Size, Value, and Momentum in International Stock Returns:

A New Partial-Segmentation Approach

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Abstract

We propose a new multi-factor model for global stock returns that includes size, value, and momentum factor portfolios but that builds them separately as "global" factors comprised of all stocks around the world and as "local" factors comprised of locally-accessible stocks for a given country or region. This "partial-segmentation" approach is evaluated using monthly returns for over 37,000 stocks from 46 developed and emerging market countries over 20 years and for a wide variety of test asset portfolios and individual stocks. The model not only captures strong common variation in global stock returns, but also achieves low pricing errors and rejection rates relative to purely global and purely local models using conventional procedures.

This Version: January 10, 2014.
First Version: November 23, 2011.
Key words: International asset pricing; investment restrictions; cross-listed stocks.
JEL Classification Codes: F30, G11, G15.

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I. Introduction

We propose a new multi-factor model for global stock returns that includes size, value, and momentum factor portfolios, but that builds them separately as "global" factors comprised of all stocks around the world and as "local" factors comprised of locally-accessible stocks for a given country or region. Just as the factor portfolios for a given firm attribute are constructed as tradable, spread portfolios to have long (short) positions in stocks with higher (lower) values of the attribute (small size, high book-to-market ratios, and higher price momentum), so too are the local factors constructed as spread portfolios of long positions in locally-accessible stocks net of short positions in equivalent globally-accessible stocks. This model is evaluated using monthly returns for over 37,000 stocks from 46 developed and emerging market countries over 20 years and for a wide variety of test asset portfolios and individual stocks. Our new "partial segmentation" approach that includes both global and local factors not only captures strong common variation in global stock returns, but also achieves low pricing errors and rejection rates relative to purely local or purely global multi-factor models.

We are motivated to pursue this question by a long-standing debate in the international asset pricing literature as to whether securities are priced locally in segmented markets or globally in a single, integrated market (Karolyi and Stulz, 2003; Lewis, 2011). The liberalization of financial markets around the world has increased market accessibility for global investors, but many regulatory restrictions, operational inefficiencies, differences in information quality, in reporting standards and in legal protections constitute *indirect* barriers to investing in oversea markets that still inhibit full market integration. A partial-segmentation model is flexible enough to capture the influence of both the direct and indirect barriers for global stock returns.

The question is well rooted in existing theory. Many international asset pricing models of partial segmentation, which date from early work of Black (1974), Stehle (1977), Stulz (1981a), Errunza and Losq (1985), Eun and Janakiramanan (1986), and Bodurtha (1999) to more recent work of

Chaieb and Errunza (2007), feature the effect on portfolio choice and pricing of such barriers to international investment. A common prediction of these models is that the returns on securities from a partially-segmented market will be higher than the returns under full global integration. For example, in Errunza and Losq (1985, hereafter EL), a "local" risk premium over and above a "global" risk premium in a given partially-segmented market is conditionally proportional to the remaining risk that cannot be diversified away by investing in unrestricted, globally-accessible securities. The condition under which local risk is priced depends on the availability of substitute assets that can help span the set of the restricted, locally-accessible securities. The EL model can reduce to the two polar cases of full integration or full segmentation and, most importantly, allows for intermediate cases in between so that both global and local risks can be priced. In general, partial-segmentation models offer powerful predictions about how to measure the link between expected returns and risk in international markets.

Most empirical evidence evaluating partial-segmentation models to date has focused only on whether aggregate market or consumption risks are priced locally or globally. Such tests do follow naturally from the predictions of the classic models of Solnik (1974, 1977), Grauer, Litzenberger and Stehle (1976), Stehle (1977), Sercu (1980), Stulz (1981b), and Adler and Dumas (1983).[1] But recent research has uncovered that the cross-section of average returns in global markets are importantly linked to firm characteristics, such as size, book-to-market-equity ratios, and momentum (Bekaert, Hodrick, and Zhang, 2009; Hou, Karolyi, and Kho, hereafter HKK, 2011). An important debate has emerged over whether the explanatory power of these characteristics arises locally or globally. For example, Griffin (2002) studies a global variant of the three-factor model similar to that of Fama and French (1993, 1998), which includes a market factor, a size factor and a book-to-market-equity factor for four countries (U.S., U.K., Canada, and Japan). He finds that only the local, country-specific components of the global factors are able to explain the time-series variation in the stock returns and

[1]Among many others, consider Harvey (1991), Bekaert and Harvey (1995), Errunza, Hogan, and Hung (1999), de Jong and de Roon (2005), Carrieri, Errunza, and Hogan (2007), Pukthuanthong and Roll (2009), Eun, Lai, de Roon, and Zhang (2010), Bekaert, Harvey, Lundblad, and Siegel (2011), and Carrieri, Chaieb, and Errunza (2013).

multi-factor models built from local factors yield lower pricing errors than those built from global factors. Newer evidence by Fama and French (2012) affirms Griffin's basic inference showing that purely global multi-factor models perform only passably for average returns on global size/book-to-market ratios ("B/M" hereafter) and size/momentum portfolios, and they work poorly when asked to explain average returns on equivalent regional (for North America, Europe, Japan, Asia-Pacific) test asset portfolios.[2]

Our study makes an important contribution to this debate. We incorporate the theoretically-based pricing rule under partial segmentation into empirical-based asset pricing models that are allowed to capture the common covariation in size, value, and momentum returns so prevalent in global markets. Specifically, we propose a new partial-segmentation multi-factor model that includes extra-market factor portfolios based on firm characteristics and that builds *separate* factor portfolios comprised of all stocks around the world, which we call "global factors," and only of locally-accessible stocks for a given region, our so-called "local factors." The local factors are built as tradable, spread portfolios with long positions in the locally-accessible stocks for a given region and short positions in globally-accessible stocks. The partial-segmentation model is able to reject reliably the alternative purely-global and purely-local versions of the model in an analysis of model comparisons using the methods of Kan, Robotti, and Shanken (KRS, 2013) based on differences in cross-sectional regression R^2 (CSR R^2). Specifically, relative to a purely-global factor model for global test asset portfolios, the CSR R^2 differences are large and statistically significantly different from zero, regardless of the type of test asset portfolios and model specifications. The gains are even larger for tests that include microcap stocks in test asset portfolios, for those that focus on global test asset

[2] HKK (2011), in particular, examine the relative performance of global, local, and what they call "international" versions of various multifactor models to explain the returns of industry and characteristics-sorted test portfolios in each country. The international versions of their model represent a factor structure that includes separately local, country-specific factors as well as foreign factors built from stocks outside the country of interest. They show that the international version of their proposed multifactor model with the market factor, a value factor constructed from cash-flow-to-price ratios, and a momentum factor (following Jegadeesh and Titman, 1993; Rouwenhorst, 1998; Griffin, Ji, and Martin, 2003; and Asness, Moskowitz, and Pedersen, 2013) provides the lowest average pricing error and rejection rates among various versions of competing multi-factor models.

portfolios that exclude North America, and that include a momentum factor in the model. The average absolute pricing errors are smaller and the rejection rates implied by the Gibbons, Ross, and Shanken (GRS, 1989) *F*-test are substantially fewer. Also, relative to a purely-local factor model for regional test asset portfolios - for which Fama and French (2012) uncover the only passable result - the CSR R^2 differences are negligible in almost all cases. There are a few rejections of the purely-local model in favor of the partial-segmentation model for tests on developed markets, such as Europe and Asia Pacific, and emerging markets, such Eastern Europe, the Middle East and Africa (EEMEA) and Latin America. But, the pricing errors for the partial-segmentation model are generally similar to those of the purely local model for regional test asset experiments.

How we identify the sets of globally-accessible and locally-accessible stocks is a critical step in our exercise. Partial segmentation is about direct and indirect barriers and must reflect the ability and willingness of global investors to access certain markets and securities in those markets. So any definition should include consideration of openness (limits on foreign equity holdings), as well as liquidity, size, and float at the market and individual security level. We choose to define globally-accessible stocks in our equity universe as those for which shares are actively traded in the markets fully open to global investors, whether they are listed in their domestic exchange that is open or secondarily cross-listed on exchanges outside of their main listing in their country of domicile that are open.[3] Locally-accessible stocks are, therefore, those that are *only* traded in their respective home markets and in a way that is not easily accessible for global investors. That is, they are constructed from among the stocks that are not globally accessible *in the region* in which our model is seeking to explain the cross-section of average returns. This is critically different from the construction of factors for the so-called international models in Griffin (2002) and HKK (2011), as we reassign what would be

[3] We will define the globally accessible set to include stocks that secondarily cross-list their shares on one of seven different target markets: the U.S. on one of the major exchanges, New York Stock Exchange (NYSE), American Stock Exchange (AMEX) or Nasdaq, or on the over-the-counter (OTC) markets, the U.K. on the London Stock Exchange, London OTC, or SEAQ International, Euronext Europe, Germany, Luxembourg, Singapore, or Hong Kong. We later discuss the rationale behind these target markets.

local stocks in their local factors to the global factors if those stocks are deemed globally accessible by our definition.[4] Our motivation for this particular identification strategy comes from existing research on risk and return attributes and institutional features of internationally cross-listed stocks.[5] Some studies (Foerster and Karolyi, 1993, 1999; Errunza and Miller, 2000) show that the systematic risk exposures of these stocks change dramatically around their secondary listing decisions: local market betas (measured relative to local market proxies) decline and foreign market betas (measured relative to global market proxies) rise. Newly globally-accessible, these cross-listed stocks are more likely to be held and traded by institutional investors from outside their own markets (Ferreira and Matos, 2008).

We acknowledge, of course, that ours is an imperfect identification strategy. There are many other ways in which stocks can become globally accessible (e.g., Bekaert and Urias, 1996; Carrieri, Chaieb and Errunza, 2008, 2013; Errunza and Ta, 2011), such as being included in a closed-end country fund, or in one of Morgan Stanley Capital International (MSCI) or Standard & Poor's (S&P) global indexes (especially, in their investable indexes for emerging markets). Indeed, if they do not face insurmountable or costly foreign investment restrictions that preclude them from doing so, many institutions do hold shares of foreign stocks in their home markets even if they are not secondarily cross-listed elsewhere. Though narrow in its definition, we prefer to consider only those stocks listed and trading in fully-open markets and among secondary cross-listings for our globally-accessible set because of its simplicity and transparency; indeed, the timing of a given listing event is easily determinable. We explore the robustness of our findings to alternative definitions of global accessibility. For instance, additional restrictions are imposed that account for how actively the cross-listed shares are traded in the respective target markets. We refer to these are our viability constraints.

[4] Brazil-based Petrobras has over 370 global institutional investors (as of 09/30/2013, according to S&P Capital IQ) in addition to the Brazilian government's 26% stake. Among its top five institutional investors are BlackRock (2.15%) and Aberdeen Asset Management (2.25%) as well as Caixa de Provencia do Banco de Brasil (2.79%) and BNDES Participacoes (17.29%). Petrobras returns may thus comove with the U.S.'s ExxonMobil or Germany's SAP, also held by global investors, as much as with other Brazilian stocks.

[5] Consider, among many others, studies by Foerster and Karolyi (1993, 1999), Bodurtha (1994), Errunza, Hogan, and Hung (1999), Errunza and Miller (2000), Bekaert, Harvey, and Lumsdaine (2002), Doidge, Karolyi, and Stulz (2004), Carrieri, Errunza, and Hogan (2007), and Carrieri, Chaieb, and Errunza (2013). Karolyi (2012) provides a recent survey of the cross-listing literature.

