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Local, Regional, or Global Asset Pricing?

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*

Abstract

Analyzing several developed and emerging international markets, I test the ability of global, regional, and local models to explain a large set of 134 cross-sectional anomalies. My main finding is that both global and regional factor models create substantially larger average absolute alphas than local factor models. Annual (absolute) anomaly portfolio alphas are on average 1.7 and 1.1 percentage points higher, respectively, with global and regional than with local factor models. Even for the most recent period, there is no evidence of a catch-up of global and regional factor models. There is substantial potential for international diversification of anomaly strategies.

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I Introduction

There is still a debate in the literature as to whether global, regional, or local factor models are more useful in international cross-sectional asset pricing. The theoretical literature focuses mainly on global asset pricing models (e.g., Solnik (1974), Grauer, Litzenberger and Stehle (1976), Sercu (1980), and Stulz (1981)). The empirical findings of, for example, Fama and French (1998), Brooks and Del Negro (2005), and Hau (2011) also underline the importance of cross-country components of asset pricing factor models. On the other hand, the results of, among others, Griffin (2002) and Hou, Karolyi and Kho (2011) support local rather than global pricing.

With this paper, I step into this debate. The main contribution of my paper is a detailed analysis of whether global, regional, or local factor models best characterize the cross-section of international stock returns. I use a very comprehensive dataset, which covers the 48 MSCI Developed and Emerging Markets. For each country, I obtain up to 134 cross-sectional anomalies. This large set of anomaly portfolios corresponds to what investors in the different countries might reasonably invest in. Finally, I also examine a wide array of cross-sectional factor models. I create global, regional, and local versions for each of the factor models and analyze which class of models best explains the anomaly portfolio returns.

The key questions underlying my analysis are: Are there systematic differences between the alphas for global, regional, and local factor models? Hence, do alphas depend on the systematic risks an investor is exposed to? Are anomaly alphas different for globally and regionally diversified investors than for local investors? How much alpha would portfolio managers claim if they used the different classes of models? Answers to these questions are important for portfolio managers, investors, and academics alike. For an adequate evaluation, it is essential for investors to isolate the alpha of any strategy. Thus, it is important to document the sensitivity of the alpha measures to the factors used. Each investor may need to choose the type of factor model that is appropriate for her.

I address these questions by using time-series tests for all anomaly-quintile portfolios. From these tests, I obtain the average absolute alphas. My first main finding is that global factor models strongly underperform their local counterparts in explaining anomaly returns. On average, a portfolio manager that uses global benchmarks would claim an alpha that is 1.7 percentage points higher per annum than what she could claim when using local factor models. Conversely, a globally diversified investor can earn substantially higher abnormal returns than local investors can. Global factor models yield higher absolute alphas than their local counterparts for *all* the models examined. The differences in (absolute) performance between global and local factor models are larger on average for Emerging Markets (2.5 percentage points on average), but also exceed 1.0 percentage points on average for Developed Markets. More importantly, local factor models outperform global factor models in all except for one of the individual country cross-sections.

While also rejecting global asset pricing models, an important strand of the literature follows the approach of Fama and French (2012, 2017) and analyzes international asset prices at the regional level. An implicit assumption underlying this procedure is that financial markets are regionally integrated in that regional factor models can price local assets in the different countries.[1] Therefore, I also examine the performance of regional models for explaining the anomaly portfolio returns. I find that these fare little better than their global peers. Using regional models, the average absolute alphas of the anomaly portfolios are 1.1 percentage points higher per year than when using local models. Thus, my results also reject regional asset pricing.

Next, I perform factor spanning regressions. With this approach I can test whether global and regional factor models can explain the local factors. My results also reject the spanning hypothesis for both global and regional models: local factors generate sizable alphas when regressed on regional and global factor models.

These results indicate that anomaly investors likely benefit from international diversification of their strategies. Indeed, I find that the average international correlations on the anomaly-category level are moderate at most, indicating large potential for diversification. Importantly, global and regional factor models account only for part (typically not more than half) of the average anomaly-strategy correlations across countries. Thus, global and regional factors miss a substantial fraction of the international comovement in anomaly-strategy returns.

In a further step, I examine the time-trends in global, regional, and local factor alphas. In recent years product markets have become more globalized and capital markets have arguably become increasingly open. One might expect that these developments would lead to a decrease in the alpha differences. Using 100-month rolling windows to determine the factor alphas, however, I detect no evidence of a catch-up of the global and regional to

[1]Put differently, investment opportunities, i.e., alphas of different strategies, are similar for local and regionally diversified investors.

the local models.

Finally, I examine the relation of average absolute anomaly alpha differences of global and local models with capital controls and political risk variables. Traditionally, one would associate these variables with the integration of a local financial market into world markets (Karolyi and Stulz (2003), Cooper, Sercu and Vanpée (2013)). I find that there is some relation between capital controls, political risk, and the size of the local capital markets with the alpha differences of global, regional, and local models. However, this relation appears to be restricted to the least open, most risky, and smallest capital market countries. There is little difference between the medium and highly open countries, etc. Thus, direct and indirect barriers to capital investing do not serve to explain the differential performance of global, regional, and local factor models.

However, these results do not necessarily imply that financial markets are not globally or regionally integrated. Previous studies show that investors have preferred habitats (e.g., French and Poterba (1991)). On an international level, such preferred habitats in local stock markets can create comovement limited to these markets (Barberis, Shleifer and Wurgler (2005)). This purely local comovement naturally cannot be captured by broader, global or regional, factor models.

This paper adds to several strands of the literature. First, I address the debate whether global, regional, or local models best describe the cross-section of stock returns. In more detail, Fama and French (1998) detect a large international component in countries' value returns and advocate the use of a global factor model. Brooks and Del Negro (2005) show that in the Heston and Rouwenhorst (1995) model region factors capture a large part of the information contained in country factors. Hau (2011) uses a natural experiment based on a major MSCI benchmark index recomposition and shows that stocks are priced globally rather than locally. On the other hand, using a sample that includes the U.S. and 3 big global economies, Griffin (2002) shows that the country-specific Fama and French (1993) factors generally outperform their global counterparts. Hou et al. (2011) compare local and global empirical asset pricing models that include size, value, and momentum factors, and find that, for a set of 7 examined anomalies, local models typically provide lower pricing errors than global models.

Based on the results of Brooks and Del Negro (2005), one might advocate regional instead of global factor models when pricing local assets. Fama and French (2012, 2017) examine the cross-section of stock returns of different regions. Subsequent studies often use the same region definition to conduct their tests. Among these is Karolyi and Wu (2018), who show that global impacts in the form of externality factors are important for a region's asset prices. I contribute to the debate outlined in the first paragraph (including these more subtle points) with a comprehensive analysis of global, regional, and local asset pricing models for a wide range of anomaly variables and factor models. Using a broad set of anomaly portfolio strategies that investors might invest in, I am able to thoroughly analyze the basic question underlying this debate. I find that local factor models yield substantially lower pricing errors on average.

This study also adds to the literature on time-trends in asset pricing. Petzev, Schrimpf and Wagner (2016) compare the performance of local and global versions of the capital asset pricing model (CAPM) as well as the Fama and French (1993) and Carhart (1997) models over time for explaining size, book-to-market, and momentum portfolios and a sample that consists mainly of Developed Markets. The authors find that the explanatory power (in terms of R^2) of global factor models has increased strongly in recent years. However, they do not observe such a catch-up in pricing errors. Drawing from my large set of countries, test assets, and factor models, I can shed further light on the latter issue. I show that there is a catch-up in average absolute alphas neither in Developed nor in Emerging Markets. Additionally, even when using the best among the regional and global models at each point in time, the observation is still the same: local models price the anomaly portfolios significantly better than their global and regional counterparts throughout my sample period.

The remainder of this paper is organized as follows. Section II introduces the data and presents summary statistics. I examine the ability of factor models to explain various anomalies in Section III. In Section IV, I present the results of spanning regressions. I analyze the anomaly correlations in Section V, time-trends in the relative model performance in Section VI, and the relation of the alpha differences with traditional measures of financial market integration in Section VII. I use Section VIII to draw conclusions.

II Data and Summary Statistics

A Data

My primary dataset includes stock returns of all MSCI Developed and Emerging Markets. In total, my dataset comprises the cross-sections of 48 different countries. Equity price and market capitalization data are from Datastream. Accounting data are from

Worldscope.[2] I include stocks traded at the countries' respective major exchanges, which are defined as the exchanges on which the majority of stocks are traded (Lee (2011)).[3] The data span the period from January 1990 to December 2017, including a total of 7,457 trading days.[4,5]

In this study, I calculate all returns in U.S. dollars. Thus, I take the perspective of an investor that is unhedged in exchange rates.[6] Before calculating returns, I convert the total return indices from Datastream into U.S. dollars using the corresponding exchange rates. For the risk-free rate, I use data on the 1-month U.S. Treasury Bill yield from Kenneth French's website.

Following Lesmond (2005) and Lee (2011), I include all listed and delisted companies provided in the Datastream database and exclude Depository Receipts (DRs), Real Estate Investment Trusts (REITs), and preferred stocks. In doing so, I apply the filters described in Appendix B, Tables B.1 and B.2, of Griffin, Kelly and Nardari (2010). I include only major securities and primary quotes. As in Hou et al. (2011) and Lee (2011), I exclude anomalous observations. More specifically, if the current or past return, r_t or r_{t-1}, are higher than 100% and $(1 + r_t)(1 + r_{t-1}) - 1 < 20\%$ both r_t and r_{t-1} are set missing. Furthermore, following Griffin et al. (2010), I set any daily return greater than 200% as

[2]Worldscope makes use of standard data definitions for financial accounting items, attempting to minimize differences in treatment and accounting terminology. See the "Thomson Reuters Worldscope Fundamentals" document for further details.

[3]Most countries have a single major exchange while there are two for Canada (Toronto and TSX), China (Shenzen and Shanghai), Germany (Frankfurt and Xetra), India (BSE Ltd. and National India), Japan (Osaka and Tokyo), South Korea (Korea and KOSDAQ), and the United Arab Emirates (Abu Dhabi and Dubai Financial Market) and three for the U.S. (AMEX, NYSE, and NASDAQ).

[4]As in Fama and French (2012, 2017), I choose 1990 as a starting date. This is mainly motivated by the fact that Worldscope added many firms to the database during the late 1980s, but did not backfill the historical data for these firms (Hou et al. (2011)).

[5]In order to be able to start directly in January 1990, I use data prior to January 1990 to create factors and variables if these data are available (and necessary).

[6]Reporting all portfolio returns in U.S. dollars ensures their comparability across countries.

missing. To further limit the effect of outlier observations, I winsorize daily return observations at the 1% and 99% levels each day. Moreover, I require a minimum number of return observations per trading day. If more than 90% of the stocks have zero returns (in local currency) on a day, the day is declared as non-trading day and is dropped from the analysis (see, e.g., Amihud (2002), Lesmond (2005), Lee (2011)). I handle delistings following Ince and Porter (2006) by setting all observations from the end of the sample period to the first non-zero domestic return as missing.

