406	0.1133	217
HML_Asia-Pacific	0.5626	0.5689	0.7057	0.3845	0.0593	217
HML_North America	0.5729	0.5735	0.7087	0.3975	0.0570	217
HML_Global	0.5308	0.5465	0.6608	0.3743	0.0582	217
Panel D						
RMW_AUT	0.3511	0.3534	0.7485	0.0000	0.1976	217
RMW_CHE	0.4349	0.4596	0.8717	0.0000	0.1606	217
RMW_DEU	0.5867	0.6004	0.9391	0.1616	0.1453	217
RMW_DNK	0.4396	0.4833	0.7840	0.0000	0.1617	217
RMW_ESP	0.3805	0.4200	0.8077	0.0000	0.2261	217
RMW_FIN	0.4020	0.4579	0.8665	0.0000	0.2248	217
RMW_FRA	0.4633	0.5005	0.8271	0.0000	0.1471	217
RMW_GBR	0.5518	0.5526	0.8614	0.2946	0.1019	217
RMW_GRC	0.4172	0.4549	0.9092	0.0000	0.2000	217
RMW_ITA	0.4627	0.4986	0.9094	0.0000	0.1929	217
RMW_NOR	0.4272	0.4569	0.7441	0.0000	0.1702	217
RMW_SWE	0.4984	0.5052	0.8484	0.1165	0.1460	217
RMW_AUS	0.5112	0.5348	0.7607	0.2369	0.0911	217
RMW_HKG	0.5589	0.5204	0.9807	0.2455	0.1562	217
RMW_JPN	0.5664	0.6022	0.7449	0.0834	0.1115	217
RMW_KOR	0.5475	0.5479	0.8409	0.3135	0.1025	217
RMW_MYS	0.5786	0.5664	0.9227	0.2591	0.1201	217
RMW_SGP	0.5124	0.5123	0.8295	0.1695	0.1229	217
RMW_CAN	0.5753	0.5869	0.7170	0.2746	0.0831	217
RMW_US	0.5841	0.5687	0.8947	0.3158	0.0990	217
RMW_Europe	0.4513	0.4698	0.5948	0.1789	0.0860	217
RMW_Asia-Pacific	0.5458	0.5570	0.6676	0.3799	0.0586	217
RMW_North America	0.5797	0.5896	0.7180	0.3401	0.0697	217
RMW_Global	0.4925	0.5114	0.5854	0.2773	0.0637	217
Panel E						
CMA_CHE	0.4364	0.4614	0.7961	0.0000	0.1483	217
CMA_DNK	0.4282	0.4483	0.9202	0.0000	0.2018	217
CMA_ESP	0.3407	0.3485	0.9500	0.0000	0.2090	217