The partial-segmentation model continues to capture strong common covariation with low pricing errors, and it fares well with fewer rejections relative to the purely-global and purely-local versions of the model. We also perform a sequence of placebo or falsification tests that create randomized assignments of globally- and locally- accessible stocks and other assignments based simply on differences in size, liquidity, or free float. These placebo tests fail to generate the same inferences as those using our main definition of accessibility based on secondary cross-listings.

Two crucial diagnostic tests give us guidance on what gives rise to the improvement offered by the partial-segmentation model. In one test, we account separately for the effect of investability restrictions on the market factor and extra-market factors linked to size, value, and momentum. An important source of power for our ability to reject the purely-global and purely-local versions in favor of the partial-segmentation model stems from the inclusion of separate global and local size, value, and momentum factors. When we perform the KRS model comparison tests using just a market factor (i.e., a global Capital Asset Pricing Model, CAPM), we are unable to reject either polar alternative (purely local CAPM, purely global CAPM) relative to our partial-segmentation model for a variety of test assets. One advantage of our definition of accessibility is that it naturally evolves over time as ever-increasingly more stocks are secondarily listed abroad. In other words, when a market in a given region comes closer to completely globally integrated, the role of local factors diminishes and a purely-global multi-factor model emerges. A second over-identification test of this conjecture is run by building our test asset portfolios from *only* the globally-accessible stocks in a region and by repeating our KRS model-comparison tests. Indeed, we are much less likely to reject the purely-global model in favor of the partial-segmentation model.

Our analysis includes more than 11,000 stocks from 23 emerging markets, an effort which distinguishes our experiments from Fama and French (2012) and Asness, Moskowitz, and Pedersen (2013). Expanding our analysis into emerging markets is important because it is there that the investability restrictions at the core of a partial-segmentation model are most likely to bind. We expect that this is where a global or partial-segmentation model is likely to face the greater challenge compared to a purely-local factor model. It turns out that this is the case. But we also show our partial-segmentation model performs well relative to a purely-local model in emerging markets. In a separate test of segmentation-versus-integration focused on the Euro bloc, especially after its launch in 1999, we find a purely-local model is rejected in favor of the partial-segmentation model in KRS model-comparison tests. Finally, like Fama and French (2012), we provide separate evidence for different size groups. Our sample, like theirs, covers all size groups, and indeed very small, microcap stocks produce challenging results (Fama and French, 2008). We control for the potential influence of microcap stocks globally and in each region by performing our tests with and without the extremely-small test asset portfolios and also by building the factor portfolios using value and momentum breakpoints using the top 90% of market capitalization for each region to limit their influence.

II. The Design of the Experiment

Fama and French (1993) propose a three-factor model to capture the patterns in U.S. average returns associated with size and value versus growth:

$$R_{it} - R_{ft} = \alpha_i + \beta_i\,(R_{mt} - R_{ft}) + s_i\,F_{Size,t} + h_i\,F_{B/M,t} + \varepsilon_{i,t} \tag{1}$$

Where R_{it} is the return on asset i in month t, R_f is the risk free rate, R_{mt} is the market return, $F_{Size,t}$ is the difference between the returns of diversified portfolios of small stocks and big stocks (F denotes a factor portfolio), and $F_{B/M,t}$ is the difference between the returns on diversified portfolios of high B/M (value) stocks and low B/M (growth) stocks. To explain the size, value, and momentum effects in international stock returns, Fama and French (2012) build the global and local versions of model (1) for global and local stock returns, respectively:

$$R_{it} - R_{ft} = \alpha^G{}_i + \beta^G{}_i\,(R^G{}_{mt} - R_{ft}) + s^G{}_i\,F^G{}_{Size,t} + h^G{}_i\,F^G{}_{B/M,t} + \varepsilon_{i,t} \tag{2a}$$

$$R_{it} - R_{ft} = \alpha^L{}_i + \beta^L{}_i\,(R^L{}_{mt} - R_{ft}) + s^L{}_i\,F^L{}_{Size,t} + h^L{}_i\,F^L{}_{B/M,t} + \varepsilon_{i,t} \tag{2b}$$

The superscript "G" on the market and factor portfolios implies that they are constructed from all stocks around the world and the superscript "L" implies that they are constructed only from local - or regional, in our experiments - stocks. Extending the experiment in this way is naturally complicated by the fact that asset pricing globally, or even in a particular region, may not be fully integrated.

To capture the impact of investability restrictions on international asset pricing, we propose a partial-segmentation model based on the Fama-French three-factor model:

$$R_{it} - R_{ft} = \alpha^{PS}{}_i + \beta^G{}_i\,(R^G{}_{mt} - R_{ft}) + s^G{}_i\,F^G{}_{Size,t} + h^G{}_i\,F^G{}_{B/M,t}$$

$$+ \beta^{\bar{A}-A}{}_i\,R^{\bar{A}-A}{}_{mt} + s^{\bar{A}-A}{}_i\,F^{\bar{A}-A}{}_{Size,t} + h^{\bar{A}-A}{}_i\,F^{\bar{A}-A}{}_{B/M,t} + \varepsilon_{i,t} \qquad (3)$$

where the superscript "PS" denotes the intercept for the partial-segmentation model, the superscript "A" (for "accessibility") designates a market or factor portfolio comprised of stocks only in the globally-accessible sample, and the superscript "$\bar{A}$-A" denotes a spread factor portfolio that consists of a long position in locally-accessible stocks in a given region (represented by "$\bar{A}$") and a short position in the globally-accessible sample ("A"). The spread factor portfolio is built in the spirit of a "*hedged portfolio*" in Errunza and Losq (1985) or like Eun and Janakiramanan's (1986) "*pure*" portfolio – which they refer to as foreign portfolios net of "*adjustment*" portfolios. For example, $F^{\bar{A}-A}{}_{Size,t}$ is the returns difference between the size-based factor portfolio of locally-accessible stocks in a given region and that of all globally-accessible stocks around the world. Important sources of common covariation among stocks in that region related to local size-based return variation orthogonal to that of globally-accessible stocks in the hedged portfolio, $F^{\bar{A}-A}{}_{Size,t}$, can be described by their loading on that portfolio, $s^{\bar{A}-A}{}_i$. Each of the local size-based factor portfolios are constructed as returns of diversified portfolios of small stocks and big stocks among the respective samples of stocks in a given region. The spread portfolios for the market ($R^{\bar{A}-A}{}_{mt}$) and value-based factors ($F^{\bar{A}-A}{}_{B/M,t}$) are built in a similar fashion.

For a given set of test asset portfolios (for instance, 5×5 portfolios double-sorted by size and B/M), the model performance is measured by its time-series explanatory power (R^2), the magnitude of model pricing errors (reported as the simple average of the absolute magnitude of the intercepts), and the GRS F-test statistic for the hypothesis that the intercepts are jointly equal to zero across the test assets of interest.[6] Beyond these conventional testing procedures, we also compare the performance of among alternative asset pricing models based on their cross-sectional regression R^2 (CSR R^2). CSR R^2 is computed from a second-pass regression of the cross-section of average returns on the estimated loadings from Models (1) or (2) above. We implement the tests of equality of CSR R^2 proposed by Kan, Robotti, and Shanken (KRS, 2013) in which they derive the asymptotic distribution of this statistic and develop associated model comparison tests taking into account the impact of model misspecification on the variability of the CSR R^2 estimates.[7] We propose the null hypothesis that the CSR R^2 difference in favor of the partial-segmentation over the purely-global model for global test asset portfolios in the first round of experiments and the same in favor of the partial-segmentation over the purely-local model for regional test asset portfolios in the second round of experiments. To study the robustness of our inferences, we include portfolios sorted by industry or other firm characteristics as test assets, examine the magnitude of the cross-sectional slopes coefficients (which stand in for the estimated risk premia for each factor), and estimate both the GLS CSR R^2 as well as OLS CSR R^2 as recommended by Lewellen, Nagel, and Shanken (2010).

One natural question arises as to whether the cross-sectional explanatory power of the partial-segmentation model is specific to the Fama-French three-factor model in explaining the portfolios sorted on size and B/M. Carhart (1997) proposes a four-factor model for U.S. returns in order to capture momentum:

$$R_{it} - R_{ft} = \alpha_i + \beta_i\,(R_{mt} - R_{ft}) + s_i\,F_{Size,t} + h_i\,F_{B/M,t} + m_i\,F_{Mom,t} + \varepsilon_{i,t} \tag{4}$$

[6] We also report $SR(\alpha)$, the core component of the GRS statistic, $SR(\alpha) = (\alpha' S^{-1}\alpha)^{1/2}$, where α is the vector of regression intercepts produced by Model (1) across a set of test asset portfolios. S is the covariance matrix of regression residuals. GRS (1989) relate $SR(\alpha)^2$ to the difference between the square of the maximum Sharpe ratio for the portfolios constructed from the test asset portfolios and factor portfolios and that constructed from the factor portfolios alone. As Fama and French (2012) argue, the advantage of this statistic is that it combines the regression intercepts with a measure of their precision captured by the covariance matrix of the regression residuals.

[7] We are especially grateful to Raymond Kan for furnishing the KRS code for the model-comparison tests on his website.

which is Model (1) enhanced with a momentum return, $F_{Mom,t}$, which is the difference between the month t returns on a diversified portfolios of the trailing 12-month returns winners and losers of the past year. Similarly, we test a partial-segmentation model based on the Carhart four-factor model:

$$R_{it} - R_{ft} = \alpha^{PS}_i + \beta^G_i (R^G_{mt} - R_{ft}) + s^G_i F^G_{Size,t} + h^G_i F^G_{B/M,t} + m^G_i F^G_{Mom,t}$$
$$+ \beta^{\bar{A}-A}_i R^{\bar{A}-A}_{mt} + s^{\bar{A}-A}_i F^{\bar{A}-A}_{Size,t} + h^{\bar{A}-A}_i F^{\bar{A}-A}_{B/M,t} + m^{\bar{A}-A}_i F^{\bar{A}-A}_{Mom,t} + \varepsilon_{i,t} \qquad (5)$$

which is Model (3) with two momentum factor portfolio returns: $F^G_{Mom,t}$ for all stocks and $F^{\bar{A}-A}_{Mom,t}$, for the spread portfolio of locally-accessible stocks net of those for the globally-accessible stocks.

III. Data and Summary Statistics

A. The Global Equity Universe

We obtain U.S. dollar-denominated stock returns and accounting data from Datastream and Worldscope. To ensure that we have a reasonable number of firm-level observations in each country, the sample period begins in November 1989 and ends in December 2010, which encompasses the widest coverage in the Worldscope database. Our final sample of the global equity universe includes 37,399 stocks from 46 countries.[8] To ensure that there are sufficient numbers of stocks in each test asset portfolio, as in Fama and French (2012), 23 developed markets are combined into four regions: (i) *North America*, including the U.S. and Canada; (ii) *Japan*; (iii) *Asia Pacific*, including Australia, New Zealand, Hong Kong, and Singapore (but not Japan); and (iv) *Europe*, including Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the U.K. The remaining 23 countries are combined into *Emerging Markets*, the fifth region in our tests; it includes Israel, Turkey, Pakistan, South Africa, Czech Republic, Poland, Hungary, Russia, China, India, Indonesia, Malaysia, Philippines, South Korea, Taiwan, Thailand, Argentina, Brazil, Chile, Colombia, Mexico, Peru, and Venezuela. Figure 1 shows the distribution across region by average market capitalization and the total number of stocks across regions over time.

[8] Appendix B describes in detail the procedures used to construct the global equity universe and discusses its composition across regions and over time.