I use the following region definitions, which are based primarily on those of Fama and French (2012), augmented with MSCI Emerging Markets economies: i) Asia Pacific (Australia, China, Hong Kong, India, Indonesia, Malaysia, New Zealand, Philippines, Singapore, South Africa, South Korea, Taiwan, and Thailand), ii) Europe (Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Netherlands, Norway, Poland, Portugal, Russia, Spain, Sweden, Switzerland, and the U.K.), iii) Japan, iv) the Middle East (Egypt, Pakistan, Qatar, Saudi Arabia, Turkey, and the United Arab Emirates), v) North America (Canada, Mexico, and the U.S.), and vi) South America (Brazil, Chile, Colombia, and Peru).[7]

B Summary Statistics

Table 1 presents the summary statistics for each country and the different regions. In total, I have data on 58,348 stocks. For the regions Asia Pacific, Europe, Japan, and North America, the cross-sections are large, with well over 2,000 stocks on average. For the

[7]In cases where the allocation is non-straightforward, I base it on the trade statistics provided by the World Bank.

Middle East and South America, the cross-sections are smaller. Reflecting this reduced size, as indicated in the rightmost column of the table, the factor time-series for these two regions do not start before December 1997.[8] Naturally, for the individual countries, the cross-sections are substantially smaller. However, for the vast majority of countries, I have data on more than 100 stocks, which should enable the creation of sufficiently diversified portfolios. For most Developed and part of the Emerging Markets, the factor time-series start in the early 1990s. On the other hand, the cross-section of Qatar is too small throughout the sample period.

The annual value-weighted market returns for individual countries range between −3.7% for Peru and 21.6% for Russia. For most countries, these are between 7% and 13%. For the regions, it ranges between 3% and 14% per annum. Among the regions, the market return is lowest for Japan, which suffered from weak economic performance during most of my sample period. In contrast, I observe the highest average market return of 11% per annum for North America.

C Factor Models

For the main analysis, I consider the following factor models: i) the CAPM, ii) the Fama and French (1993) 3-factor model (FF-3), iii) the Carhart (1997) 4-factor model (C-4), iv) the Fama and French (2015) 5-factor model (FF-5), v) the Hou, Xue and Zhang (2015) 4-factor model (HXZ-4), vi) the Hou, Mo, Xue and Zhang (2020) 5-factor model (HMXZ-5), and vii) the Stambaugh and Yuan (2017) 4-factor model (SY-4). Detailed

[8] I only include a region or country in the analysis if data on all factors of the main factor models are available. To generate the factors, I require at least 30 stocks with valid observations for all sorting variables (Titman, Wei and Xie (2013)).

descriptions of the factor models are in Section OA1 of the Supplementary Material.

III Explaining Anomalies

The first pillar of my analysis of global, regional, and local factor models is a test for whether, and to what degree, these can explain the returns of anomaly portfolios. The main questions I want to answer in this section are: Are there systematic differences between the alphas for global, regional, and local factor models? How much alpha would portfolio managers additionally claim if they used different classes of models?

A Methodology

I use a set of 134 anomaly variables. The anomaly selection and definition are based mainly on Hou et al. (2015) and Green, Hand and Zhang (2017). I have to perform minor adjustments to some of the anomalies for the international data set. In addition, I add a few (recent) anomalies not contained in those lists. The anomalies belong to six different categories: i) momentum, ii) value versus growth, iii) investment, iv) profitability, v) intangibles, and vi) trading frictions. For most anomaly variables, I build 5 value-weighted portfolios based on breakpoints derived from big stocks (those in the top 90% of cumulative market capitalization). This study design, with value-weighted portfolios and breakpoints from big stocks, mitigates the impact of micro-cap stocks, which are difficult to trade in practice. Detailed definitions of the anomaly variables, as well as further details on the procedure, are in Section OA2 of the Supplementary Material.

For each portfolio, I regress the time-series of monthly portfolio excess returns on that of the different global, regional, and local factor models

$$r_{j,t} - r_{f,t} = \alpha_j + \beta_j' f_t^{glob/reg/loc} + \epsilon_{j,t}, \tag{1}$$

for each anomaly portfolio j. $r_{j,t}$ denotes the return during month t of the anomaly portfolio and $r_{f,t}$ is the risk-free rate over the corresponding period. α_j is the intercept (alpha), β_j is a $k \times 1$ vector of factor sensitivities, and $f_t^{glob/reg/loc}$ is a $k \times 1$ vector which contains the returns of all k factors of a global, regional, or local factor model at time t. $\epsilon_{j,t}$ is the regression residual. To run the regression in equation (1), I require a minimum of 100 time-series observations. The main tests are based on the average absolute alphas of the different portfolios for the different models.

B Aggregate Results

Figure 1 visualizes the main results (the corresponding numbers and significance tests can be found in Table 2). Reported are the (equally weighted) aggregated absolute alphas. The aggregation scheme proceeds as follows: first alphas are averaged across all portfolios of an anomaly, then over the up to 134 anomalies within a country, and finally across countries. On average, I have data on 122 anomalies per country. The average absolute annualized return per anomaly portfolio and country amounts to 8.87%. Global factor models can explain about half of this return on average. For example, for the CAPM the average absolute annualized alpha amounts to 4.73%. Other models perform better than the CAPM, though. The best-performing global model is the C-4 model, which leaves an average absolute alpha of 4.25% per annum.

Regional models perform somewhat better. The average absolute annualized alphas are up to 1 percentage point lower than for the global factor models. The regional CAPM and C-4 models yield average absolute alphas of 4.30% and 4.01% per annum, respectively. These results are consistent with Fama and French (2012), who find that global factor models do not perform well for explaining regional portfolios sorted on size, book-to-market, and momentum.

However, Fama and French (2012) stop at the regional level and do not examine local factor models. I find that for all factor models the local versions of the models perform clearly best. For the CAPM and C-4 models, the local average absolute annualized alphas amount to 3.12% and 2.76%, respectively.

Thus, for globally and regionally diversified investors, anomaly portfolio alphas are substantially larger than for purely local investors. Portfolio managers that use global or regional rather than local factor models would claim alphas of substantially larger magnitudes. For the Carhart (1997) C-4 model, which is commonly used in portfolio evaluation, the differences between absolute local and global or regional factor model alphas amount to 1.49 and 1.25 percentage points, respectively, per annum *on average*.[9] For other factor models, in many instances the differences are even larger. For all models, the differences in alphas between local and global as well as regional factor models are highly statistically significant.

One possibility is that the aggregate results are driven by Emerging Markets, whose market integration might be lagging behind that of Developed Markets. To account for this

[9]Since the focus is on absolute alphas, the alphas of the global and regional model could both be larger (mainly if the alpha of the portfolio is positive) or smaller (primarily for negative alphas). Since it is at the discretion of the investor whether to go long or short in a portfolio, the magnitude of the alphas is of primary importance.

possibility, I split the sample into a part that only includes Developed Markets and one that only includes Emerging Markets. The main results hold for both Developed and Emerging Markets. The differences in alphas are somewhat smaller for Developed than for Emerging Markets on average, but still in the range of approximately 1.0 percentage points per annum. For Emerging Markets, the differences between the average absolute annualized alphas of global and local models are close to 2 percentage points. For all models, the differences in average absolute alphas between local and global or regional factor models are statistically significant.

C Disaggregated Results

In a next step, I examine the performance of global, regional, and local factor models separately for each country. The relative performance of global, regional, and local factor models could be strongly heterogeneous. It is, for example, possible that European countries that have largely implemented the open market provisions of the European Union are more strongly financially integrated among each other and in global markets than more isolated countries in other regions are. Increased financial integration could be associated with a better relative performance of global and regional factor models.

I present the results in Figures 2 and 3, while Table A1 of the Supplementary Material presents more detailed numbers and significance tests on a regional level.[10] Reported are the (equally weighted) aggregated absolute alphas. The aggregation scheme

[10]For Figures 2 and 3 the average global, regional, and local factor alphas are averaged across all the main factor models. As an alternative, Figures A1 and A2 of the Supplementary Material present the results when picking the respective best among the global, regional, and local factor models. Although the differences between the classes of factor models are somewhat less strongly pronounced, the main patterns in these figures are similar to those presented here.

proceeds as follows: first alphas are averaged across all portfolios of an anomaly and then over all 134 anomalies within a country, and finally over the main factor models. Indeed, I find that there are differences across countries. However, the common theme is that local factor models explain anomaly portfolio returns better than global and regional factor models.

Comparing the ability of global and local models to explain the anomaly portfolio returns, in Figure 2, I find that in all countries except for Ireland the average alphas toward the global factor models are higher than those toward the local factor models. The differences are also economically large for many important Developed Markets, e.g., 1.5 percentage points for Hong Kong, 0.6 percentage points for Germany, 0.5 percentage points for the U.K., 1.6 percentage points for Japan, and 2.2 percentage points for the U.S. Among Developed Markets it is visible that the difference in performance between global and local factor models is relatively smaller for countries perceived as particularly open, such as France, Germany, the Netherlands, Switzerland, and the U.K. On the other hand, the substantial difference in performance between the global and local factor models for the U.S. might be surprising at first glance since, by most measures, the U.S. should be well integrated into global financial markets.

Consistent with my previous results, the lower part of Figure 2 shows that the differences in performance between the global and local factor models are substantially larger in Emerging Markets. For example, for China the difference in average annualized absolute alphas amounts to 0.9 percentage points and for South Korea to 2.5 percentage points; but the differences can also be as huge as 10.6 percentage points for Pakistan and Turkey.

For all countries, except for Ireland, Spain, and Israel, the differences between the average absolute alphas of global and local factor models are statistically significant toward the 1% level (results untabulated). For Spain, these differences are statistically significant toward the 5% level.

Figure 3 further presents the average differences between regional and local factor alphas for the anomalies. These results are similar to those for the comparison of global and local factor models. The average absolute alphas toward regional factor models are significantly higher than those for local factor models for all countries except for Ireland, Germany, and Spain. The magnitudes of the differences are reduced for some countries, most notably the U.S., but are also material for most countries. Thus, the alphas reported by portfolio managers for their international holdings are strongly sensitive to the type of factor models used for performance evaluation. Investors should choose, based whether they are globally, regionally, or only locally diversified, the suitable class of factor models when evaluating potential investments and the performance of money managers.

Table 3, as well as Tables A2 and A3 of the Supplementary Material, presents results that are even further disaggregated. That is, these tables show the results for the different anomaly categories within the individual countries. For example, for the C-4 model (presented in Table 3), one can see that there are very few country–category combinations for which the global or regional models yield lower average absolute alphas than the local models. On the other hand, there are various country–category combinations for which the average absolute local alphas are substantially smaller than their global or regional counterparts, with the differences partly far exceeding the average differences.

D Robustness

While including a large set of factor models, the main part of my analysis still covers only a subset of the models available. It might be that for others the global or regional versions perform better than their local counterparts. In this section, I thus additionally examine (viii) the Carhart (1997) model augmented by Pástor and Stambaugh (2003) liquidity (C-5), (ix) the Daniel, Hirshleifer and Sun (2020) 3-factor model (DHS-3), (x) the Barillas and Shanken (2018) 6-factor model (BS-6), (xi) the Fama and French (2018) 5-factor model with a cash profitability factor (FF-5^{cash}), (xii) the Fama and French (2018) 6-factor model (FF-6), (xiii) the Hou et al. (2011) 3-factor model (HKK-3), and (xiv) the Zhang (2006) 4-factor model (Z-4). Models (viii) to (xii) have been studied mainly for the U.S., while Zhang (2006) and Hou et al. (2011) explicitly design their model for international asset markets. I present the results in Figure A3 and Table A4 of the Supplementary Material. For all factor models, these are qualitatively similar to those of the main models.