CMA_FIN	0.4080	0.4406	0.9133	0.0000	0.2170	217
CMA_FRA	0.5315	0.5228	0.8867	0.1038	0.1246	217
CMA_GBR	0.5603	0.5630	0.8566	0.0891	0.1303	217
CMA_GRC	0.4450	0.4917	0.9552	0.0000	0.2036	217
CMA_ITA	0.4585	0.4837	0.8696	0.0000	0.1988	217
CMA_NLD	0.4565	0.4756	0.8679	0.0000	0.1585	217
CMA_SWE	0.4084	0.4407	0.7931	0.0000	0.1726	217
CMA_HKG	0.5288	0.4873	0.9876	0.1900	0.1676	217
CMA_KOR	0.5772	0.5699	0.9306	0.1573	0.1299	217
CMA_CAN	0.5806	0.5832	0.8519	0.4076	0.0764	217
CMA_Europe	0.4473	0.4650	0.6064	0.2072	0.0807	217
CMA_Asia-Pacific	0.5530	0.5369	0.8516	0.2885	0.0994	217
CMA_North America	0.5806	0.5832	0.8519	0.4076	0.0764	217
CMA_Global	0.4738	0.4880	0.6132	0.2795	0.0674	217
Panel F						
WML_AUT	0.3807	0.3783	0.8761	0.0000	0.1930	217
WML_CHE	0.4899	0.5231	0.9462	0.0000	0.2010	217
WML_DEU	0.5905	0.5844	0.8456	0.1615	0.1330	217
WML_DNK	0.4476	0.4846	0.8483	0.0000	0.1686	217
WML_FIN	0.4617	0.4884	0.8834	0.0000	0.2116	217
WML_FRA	0.5493	0.5584	0.9004	0.0000	0.1224	217
WML_GBR	0.6108	0.6066	0.8822	0.2502	0.1212	217
WML_GRC	0.4688	0.5042	0.9719	0.0000	0.2138	217
WML_ITA	0.4518	0.4715	0.8902	0.0000	0.1842	217
WML_NOR	0.5438	0.5691	0.9189	0.0000	0.1902	217
WML_SWE	0.4611	0.4717	0.8527	0.0000	0.1864	217
WML_AUS	0.5520	0.5643	0.8534	0.2040	0.1133	217
WML_HKG	0.5234	0.5050	0.9842	0.2933	0.1500	217
WML_JPN	0.5784	0.5940	0.8161	0.1321	0.1181	217
WML_KOR	0.5484	0.5379	0.8280	0.2868	0.1131	217
WML_MYS	0.6036	0.5995	0.9733	0.2125	0.1302	217
WML_SGP	0.5899	0.6161	0.8417	0.1081	0.1368	217
WML_THA	0.5616	0.5896	0.8693	0.2095	0.1303	217
WML_CAN	0.6106	0.5950	0.9301	0.3890	0.1086	217
WML_US	0.6045	0.5729	0.9050	0.4481	0.0983	217
WML_Europe	0.4960	0.5081	0.6961	0.2615	0.0817	217
WML_Asia-Pacific	0.5653	0.5751	0.7581	0.3332	0.0737	217
WML_North America	0.6076	0.5915	0.9011	0.4429	0.0885	217
WML_Global	0.5314	0.5353	0.6644	0.3325	0.0596	217

WML_AUT	0.3807	0.3783	0.8761	0.0000	0.1930	217
WML_CHE	0.4899	0.5231	0.9462	0.0000	0.2010	217
WML_DEU	0.5905	0.5844	0.8456	0.1615	0.1330	217
WML_DNK	0.4476	0.4846	0.8483	0.0000	0.1686	217
WML_FIN	0.4617	0.4884	0.8834	0.0000	0.2116	217
WML_FRA	0.5493	0.5584	0.9004	0.0000	0.1224	217
WML_GBR	0.6108	0.6066	0.8822	0.2502	0.1212	217
WML_GRC	0.4688	0.5042	0.9719	0.0000	0.2138	217
WML_ITA	0.4518	0.4715	0.8902	0.0000	0.1842	217
WML_NOR	0.5438	0.5691	0.9189	0.0000	0.1902	217
WML_SWE	0.4611	0.4717	0.8527	0.0000	0.1864	217
WML_AUS	0.5520	0.5643	0.8534	0.2040	0.1133	217
WML_HKG	0.5234	0.5050	0.9842	0.2933	0.1500	217
WML_JPN	0.5784	0.5940	0.8161	0.1321	0.1181	217
WML_KOR	0.5484	0.5379	0.8280	0.2868	0.1131	217
WML_MYS	0.6036	0.5995	0.9733	0.2125	0.1302	217
WML_SGP	0.5899	0.6161	0.8417	0.1081	0.1368	217
WML_THA	0.5616	0.5896	0.8693	0.2095	0.1303	217
WML_CAN	0.6106	0.5950	0.9301	0.3890	0.1086	217
WML_US	0.6045	0.5729	0.9050	0.4481	0.0983	217
WML_Europe	0.4960	0.5081	0.6961	0.2615	0.0817	217
WML_Asia-Pacific	0.5653	0.5751	0.7581	0.3332	0.0737	217
WML_North America	0.6076	0.5915	0.9011	0.4429	0.0885	217
WML_Global	0.5314	0.5353	0.6644	0.3325	0.0596	217
Panel G						
MGMT_AUT	0.3633	0.3812	0.8854	0.0000	0.2050	217
MGMT_DEU	0.5486	0.5630	0.7805	0.3056	0.0989	217
MGMT_DNK	0.4180	0.4547	0.6909	0.0000	0.1521	217
MGMT_FIN	0.4104	0.4499	0.7844	0.0000	0.1835	217
MGMT_FRA	0.5106	0.5400	0.8168	0.1022	0.1188	217
MGMT_NLD	0.4299	0.4418	0.6875	0.0000	0.1430	217
MGMT_NOR	0.4231	0.4744	0.6625	0.0000	0.1777	217
MGMT_AUS	0.5362	0.5403	0.8299	0.0980	0.1112	217
MGMT_JPN	0.5683	0.5959	0.8421	0.1321	0.1158	217
MGMT_MYS	0.4971	0.5111	0.8524	0.0000	0.1253	217
MGMT_SGP	0.5149	0.5070	0.8402	0.2163	0.1118	217
MGMT_THA	0.5465	0.5658	0.9186	0.0000	0.1561	217
MGMT_US	0.5737	0.5811	0.8141	0.3060	0.0907	217
MGMT_Europe	0.4434	0.4635	0.6240	0.1864	0.0813	217