B. Identifying Globally-Accessible and Locally-Accessible Stocks

We categorize stocks into two subsets based on accessibility constraints as defined by whether or not the stock is actively traded in a market fully open to global investors. Ultimately, we identify a set of over 5,700 stocks accessible to global investors by means of a secondary cross-listing in major markets. Another group of around 32,000 individual stocks are locally accessible to domestic investors.

We require that the stocks in the globally accessible sample need to be listed in home markets which are fully open to global investors or to be secondarily cross-listed in those as target markets. Within those target markets, we include secondary listings from overseas that can trade on many different venues or platforms. We confine the list to seven target markets: (i) *U.S.*, which includes NYSE/AMEX, NASDAQ, and the Non-NASDAQ OTC markets;[9] (ii) *U.K.*, which includes the London Stock Exchange, London OTC Exchange, London Plus Market, and SEAQ International;[10] (iii) *Europe*, which includes Euronext at Amsterdam, Brussels, Lisbon, Paris, and EASDAQ;[11] (iv) *Germany*, in which the Frankfurt Stock Exchange and XETRA are located; (v) *Luxembourg*, in which the Luxembourg Stock Exchange is located; (vi) *Singapore*, which includes the Singapore Stock Exchange, Singapore OTC Capital, and Singapore Catalist;[12] and (vii) *Hong Kong* in which the Hong Kong Stock Exchange is located. The distinguishing feature of these target exchanges is that they are fully open to global investors, having minimum foreign investment restrictions and reasonably active trading in foreign cross-listed issues. We try to strike a balance between obtaining maximum breadth of stock exchange platforms accessible for international investors and avoiding problems related to

[9] Non-Nasdaq OTC markets include both the OTC Bulletin Board and the OTC Markets Group, for which its OTCQX International trading platform is designed for listings from overseas.

[10] The London Plus Stock Exchange (www.plusmarketsgroup.com) is a London-based stock exchange providing cash trading and listing services under the auspices of the Markets in Financial Instruments Directive (2004/39/EC, "MiFiD"), a European Union law providing for harmonized investment services. London OTC trading falls under the auspices of the London Stock Exchange (LSE) Group and is done under MiFiD with the exchange furnishing trade reporting and publication services. The Stock Exchange Automated Quotation (SEAQ) International is the LSE's electronic quotations system for non-U.K. securities.

[11] EASDAQ was an electronic securities exchange based in Brussels founded originally as an equivalent to Nasdaq, was purchased by the American Stock Exchange in 2001 and then shut down in 2003.

[12] See www.sgx.com for details on main board versus Catalist listing requirements. A listing applicant must be sponsored by an approved sponsor of Catalist and must satisfy some disclosure and performance requirements. Singapore's OTC Capital (www.otccapital.com) is an unaffiliated trading platform for unlisted public companies.

differences in cross-listing trading mechanisms and conventions. For the Frankfurt Stock Exchange and OTCQX International trading platforms, for example, there are "unregulated" cross-listed stocks alongside the "regulated" cross-listed stocks, in which trading takes place without the sponsorship of the company.[13] We include both unregulated and regulated secondary cross-listings in Frankfurt and OTCQX International. In later robustness tests, we exclude these unregulated secondary listings.

Appendix C describes the procedure for constructing the globally accessible set. Our sample begins with all non-domestic stocks listed in the target exchanges and then filters out those that fail to meet a sequence of selection criteria. We then add domestic stocks from the seven target markets as long as three criteria are satisfied: (i) they are among those stocks in the top 75% of market capitalization for the market; (ii) they have a minimum price of U.S. $5 and equivalent levels in terms of percentile rank for non-U.S. markets; and, (iii) they are among those stocks with a minimum 75% public float for listed stocks. These filters leave 11,057 qualified stocks, which we label as "CL 1st Tier" to denote the most all-encompassing group of cross-listed (CL) stocks. To construct our final sample, we impose additional restrictions on how actively the secondarily cross-listed shares are traded, which we refer to as our "viability" constraints. Several viability constraints are imposed (see Appendix C). There are ultimately 5,747 globally-accessible stocks left, which we refer to as the "Main CL Tier." Figure 2 exhibits the size of the globally-accessible sample by region and country as well as the total number of stocks over time that qualify by country of domicile and cross-listing target market. In addition to the Main CL Tier, we evaluate two other definitions for the globally-accessible sample, together with CL1st Tier, to ensure the reliability of the partial-segmentation model. For each globally-accessible sample, we group the stocks left in each respective region as the locally-accessible set.

[13] If a company is already listed on an approved foreign stock exchange ("Like Exchanges"), it is exempt from the primary registration rules and can be dual listed on the Frankfurt Stock Exchange without an underwriter. There are over 200 such "Like Exchanges" approved by the Frankfurt Stock Exchange (www.franfurtstockexchange.de).

C. Building Factor Portfolios and Test Assets

We construct factor portfolios and test asset portfolios for each of these five regions and four global settings: all global markets, developed markets, global markets excluding North America, and developed markets excluding North America. We follow Fama and French (1993, 2012) in constructing proxy factors as returns on zero-investment portfolios that go long in stocks with high values of a characteristic and short in stocks with low values of the characteristic. Our asset pricing models then employ 2×3 factor portfolios sorted on size and B/M (2×3 factor portfolios sorted on size and momentum) as explanatory factors and 5×5 size/B/M portfolios (5×5 size/momentum portfolios) as test assets. Appendix D furnishes additional details on factor portfolio and test asset construction.

Summary statistics for factor portfolio returns of the equity universe are reported on the left side of the two panels in Table 1. Panel A is for the global experiments and Panel B for the regional ones. The global market excess return is 0.46% per month for 1990-2010, very close to that of Developed Markets only. Excluding North America lowers the market excess return to 0.33% per month. Across regions, equity market premiums are higher in Asia Pacific (0.74% per month), North America (0.68% per month), and Europe (0.58% per month). The size premiums are positive in North America and in the Emerging Markets, but negative in three other regions. In contrast, higher value premiums obtain reliably everywhere in the sample.

On the right side of Table 1, summary statistics are shown for the local spread factor returns. There are some local market spread discounts in all four of the global experiments and three of the five regions, ranging from -0.72% per month for Japan to -0.11% per month for Europe. North America and Asia Pacific are the two exceptions, with positive premiums of 0.11% and 0.19% per month, respectively. Size spread discounts are observed almost everywhere, except Emerging Markets with an insignificant mean of 0.16% per month. Europe, Asia Pacific, and Japan are the regions with discounts in excess of 0.50% per month on the size local spread. The global value spread premium, a notable

0.40% (for B/M) and 0.44% (for C/P) on average per month, is statistically reliably different from zero. Relatively high value spread premium can also be found in other global experiments and in most of the regions. Momentum local spread premiums range from 0.56% per month (t-statistic of 1.00) for Emerging Markets to -0.08% per month (t-statistic of -3.02) in Japan, which reaffirms earlier findings in Griffin, Ji, and Martin (2003) and Fama and French (2012). The correlations (unreported, but available) between the global factor returns and the local spread factor returns are, as expected, relatively low, whether in the global or regional experiments and for each of the size-, value- and momentum-related factors.

IV. Asset Pricing Tests for Global Test Assets

In this section, we perform the first set of model comparison tests between the global model and the partial-segmentation model. Can partial-segmentation models improve upon the performance of purely-global models for various global test asset portfolios? Our criteria for success focuses on the increases in the CSR R^2 (both OLS and GLS) and the associated p-values of Kan, Robotti, and Shanken (2013) model comparison test. A complementary set of evaluation criteria consist of the explanatory power of the time-series regressions (average adjusted R^2 across the test asset portfolios), the GRS statistic, the Sharpe Ratio, $SR(\alpha)$, and summary statistics for the intercepts, including the difference between the highest/lowest regression intercepts ("H-L α") and the average absolute intercepts ("$|\alpha|$").

A. The Main Experiment

We start with the time-series regression tests in which test assets are 5×5 size/B/M portfolios, as applied by Fama and French (1993, 1996, and 2012). The main empirical analysis uses the Fama-French three-factor model. Table 2 summarizes the pairwise tests of the equality of CSR R^2s between the global model and the partial-segmentation model. The top part of Panel A corresponds to the OLS comparison and the lower part to the GLS comparison. The results show that the global model is outperformed by the partial-segmentation model in the global mandates. The increase in OLS (GLS) CSR R^2 ranges from 8% (12%) for Global Markets excluding North America to as high as 13% (25%) for Global Markets overall. For the Global Markets experiment, the KRS test rejects the null hypothesis that these differences are zero at the 5% level (both OLS and GLS), so too for Developed Markets Only portfolios (again, both OLS and GLS). The improvement on the CSR R^2 by the partial-segmentation model is reliably large at the 5% level for Global portfolios excluding North America (OLS) and at the 10% level for Developed Markets Only portfolios excluding North America (GLS). One possible concern is that the model performance test is plagued by microcap influences. As shown on the right side of Panel A, when we only consider the 4×5 global test asset portfolios excluding the five in the smallest size quintile, the partial-segmentation model again dominates the purely-global model in all of the four global experiments.

Lewellen, Nagel, and Shanken (2010) suggest that it is not enough for a model to have a high cross-sectional R^2. The estimated slopes and zero-beta rates need to be economically reasonable. More specifically, theory says that the zero-beta rate should equal the risk-free rate. However, as in many past studies, the zero-beta rates based on the purely-global model comfortably exceed the risk-free rate by large amounts shown in Panel B, ranging from 2.32% for Global portfolios to 1.10% for Developed Market portfolios excluding North America. In contrast, when we use the partial-segmentation model, the estimates of the zero-beta rate are much smaller and insignificantly different from the risk-free rate in almost all experiments. Secondly, the market factor estimated by the purely-global model is negatively priced in several global experiments, contrary to the usual theoretical prediction. Interestingly, in the partial-segmentation model, the market factor is usually positively priced; even it is negatively priced, its risk premium (or the price of covariance risk) is not statistically significant and the magnitude is smaller. Third, as for the pricing of the value factor, Kan, Robotti, and Shanken (2013) find inconsistent estimates between the risk premium and the price of covariance risk, and then question the role of the value factor. Surprisingly, results for the partial-segmentation model show that both the risk premium and the price of covariance risk are significantly positive for the global value factor. Furthermore, the risk premiums (as well as the prices of covariance risk) of the local spread factors are typically positive, consistent with theories of partial segmentation (among others, Errunza and Losq, 1985).

Next, we turn to diagnostics. Time-series regressions R^2, the GRS *F*-statistics, and the summary statistics on the intercepts are shown in Panel C. Details on the intercepts and their *t*-statistics, as well as the betas for the partial-segmentation model are not reported here, but are furnished in a separate appendix. The top part of Panel C shows the results for the global model and the lower part for the partial-segmentation model. The purely-global model offers acceptable explanatory power for Global portfolios, but fares poorly for other global test asset portfolios. The average R^2 is 0.92 for the global portfolios, but it is lower (only 0.83) if North America is excluded. The GRS statistics for the Global portfolios (3.12) and for Developed Markets only (2.67) are well into the right tail of the relevant *F*-distribution. The average absolute intercepts average 0.16% per month. One possible reason for the high model rejection rates is the presence of extremely small stocks. In the right side of Panel C, we present the same statistics for the case excluding microcap stocks. There is modest improvement in average R^2, but the GRS statistics and their Sharpe ratio ($SR(\alpha)$) core components are much lower.