Furthermore, Fama and French (2017) caution that sorts based on accounting variables could be affected by regional differences in accounting standards. While the global standard data definitions of Worldscope should mitigate most of these differences, I also examine the robustness of my results to forming global portfolios based on regional breakpoints. That is, when obtaining global factors, I allocate the stocks based on the accounting variable breakpoints derived separately for each region. I present the results in Figure A4 and Table A5 of the Supplementary Material. I find that using regional breakpoints does not materially improve the performance of the global factor models.

Finally, I check whether adding foreign components to local factor models further boosts their performance. This analysis is similar in spirit (although different in the empirical details) to the partial segmentation approach of Karolyi and Wu (2018), as well as earlier tests in Griffin and Stulz (2001) and Hou et al. (2011). I start with the local factor models and expand the model using the equivalent foreign global and foreign regional factors (global and regional factors that exclude a certain country). If foreign components matter for local asset prices, I expect the average absolute alphas to be substantially smaller for the local plus foreign model specifications than for the purely local model.

I present the results in Table A6 of the Supplementary Material. I find that the improvements when adding foreign factor components are very modest. In some cases, the average absolute alphas of the anomaly portfolios are even higher with than without the foreign components. These results contrast with Hou et al. (2011) and Karolyi and Wu (2018). Hou et al. (2011) find that "foreign components (...) are as important as local components for pricing" (p. 2530). However, this conclusion is mainly based on the number of rejections of a Gibbons, Ross and Shanken (1989) GRS test statistic for different anomalies. Since the results of such GRS tests can be highly misleading (Fama and French (1996)), in this paper I focus on the average absolute alphas. In Hou et al. (2011) adding foreign factor components also does not serve to materially reduce these.

Karolyi and Wu (2018) find that models with so-called "externality factors" outperform purely local and global factor models. These externality factors capture foreign components based on local stocks traded in open global markets. The authors find that the models with such foreign components generally yield lower average absolute alphas on a regional level than the purely regional versions of the factor models. Based on a substantially larger set of anomalies, I find that simple foreign factors are of little value beyond the local factor models.

IV Factor Spanning

In a next step, in this section, I analyze to what extent global and regional factor models are able to span the factors in the corresponding regional and local models.

A Methodology

For each factor of a factor model, I regress its time-series on that of the factor model at a broader level. That is, I regress each factor of a local model on those of the corresponding global as well as (for a separate analysis) the corresponding regional models and each factor of a regional model on those of the corresponding global model. For example, when comparing global and local factor models I run the regression

$$f_{j,t}^{loc} = \alpha_j + \beta_j' f_t^{glob} + \epsilon_{j,t} \tag{2}$$

for each factor, where $f_{j,t}^{loc}$ is one of the k factors of a local model. All other variables are as previously defined. Again, I require a minimum of 100 time-series observations.

For each factor model, I save the average absolute factor return, the average absolute alpha, and the average adjusted R^2 of the regressions. In addition, I test the hypothesis that the alphas of all factors with respect to the broader factor model are jointly zero. For this purpose, I use the GRS test, which is described in Section OA3 of the

Supplementary Material.

B Main Results

I present the main factor spanning results in Table 4. If the spanning hypothesis is rejected at the 10% significance level for part of the countries of one category, the GRS test statistic is printed in *italic* font and if the hypothesis is rejected for all countries of one category, the GRS test statistic is printed in **bold** font. As can be seen in the table, there is barely any subcategory of factor model spanning and region combinations for which the GRS test is not printed either in *italic* or **bold** font. Thus, global and regional factor models generally cannot explain the average returns of local factors. In the following, I will discuss this result in more detail.

The first question I examine is whether global factor models can span regional factor models. The previous section shows that the absolute alphas of regional models for a broad set of anomalies are smaller on average than those of global models. I thus expect that the global factors are generally unable to fully span regional factors.

The results for the comparison between global and regional factor models are in the first panel of Table 4. Starting with the CAPM, I find that the global market excess return has substantial explanatory power for market excess returns of different regions. R^2s are highest for Europe and North America with 82% and 79%, respectively, and comparably lowest for Japan and the Middle East with 49% and 32%, respectively. For Asia Pacific, Europe, and the Middle East the global market excess return is able to span the regional market excess returns, while the GRS test detects a statistically significant alpha for Japan and North America. One would thus be ill advised to use a global CAPM for these markets.

For the other factor models, the picture is similar. While global factor models are able to explain a substantial part of the time-series variation of regional factors on average, at least part of the factors yield substantial alphas. The GRS test rejects the hypothesis that all alphas of regional factors with respect to global factors are jointly zero for at least 2 of the 6 regions for each model. The GRS test rejects the hypothesis that the global FF-5 model can span its regional counterparts even for 4 out of 6 regions.

The second panel of Table 4 presents the results of factor spanning regressions of local models by their global counterparts. For this analysis, I split the regions into Developed Markets ("DEV") as well as a subset of Emerging Markets ("EM"). Naturally, given the modest performance for explaining regional models, the global models are also largely unable to explain the factor returns of the local models. The average absolute alphas of the local factors are only rarely substantially smaller than the average absolute local factor returns. In some cases, the average absolute alphas even exceed the average absolute returns. Thus, for the majority of countries, global factor models appear to be unable to fully explain local stock returns. The performance of the global factor models seems to be overall somewhat better in Developed Markets than in Emerging Markets. The finding that global factors do not span those in Emerging Markets is consistent with and updates the early evidence on this issue in Harvey (1995) and Rouwenhorst (1999).

The studies of Fama and French (2012, 2017), among others, combine individual countries into regions and perform all asset pricing tests on a regional level. An implicit assumption of this research design is that financial markets are regionally financially integrated. A very important final question, thus, relates to whether regional factors are able to span local factors.

In the final panel of Table 4, I therefore present the results of the tests whether regional factor models can span their local counterparts. The R^2s of the regional factor models are generally somewhat higher than those of the global factor models. Thus, risk factors seem to comove more strongly on the regional level than they do on the global level. The absolute alphas of the local factors are also somewhat smaller on average for the regional factor models than for the global factor models. However, in particular for Emerging Markets, these are partially still sizable. Overall, regional factor models also generally fail to span local factor models.

C Robustness

In Table A7 of the Supplementary Material, I present the results for the further factor models. These are very similar to those of my main models.

Furthermore, I present the results for regional breakpoints in global factors in Table A8 of the Supplementary Material. The R^2s for most regions are similar to those of the global factors without regional breakpoints. Interestingly, for Europe, and most strongly pronounced for North America, these are generally higher when using regional breakpoints. However, the average absolute alphas are often even higher when using the global factors with regional breakpoints. Overall, also with regional breakpoints, the global factors fail in spanning regional and local factors.

V Can Factor Models Explain Anomaly Correlations?

The previous sections show that local factor models outperform their global and regional counterparts in explaining anomaly portfolio returns and that the local factor models cannot be spanned by regional and global factor models. Thus, anomaly investments in different countries across the globe seem to be not only exposed to the same global factors, but in part to potentially diversifiable local factor components.

In this section, I thus examine to what extent anomaly investments are correlated across different markets. In a second step, I check whether the global, regional, and local factor models are able to explain the correlations between the different categories of anomalies across countries. For this analysis, I aggregate all anomalies of a certain category (momentum, value, investment, profitability, accruals, and trading) within a country. To gain maximum exposure to an anomaly category, I focus on the long–short returns, while defining the long and short sides for each single anomaly based on which of the two extreme portfolios yields higher returns for the full sample in the U.S. I weight the long–short returns for each individual anomaly equally when aggregating to a category. Thus, for each category in each country I have one time-series.

Table 5 reports the average pairwise correlations of the anomaly categories across countries. For all countries, the average correlation in momentum strategy returns amounts to 19.7%, indicating that there is only moderate momentum comovement across countries.[11] These results suggest that for investors there is substantial diversification potential when following cross-country momentum strategies. For the value and trading categories, the

[11] For comparison, the average pairwise correlation of the countries' market excess returns amounts to 41.2% in my sample.

average pairwise correlations are also moderate, with 10.5% and 22.8%, respectively. The correlations among the investment, profitability, and accruals categories across countries are at an even much smaller scale, with 5.58%, 1.85%, and 3.95%, respectively, on average. Thus, for all categories there emerge sizable diversification benefits.

When focusing on Developed Markets of certain regions only, presented in Table A9 of the Supplementary Material, the average pairwise correlations are somewhat higher, especially in Europe and North America. Nevertheless, the highest correlation in North America (with only Canada and the U.S.) amounts to only 54.1%. The highest correlation among European Developed Markets is 43.9%. Both numbers indicate that there is still potential for diversification.

On the other hand, it is important to examine the prevailing correlations in more detail. These could be due to commonalities in fundamentals and/or investor bases: comovement, e.g., in momentum strategies, across markets may be due to systematic similarities of momentum stocks across markets. In addition, the cause could be global capital investing, where money managers simultaneously invest and divest in momentum strategies across a wide variety of countries.

An important question thus relates to whether the global and regional factor models can account for the correlations. If there are fundamental common movements in these stocks, the global factor models should be able to explain them. To analyze this, I subtract the full-sample systematic return components from the local anomaly-category return time-series. That is, for each anomaly long–short return, I estimate equation (1) and subtract the part $\hat{\beta}_j' f_t^{glob/reg/loc}$ from the portfolio excess return.

Afterwards, I examine the average pairwise correlations of these remaining unsystematic return components across countries. When considering all countries, I find that for the momentum category global factors can explain only little of the average correlations. After removing the systematic components, on average the correlation decreases from 19.7% to 15.2%.[12] Thus, about three quarters of the correlation cannot be explained by the factor models. For the value category, about two thirds of the correlation cannot be explained. For the investment, accruals, and trading categories, the global factor models can explain roughly half of the average pairwise correlations across countries.

The regional models and, naturally, the local models fare little better than the global models in explaining the average correlations.[13] When focusing on subsets of the countries, like for example the Developed Markets of a certain region (in Table A9 of the Supplementary Material), the share of the correlations that can be explained by global factor models is even smaller in many cases. Thus, there appears to be substantial international comovement in the strategy returns that is not accounted for by global factor models. Similarly, there is large systematic comovement in anomaly returns across countries within a region, which is not accounted for by the regional factors.

Finally, in Figure 4, I present the results for 20 (subjectively selected) of the most important anomaly variables, while making sure that each anomaly category is represented with at least 2 anomalies. I find that there is a large heterogeneity in the average anomaly long–short correlations of these variables.[14] For $\text{MOM}_{0,6}^{6}$, $\text{MOM}_{0,1}^{12}$, and DISTRESS, the average correlations are highest. On the other hand, for EXPGRWTH, ACCQ, and

[12]For comparison, the average pairwise correlation of the countries' market excess returns shrinks from 41.2% to 8.34% after subtracting the systematic parts that can be explained by the global market excess return.

[13]The local models are not designed to capture global comovement in a strategy. They can only account for the part of the global comovement that also shows up in the local factors.

[14]The definitions of the anomaly variables can be found in Section OA2 of the Supplementary Material.

OPLEV the anomaly correlations are rather low. The common theme, though, is that the global and regional factor models largely cannot explain the correlations. The systematic factor-related components can explain at most 50% of the average correlations for most of the anomalies.