MGMT_Asia-Pacific	0.5326	0.5560	0.6615	0.2644	0.0809	217
MGMT_North America	0.5737	0.5811	0.8141	0.3060	0.0907	217
MGMT_Global	0.4877	0.5091	0.5848	0.2941	0.0618	217
Panel H						
PERF_AUT	0.2760	0.2949	0.8245	0.0000	0.1956	217
PERF_ESP	0.3924	0.4054	0.8246	0.0000	0.2489	217
PERF_NLD	0.4551	0.4555	0.8666	0.0000	0.1840	217
PERF_THA	0.6754	0.7010	0.9058	0.1692	0.1442	217
PERF_Europe	0.3745	0.3918	0.6616	0.0000	0.1328	217
PERF_Asia-Pacific	0.6754	0.7010	0.9058	0.1692	0.1442	217
PERF_North America	NA	NA	NA	NA	NA	NA
PERF_Global	0.4497	0.4649	0.7164	0.1340	0.1085	217

Table A5

The Best-Augmented Student-t Distributed Factor Pricing Models Incorporating Local and Regional Factors for International Stock Markets

Table A5 presents the best-augmented student-t distributed factor models, which incorporate local and regional factors for 22 individual stock markets. The 22 stock markets include three regions: 13 markets in Europe, 7 in Asia-Pacific and two in North America, respectively. These markets are Austria (AUT), Switzerland (CHE), Germany (DEU), Denmark (DNK), Spain(ESP), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Italy (ITA), Norway (NOR), Netherland (NLD), Sweden(SWE), Australia(AUS), Hong Kong (HKG), Japan (JPN), Korea (KOR), Malaysia (MYS), Singapore (SGP), Thailand (THA), Canada (CAN) and the United States (US). MKT, SMB, HML, RMW and CMA are Fama and French five factors (Fama and French, 1993, 2012, 2015, 2017); WML is momentum factor (Jegadeesh and Titman, 1993; Carhart, 1997); MGMT is management factor and PERF is performance factor developed by Stambaugh and Yuan (2017); CARRY and DOLLAR factors are two currency risk factors developed by Lustig, Roussanov, and Verdelhan (2011). "EU", "AP" and "NA" represent "Europe", "Asia-Pacific" and "North America", respectively. "pEU", "pAP" and "pNA" represent "pure Europe", "pure Asia Pacific" and "pure North America", respectively. See Section 5.3 for detailed descriptions about these notations. "1" indicates that the factor is selected by the best model, and '0' otherwise. Log-marg is the estimated log-marginal likelihood and v_f is the degree of freedom. The estimation sample period is from October 1997 to October 2017 (241 observations).