We see in the lower part of Panel C how the partial-segmentation model improves upon the purely-global model. Note, for example, that for the Global portfolios, the GRS statistic falls from 3.12 for the global model to 2.30 for the partial-segmentation model. Dropping microcap stocks leads to an even smaller GRS statistic, 1.16, which is well below the critical value for a rejection at the 90% level. The evidence on the GRS test is noteworthy because the precision of the tests is high. The average absolute intercept is 0.10% or lower, depending on the experiment, and the average R^2 is 0.93 or higher. Similarly, the partial-segmentation model produces improvement when asked to explain the returns on the Developed Markets portfolios. Additional diagnostics (not shown, but available) indicate that the only two remaining statistically significant intercepts fall within the set of the smallest five quintile portfolios. Excluding microcap stocks on the right side of Panel C, we see the GRS statistic falls from 2.06 to 1.17 for the Developed Only test, below the 90th percentile of the relevant *F*-distribution.

The improved performance from the partial-segmentation model is more notable when we turn to the regressions on the Global and Developed Markets test asset portfolios excluding North America. For the Global portfolios excluding North America, the partial-segmentation model improves upon the performance of the global model in terms of goodness of fit. The average R^2 is 0.88 or higher, and the average absolute intercept is 0.16% or smaller. The partial-segmentation model produces an even greater improvement over the purely-global model when it is challenged to explain the average returns on the Developed Markets portfolios excluding North America. With microcap stocks excluded from the test assets, the average R^2 rises from 0.78 for the purely-global model to 0.92 for the partial-segmentation model, the average absolute intercept drops from 0.35% to 0.12%, the Sharpe ratio falls from 0.38 to 0.29, and the GRS is only 0.76. Even with microcap stocks, the partial-segmentation model still performs well, improving on the purely-global factor model by any of the evaluation criteria.

B. Tests for Alternative Factor Models

Given the superior performance of the partial-segmentation model in the experiments described above, we would like to know whether the improvement is due to the partial-segmentation structure of the model or whether it is specific to the Fama-French three-factor model. Table 3 presents regressions using alternative factor models in which the left side of the two panels is for the purely-global and partial-segmentation versions of the CAPM model on 5×5 size/B/M portfolios and the right side is for both versions of the Carhart four-factor model when applied to 5×5 size/Momentum portfolios. Panel A reports the KRS model comparison test results and Panel B, the other model diagnostics.

A salient result is that using just a market portfolio with a CAPM leads to a less impressive performance by the partial-segmentation model compared to previous results in Table 2. The GLS CSR R^2 differences in favor of the CAPM-based partial-segmentation model range from as little as zero (Global portfolios excluding North America) to as high as 3% (Developed Market portfolios, and Developed Markets portfolios excluding North America). The CSR R^2differences in OLS estimates are somewhat larger, ranging from 2% (Global portfolios excluding North America) to 29% (Global portfolios). The overall CSR R^2 differences are rarely large enough statistically; there is only one rejection of the purely-global model in favor of the partial-segmentation version out of the eight model comparison tests (OLS and GLS together). Consider, for example, that despite a CSRR^2 difference of 21%, the *p*-value is 0.11 for the OLS comparison test on the Developed Market Portfolios.

Results in Panel B provide additional diagnostic evidence against the CAPM-based partial-segmentation model. There is no reduction in the rejection rate of the GRS test. The average absolute intercept increases for all of the four global asset pricing tests. For example, the average absolute intercepts are 0.26% for the global CAPM but 0.36% for the partial segmentation version of the CAPM. The only improvement comes from the regression fits. The average time-series R^2s rise to 0.80 or higher while those for the global CAPM are only 0.74 on average. In short, nothing much is gained in switching from the purely-global CAPM or the partial segmentation version of the CAPM. It is necessary to include the extra-market factors based on firm-specific attributes in the partial-segmentation model in order for it to capture more reliably the cross-sectional and time-series variation of test asset returns. This finding complements in an important way those existing studies that evaluate partial-segmentation models using only CAPM versions of the model for national stock index returns (among others, Carrieri, Errunza, and Hogan, 2007; Carrieri, Chaieb, and Errunza, 2013). They may be failing to reveal the full potential of such partial-segmentation models with richer sets of global test assets.[14]

We also explore the sensitivity of our inferences on model comparison tests to alternative multi-factor asset pricing models, like the Carhart four-factor version. On the right side of Panel A, we note that the experiment on global size/momentum portfolios produces the most disappointing results among all asset pricing tests for the purely-global versions of the Carhart model. The global size/momentum portfolios represent a big challenge for any model. But, even with this challenge, the partial-segmentation model fares reasonably well. There are sizeable increases in the CSR R^2 for the partial-segmentation model over the purely-global model ranging from 21% to over 40%. More importantly, six out of the eight economically-large CSR R^2 differences give rise to statistical rejections using KRS tests of the purely-global model in favor of its partial-segmentation version. For example, in the test on Developed Markets portfolios excluding North America, the OLS CSR R^2 in favor of the partial-segmentation model exceeds that of global model by a full 43% and successfully become statistically significant at the 1% level. The GLS results are similar. The GLS CSR R^2 differences exceed 30%, which leads to the dominance of the partial-segmentation model over the global model at around the 10% level.

As shown on the right side of Panel B in Table 3, there are power problems with the global version of the Carhart four-factor model, given relatively low average time-series R^2s and high Sharpe ratios. The purely-global model confirms the kind of passable evidence Fama and French (2012) describe achieved in the Global portfolio tests: the average time-series R^2 is 89%, the GRS statistic is 2.19, which is above the 99th percentile threshold, and the average absolute intercept is 0.20%. For the

[14]In unreported tests, we further separate the effects of characteristic-based factors from the market-wide factors alone on two sets of the partial-segmentation models. One test compares the CAPM and the Fama-French three-factor partial-segmentation models, and the other test is between the CAPM and the Carhart four-factor partial-segmentation models. Two main observations emerge in the KRS (2013) model comparison tests. First, the CAPM-based model is always outperformed at the 1% and 5% levels in the global experiments. Secondly, in the regional mandates, the characteristic-based factors are especially important in North America, Europe, and Emerging Market in that they make the CAPM-based model dominated at the 5% and 10% levels.

three other global test asset portfolios, the purely-global model fares worse. The rejections of the model are high and the average absolute intercepts reach 0.31%. Recall, for example, for the Developed Markets portfolio excluding North America, the pure global factor model works well if only judged by the GRS test. However, without a presumption of integrated pricing around the world, the power loss is significant with an average time-series R^2 of only 0.75. On the other hand, given similar GRS statistics, the power problems are usually less severe for the partial-segmentation model. In the test described above, the R^2 rises to 91% and the average absolute intercepts drop from 0.31% to 0.21%.

Unreported results show that a partial-segmentation version of the HKK (2011) three-factor model does reasonably well for the size/momentum portfolios in the global mandates. We compare the Carhart four-factor model and the extended version of the HKK (2011) three-factor model in which an SMB factor in Fama and French (1993, 1996, 2012) is added; the key difference is that the value-based factor is constructed from C/P instead of B/M as a firm characteristic. The HKK (2011) extended four-factor model performs similarly to the Carhart four-factor model when applied to the size/momentum portfolios. Using the example of the Developed Markets portfolio excluding North America, the average time-series R^2 is 91%, the average absolute intercept is 0.22%, and the GRS statistic is 1.71.[15]

C. Tests with Expanded Test Assets

Following a key prescription of Lewellen, Nagel, and Shanken (2010), we expand test asset portfolios beyond those sorted on just firm-specific attributes. In Table 4, we reports regression results for the 5×5 size/B/M portfolios but now also add 10 industry portfolios using the Fama-French three-factor model (on the left side of the panels) and those for the 5×5 Size/Momentum plus 10 industry portfolios using the Carhart four-factor model (on the right side). The industry portfolios are

[15] In unreported tests, we repeated this analysis with a set of size/C/P test asset portfolios. In the regressions to explain returns on the 5×5 size/C/P portfolios with the HKK (2011) extended four-factor model, the GRS test rejects the global model in almost all four global regions at the 99th percentile level; Global portfolios excluding North America is the exception. For the partial-segmentation model, in contrast, all of the GRS statistics fall below the 99th percentile of the relevant *F*-distribution. Again, the regression fits are tighter: the Sharpe ratios and the average absolute intercepts are much smaller. At the same time, we see similar results on the rejection rate in the model comparison test based on the CSR R^2 with previous experiments.

constructed using the FTSE/Dow Jones Industry Classification Benchmark (Level 1 Industrial Classification in Datastream) for the specific region for which the experiment is performed.

The first thing to note in Panel A is that adding industry portfolios worsens the performance of all models with respect to each of the evaluation criteria. Indeed, our choice of industry portfolios is based on the notion that they should provide a higher hurdle for any proposed model. The superior performance of the partial-segmentation model turns out to be a fairly robust empirical finding even in the new experiments. Using 5×5 size/B/M portfolios plus 10 industry portfolios as the test assets, the purely-global model is rejected in favor of the partial-segmentation version at the 1% level on the Global portfolios, Developed Markets portfolios, and Global portfolios excluding North America (all both OLS and GLS). The magnitude of the improvement on the CSR R^2 by the partial-segmentation model with the Carhart model becomes somewhat smaller on the 5×5 Size/Momentum plus 10 industry portfolios. But six of the eight experiments show statistically significant differences at the 10% levels. We see the rejections of the purely-global model on all global experiments, more precisely, on the Global portfolios (OLS and GLS), Developed Market portfolios (GLS), Global portfolios excluding North America (OLS and GLS), and Developed Markets portfolios excluding North America (OLS). Clearly, augmenting test assets with industry portfolios does not impede the significantly improved performance of the partial-segmentation model.

Another point is worth emphasizing. The partial-segmentation model also helps to better capture the time-series variation of the returns for the tests with expanded test assets. Panel B exhibits the key diagnostics. In the regressions to explain returns on the 5×5 Size/Momentum plus 10 industry portfolios with the Carhart four-factor model, for instance, the average absolute intercept declines from 0.29% for the purely-global version to 0.17% for the partial segmentation version on the Global portfolios. Consider another example in which we assess the Fama-French three-factor model on the 5×5 Size/B/M plus 10 industry portfolios. Here, the GRS test rejects the purely-global model in three out of the four global experiments at the 99% level. In contrast, accompanied with similar or even tighter time-series regression R^2, the partial-segmentation model passes the GRS test in three out of the four global experiments at the same confidence level.

We make the asset-pricing tests even more challenging by exclusively using a set of industry portfolios as the test assets; namely, we build 33 industry portfolios based on the Level 4 FTSE/Dow Jones Industry Classification Benchmark for each region. In unreported tests, we see in many cases that the partial-segmentation model dominates the global model, such as in the tests of the Global portfolios (OLS), Developed Markets portfolios (GLS and OLS), and Global portfolios excluding North America (OLS).

D. Over-identification Tests

Thus far, we have considered model comparisons between the purely-global and the partial-segmentation models in the global experiments. The dominance of the partial-segmentation model over the global model is robust to different model specifications and to different test asset portfolios employed in the test. Before moving on to a second set of model comparisons in the regional experiments, we investigate where the improvement comes from by the partial-segmentation model by introducing a sequence of what we call "over-identification" tests.[16]

We start exploring the underpinning of the success by means of a new round of experiments based on global test-asset portfolios that include *just* globally accessible stocks. Theoretically, our model of partial segmentation should reveal that the local spread factor portfolios might not be needed to span test assets that comprise only globally accessible stocks. Intuitively, we expect many asset managers with global investment mandates would impose the very kind of accessibility (and viability) constraints to limit their investment universe. We therefore conduct the nested model comparison test of the purely-global model versus the partial-segmentation model again for just globally accessible test

[16] We are grateful to both John Griffin and Magnus Dahlquist who independently suggested these additional tests to us.

assets in each of the global mandates. If our identification approach is reasonable, we predict the purely-global model is less likely to be rejected in favor of the partial-segmentation version.