VI Time-Trends in the Model Performance

In the period after World War II, there were substantial barriers to cross-country capital flows. Over time, these barriers have been substantially reduced by a wave of liberalization of financial markets across the globe. Reflecting these changes, as Karolyi and Stulz (2003) note, the home bias of U.S. investors was substantially reduced between the years 1985 and 1994. While my sample period starts *after* most of these changes have taken place, it is possible that during the most recent period, financial market integration has increased further. Connected to this, Petzev et al. (2016) argue that global financial markets may have recently become more integrated. It is therefore conceivable that my results are driven by lack of financial integration for the first part of my sample period and things are different in more recent times.

To test for time-trends in the model performance, I use 100-month rolling window estimates of equation (1). In Figure 5, I present the results. Reported are the (equally weighted) aggregated absolute alphas. The aggregation scheme proceeds as follows: first alphas are averaged across all portfolios of an anomaly, then over all 134 anomalies within a country, then over the main factor models, and finally over the countries indicated in the figure headings.[15]

Throughout the entire sample period, the average absolute global and regional alphas of the anomaly portfolios are substantially higher than those for the local factor models. The average difference between annualized absolute global and local alphas is often 2 percentage points or more. The difference between the average global or regional and local absolute alphas is statistically significant throughout the sample period (untabulated). The regional models explain average anomaly portfolio returns significantly better than the global models 70% of the time.

I find that the average absolute alpha levels increase in the first part of the sample, as more and more smaller countries enter. Furthermore, I observe a pronounced increase in average global and regional factor alphas around the outset of the 2007 financial crisis. Thus, it seems that the crisis has made asset prices more local. Interestingly, there is another upward spike in the difference between average global and local absolute alphas toward the end of my sample period. The results are similar for Developed and Emerging Markets. Thus, one might wonder what these results imply for the question of how integrated global financial markets are.

VII Alpha Differences and Financial Market Integration

The previous sections show that local factor models outperform regional and global factor models when it comes to explaining anomaly portfolio returns. However, I also find

[15]In Figure A5 of the Supplementary Material, I repeat the analysis using only the best models. That is, at each point in time I pick the respective global, regional, and local model with the lowest average absolute alpha. The results are qualitatively similar.

that there is substantial heterogeneity across countries regarding the relative performance of global, regional, and local models. Thus, in this section, I examine to what extent differences across countries can be traced back to traditional measures of financial market integration, such as the market openness, political risk, and the size of the local stock markets. I measure market openness with the Chinn and Ito (2006) index of financial openness. Higher values imply less capital controls and, hence, more market openness. In addition, I examine a political risk rating (ICRG; higher index implies lower risk) and the size of the stock market relative to GDP (MC to GDP). More detailed definitions of these variables can be found in Section OA4 of the Supplementary Material. As can be seen from Table 10 of the Supplementary Material, these country characteristics are moderately, but far from perfectly, correlated.

I sort the countries into terziles based on each of these measures and examine the average global, regional, and local absolute anomaly portfolio alphas. In Figure 6, I present the results. I find that there is some relation between capital controls and the relative performance of global, regional, and local factor models. For the countries with the least capital controls, I observe the largest differences between average absolute global and local alphas. However, the effect is mostly restricted to the smallest terzile. There is little difference between terziles 2 and 3.

I observe a similar pattern for the political risk and relative stock market size variables. The alpha differences are generally largest for the countries in the low-openness and high-risk terziles, but there seems to be little difference between the countries in terziles 2 and 3.

Thus, there seems to be no strong relation between traditional concepts of the free movement of capital and the relative performance of global and local factor models on average. If it is not capital controls and barriers to investing, how can we reconcile this with the results on the relative performance of global and local models?

It is possible that investor behavior rather than capital controls drives a wedge between the performance of global, regional, and local factor models. There are several mechanisms that could create comovement in asset returns that is mainly local. These mechanisms mainly create preferred habitats in certain markets for part of the investors (Barberis et al. (2005)), while typically their preferred habitat is their home country. These preferred habitats could result from capital controls and limits to foreign investments. However, there are various further possibilities. First, local investors may believe that they have information advantages in local stocks. Second, the community effects theory of DeMarzo, Kaniel and Kremer (2004) states that investors' main objective is their relative wealth compared to their peers, hence they choose similar assets. Third, institutional investors may be evaluated relative to local benchmarks, which makes them tilt their holdings toward local assets (Basak and Pavlova (2013)). Whenever a sufficiently large investor base has a common preferred habitat, then systematic changes in these investors' preferences (e.g., risk aversion, sentiment) or liquidity demand induce common comovement in local stock returns. This comovement naturally cannot be explained by global or regional factors.

Indeed, French and Poterba (1991), Baltzer, Stolper and Walter (2013), and Bartram, Griffin, Lim and Ng (2015), among others, show that such investment habitats exist and are important drivers of the degree of international stock return comovement. Thus, my findings do not necessarily imply that financial markets are globally disintegrated. Local return comovement, caused by the trading behavior of local investors and different views of global investors on local markets are probably the principal cause of the strong importance of local factors.

VIII Conclusion

In this paper, I examine the performance of various global, regional, and local asset pricing models. Using a set of 134 anomaly variables I find that local models can price local assets best. Absolute anomaly portfolio alphas are on average 1.7 and 1.1 percentage points higher for globally and regionally diversified investors, respectively, than for purely local investors. I find that local factor models yield lower average absolute alphas for all but one of the countries in my sample. Factor spanning tests also reveal that the local factors generally create significant alphas when regressed on regional and global factor models.

The average international correlations among the anomaly strategies are moderate. Indeed, global and regional factors account for only part of these correlations. For investors, it thus appears useful to widely spread their holdings and simultaneously invest in anomaly strategies in various markets. This generates substantial diversification benefits.

Finally, I find that traditional concepts of financial market integration like, e.g., capital controls or political risk, cannot account for the full scale of alpha differences between global and local factor models. Investors should thus be careful to choose, based on to what extent they are globally or regionally diversified, which type of factor models to use to evaluate investments and asset managers. If one wants to control for all sources of systematic return variation, it is important to benchmark with local factors. On the whole, alphas seem to be not only investment- but also investor-specific.

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Figure 1: Factor Alpha Summary

Figure 1 plots the average absolute annualized alphas (in percentage points) of all anomaly quintile portfolios for different factor models. For each anomaly portfolio, equation (1) is estimated for each of the global, regional, and local factor models (see Section OA1 of the Supplementary Material for the definition of the factor model acronyms). Reported are the (equally weighted) aggregated absolute alphas. The aggregation scheme proceeds as follows: first absolute alphas are averaged across all portfolios of an anomaly, then over all 134 anomalies within a country, and finally across countries. The dark blue bar denotes alphas toward the global version of the factor models. The orange and light blue bars present the alphas toward the regional and local factor models, respectively. The average absolute returns for the different graphs are 8.87% (All Countries), 8.06% (Developed Markets), and 9.81% (Emerging Markets).

Figure 1 (continued)

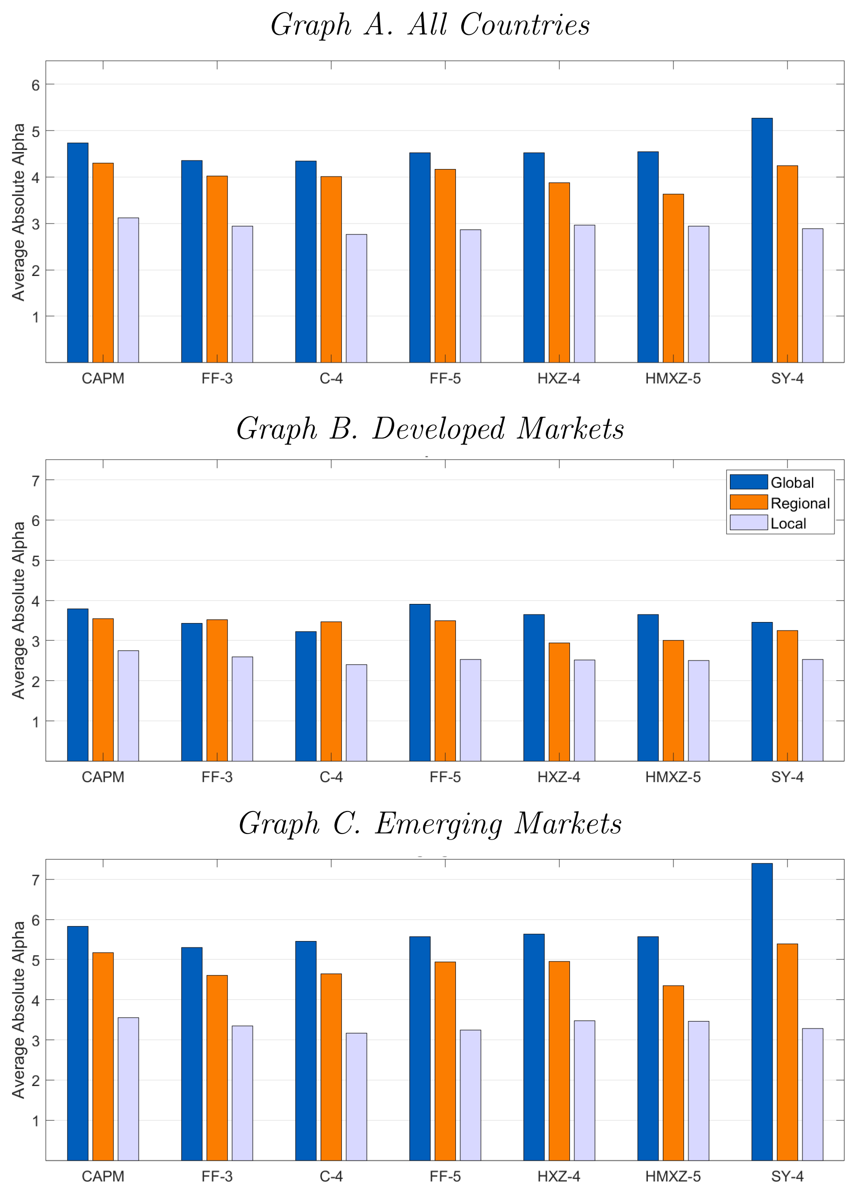
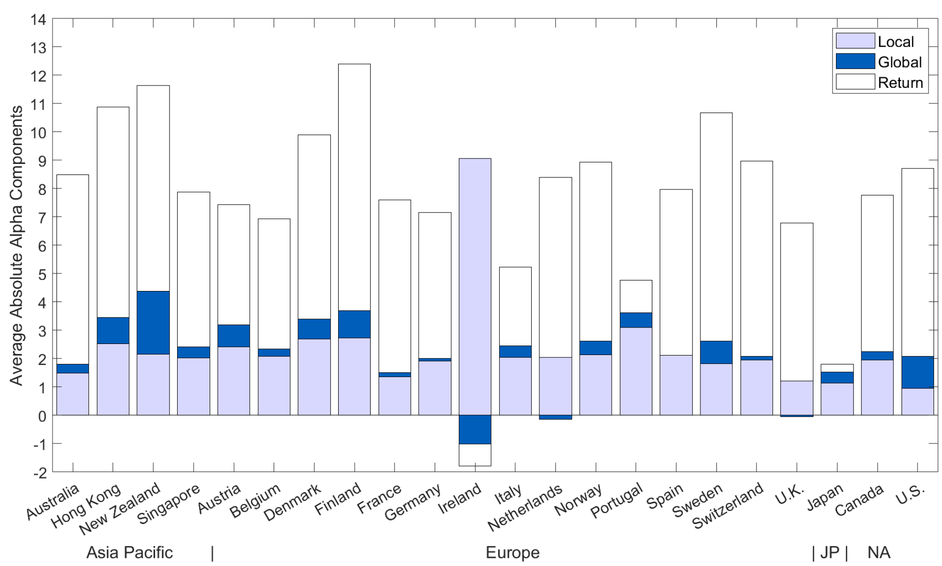


Figure 2: Factor Alpha Summary: Global Versus Local

Figure 2 plots the average absolute annualized returns and alphas (in percentage points) of all anomaly quintile portfolios for each country. For each anomaly portfolio, equation (1) is estimated for each of the global and local factor models. Reported are the (equally weighted) aggregated absolute alphas. The aggregation scheme proceeds as follows: first absolute alphas are averaged across all portfolios of an anomaly and then over all 134 anomalies within a country, and finally over the main factor models. The light blue bar presents the average absolute alpha of the local versions of the factor models. The dark blue bar indicates the additional average absolute alpha when using global factor models. The average absolute return is the sum of the light blue, dark blue, and white bars. If the dark blue (white) bar is in the negative area, it means that the global absolute alphas (absolute returns) are on average lower than the local absolute alphas (global absolute alphas).