	MKT_pEU	RMW_pEU	WML_pEU	MGMT_pEU	SMB_EU	CMA_EU	MKT	HML	RMW	WML	MGMT	PERF	CARRY	v_f	Log-marg
AUT	1	1	0	1	1	0	0	1	1	1	0	0	0	8.5	7838.41
	MKT_pEU	SMB_pEU	RMW_pEU	CMA_pEU	WML_pEU	MGMT_EU	MKT	SMB	HML	RMW	CMA	WML	CARRY		
CHE	0	1	1	0	0	1	1	0	1	0	0	1	1	8.5	9002.2
	SMB_pEU	RMW_pEU	WML_pEU	MGMT_pEU	MKT_EU	CMA_EU	SMB	HML	RMW	WML	MGMT	DOLLAR	CARRY		
DEU	1	0	1	1	1	0	0	1	1	0	1	0	0	12.5	8268.98
	MKT_pEU	SMB_pEU	RMW_pEU	CMA_pEU	WML_pEU	MGMT_pEU	MKT	SMB	RMW	CMA	WML	MGMT	CARRY		
DNK	1	0	1	1	0	0	0	1	1	1	1	0	0	6	9058.33
	SMB_pEU	RMW_pEU	CMA_pEU	MKT_EU	WML_EU	MGMT_EU	SMB	HML	RMW	CMA	PERF	DOLLAR	CARRY		
ESP	0	1	0	1	0	1	1	1	0	1	1	0	0	13.5	7724.57
	SMB_pEU	RMW_pEU	CMA_pEU	WML_pEU	MGMT_pEU	MKT_EU	SMB	RMW	CMA	WML	MGMT	DOLLAR	CARRY		
FIN	1	1	1	0	0	1	0	1	0	1	1	0	0	22.5	7239.76
	MKT_pEU	SMB_pEU	RMW_pEU	CMA_pEU	WML_pEU	MGMT_pEU	MKT	SMB	RMW	CMA	WML	MGMT	CARRY		
FRA	1	0	1	0	0	1	0	1	0	1	1	0	1	11.5	10199.1
	SMB_pEU	RMW_pEU	CMA_pEU	WML_pEU	MKT_EU	MGMT_EU	SMB	HML	RMW	CMA	WML	DOLLAR	CARRY		
GBR	0	1	0	0	1	1	1	1	0	1	1	0	0	14	8245.81
	MKT_pEU	SMB_pEU	RMW_pEU	CMA_pEU	WML_pEU	MGMTL_EU	MKT	SMB	HML	RMW	CMA	WML	CARRY		
GRC	0	0	1	1	0	0	1	1	0	0	1	1	1	13.5	6559.84
	SMB_pEU	RMW_pEU	CMA_pEU	WML_pEU	MKT_EU	MGMT_EU	SMB	HML	RMW	CMA	WML	DOLLAR	CARRY		

ITA	1	1	1	0	1	0	0	1	0	0	1	0	1	18	7761.94
	SMB_pEU	CMA_pEU	MGMT_pEU	MKT_EU	RMW_EU	WML_EU	SMB	HML	CMA	MGMT	PERF	DOLLAR	CARRY		
NLD	0	0	1	1	1	0	1	1	1	0	1	0	0	14	7486.16
	SMB_pEU	RMW_pEU	WML_pEU	MGMT_pEU	MKT_EU	CMA_EU	SMB	HML	RMW	WML	MGMT	DOLLAR	CARRY		
NOR	1	1	0	0	1	1	0	0	0	1	1	0	1	15	7351.41
	SMB_pEU	RMW_pEU	CMA_pEU	WML_pEU	MKT_EU	MGMT_EU	SMB	HML	RMW	CMA	WML	DOLLAR	CARRY		
SWE	0	1	0	0	1	1	1	0	0	1	1	0	1	12	7955.35
	SMB_pAP	HML_pAP	RMW_pAP	WML_pAP	CMA_AP	MKT	SMB	HML	RMW	WML	MGMT	DOLLAR	CARRY		
AUS	0	1	1	0	0	0	1	0	0	1	1	1	1	21.5	7473.21
	SMB_pAP	HML_pAP	RMW_pAP	CMA_pAP	WML_pAP	SMB	HML	RMW	CMA	WML	DOLLAR	CARRY			
HKG	0	1	1	0	0	1	1	0	1	1	0	1		18	6593.3
	SMB_pAP	HML_pAP	RMW_pAP	WML_pAP	CMA_AP	MKT	SMB	HML	RMW	WML	MGMT	DOLLAR	CARRY		
JPN	1	1	0	1	0	1	0	0	1	0	1	0	1	15	7680.65
	SMB_pAP	HML_pAP	RMW_pAP	CMA_pAP	WML_pAP	SMB	HML	RMW	CMA	WML	DOLLAR	CARRY			
KOR	1	1	1	0	0	0	0	1	1	1	0	1		10.5	6769.31
	SMB_pAP	RMW_pAP	WML_pAP	HML_AP	CMA_AP	MKT	SMB	RMW	WML	MGMT	DOLLAR	CARRY			
MYS	1	0	1	0	1	0	0	1	1	0	1	1		15.5	6936.28
	SMB_pAP	HML_pAP	RMW_pAP	WML_pAP	CMA_AP	SMB	HML	RMW	WML	MGMT	DOLLAR	CARRY			
SGP	1	1	1	0	0	0	0	1	1	1	0	1		12.5	7094.62
	SMB_pAP	HML_pAP	WML_pAP	RMW_AP	CMA_AP	SMB	HML	WML	MGMT	PERF	DOLLAR	CARRY			
THA	0	0	1	0	1	1	1	0	1	1	0	1		27.5	6466.2
	SMB_pNA	HML_pNA	RMW_pNA	WML_pNA	MGMT_NA	MKT	SMB	HML	RMW	CMA	WML	DOLLAR	CARRY		
CAN	1	0	0	1	1	0	0	1	1	0	0	1	1	12	7549.59
	SMB_pNA	HML_pNA	RMW_pNA	WML_pNA	MGMT_pNA	SMB	HML	RMW	WML	MGMT	DOLLAR	CARRY			
US	1	1	1	0	0	1	0	0	1	1	0	1		8	7382.91