Results in Table 5 show that there are indeed fewer rejections of the purely-global model now. In Panel A of Table 5, we provide the OLS and GLS comparisons on the left and right sides, respectively. The differences in the CSR R^2s (OLS and GLS) are smaller between the partial-segmentation model and the purely-global model. Recall from Table 3, for example, that the partial-segmentation model increases by 21% for the GLS CSR R^2 over the purely-global model in the test of Global portfolios excluding North America portfolios (5×5 Size/B/M plus 10 industry portfolios). Restricting test assets to globally accessible stocks limits the incremental contribution by the partial-segmentation model producing only a 9% difference in GLS CSR R^2. Even for those that appear to be large CSR R^2 differences in Table 5, few give rise to statistical rejection due to limited precision of the estimates. Consider the test on 5×5 Size/Momentum plus 10 industry portfolios as an example, despite a 28% increase in OLS CSR R^2 in favor of the partial-segmentation model over the purely-global version for the Global portfolios excluding North America, the *p*-value for that difference is 0.13. Consistent with our conjecture, the overall rejection rate across the four experiments averages only 12.5% with OLS estimation and somewhat higher at 37.5% with GLS estimation. Recall the rejection rate reported in Table 3 averages 75% when the test assets include both globally-accessible and locally-accessible stocks from the specific global region for which the test is performed.

The partial-segmentation model neither helps to increase the average time-series R^2 relative to the purely-global version nor lowers the GRS *F*-statistics, the average absolute intercepts, and their associated Sharpe ratios. Panel B offers the test diagnostics. For example, the GRS statistics are 3.69 for the global version of the Carhart four-factor model and 3.25 for the partial-segmentation version, using 5×5 Size/Momentum plus 10 industry portfolios as test assets on Developed Markets excluding North America. Both of the GRS statistics lie well in the right tail of the relevant *F*-distribution. The average absolute intercepts are 0.23% and 0.25%, respectively. There is less reliable evidence in support of the partial-segmentation model over the purely-global model if test assets consist of just globally accessible stocks.

In a second over-identification test, we drop microcap stocks and restrict test asset portfolios to 4×5 size/B/M (or size/momentum) plus 10 industry portfolios. The logic is that global institutions prefer to invest in large stocks, all else being equal.[17] This is a more stringent test than the one above. We predict that the explanatory power of the local spread factor portfolio in the partial-segmentation model will become much less important yet again. In unreported tests, we uncover supportive evidence. The rejections are much weaker and less prevalent in the experiments: the global model is dominated (OLS and GLS) at the 10% level in only one test, in which the Fama-French three-factor model is asked to explain the Global portfolios of 4×5 Size/B/M plus 10 industry portfolios.

A third way to define test assets as more accessible for global investors is to focus on the most recent ten years for our experiments shown in Table 5 because it is the period when equity markets have increasingly become more integrated around the world (Bekaert, Harvey, Lundblad, and Siegel, 2011; Carrieri, Chaieb, and Errunza, 2013). Theory predicts that the partial-segmentation model should be more vulnerable with test assets that are associated with lower degrees of segmentation. We uncover no rejections of the purely-global model in this new experiment, regardless of what estimation method is employed and regardless of which test assets are considered.

Although the local spread factors in our global experiments mix assets from five different regions together with the global factors, they fare well in those tests. But, it is possible that, when it comes to explaining the cross-section of average returns of the assets of a specific region, the region-specific local spread factors may fail in capturing the "super local risk premium". To investigate this possibility, we transition to tests that evaluate partial-segmentation versions of multi-factor models

[17] Institutional investor preferences for large-cap stocks have been documented both in the U.S. and in developed and emerging markets around the world (Falkenstein, 1996; Gompers and Metrick, 2001; Dahlquist and Robertsson, 2001; and, Ferreira and Matos, 2008).

relative to purely-local versions in order to explain the returns on test asset portfolios for each of the five basic regions of our study.

V. Asset Pricing Tests for Regional Test Assets

Does a partial-segmentation model fare poorly relative to a local model for a given set of regional test assets? This is an important question that we pursue in this section. Recall our earlier discussion about how Griffin (2002) demonstrated that the success of a global variant of the three-factor model of Fama and French (1993, 1998) arose from the local, country-specific components of the respective global factors. Fama and French (2012) confirmed that purely-global multi-factor models perform poorly when asked to explain the cross-section of average returns on equivalent regional (for North America, Europe, Japan, Asia-Pacific) test asset portfolios. It is important to determine whether the superior performance of the partial-segmentation model relative to the purely-global version for global test asset experiments observed in the previous section is offset by inferior performance of the partial-segmentation model relative to a purely-local version for regional test asset experiments. We show that this is not the case.

A. Model Comparison Tests for Regional Portfolios

The key findings are in Table 6 and can be summarized as follows. KRS (2013) tests and associated test diagnostics are presented for the Fama-French model using 5×5 size/B/M plus 10 industry portfolios as test assets constructed for each region (left side of table) and for the Carhart model on 5×5 size/momentum plus 10 industry portfolios (right side of table). Indeed, it is the partial-segmentation model, rather than the purely local factor model, that is more likely to produce superior performance for almost all the cross-sectional regressions in the regional mandates. Taking the GLS estimates of the Carhart model as an example, we see the CSR R^2 increases by 3% for the partial-segmentation over the purely-local model in North America, 23% in Europe, 11% in Asia Pacific, 5% in Japan, and 17% in Emerging Markets. It is interesting to note that, although the CSR R^2 differences

(OLS and GLS) in favor of the partial-segmentation model exceed 10 percentage points for half of the tests, there is only one statistically-reliable rejection of the purely-local model in favor of the partial-segmentation version at the 1% level. This arises in the OLS CSR R^2 comparison when asked to explain returns of the 5×5 European size/momentum plus 10 industry portfolios using the Carhart four-factor model. Basically, these two models perform very similarly across all regions and both GLS and OLS cross-sectional regressions (including the estimates of the zero-beta rate, the risk premia and prices of covariance risk in Panel B).

In the GRS test and other model diagnostics in Panel C, the partial-segmentation model and the purely local factor model reveal very similar statistics across regions. In North America and Japan, the local model has relatively lower GRS statistics and smaller average absolute intercepts. In unreported supplementary tests, we discovered that the relatively poor performance of the partial-segmentation model in North America is due to the first five years of our sample, 1991-1995. Given the somewhat slower pace of globalization during the earlier period, not only stocks from Europe were less correlated with stocks from North America, but also the correlation between Japanese stock markets and America stock markets was as low as just 15%. The problem for the partial-segmentation model appears to be the greater representation of large-cap stocks from four regions outside North America in the globally-accessible sample, which adversely affects the performance of both the global market factor and the local market factor in the partial-segmentation model. When the first five years are excluded, the partial-segmentation model works at least as well as the purely local factor model in the North America experiments: the GRS statistic was 1.94 for 5×5 size/B/M portfolios plus 10 industry portfolios, and 1.70 for 5×5 size/momentum portfolios plus 10 industry portfolios.[18]

From the theoretical point of view, we propose that, as in Errunza and Losq (1985) and Eun and Janakiramanan (1986), it is the extent to which stocks are inaccessible for global investors that

[18] Another solution we investigated for the North American experiment was to construct *three* sets of factors in the partial-segmentation model: (i) globally-accessible stocks from outside the U.S. only; (ii) globally-accessible stocks from the U.S. only; and,(iii) the locally-accessible stocks from U.S. This approach helped to recover some of the weak performance in the early part of the sample and overall.

yields a super local risk premium and that therefore gives rise to the partial-segmentation structure of our multi-factor models. As stocks become increasingly more globally accessible during the period of analysis (as shown in Figure 2, by our definition), the unconditional form of the partial-segmentation model should become less appropriate for describing the cross-section of average returns of test assets. Unsurprisingly, for the Emerging Markets region in which the global integration process has been relatively slower, the pricing errors and model rejection rates for the partial-segmentation model are lower. When test assets include 5×5 size/B/M portfolios and 10 industry portfolios, the average time-series R^2 are close (61%), but the GRS F-statistic is lower (1.66 rather than 1.79) as is the average absolute model intercepts (0.37% rather than 0.45%). We see similar improvements on the diagnostics by the partial-segmentation model when other test assets and model specifications are considered (unreported, but available). Recall from previous tables how the partial-segmentation model actually fares reasonably well for the global test asset portfolios when stocks from North America are excluded. We interpret this evidence as further the empirical verification for the underlying theory prediction.[19]

B. The Need to Disaggregate Europe and the Emerging Markets

There is considerable heterogeneity among countries that constitute Europe, which means that a "local" model for the entire region may not be a fair benchmark against which to demonstrate the superior performance for our partial-segmentation model. A logical question is then whether our partial-segmentation model can improve upon a purely-local model redefined in Europe separately only among the original 11 members of the Euro bloc and only among those that remained outside the new currency bloc. Panel A of Table 7 provides evidence using the Carhart four-factor model on 5×5 size/momentum plus 10 industry portfolios that distinguishes between the original Eurozone members and separately before and after January 1999 when the new currency was launched.

[19]Another supporting example can be found by employing the KRS (2013) model comparison tests on the global model and the partial-segmentation model in the five regions. Unreported results show that, with OLS estimates, there are two regions, Europe and Emerging Markets, in which the partial-segmentation model outperforms the global model at the 1% level. With GLS estimates, it is still these two regions where the partial-segmentation model dominates the global model at the 10% level.

We confirm the superior performance of the partial-segmentation model for the whole sample period and especially after January 1999 for the original Eurozone members. The increases in CSR R^2 of the partial-segmentation model over the purely-local model are large (24% for the OLS estimates and significant at the 5% level) for the countries in the Euro bloc. Interestingly, among the Euro bloc countries, the sample GLS cross-section R^2 difference for the partial-segmentation model against the local model experience increase substantially after January 1999, giving rise to the rejection of the local model. Diagnostics show how the GRS F-statistic decreases from 1.67 for the purely-local model to 1.10 for the partial-segmentation model, and the Sharpe ratio for the intercept goes down from 0.80 to 0.70. The increases in CSR R^2 are positive, but smaller in magnitude among non-Eurozone countries and they are never statistically different from zero.

The performance of the local model in a region examines the extent of equity markets across countries have been integrated within the given region; the partial-segmentation model, on the other hand, focuses on the extent of equity markets of the given region has been integrated with other countries outside the region. The results reported in Panel A of Table 7 demonstrate that global integration, especially integration between Euro bloc and other non-Euro countries, may have been facilitated by the introduction of a common currency among a subset of its members (see evidence in Hardouvelis, Malliaropulos, and Priestley, 2006; Bekaert, Harvey, Lundblad, and Siegel, 2013).[20]

A similar argument about the heterogeneity of countries can be made in the Emerging Markets. We therefore work to pin down the model comparison more rigorously by decomposing the Emerging Markets into three sub-areas: EEMEA, Latin America, and Southeast Asia. The partial-segmentation model exhibits higher CSR R^2 than the respective purely-local version of the Carhart four-factor model in each of the three sub-areas. But, as shown in Panel B of Table 7, in the comparisons between the

[20] A related argument about the heterogeneity of countries can also be made in Europe in which the membership in the EU has lowered discount rate across countries (see evidence in Bekaert, Harvey, Lundblad, and Siegel, 2013). We run another set of experiment to see whether our partial-segmentation model can improve upon a local model redefined in Europe separately only among the EU members and only among those non-EU members. Results show that the partial-segmentation model dominates the local model in KRS (2013) tests but only among the EU members. These are presented in the bottom half of Panel A of Table 7.

purely-local model and the partial-segmentation model by sub-area, the differences in CSR R^2 are never statistically reliably different from zero. On the other hand, there is a notable decrease in the average absolute intercepts in the EEMEA region (from 0.86 for the purely-local model to 0.73 for the partial-segmentation model). In the test on Latin America, the partial-segmentation model furnishes lower GRS statistics, but negligible differences in absolute average intercepts. The model comparison tests for Southeast Asia yield almost equivalent results. The partial-segmentation version of the multi-factor models is never dominated by local versions of those models even for the sub-regions among Emerging Markets.