Graph A. Developed Markets



Graph B. Emerging Markets

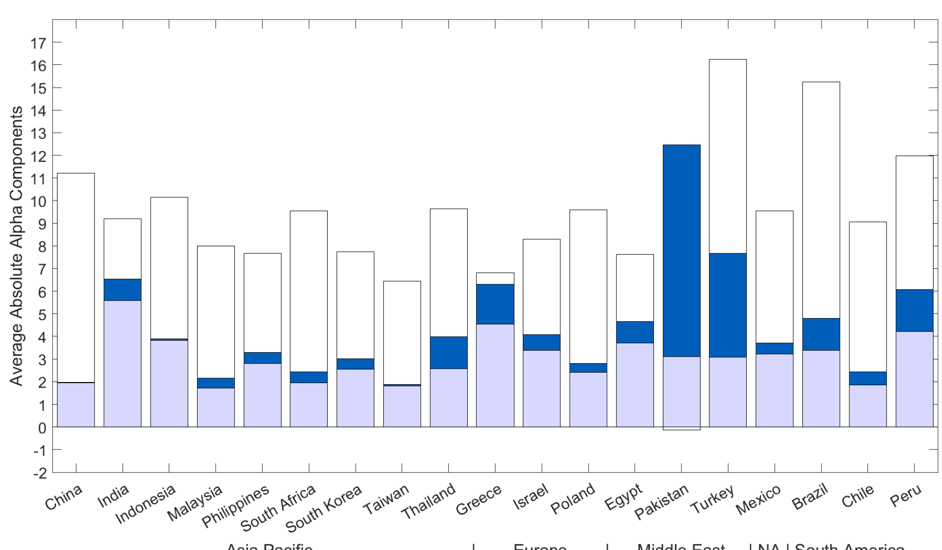
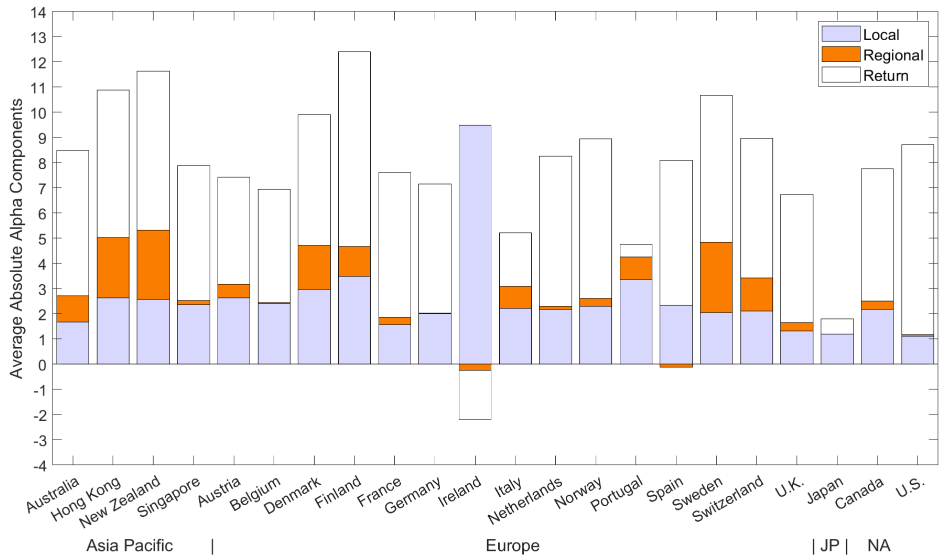


Figure 3: Factor Alpha Summary: Regional Versus Local

Figure 3 plots the average absolute annualized returns and alphas (in percentage points) of all anomaly quintile portfolios for each country. For each anomaly portfolio, equation (1) is estimated for each of the regional and local factor models. Reported are the (equally weighted) aggregated absolute alphas. The aggregation scheme proceeds as follows: first absolute alphas are averaged across all portfolios of an anomaly and then over all 134 anomalies within a country, and finally over the main factor models. The light blue bar presents the average absolute alpha of the local versions of the factor models. The orange bar indicates the additional average absolute alpha when using regional factor models. The average absolute return is the sum of the light blue, orange, and white bars. If the orange (white) bar is in the negative area, it means that the regional absolute alphas (absolute returns) are on average lower than the local absolute alphas (global absolute alphas).

Graph A. Developed Markets



Graph B. Emerging Markets

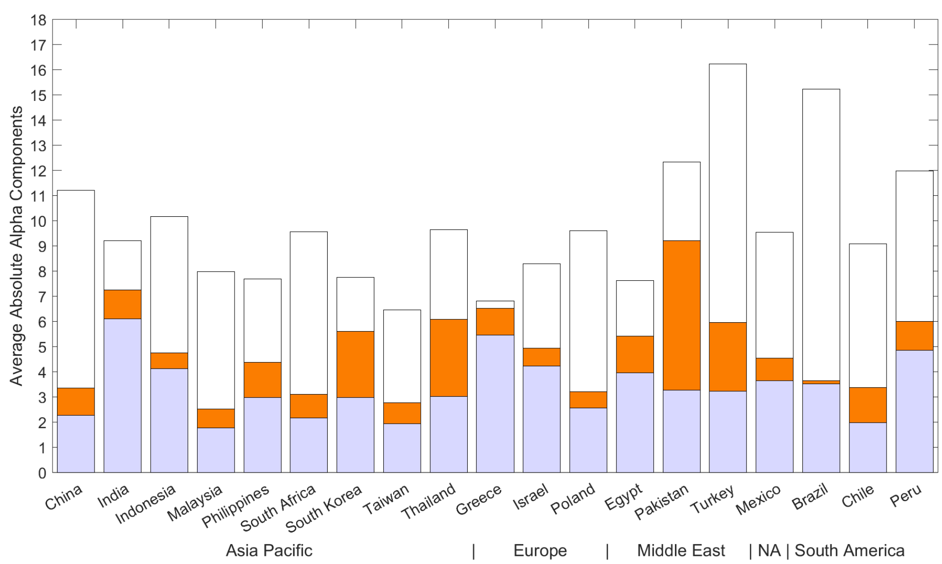
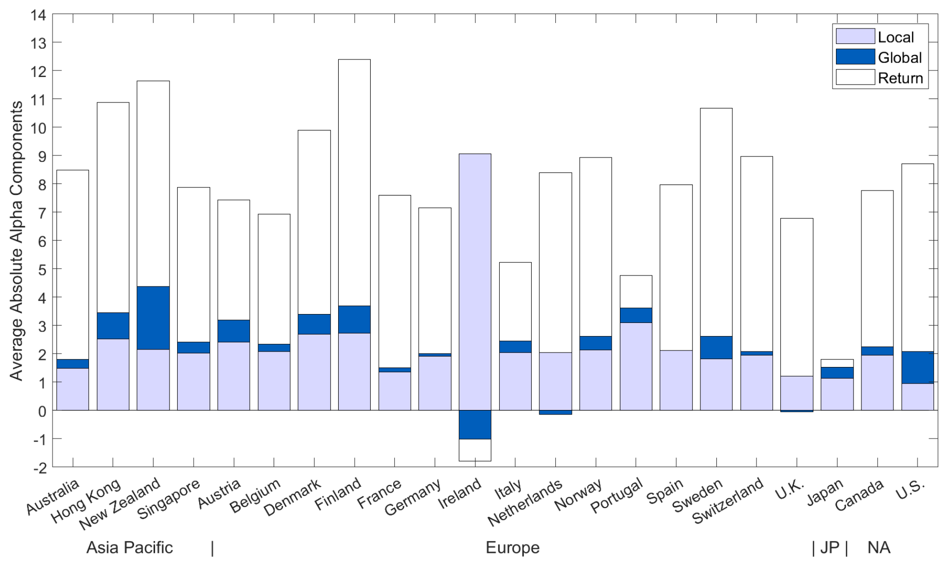


Figure 4: Anomaly Correlations

Figure 4 plots the average correlations of selected anomaly strategies across countries before and after removing global and regional systematic return components. I present the average of all bivariate correlations of the anomaly return time-series in the different countries as well as the average of all bivariate correlations of these time-series after removing the expected return components implied by the global and regional factor models. For removing the expected return components, for each anomaly long–short return, I estimate equation (1) and subtract the part $\hat{\beta}_j' f_t^{glob/reg}$ from the portfolio excess return. The white bar indicates the average bivariate anomaly correlation. The dark blue and orange bars indicate the average correlations that result after removing the global and regional systematic return components, respectively. The correlations are aggregated equally across the main factor models. Definitions of the anomaly acronyms can be found in Section OA2 of the Supplementary Material.