Table A6
The Best-Augmented Student-t Distributed Factor Pricing Models Incorporating Local and Global Factors for International Stock Markets

Table A6 presents the best-augmented student-t distributed factor models, which incorporate local and global factors for 22 individual stock markets. The 22 stock markets include three regions: 13 markets in Europe, 7 in Asia-Pacific and two in North America, respectively. These markets are Austria (AUT), Switzerland (CHE), Germany (DEU), Denmark (DNK), Spain(ESP), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Italy (ITA), Norway (NOR), Netherland (NLD), Sweden(SWE), Australia(AUS), Hong Kong (HKG), Japan (JPN), Korea (KOR), Malaysia (MYS), Singapore (SGP), Thailand (THA), Canada (CAN) and the United States (US). MKT, SMB, HML, RMW and CMA are Fama and French five factors (Fama and French, 1993, 2012, 2015, 2017); WML is momentum factor (Jegadeesh and Titman, 1993; Carhart, 1997); MGMT is management factor and PERF is performance factor developed by Stambaugh and Yuan (2017); CARRY and DOLLAR factors are two currency risk factors developed by Lustig, Roussanov, and Verdelhan (2011). "G" represents "Global". "pG" represents "pure Global". See Section 5.3 for detailed descriptions about these notations. "1" indicates that the factor is selected by the best model, and '0' otherwise. Log-marg is the estimated log-marginal likelihood and v_f is the degree of freedom. The estimation sample period is from October 1997 to October 2017 (241 observations).

	HML_pG	RMW_pG	WML_pG	SMB_G	CMA_G	MKT	HML	RMW	WML	MGMT	PERF	DOLLAR	CARRY	vf	Log-marg
AUT	1	0	1	1	0	1	0	0	0	1	1	0	1	10	7511.1316
	SMB_pG	HML_pG	RMW_pG	CMA_pG	WML_pG	MKT	SMB	HML	RMW	CMA	WML	DOLLAR	CARRY		
CHE	1	1	0	0	1	1	0	0	1	1	0	0	1	12	7969.6082
	SMB_pG	HML_pG	RMW_pG	WML_pG	CMA_G	SMB	HML	RMW	WML	MGMT	DOLLAR	CARRY			
DEU	1	1	0	0	0	1	0	1	1	1	0	1		8.5	7654.0159
	SMB_pG	RMW_pG	CMA_pG	WML_pG	HML_G	MKT	SMB	RMW	CMA	WML	MGMT	DOLLAR	CARRY		
DNK	1	0	0	1	1	1	0	1	1	0	0	0	1	8.5	7672.377
	SMB_pG	HML_pG	RMW_pG	CMA_pG	WML_G	SMB	HML	RMW	CMA	PERF	DOLLAR	CARRY			
ESP	0	1	1	0	0	1	1	0	1	1	0	1		9	7339.0946
	SMB_pG	RMW_pG	CMA_pG	WML_pG	HML_G	SMB	RMW	CMA	WML	MGMT	DOLLAR	CARRY			
FIN	1	1	1	0	0	0	1	0	1	1	0	1		13.5	6890.6047
	SMB_pG	RMW_pG	CMA_pG	WML_pG	HML_G	MKT	SMB	RMW	CMA	WML	MGMT	DOLLAR	CARRY		
FRA	1	0	1	1	0	1	0	1	0	0	1	0	1	10	8439.8121
	SMB_pG	HML_pG	RMW_pG	CMA_pG	WML_pG	SMB	HML	RMW	CMA	WML	DOLLAR	CARRY			
GBR	1	0	1	1	1	0	1	0	1	0	0	1		8.5	8182.8365