Empirically, our interest in this section is to better understand the implication of the financial integration around the world and link it to the sources of the gains in model performance for the partial-segmentation model over the purely-local model. To this end, we repeat the model comparison analysis by trimming off the earlier years of the sample period. Focusing the analysis on the more recent sub-period of the 2000s provide additional evidence in favor of the partial-segmentation over the purely-local models. There are a few statistical rejections of the local model in the tests on developed markets, such as Europe and Asia Pacific, and emerging markets, for instance, EEMEA and Latin America. For example, the increase in the GLS CSR R^2 for the partial-segmentation model has a *p*-value of 0.07 for Asia Pacific for the decade of the 2000s on the test of 5×5 Size/Momentum portfolios plus 10 industry portfolios and the Carhart four-factor model. Another rejection of the local model is that the increase in the OLS CSR R^2 has a *p*-value of 0.09 for EEMEA since the 1999 on the test of 5×5 Size/B/M portfolios plus 10 industry portfolios by the Fama-French three-factor model. For Latin America, the partial-segmentation model reveals superior explanatory power from 1999 onward.

C. Using Individual Securities Instead of Test Asset Portfolios

As Kan (1998) and Ang, Liu, and Schwarz (2010) point out, asset pricing models should hold for all assets, whether these assets are individual stocks or whether the assets are portfolios. Forming portfolios dramatically reduces the standard errors of factor loadings due to decreasing idiosyncratic risk, but Ang, Liu, and Schwarz (2010) show that more precise estimates of factor loadings do not lead to more efficient estimates of factor risk premia. We do not necessarily seek more efficient estimates of factor risk premia in our partial-segmentation model, but using individual stocks may be a useful way to judge the relative explanatory powers of the local and partial-segmentation models for their returns.

Each month, beginning with November 1990, individual security regressions are estimated over 182 rolling 60-month periods. We confirm in unreported tests that in all regions the partial segmentation version of the Fama-French three-factor models achieves statistically significant and large increases in the average time-series adjusted R^2. The median incremental adjusted R^2s across time is 14.9%, 7.3%, 8.7%, 1.8%, and 24.4% in North America, Europe, Asia Pacific, Japan, and Emerging Markets, respectively. To further gauge the sources of these increases in explanatory power, we decompose our partial-segmentation model in order to evaluate separately the incremental R^2 from adding the global factors to the local spread factors. The global factors in the partial-segmentation model alone increase the median adjusted R^2 by 7.9%, 9.0%, 8.8%, 11.2%, and 6.8% in North America, Europe, Asia Pacific, Japan, and Emerging Markets, respectively. Proportionally, these are large increases relative to the base adjusted R^2 of the purely-local Fama-French three-factor model. But the local spread factors increase the median adjusted R^2 by 2.7%, 5.6%, 7.2%, 24.7%, and 5.8% in North America, Europe, Asia Pacific, Japan, and Emerging Markets, respectively, accounting for a large fraction of the overall variance explained by the partial-segmentation model for the respective region.

Results on the individual stocks experiments show that both the global factors and the local spread factors are important and complement to each other in the partial-segmentation model.

VI. Robustness Checks and a Placebo Test

In this section, we test the reliability of the partial-segmentation model by carrying out a series of robustness checks and one placebo test on our identification strategy for global accessibility.

A. Evaluating Alternative Definitions of Global Accessibility

We first check the partial segmentation versions of the Fama-French three-factor model using other definitions of the globally-accessible sample by varying our viability constraints on the extent of cross-listed trading in the target market. A second round of robustness checks examines whether the inclusion of the Frankfurt Stock Exchange and non-Nasdaq OTC market – especially its unusually large number of unsponsored secondary foreign listings, respectively, in their unregulated and OTCQX International segments - among target exchanges for the globally-accessible sample changes the results.

Table 8 summarizes regressions to explain excess returns on 5×5 size/B/M plus 10 industry portfolios when the Main CL Tier is replaced by three alternative sets of the globally-accessible stocks.[21] First, we disregard the viability constraints completely and start with the largest globally accessible sample of stocks, what we call the CL 1st Tier. The partial-segmentation versions of the Fama-French model still dominate the purely-global model when asked to explain test asset portfolios in all four global experiments (Panel A of Table 8). The differences in CSR R^2 for both OLS and GLS estimates are reliably different from zero in three of the experiments (Developed Only excluding North America is the exception). Taking the Developed Markets only portfolios as an example, the CSR R^2 is 0.61 for the OLS estimation and 0.25 for the GLS estimation, which gives rise to statistical rejections of the purely-global model at the 10% and 5% levels, respectively. The diagnostics in Panel B of the table show some concerning patterns: the GRS statistic of 2.34 in this experiment is over 2.05, the 99th percentile of the relevant F-distribution. The average absolute intercept increases from 0.15% for the Main CL Tier to 0.20% for the CL 1st Tier.

[21]For the sake of brevity, we focus on the four global experiments. Equivalent results for the regional mandates are not reported but available upon request.

Problems might also arise when we tighten instead of loosen the viability constraints. Consider the globally accessible set defined by what we call the "CL 2nd Tier." Here we change from *relative* viability constraints to an *absolute* viability constraint to define a globally-accessible stock.[22] In the KRS (2013) model comparison tests, the partial-segmentation model does outperform the purely-global model in the Global portfolios and Global excluding North America portfolios at the 5% level. But it is not so in the two other experiments using just Developed Markets. The absolute viability constraint appears to break some consistency in our time-series explanatory returns: we were able to uncover that some companies are identified as locally-accessible stocks when there are no overseas trading records, but as globally-accessible stocks when trading actually occurs in the target markets. Allowing these companies to switch between the two samples at a relatively high frequency alters the profile of the returns of the explanatory factor portfolios.

The last column of Table 8 reports model comparison test results when the "CL 3rd Tier" is used. In this experiment, even more stringent relative viability constraints apply.[23] The globally-accessible sample shrinks down to about 62% of the total market capitalization for the global equity universe. Nevertheless, tests using the tighter constraints perform similarly to the Main CL Tier in the global experiments, both on the KRS (2013) model-comparison tests and other test diagnostics. These findings show how important are the relative viability constraints.

Given the looser secondary cross-listing rules on the Frankfurt Stock Exchange and OTCQX International, we repeat the experiments above for the case where these two markets are excluded from the list of target exchanges. In unreported tests, we find the partial-segmentation model always achieves the highest CSR R^2, with or without microcaps, in all of the global and regional experiments. Especially when the new globally-accessible sample is screened by our relative viability constraints,

[22] Our *relative* viability constraint requires (i) at least 0.1% of global trading volume to occur in all target markets relative to the home market for a globally-accessible stock or (ii) at least 0.5% of total trading value in target markets relative to all secondarily cross-listed stocks from the same country trading to be concentrated in a globally-accessible stock. Our *absolute* viability constraint requires at least one month in a given trailing year to have non-zero trading volume in a target cross-listing market.

[23] above 1% of own-stock global trading volume in target markets or above 5% of all secondary cross-listing trading by country.

the partial-segmentation model performs much better than the purely global factor model for the global test asset portfolios, and it works as well as the purely local factor model for most of the regional test asset portfolios, either in the GRS test or the regression power (captured by higher time-series R^2 and lower average absolute intercepts). The rejection of the GRS test in North American is again due to the relatively the early years of the sample. In the case of the Main CL Tier as the globally accessible set, without microcaps, adding the first five years observations produces a high GRS statistic, 2.69, which rejects at the 99% level. But, if we only focus on the period of 1995-2010, the GRS statistics decline to 1.58, which we could not reject even at the 95% level.

B. A Placebo Test: Is Global Accessibility Just a Proxy for Size or Liquidity?

The investigation so far suggests that the partial-segmentation model based on our definition of global accessibility is a reliable choice in improving the description of average returns of global test assets. A logical question is then whether secondary listings on major target markets are really nothing more than just a manifestation of larger firm size or greater stock liquidity?

One way to address this concern is to redo our tests but only use a size threshold in the definition of accessibility. Consider one in which any stocks in the top 75% of market capitalization for the regional market in which they are domiciled is deemed globally accessible. The partial-segmentation model using this simpler identification approach fares relatively poorly. KRS (2013) model comparison test results in Table 9 for the Fama-French model and 5×5 Size/B/M plus 10 industry portfolios show that there are fewer rejections of the purely-global model in favor of the partial-segmentation version now. In many cases, we cannot statistically distinguish the partial-segmentation model from the benchmark purely global factor model with respect to the CSR R^2. The large OLS CSR R^2 differences for the test on Developed Markets portfolios excluding North America of 17% are not associated with a statistical rejection at conventional criteria. As another example, note that the GLS

CSR R^2 differences for the new partial-segmentation model miss being statistically significant on almost all global tests except the Global portfolios excluding North America.

Negligible improvements arise also for the GRS *F* statistic and other diagnostic criteria in Panel B. We cannot reject the partial-segmentation model in the test of Global portfolios without North America, but, as long as North America is added, the model produces no improvements upon the purely global factor model in the GRS statistic. For instance, when the test asset portfolios are for Developed Markets, the GRS statistic is 3.00 considerably higher than the 2.05 for the Main CL Tier. In addition, higher average absolute intercepts (0.22% compared to 0.15% for the Main CL Tier) also occur. For the Global test asset portfolios, the new partial-segmentation model using just size produces a larger average intercept of 0.20% compared to only 0.11% with the Main CL Tier. In the regional mandates (unreported but available), compared with the purely-local model, the new partial-segmentation model using size to define global accessibility produces a marginal improvement in the CSR R^2, but it fares poorly in the GRS tests especially for the North America and Europe tests.

Studies have found that liquidity interacts significantly with value and momentum, so our definition of global accessibility may simply be just picking this up. To examine the role of liquidity in our accessibility definition, we run a second placebo test constructing a second globally accessible sample by grouping all stocks over U.S. $5 and equivalent levels in terms of percentile ranks for non-U.S. markets into the set. We also follow Lesmond, Ogden, and Trzcinka (1999), Lesmond (2005), and Bekaert, Harvey and Lundblad (2007) to construct the proportion of zero daily returns over the relevant months (ZR) for each market; the globally accessible stocks are redefined to be those in the bottom 75 percentile of ZR for each country each year. Using the new globally accessible set based on liquidity, we show in Table 9 there is even weaker evidence against the purely-global model in favor of the partial-segmentation version. Among the OLS estimates for the global experiments, we see only one rejection in favor of the new partial-segmentation model for the Global portfolios. Among the GLS estimates, there are no rejections at the 10% level. The new partial-segmentation model never outperforms the purely-global model, and the CSR R^2 differences decline to at most 9% for all the four global tests. Liquidity appears to be an inferior identification approach for global accessibility than our main approach based on secondary cross-listings on major target markets around the world.