Graph A. Removing Global Factor Components



Graph B. Removing Regional Factor Components

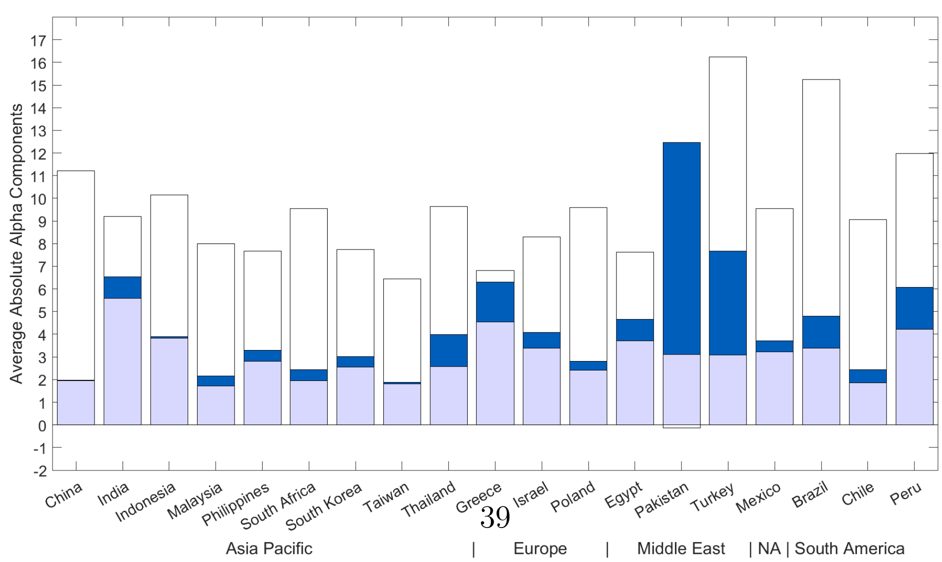
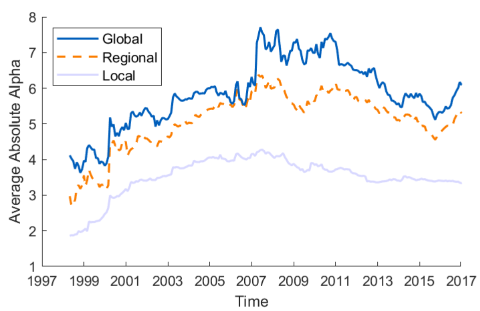


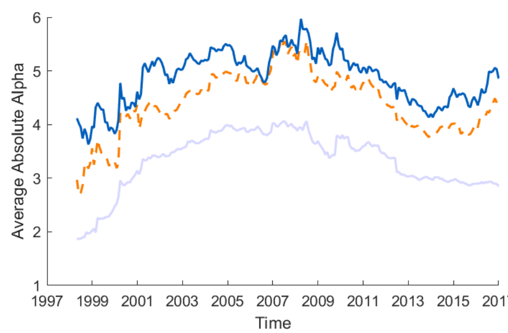
Figure 5: Global, Regional, and Local Alpha Trends

Figure 5 plots 100-month rolling average absolute annualized alphas (in percentage points) for global, regional, and local factor models. For each anomaly portfolio, equation (1) is estimated for each of the global, regional, and local factor models using the past 100 months. Reported are the (equally weighted) aggregated absolute alphas. The aggregation scheme proceeds as follows: first absolute alphas are averaged across all portfolios of an anomaly, then over all 134 anomalies within a country, then over the main factor models, and finally over the countries indicated in the figure headings. The dark blue line represents the global, the dashed orange line the regional, and the light blue line the local factor models. For the figure, the results are allocated to the end dates of the 100-month windows.

Graph A. All Countries



Graph B. Developed Markets



Graph C. Emerging Markets

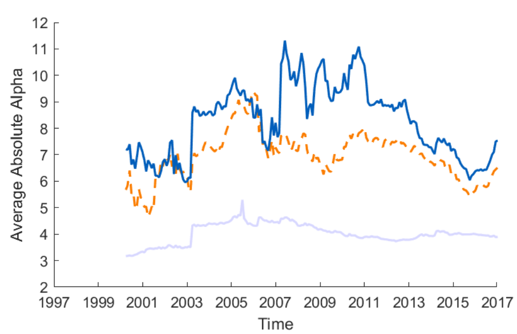
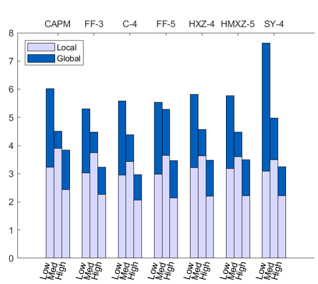


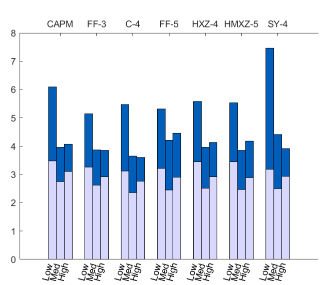
Figure 6: Global and Regional Versus Local Alphas and Country Characteristics

Figure 6 plots average absolute annualized alphas (in percentage points) for global and local factor models for countries with different characteristics. For each anomaly portfolio, equation (1) is estimated for each of the global, regional, and local factor models (see Section OA1 of the Supplementary Material for the definition of the factor model acronyms). Reported are the (equally weighted) aggregated absolute alphas. The aggregation scheme proceeds as follows: first absolute alphas are averaged across all portfolios of an anomaly, then over all 134 anomalies within a country, then across countries. In this final step, the countries are sorted into terziles based on their market openness (Chinn–Ito index), their political risk rating (ICRG; higher index implies lower risk), or their average total ratio of stock market capitalization to GDP (see Section OA4 of the Supplementary Material for the definition of the country characteristics). The light blue bar presents the average absolute alpha of the local versions of the factor models. The dark blue and orange bars indicate the additional average absolute alpha when using global and regional factor models, respectively.

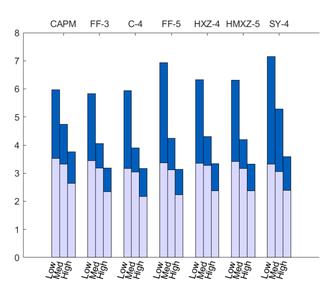
Graph 6A. Market Openness



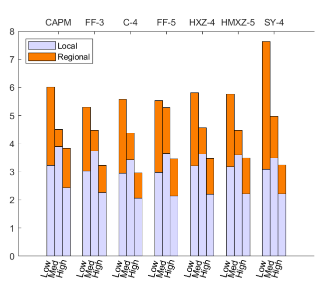
Graph 6B. ICRG



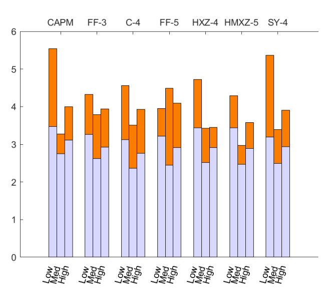
Graph 6C. MC to GDP



Graph 6D. Market Openness



Graph 6E. ICRG



Graph 6F. MC to GDP

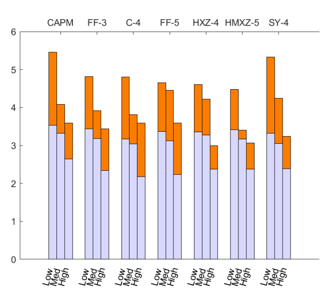


Table 1: Summary Statistics

Table 1 presents summary statistics for the regions and countries. $\#^{firms}$ is the total number of firms in the sample. Avg. $\#^{firms}$, Min $\#^{firms}$, and Max $\#^{firms}$ denote the average, minimum, and maximum number of firms available per month, respectively. Avg. Ret is the time-series average of the annualized value-weighted average U.S. dollar market return (in percentage points). SD, Skew, and Kurt denote the time-series average cross-sectional standard deviation, skewness, and kurtosis, respectively. Avg. MC is the time-series average of the cross-sectional mean market capitalization of the firms (in millions of U.S. dollars). First Obs indicates the year and month in which the data for the respective country starts, while First Obs^{Fac} presents the first date for which data on all the main factor models are available.

	$\#^{firms}$	Avg. $\#^{firms}$	Min $\#^{firms}$	Max $\#^{firms}$	Avg. Ret	SD	Skew	Kurt	Avg. MC	First Obs	First Obs^{Fac}
World	58,348	24,065	13,351	29,886	7.90	60.2	2.08	19.0	1,227	Jan. 1990	Jan. 1990
Asia Pacific	19,127	8,211	2,126	13,435	7.50	61.9	1.97	17.0	547	Jan. 1990	Jan. 1990
Australia	3,209	1,203	519	1,706	11.2	67.9	1.82	14.7	479	Jan. 1990	Dec. 1991
China	3,340	1,237	6	3,247	18.3	38.9	1.38	12.7	981	Feb. 1991	Dec. 2000
Hong Kong	1,783	751	183	1,556	14.1	57.8	1.79	15.7	954	Jan. 1990	Dec. 1991
India	2,307	968	3	1,450	6.69	71.9	1.79	12.4	13	Jan. 1990	Dec. 1998
Indonesia	594	286	64	467	8.66	56.3	1.79	15.5	437	May. 1990	Dec. 1997
Malaysia	982	589	182	776	10.5	41.8	1.85	19.9	332	Jan. 1990	Dec. 1991
New Zealand	298	107	73	131	12.5	48.7	1.04	13.6	263	Jan. 1990	Dec. 2000
Philippines	248	152	39	193	7.57	55.7	1.95	15.5	383	Jan. 1990	Dec. 1997
Singapore	743	362	104	552	9.62	43.4	1.47	14.5	534	Jan. 1990	Dec. 1991
South Africa	885	341	80	512	11.2	55.8	1.78	16.9	889	Jan. 1990	Dec. 1991
South Korea	2,837	1,268	580	1,877	8.49	58.1	1.48	14.8	366	Jan. 1990	Dec. 1994
Taiwan	1,073	592	159	894	6.64	39.0	1.38	13.1	736	Jan. 1990	Dec. 1997
Thailand	828	407	165	608	9.86	46.9	1.71	15.2	325	Jan. 1990	Dec. 1997

to be continued on the next page

Table 1: Summary Statistics (continued)

	$\#^{firms}$	Avg. $\#^{firms}$	Min $\#^{firms}$	Max $\#^{firms}$	Avg. Ret	SD	Skew	Kurt	Avg. MC	First Obs	First Obs^{Fac}
Europe	14,673	5,591	3,575	6,827	9.15	51.6	1.81	21.0	1,384	Jan. 1990	Jan. 1990
Austria	168	74	38	103	8.28	38.7	0.43	11.2	835	Jan. 1990	Dec. 1995
Belgium	235	117	68	155	8.94	35.8	1.06	14.5	1,431	Jan. 1990	Dec. 1993
Czech Republic	250	68	9	236	12.8	43.5	0.97	8.16	1,232	Jul. 1993	Jul. 2003
Denmark	353	174	122	216	12.0	37.9	1.06	15.5	888	Jan. 1990	Dec. 1994
Finland	221	106	31	139	12.9	37.4	0.89	10.1	1,171	Jan. 1990	Dec. 1995
France	1,658	711	305	928	9.58	48.1	1.94	21.9	1,648	Jan. 1990	Jan. 1990
Germany	1,371	592	294	895	8.65	50.7	1.60	18.2	1,701	Jan. 1990	Dec. 1990
Greece	379	210	65	308	6.86	54.3	1.45	12.0	272	Jan. 1990	Dec. 1996
Hungary	94	34	2	49	12.4	52.9	0.58	7.81	340	Feb. 1991	Jul. 2010
Ireland	80	39	27	52	7.75	48.2	0.59	7.30	1,623	Jan. 1990	Jul. 2001
Israel	680	376	114	490	4.74	50.9	1.09	15.3	227	Jan. 1990	Dec. 2004
Italy	536	221	123	294	7.09	34.5	1.25	14.0	1,941	Jan. 1990	Dec. 1992
Netherlands	238	122	82	183	10.4	36.7	0.56	12.3	3,671	Jan. 1990	Dec. 1992
Norway	573	165	91	224	11.6	48.9	0.99	10.7	774	Jan. 1990	Dec. 1993
Poland	1,037	308	3	787	14.7	56.0	1.20	10.4	220	May. 1991	Jul. 2002
Portugal	138	68	40	110	5.56	48.8	0.98	13.1	514	Jan. 1990	Jul. 1996
Russia	323	125	2	253	21.6	58.5	1.34	12.7	2,560	Oct. 1995	Dec. 2009
Spain	322	141	90	173	9.91	34.2	1.06	14.4	3,217	Jan. 1990	Dec. 1993
Sweden	1,113	300	128	547	12.2	53.3	1.18	12.6	904	Jan. 1990	Dec. 1992
Switzerland	378	208	179	236	11.3	32.4	0.70	16.3	3,832	Jan. 1990	Dec. 1990
U.K.	4,526	1,482	1,246	1,826	8.97	52.4	1.51	17.8	1,481	Jan. 1990	Jan. 1990
Japan	3,624	2,398	1,703	2,738	3.17	37.0	1.96	23.7	1,450	Jan. 1990	Jan. 1990
Middle East	1,325	664	4	1,048	12.9	53.5	1.95	16.3	533	Jan. 1990	Dec. 1997
Egypt	176	98	3	141	6.41	45.8	1.36	11.6	348	Nov. 1994	Dec. 2008
Pakistan	351	217	4	276	14.5	50.6	1.79	15.4	117	Jan. 1990	Dec. 1998
Qatar	44	35	14	41	13.3	29.0	0.77	5.45	2,771	Jan. 2004	–
Saudi Arabia	174	93	1	169	13.8	33.7	0.97	8.24	3,800	Dec. 1999	Dec. 2011
Turkey	475	287	145	379	16.8	53.3	1.87	14.2	434	Jan. 1994	Dec. 1998
United Arab Emirates	105	85	31	98	12.6	40.1	1.31	10.9	1,551	Jan. 2004	Dec. 2011
North America	18,623	6,772	5,814	7,581	11.1	67.4	2.02	16.8	1,995	Jan. 1990	Jan. 1990
Canada	6,932	2,529	1,873	2,905	10.0	87.4	1.84	11.8	307	Jan. 1990	Jan. 1990
Mexico	170	60	39	82	12.8	38.7	0.91	10.3	865	Jan. 1990	Dec. 2000
U.S.	11,521	4,183	3,716	4,868	11.2	50.2	1.74	19.9	3,080	Jan. 1990	Jan. 1990
South America	976	430	121	520	8.45	48.6	2.29	26.0	1,026	Jan. 1990	Dec. 1997
Brazil	333	125	15	219	16.4	52.2	1.52	15.6	1,983	Jul. 1994	Dec. 2001
Chile	278	170	121	196	13.3	36.6	1.52	20.1	731	Jan. 1990	Dec. 1997
Colombia	115	52	23	70	11.6	35.8	0.74	12.2	1,277	Feb. 1992	Dec. 2011
Peru	250	111	20	133	−3.67	52.2	1.44	17.8	587	Feb. 1991	Dec. 2005