	SMB_pG	HML_pG	RMW_pG	CMA_pG	WML_pG	MKT	SMB	HML	RMW	CMA	WML	DOLLAR	CARRY		
GRC	1	1	0	0	1	1	1	0	1	0	0	0	1	19.5	6529.3991
	SMB_pG	HML_pG	RMW_pG	CMA_pG	WML_pG	SMB	HML	RMW	CMA	WML	DOLLAR	CARRY			
ITA	1	1	0	0	1	1	0	1	1	0	0	1		13.5	7240.9152
	SMB_pG	HML_pG	CMA_pG	RMW_G	WML_G	SMB	HML	CMA	MGMT	PERF	DOLLAR	CARRY			
NLD	1	0	1	0	1	1	1	1	0	0	0	1		8.5	7097.2846
	SMB_pG	HML_pG	RMW_pG	WML_pG	CMA_G	SMB	HML	RMW	WML	MGMT	DOLLAR	CARRY			
NOR	0	0	1	1	1	1	1	0	0	1	0	1		9.5	6941.1566
	SMB_pG	HML_pG	RMW_pG	CMA_pG	WML_pG	SMB	HML	RMW	CMA	WML	DOLLAR	CARRY			
SWE	1	0	0	1	1	1	1	1	0	0	0	1		7	7637.7977
	SMB_pG	HML_pG	RMW_pG	WML_pG	CMA_G	MKT	SMB	HML	RMW	WML	MGMT	DOLLAR	CARRY		
AUS	0	0	1	0	1	1	1	1	1	1	0	0	0	13.5	7901.0613
	SMB_pG	HML_pG	RMW_pG	CMA_pG	WML_pG	SMB	HML	RMW	CMA	WML	DOLLAR	CARRY			
HKG	0	0	1	1	0	1	1	0	1	1	0	1		16	6679.35
	SMB_pG	HML_pG	RMW_pG	WML_pG	CMA_G	MKT	SMB	HML	RMW	WML	MGMT	DOLLAR	CARRY		
JPN	1	0	0	1	1	1	0	1	0	0	1	0	1	12	7942.4117
	SMB_pG	HML_pG	RMW_pG	CMA_pG	WML_pG	SMB	HML	RMW	CMA	WML	DOLLAR	CARRY			
KOR	1	0	0	1	1	0	1	1	0	1	0	1		7.5	7083.5624
	SMB_pG	RMW_pG	WML_pG	HML_G	CMA_G	MKT	SMB	RMW	WML	MGMT	DOLLAR	CARRY			
MYS	1	0	1	0	1	0	0	1	0	1	1	1		10.5	7193.8578
	SMB_pG	HML_pG	RMW_pG	WML_pG	CMA_G	SMB	HML	RMW	WML	MGMT	DOLLAR	CARRY			
SGP	1	1	1	0	0	1	1	0	1	0	0	1		9	7382.1713
	SMB_pG	HML_pG	WML_pG	RMW_G	CMA_G	SMB	HML	WML	MGMT	PERF	DOLLAR	CARRY			
THA	1	1	1	0	0	1	0	0	1	1	0	1		16.5	6658.3453
	SMB_pG	HML_pG	RMW_pG	CMA_pG	WML_pG	MKT	SMB	HML	RMW	CMA	WML	DOLLAR	CARRY		
CAN	1	0	0	1	1	1	0	1	1	0	0	0	1	12	8042.4303
	SMB_pG	HML_pG	RMW_pG	WML_pG	CMA_G	SMB	HML	RMW	WML	MGMT	DOLLAR	CARRY			
US	1	0	0	1	1	0	1	1	0	0	1	1		14	7919.8331