One robustness check we conduct evaluates how robust our partial-segmentation model is to the size, liquidity and float screens that we apply for the domestic stocks in the seven target markets to qualify them as globally-accessible. After all, those stocks that are secondarily cross-listed in a target market may simply be those that meet those screens in their respective markets and so the extra criterion of cross-listing may be redundant. In this additional test, we redefine the globally-accessible set of stocks around the world to be those that meet the same size, liquidity and float screens as for the stocks in the target markets. The new globally-accessible sample, when compared with the Main CL Tier, has smaller counts but similar market capitalizations across five regions. We find that the partial-segmentation model built from this new sample, unlike that constructed from the Main CL Tier, produces smaller improvement relative to the purely-global model for the global test asset portfolios (in unreported tests). Data issues arise for this alternative globally-accessible sample. Less than half of the stocks from markets outside the seven target exchanges have float records in Datastream, and they are automatically dropped out.[24] Identifying those stocks that are secondarily cross-listed on one of the target markets likely furnishes a more complete assessment of the global accessibility of stocks.

We conduct one final placebo test in Table 9.[25] There is another concern that much of the success of our partial-segmentation model is a mechanical one in that an additional three (or four, in the case of a Carhart model) factors are built over and above the base three (or four) factors in the

[24] The distribution of free floats varies substantially across countries outside the seven target markets. If using a universal float screening, there will be few or even no stocks selected for many countries as the globally accessible stocks. Therefore, the median float (75% for U.S. and equivalent levels for other markets) is applied in this case.

[25] In fact we conduct another placebo test (unreported but available) in which we create randomized assignments of globally- and locally accessible stocks. In this setting, the new partial-segmentation model neither improves upon the purely-global model nor works comparably with the purely-local model. The sequence of randomization includes sorting stocks by their Datastream (DS) codes using the last four digits of their respective codes.

purely-global and purely-local models. Most test statistics (such as, GRS and CSR R^2) for our model comparisons account for this fact in terms of different degrees of freedom, but they may still be inadequate in finite samples. To take on this challenge, we compare our partial-segmentation model against a competing partial-segmentation model in which local factors are constructed not based on fundamental factors such as size, B/M, C/P, or momentum, but using principal component analysis (PCA). These factors are purely statistical and are designed to maximally capture the common variation among the stocks. We first orthogonalize all the test asset stock returns for the specific region for which the test is performed relative to the global factors. We next identify up to three principal components of the residuals and build local factor portfolios from the extracted principal components using portfolio weights given by the scaled eigenvectors.

The final three columns on the right side of Table 9 show KRS (2013) model comparison test results for the PCA-based alternative model. Our findings suggest that it is very hard, using the PCA local factors in addition to the global factors, to explain the common variation in returns. When the global portfolios include stocks from North America, the CSR R^2 differences are not reliably different from zero (both OLS and GLS). When North America is excluded, we see two rejections on the GLS comparison test. But the rejections are weak as shown in Panel B with higher GRS statistics, larger average absolute intercepts, and higher Sharpe ratios. For example, the GRS statistic is 1.92 for the PCA-based alternative partial-segmentation model for the Global portfolios excluding North America relative to 1.53 for the Main CL Tier definition of accessibility, which can be rejected at the 95% level.

VII. Conclusions

Using monthly returns for over 37,000 stocks from 46 developed and emerging market countries over a two-decade period, we propose and test a new multi-factor model that includes factor portfolios based on firm characteristics like size, value, and momentum but that builds them separately as "global" factors comprised of all stocks around the world and as "local" factors comprised of locally-accessible stocks for a given country or region. Our new partial-segmentation model not only captures strong common variation in global stock returns, but also achieves low pricing errors and rejection rates relative to purely global and purely local models using conventional procedures.

A critical ingredient of our analysis is how we categorize the equity universe into two subsets - the globally-accessible sample and locally-accessible sample of stocks – based on constraints as defined by whether or not the stock has shares actively traded in the markets fully open to global investors. To capture the impact of accessibility constraints on the size, value, and momentum patterns in international stock returns, we then build *separate* factor portfolios – global factors comprised of any stock from the global equity universe, and local factors are built as tradable, spread portfolios with long positions in the locally-accessible stocks for a given region and short positions in globally-accessible stocks – and propose a new "partial segmentation" multifactor model. In a series of robustness checks and one placebo test, we find that alternative identification approaches for accessibility based on just size, liquidity, or float considerations do not perform as well.

We interpret our findings in this study as a step forward in the international asset pricing literature with important implications for practitioners in guiding cost-of-capital calculations and risk control and performance evaluation analysis of global portfolios. Of course, we acknowledge several limitations in the scope of our work as well as in the implementation. There may be alternative ways in which stocks become globally accessible beyond secondarily cross-listing on overseas exchanges that we have not considered. Including other mechanisms for global investor accessibility, such as being included in one of MSCI or S&P global indexes (especially, in their investable indices in emerging markets), emerging market ETFs and closed-end country funds, would be valuable to explore how the returns of global factor portfolios have changed over time. We also cannot disregard the fact that simply being accessible does not necessarily mean global investors will actually pursue these opportunities. Although this fact is taken into consideration to a certain extent by imposing additional viability restrictions on how actively the cross-listed shares are traded in our experiments, a more comprehensive picture of institutional trading around the world would reveal the varying preferences and constraints face by different groups of institutional investors. One could also hope for a more reliable proxy for the measure of viability than the relative (and absolute) criteria in this study.

There are also other possible avenues for future work. We can study the effect of exchange rate risks on the relative performance of global factors and local factors in the new "partial segmentation" model. All of our returns are U.S. dollar denominated at prevailing exchange rates. Because what constitutes globally-accessible stocks and locally-accessible stocks vary for investors by country of domicile, the need to hedge exchange rates varies and exchange rate risks are expected to play different roles in the risk prices of global factors and local factors. Exchange rate risk is certainly a potential problem in global asset pricing. A key contribution of Solnik's (1974) influential international asset pricing model is that currency risk can be priced and there is also growing evidence that the magnitude of currency-risk exposures can be quite large (Dumas and Solnik, 1995; De Santis and Gerard, 1997, 1998; Griffin and Stulz, 2001). Second, we can push the new "partial segmentation" structure to incorporate cross-sectional variation in real estate, commodities and bonds, which comprise a significant portion of global investment activity. Third, we can extend our *unconditional* testing framework for the partial-segmentation model to a *conditional* one allowing for time variation in expected returns, variances and covariances, a potentially important factor for the transitioning emerging markets (Bekaert and Harvey, 1995; Bekaert, Harvey, Lundblad, and Siegel, 2011) for which our partial-segmentation model performs especially well.

References

Adler, M., and B. Dumas, 1983, International Portfolio Choice and Corporation Finance: a Synthesis, *Journal of Finance,* 38, 925-984.

Ang, A., J. Liu, and K. Schwarz, 2010, Using Stocks or Portfolios in Tests of Factor Models, Working paper, Columbia University.

Asness, C.S., T. J. Moskowitz, and L. H. Pedersen, 2013, Value and Momentum Everywhere, *Journal of Finance,* 68, 929-985.

Asparouhova, E., H. Bessembinder, and I. Kalcheva, 2010, Liquidity Biases in Asset Pricing Tests, *Journal of Financial Economics*, 96, 215-237.

Asparouhova, E., H. Bessembinder, and I. Kalcheva, 2012, Noisy Prices and Inference Regarding Returns, forthcoming in *Journal of Finance*.

Baruch, S., G. A. Karolyi, and M. L. Lemmon, 2007, Multimarket Trading and Liquidity: Theory and Evidence, *Journal of Finance*, 62, 2169-2201.

Bekaert, G., and C. Harvey, 1995, Time-varying World Market Integration, *Journal of Finance*, 50, 403-444.

Bekaert, G., C. R. Harvey, and R. L. Lumsdaine, 2002, Dating the Integration of World Equity Markets, *Journal of Financial Economics*, 65, 203-248.

Bekaert, G., C. R. Harvey, and C.T. Lundblad, 2007, Liquidity and Expected Returns: Lessons From Emerging Markets, *Review of Financial Studies*, 20, 1783-1831.

Bekaert, G., C. R. Harvey, C.T. Lundblad, and S. Siegel, 2011, What Segments Equity Markets? *Review of Financial Studies*, 24, 3841-3890.

Bekaert, G., C. R. Harvey, C.T. Lundblad, and S. Siegel, 2013, The European Union, the Euro, and Equity Market Integration, *Journal of Financial Economics*, 109, 583-603.

Bekaert, G., R. J. Hodrick, and Xiaoyan Zhang, 2009, International Stock Return Comovements, *Journal of Finance*, 64, 2591-2626.

Bekaert, G., and M. S. Urias, 1996, Diversification, Integration and Emerging Market Closed-End Funds, *Journal of Finance,* 51, 835-869.

Black, F., 1974, International Capital Market Equilibrium with Investment Barriers, *Journal of Financial Econometrics,* 1, 337-352.

Blume, M. E., and R. F. Stambaugh, 1983, Biases in Computed Returns: an Application to the Size Effect, *Journal of Financial Economics*, 12, 387-404.

Bodnar, G., and B. Dumas, 2003, Cross-Border Valuation: the International Cost of Equity Capital, Working paper, INSEAD.

Bodurtha, J., 1994, International Factors and U.S. Equity Excess Returns, Working paper, Georgetown University.

Bodurtha, J., 1999, International Investment Restrictions and Factor Pricing, Working paper, Georgetown University.

Carhart, M. M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance*, 52, 57-82.

Carrieri, F., I. Chaieb, and V. Errunza, 2008, On the Pricing of Investable Securities and the Role of Implicit Barriers, Working paper, McGill University.

Carrieri, F., I. Chaieb, and V. Errunza, 2013, Do Implicit Barriers Matter for Globalization? Working paper, Swiss Finance Institute Research Paper No. 10-55, forthcoming *Review of Financial Studies*.

Carrieri, F., Errunza, V., and K. Hogan, 2007, Characterizing World Market Integration Through Time, *Journal of Financial and Quantitative Analysis*, 42, 915-940.

Chaieb, I., and V. Errunza, 2007, International Asset Pricing Under Segmentation and PPP Deviations, *Journal of Financial Economics*, 86, 543-578.

Dahlquist, Magnus, and Göran Robertsson, 2001, Direct Foreign Ownership, Institutional Investors, and Firm Characteristics, *Journal of Financial Economics*, 59, 413-440.

De Jong, F., and F. A. de Roon, 2005, Time-varying Market Integration and Expected Returns in Emerging Markets, *Journal of Financial Economics*, 78, 583-613.

De Santis, G., and B. Gerard, 1997, International Asset Pricing and Portfolio Diversification with Time-Varying Risk, *Journal of Finance*, 52, 1881-1912.

De Santis, G., and B. Gerard, 1998, How Big Is the Premium For Currency Risk? *Journal of Financial Economics*, 49, 375-412.

Doidge, C., G. A. Karolyi, and R. M. Stulz, 2004, Why Are Foreign Firms Listed in the U.S. Worth More? *Journal of Financial Economics*, 71, 205-238.

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

Errunza, V., and D. P. Miller, 2000, Market Segmentation and the Cost of Capital in International Equity Markets, *Journal of Financial and Quantitative Analysis*, 35, 577-600.

Errunza, V., and E. Losq, 1985, International Asset Pricing under Mild Segmentation: Theory and Test, *Journal of Finance*, 40, 105-124.

Errunza, V., and H. Ta, 2011, The Impact of Investability on Asset Valuation, Working paper, McGill University.

Errunza, V., K. Hogan, and M.W. Hung, 1999, Can the Gains from International Diversification be Achieved without Trading Abroad? *Journal of Finance*, 54, 2075-2107.

Eun, C. S., and S. Janakiramanan, 1986, A Model of International Asset Pricing with a Constraint on the Foreign Equity Ownership, *Journal of Finance*, 41, 897-914.