Table 2: Explaining Anomalies

Table 2 compares the performance of several global, regional, and local factor models in explaining portfolio returns sorted by different anomaly variables. The first panel presents average results across all countries. In addition, I present panels that consider Developed and Emerging Markets separately. For each anomaly portfolio in each country, equation (1) is estimated for each of the global, regional, and local factor models (see Section OA1 of the Supplementary Material for the definition of the factor model acronyms). Avg($|\alpha|$) is the average absolute annualized alpha (in percentage points), first averaged across all portfolios of an anomaly, then over all anomalies in a country, and finally across countries. Avg(α^{L-S}) is the average absolute annualized alpha (in percentage points) of the long–short portfolios, first averaged over all anomalies in a country and then across countries. $\Delta|\alpha|$ and $\Delta\alpha^{L-S}$ present the differences in average alphas for different factor model specifications (global, regional, local). To test whether these differences are statistically significant, I use double-clustered (by country and anomaly) standard errors of Cameron, Gelbach and Miller (2011) applied to all anomaly–country observations. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Global		Regional		Local		Glob vs. Reg		Glob vs. Loc		Reg vs. Loc	
	Avg($\|\alpha\|$)	Avg(α^{L-S})	Avg($\|\alpha\|$)	Avg(α^{L-S})	Avg($\|\alpha\|$)	Avg(α^{L-S})	$\Delta\|\alpha\|$	$\Delta\alpha^{L-S}$	$\Delta\|\alpha\|$	$\Delta\alpha^{L-S}$	$\Delta\|\alpha\|$	$\Delta\alpha^{L-S}$
All Countries												
#	122	120	122	120	122	120						
RET	8.87	5.00	8.87	5.00	8.87	5.00	0.00	0.00	0.00	0.00	0.00	0.00
CAPM	4.73	5.41	4.30	5.40	3.12	5.48	0.43***	0.01	1.61***	−0.07	1.18***	−0.08
FF-3	4.30	5.53	4.02	5.61	2.94	5.26	0.28	−0.08	1.35***	0.27***	1.08***	0.34***
C-4	4.25	5.15	4.01	5.07	2.76	4.56	0.24	0.08	1.49***	0.59***	1.25***	0.51***
FF-5	4.68	5.59	4.17	5.36	2.87	4.77	0.51	0.23**	1.81***	0.81***	1.30***	0.58***
HXZ-4	4.57	5.33	3.88	5.02	2.97	4.91	0.70***	0.31***	1.61***	0.42***	0.91***	0.10
HMXZ-5	4.53	5.32	3.63	4.96	2.95	4.82	0.91***	0.35***	1.59***	0.49***	0.68***	0.14
SY-4	5.28	5.15	4.24	5.12	2.88	4.52	1.04***	0.03	2.40***	0.63***	1.36***	0.60***
Developed Markets												
#	122	120	122	120	122	120						
RET	8.06	4.28	8.06	4.28	8.06	4.28	0.00	0.00	0.00	0.00	0.00	0.00
CAPM	3.78	4.89	3.54	4.88	2.75	4.96	0.24	0.01	1.03***	−0.07	0.79***	−0.08
FF-3	3.43	4.97	3.51	5.02	2.60	4.72	−0.08	−0.05	0.83***	0.24***	0.91***	0.29***
C-4	3.22	4.42	3.46	4.27	2.40	3.90	−0.25	0.15	0.81***	0.52***	1.06***	0.37***
FF-5	3.90	4.96	3.50	4.71	2.53	4.18	0.41	0.25***	1.37***	0.79***	0.96***	0.53***
HXZ-4	3.65	4.57	2.95	4.22	2.52	4.28	0.71***	0.35***	1.13***	0.29**	0.42***	−0.06
HMXZ-5	3.64	4.53	3.00	4.17	2.50	4.19	0.64**	0.36***	1.14***	0.34**	0.50***	−0.02
SY-4	3.46	4.33	3.25	4.22	2.53	3.87	0.21	0.10	0.92***	0.46***	0.71***	0.36**
Emerging Markets												
#	122	120	122	120	122	120						
RET	9.81	5.83	9.81	5.83	9.81	5.83	0.00	0.00	0.00	0.00	0.00	0.00
CAPM	5.83	6.01	5.17	6.00	3.55	6.08	0.66**	0.02	2.28***	−0.07	1.62***	−0.09
FF-3	5.30	6.18	4.61	6.29	3.34	5.88	0.69	−0.11	1.95***	0.29	1.26***	0.40*
C-4	5.45	6.00	4.65	6.01	3.17	5.33	0.80	−0.00	2.28***	0.67***	1.48***	0.67***
FF-5	5.57	6.31	4.95	6.11	3.25	5.47	0.62	0.20	2.32***	0.84***	1.70***	0.64**
HXZ-4	5.64	6.21	4.96	5.95	3.48	5.65	0.68	0.27	2.16***	0.56***	1.48***	0.29
HMXZ-5	5.57	6.23	4.36	5.89	3.46	5.56	1.21***	0.35*	2.11***	0.67***	0.90**	0.33
SY-4	7.40	6.11	5.39	6.16	3.29	5.28	2.01**	−0.04	4.11***	0.83***	2.10***	0.87***

Table 3: Anomaly Heatmap: C-4 Model

Table 3 presents a heatmap to summarize information about the average absolute alphas of global, regional, and local versions of the Carhart (1997) C-4 factor model for different anomaly categories. At the end of each month and for each anomaly variable, I form value-weighted quintile portfolios based on breakpoints derived from big stocks. I test whether the different global, regional, and local factor models can explain the anomaly long returns. The colors visualize the magnitude of the difference between the average annualized absolute alphas toward global and regional versus those toward local models ($|\bar{\alpha}|^{glob/reg} - |\bar{\alpha}|^{loc}$; global/regional minus local) within the different anomaly categories.

Legend: <–1% <0% <1% <2% <3% <4% <5% .

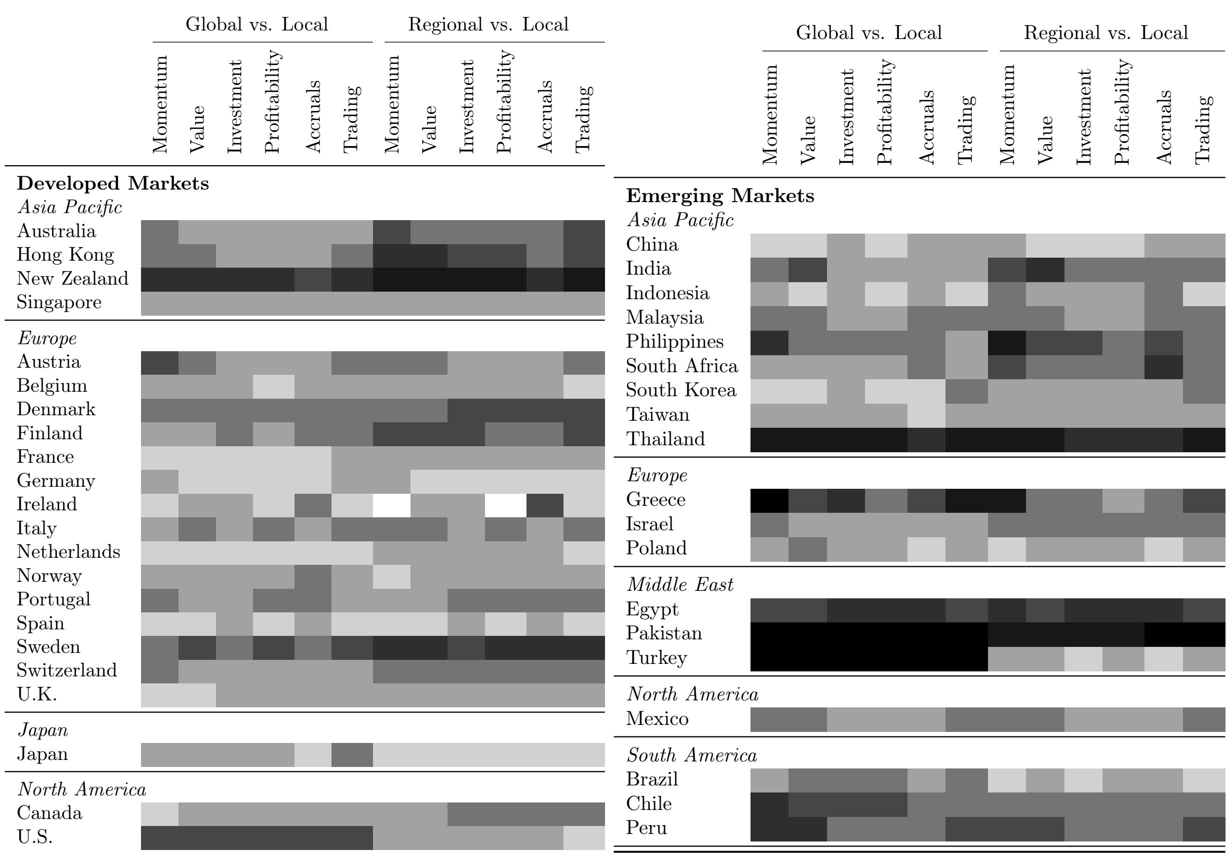


Table 4: Factor Spanning Regressions

Table 4 presents summary results about factor spanning regressions. I use equation (2) to regress the local or regional factors of each model on the corresponding regional or global factor models. The results for different specifications are allocated to separate panels. # is the number of regions or countries for which the factor models are available. $\text{Avg}(\lvert r\rvert)$ indicates the average annualized return across all factors of a model. $\text{Avg}(\lvert\alpha\rvert)$ denotes the average annualized alpha of the factors in that model when regressed on the factors of the regional or global model (as indicated in the panel headings). *GRS* presents the (average) GRS test statistic. The hypothesis of the GRS test is that all alphas of the spanning regression of a local or regional factor model are jointly equal to zero. A rejection at the 10% significance level for part of the countries is indicated by *italic* font and a rejection at 10% for a regional model or the local models of all countries is indicated by **bold** font. All alphas and R^2s are aggregated equally and presented in percentage points. DEV and EM indicate Developed Emerging Markets, respectively.

		CAPM				FF-3				C-4				FF-5				HXZ-4				HMXZ-5				SY-4			
	#	$\text{Avg}(\lvert r\rvert)$	$\text{Avg}(\lvert\alpha\rvert)$	*GRS*	R^2	$\text{Avg}(\lvert r\rvert)$	$\text{Avg}(\lvert\alpha\rvert)$	*GRS*	R^2	$\text{Avg}(\lvert r\rvert)$	$\text{Avg}(\lvert\alpha\rvert)$	*GRS*	R^2	$\text{Avg}(\lvert r\rvert)$	$\text{Avg}(\lvert\alpha\rvert)$	*GRS*	R^2	$\text{Avg}(\lvert r\rvert)$	$\text{Avg}(\lvert\alpha\rvert)$	*GRS*	R^2	$\text{Avg}(\lvert r\rvert)$	$\text{Avg}(\lvert\alpha\rvert)$	*GRS*	R^2	$\text{Avg}(\lvert r\rvert)$	$\text{Avg}(\lvert\alpha\rvert)$	*GRS*	R^2
Global vs. Regional																													
Asia Pacific	1	5.8	0.4	0.0	64	5.2	2.2	1.4	48	6.3	2.6	1.4	46	4.2	2.1	1.3	38	3.8	1.8	1.1	39	3.7	2.3	**2.2**	35	7.8	3.7	**4.5**	43
Europe	1	5.8	1.0	0.5	82	3.7	1.1	1.1	58	5.2	2.7	**4.1**	59	2.9	1.6	**2.3**	46	3.0	1.7	1.5	47	2.9	1.6	1.7	44	6.4	3.3	**5.4**	57
Japan	1	0.4	4.8	**2.8**	49	2.4	2.5	1.8	34	1.9	2.7	1.6	38	1.7	1.1	0.8	34	0.7	1.4	0.9	36	0.8	1.1	0.6	32	1.4	2.5	1.4	37
Middle East	1	11	5.9	1.1	32	8.0	5.5	1.8	14	6.1	4.9	1.4	17	6.1	6.5	**2.9**	17	6.0	8.6	**3.5**	18	5.8	7.8	**2.7**	16	5.4	6.0	1.9	20
North America	1	8.0	4.0	**9.1**	79	4.0	2.5	**3.6**	57	4.3	1.6	**2.3**	60	3.6	1.4	**3.8**	56	4.1	1.0	1.7	53	3.9	1.0	1.3	54	5.2	0.9	1.7	56
South America	1	10	3.2	0.7	58	6.9	3.3	**2.6**	29	5.7	2.5	1.6	26	6.5	5.7	**5.5**	23	6.2	3.5	**3.0**	26	5.8	3.4	**2.3**	24	5.5	4.0	1.7	28
Global vs. Local																													
Asia Pacific DEV	4	9.5	3.3	*1.8*	58	5.8	3.2	*1.9*	30	7.0	4.5	**4.4**	29	4.7	3.6	*3.6*	22	3.7	2.8	*2.1*	22	3.5	3.0	*2.1*	18	7.5	4.7	*3.4*	26
Asia Pacific EM	9	8.4	3.3	0.4	33	6.9	4.2	*1.6*	18	6.7	4.4	*1.8*	18	5.8	4.6	*2.2*	15	5.5	4.0	*2.0*	15	5.3	4.2	*2.3*	14	7.7	5.3	*1.8*	17
Europe DEV	16	7.0	2.7	*1.0*	60	4.4	3.2	*1.3*	32	5.9	4.6	*2.2*	32	4.3	3.8	*1.9*	24	4.4	3.6	*1.6*	24	4.2	3.6	*1.6*	21	6.6	4.9	*1.8*	27
Europe EM	3	11	2.0	0.4	55	5.6	2.6	0.7	23	6.2	4.1	*1.8*	23	6.1	4.3	*1.6*	19	7.5	6.7	*2.6*	21	7.1	6.0	*2.5*	19	9.9	7.3	*2.3*	25
Japan	1	0.4	4.8	**2.8**	49	2.4	2.5	1.8	34	1.9	2.7	1.6	38	1.7	1.1	0.8	34	0.7	1.4	0.9	36	0.8	1.1	0.6	32	1.4	2.5	1.4	37
Middle East	2	18	12	*3.8*	23	9.7	7.8	*2.9*	12	9.3	8.5	*3.3*	13	7.1	6.4	**2.6**	10	8.0	6.8	*3.1*	9	6.7	6.2	*2.9*	8	9.3	11	*4.8*	12
North America DEV	2	7.5	3.2	*5.2*	72	3.8	1.7	*2.1*	46	5.1	2.4	**2.6**	49	3.7	2.1	*2.6*	44	4.3	1.8	*1.9*	41	4.3	2.1	*1.7*	40	6.8	2.8	*2.5*	44
North America EM	1	12	5.5	2.0	57	6.1	2.5	0.5	25	7.2	5.3	1.7	23	4.5	3.5	1.0	18	6.8	7.0	**4.1**	23	5.5	5.4	**3.1**	20	12	12	**5.1**	23
South America	3	12	5.4	1.2	46	7.1	3.3	0.9	20	6.9	4.2	*1.5*	20	6.5	4.1	*1.5*	17	7.9	5.6	*2.7*	19	7.8	5.2	*2.2*	17	8.8	8.2	*3.1*	22
Regional vs. Local																													
Asia Pacific DEV	4	9.5	4.0	*2.1*	61	5.8	3.7	*2.9*	30	7.0	5.3	**5.8**	28	4.7	3.5	*3.5*	23	3.7	2.1	*1.9*	24	3.5	2.5	*1.9*	21	7.5	5.0	**3.7**	27
Asia Pacific EM	9	8.4	2.7	0.4	44	6.9	4.1	*1.6*	25	6.7	4.7	*2.1*	24	5.8	4.4	*2.1*	23	5.5	3.6	*2.0*	23	5.3	3.7	*2.1*	22	7.7	5.9	*2.1*	23
Europe DEV	16	7.0	2.6	*1.2*	71	4.4	3.1	*1.7*	42	5.9	3.8	*1.7*	43	4.3	3.4	*1.8*	33	4.4	2.9	*1.4*	31	4.2	2.9	*1.3*	27	6.6	4.2	*1.6*	34
Europe EM	3	11	3.6	0.9	59	5.6	2.9	1.0	26	6.2	3.9	1.2	27	6.1	5.0	*1.9*	21	7.5	5.6	*3.2*	24	7.1	5.7	*3.2*	20	9.9	6.3	1.9	27
Middle East	2	18	7.7	*3.0*	43	9.7	3.9	*2.0*	35	9.3	4.5	*2.3*	33	7.1	3.5	*1.6*	30	8.0	5.9	*3.2*	28	6.7	4.8	*2.6*	30	9.3	7.8	*4.1*	29
North America DEV	2	7.5	0.8	1.0	83	3.8	1.2	*1.9*	73	5.1	2.2	**4.7**	75	3.7	1.0	1.2	70	4.3	1.1	0.9	67	4.3	1.3	0.8	65	6.8	2.3	*2.1*	69
North America EM	1	12	4.7	1.4	54	6.1	2.6	0.6	24	7.2	5.1	1.8	22	4.5	3.0	0.9	17	6.8	6.2	**3.7**	22	5.5	4.9	**2.9**	19	12	12	**6.3**	22
South America	3	12	2.7	0.7	69	7.1	2.6	1.0	42	6.9	3.1	*1.4*	42	6.5	3.6	1.4	35	7.9	4.4	*2.2*	32	7.8	4.5	*1.9*	28	8.8	5.4	*2.2*	37

Table 5: Anomaly Correlations Across Countries

Table 5 presents the average correlations of different anomaly strategies across countries before and after removing global, regional, and local systematic return components. For each country, I first form 6 average strategies based on the anomaly categories (see Section OA2 of the Supplementary Material for details on the anomalies contained in the different categories). For each category, I aggregate the long–short returns to one strategy using an equally weighted average in each country. The definition of anomaly long and short sides is based on which of the two returns is higher for the U.S. I present the average of all bivariate correlations of the anomaly return time-series of the excess returns ($\mathrm{CORR}^{\mathrm{RET}}$) in the different countries as well as the average of all bivariate correlations of these time-series after removing the expected return components implied by the global ($\mathrm{CORR}^{-\mathrm{GLOB}}$), regional ($\mathrm{CORR}^{-\mathrm{REG}}$), and local ($\mathrm{CORR}^{-\mathrm{LOC}}$) factor models. For removing the expected return components, for each anomaly long–short return, I estimate equation (1) and subtract the part $\hat{\beta}_j' f_t^{glob/reg}$ from the portfolio excess return. The correlations are aggregated equally across the main factor models.

	Momentum	*Value*	*Investment*	*Profitability*	*Accruals*	*Trading*
All Countries						
$\mathrm{CORR}^{\mathrm{RET}}$	0.197	0.105	0.059	0.019	0.040	0.228
$\mathrm{CORR}^{-\mathrm{GLOB}}$	0.152	0.064	0.026	0.014	0.020	0.098
$\mathrm{CORR}^{-\mathrm{REG}}$	0.144	0.054	0.020	0.014	0.017	0.088
$\mathrm{CORR}^{-\mathrm{LOC}}$	0.148	0.059	0.020	0.017	0.015	0.100
Developed Markets						
$\mathrm{CORR}^{\mathrm{RET}}$	0.296	0.237	0.077	0.041	0.033	0.368
$\mathrm{CORR}^{-\mathrm{GLOB}}$	0.233	0.155	0.040	0.029	0.021	0.191
$\mathrm{CORR}^{-\mathrm{REG}}$	0.217	0.125	0.030	0.027	0.020	0.172
$\mathrm{CORR}^{-\mathrm{LOC}}$	0.223	0.137	0.032	0.031	0.021	0.200
Emerging Markets						
$\mathrm{CORR}^{\mathrm{RET}}$	0.134	0.034	0.047	0.016	0.050	0.120
$\mathrm{CORR}^{-\mathrm{GLOB}}$	0.114	0.016	0.019	0.011	0.017	0.039
$\mathrm{CORR}^{-\mathrm{REG}}$	0.106	0.012	0.011	0.011	0.013	0.026
$\mathrm{CORR}^{-\mathrm{LOC}}$	0.102	0.008	0.009	0.011	0.010	0.033