Eun, C. S., S. Lai, F. A. de Roon, and Z. Zhang, 2010, International Diversification with Factor Funds, *Management Science,* 56, 1500-1518.

Falkenstein, Eric, 1996, Preferences for Stock Characteristics as Revealed by Mutual Fund Portfolio Holdings, *Journal of Finance*, 51, 111-135.

Fama, E. F., and K. R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics*, 33, 3-56.

Fama, E. F., and K. R. French, 1996, Multifactor Explanations of Asset Pricing Anomalies, *Journal of Finance*, 51, 55-84.

Fama, E. F., and K. R. French, 1998, Value versus Growth: The International Evidence, *Journal of Finance*, 53, 1975-1999.

Fama, E. F., and K. R. French, 2008, Dissecting Anomalies, *Journal of Finance*, 63, 1653-1678.

Fama, E. F., and K. R. French, 2012, Size, Value, and Momentum in International Stock Returns, *Journal of Financial Economics*, 105, 457-472.

Ferreira, M. A., and P. Matos, 2008, The Colors of Investors' Money: The Role of Institutional Investors Around the World? *Journal of Financial Economics,* 88, 499-533.

Foerster, S. R., and G. A. Karolyi., 1993, International Listings of Stocks: The Case of Canada and the U.S., *Journal of International Business Studies*, 24, 763-784.

Foerster, S. R., and G. A. Karolyi., 1999, The Effects of Market Segmentation and Investor Recognition on Asset Prices: Evidence from Foreign Stocks Listing in the U.S., *Journal of Finance*, 54, 981-1013.

Gibbons, M. R., S. A. Ross, and J. Shanken, 1989, A Test of the Efficiency of A Given Portfolio, *Econometrica*, 57, 1121-1152.

Gompers, Paul, and Andrew Metrick, 2001, Institutional Investors and Equity Prices, *The Quarterly Journal of Economics,* 116, 229-259.

Grauer, F. L. A., R. H. Litzenberger, and R. E. Stehle, 1976, Sharing Rules and Equilibrium in an International Capital Market under Uncertainty, *Journal of Financial Economics*, 3, 233-256.

Griffin, J. M., 2002, Are the Fama and French Factors Global or Country Specific? *Review of Financial Studies*, 15, 783-803.

Griffin, J. M., and R. M. Stulz, 2001, International Competition and Exchange Rate Shocks: A Cross-Country Industry Analysis of Stock Returns, *Review of Financial Studies*, 14, 215-241.

Griffin, J. M., S. Ji, and J. S. Martin, 2003, Momentum Investing and Business Cycle Risk: Evidence from Pole to Pole, *Journal of Finance*, 58, 2515-2547.

Hardouvelis, G., D. Malliaropulos, and R. Priestley, 2006, EMU and European Stock Market Integration, *Journal of Business*, 79, 365–392.

Harvey, C. R., 1991, The World Price of Covariance Risk, *Journal of Finance*, 46, 111-157.

Hou, K., G. A. Karolyi., and B. C. Kho, 2011, What Factors Drive Global Stock Returns? *Review of Financial Studies*, 24, 2527-2574.

Huberman, G., and S.A. Kandel, 1987, Mean-Variance Spanning, *Journal of Finance*, 42, 873-888.

Iliev, P., D. P. Miller, and L. Roth, 2011, Uninvited U.S. Investors? Economic Consequences of Involuntary Cross-listings, Working paper, Pennsylvania State University.

Ince, O., and R. B. Porter, 2006, Individual Equity Return Data From Thomson Datastream: Handle with Care! *Journal of Financial Research*, 29, 463-479.

Jegadeesh, N., and S. Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance*, 48, 65-91.

Kan, R., 1998, On the Explanatory Power of Asset Pricing Models Across and Within Portfolios, Working paper, University of Toronto.

Kan, R., C. Robotti, and J. Shanken, 2013, Pricing Model Performance and the Two-Pass Cross-Sectional Regression Methodology, *Journal of Finance*, 68, 2617-49.

Karolyi, G. A., 2012, Corporate Governance, Agency Problems and International Cross-listings: A Defense of the Bonding Hypothesis, *Emerging Markets Review*, 13, 516-547.

Karolyi, G. A., and R. M. Stulz, 2003, Are Assets Priced Locally or Globally? in *The Handbook of the Economics of Finance*, G. Constantinides, M. Harris and R. Stulz (eds.), North Holland, 2003.

Lesmond, D., 2005, Liquidity of Emerging Markets, *Journal of Financial Economics*, 77, 411–452.

Lesmond, D., Ogden, J., Trzcinka, C., 1999, A New Estimate of Transaction Costs, *Review of Financial Studies*, 12, 1113–1141.

Lewellen, J., S. Nagel, and J. Shanken, 2010, A Skeptical Appraisal of Asset Pricing Tests, *Journal of Financial Economics*, 96, 175-194.

Lewis, Karen K., 2011, Global Asset Pricing, *Annual Review of Financial Economics*,3, 435-466.

Pukthuanthong, K., and R. Roll, 2009, Global Market Integration: A Better Way to Measure it and its Application, *Journal of Financial Economics*, 94, 214-232.

Rouwenhorst, K. G., 1998, International Momentum Strategies, *Journal of Finance*, 53, 267-284.

Sercu, P., 1980, A Generalization of the International Asset Pricing Model, *Revue de l' Association Française de Finance*, 1, 91-135.

Solnik, B., 1974, An Equilibrium Model of the International Capital Market, *Journal of Economic Theory*, 8, 500-524.

Solnik, B., 1977, Testing International Asset Pricing: Some Pessimistic Views, *Journal of Finance*, 32, 503-12.

Stehle, R., 1977, An Empirical Test of the Alternative Hypotheses of National and International Pricing of Risky Assets, *Journal of Finance*, 32, 493-502.

Stulz, R. M., 1981a, On the Effects of Barriers to International Investment, *Journal of Finance*, 36, 923-934.

Stulz, R. M., 1981b, A Model of International Asset Pricing, *Journal of Financial Economics*, 9, 383-406.

Table 1. Summary Statistics for Factor Portfolio Returns, November 1990 – December 2010.

Attribute	Equity Universe					Local Spread				
	Market	Size	B/M	Mom	C/P	Market	Size	B/M	Mom	C/P
<u>Panel A Return Distributions of Factor Portfolios in the Global Experiments</u>										
Global										
Mean	0.46	0.11	0.49	0.52	0.58	-0.24	-0.19	0.40	-0.04	0.44
Std Dev	4.47	2.38	2.53	4.37	2.60	1.78	2.28	2.04	2.44	2.11
t-Mean	1.59	0.74	3.02	1.84	3.46	-2.12	-1.28	3.06	-0.25	3.22
Developed Markets Only										
Mean	0.47	0.07	0.47	0.39	0.52	-0.23	-0.25	0.38	-0.22	0.42
Std Dev	4.46	2.30	2.54	4.73	2.68	1.72	2.21	1.67	1.86	1.86
t-Mean	1.63	0.46	2.86	1.29	3.05	-2.10	-1.78	3.58	-1.85	3.54
Global excl. North America										
Mean	0.33	-0.01	0.61	0.60	0.68	-0.41	-0.29	0.37	0.05	0.42
Std Dev	4.79	2.48	2.54	4.13	2.30	2.76	2.81	2.56	3.73	2.85
t-Mean	1.06	-0.07	3.75	2.26	4.58	-2.31	-1.63	2.26	0.21	2.30
Developed Markets Only excl. North America										
Mean	0.32	-0.09	0.57	0.39	0.57	-0.43	-0.41	0.32	-0.21	0.35
Std Dev	4.85	2.41	2.32	4.27	1.97	2.97	2.73	2.17	3.06	2.34
t-Mean	1.04	-0.58	3.85	1.43	4.53	-2.27	-2.36	2.27	-1.08	2.36
<u>Panel B Return Distributions of Factor Portfolios in the Regional Experiments</u>										
North America										
Mean	0.68	0.36	0.31	0.40	0.46	0.11	-0.02	0.17	-0.18	0.12
Std Dev	4.58	3.63	3.63	5.99	4.31	2.53	2.47	2.04	2.65	2.09
t-Mean	2.32	1.67	1.32	1.03	1.67	0.70	-0.12	1.28	-1.05	0.93
Europe										
Mean	0.58	-0.14	0.64	0.82	0.68	-0.11	-0.54	0.38	0.35	0.47
Std Dev	4.91	2.45	2.62	4.58	2.35	2.68	3.02	2.16	2.90	2.30
t-Mean	1.83	-0.90	3.80	2.79	4.48	-0.61	-2.78	2.72	1.90	3.21
Asia Pacific										
Mean	0.74	-0.07	0.76	1.07	0.77	0.19	-0.59	0.49	0.40	0.40
Std Dev	5.87	3.37	3.14	5.14	2.93	3.85	2.97	3.38	4.48	3.14
t-Mean	1.96	-0.34	3.77	3.24	4.11	0.78	-3.10	2.26	1.40	1.97
Japan										
Mean	-0.04	-0.16	0.51	-0.44	0.39	-0.72	-0.51	0.20	-0.96	-0.08
Std Dev	6.07	3.98	2.67	5.38	2.44	5.24	3.83	2.86	4.95	2.70
t-Mean	-0.10	-0.61	2.95	-1.28	2.47	-2.14	-2.06	1.09	-3.02	-0.45
Emerging Markets										
Mean	0.32	0.32	0.77	1.05	0.88	-0.34	0.16	0.43	0.56	0.72
Std Dev	6.33	3.25	4.03	7.38	4.78	5.30	4.07	4.45	8.67	5.72
t-Mean	0.79	1.52	2.95	2.22	2.88	-1.00	0.60	1.51	1.00	1.97

Table 1, continued.

This table shows the summary statistics for explanatory returns. It includes five regional portfolios for North America, Europe, Japan, Asia Pacific (excluding Japan) and Emerging Markets. Four sets of global portfolios are also reported, including Global portfolios that combine all the five regions, Developed Markets portfolios that combine the first four regions, Global portfolios excluding North America, Developed Markets portfolios excluding North America. For each scenario, it shows the explanatory returns for three samples, the whole sample ("Equity Universe" in the table), and the subset of locally-accessible stocks relative to the globally-accessible stocks ("Local Spread" in the table). Here the Main CL Tier stands for the globally accessible sample.

We form portfolios at the end of June of each year *t* by sorting stocks in a region into two market cap and three book-to-market (B/M) or cash flow-to-price (C/P) groups. For "Equity Universe" in the table, big stocks are those in the top 90% of market cap for the region, and small stocks are those in the bottom 10% (Fama and French, 2012).The B/M or C/P breakpoints for the five regions are the 30^{th} and 70^{th} percentiles of B/M for the big stocks of a region. The global portfolios use global size breaks, but we use the B/M or C/P breakpoints for the five regions to allocate the stocks of these regions to the global portfolios. The independent 2×3 sorts on size and B/M (or C/P) produce six value-weighted portfolios, SG, SN, SV, BG, BN and BV, where S and B indicate small or big and G, N, and V indicate growth, neutral and value. The factor portfolios based on size is the equally-weighted average of the returns on the three small stock portfolios for the region minus the equally-weighted average of the returns on the three big stock portfolios where all the six portfolios are all based on B/M. The factor portfolios based on B/M (or C/P) are calculated as the equally-weighted average of value-growth returns for small and big stocks, SV-SG and BV-BG. The 2×3 sorts on size and lagged momentum are similar, but the size/momentum portfolios are formed monthly. For portfolios formed at the end of month *t*, the lagged momentum return is a stock's cumulative return for *t-11* to *t-1*. The independent 2×3 sorts on size and momentum produce six value-weighted portfolios, SL, SN, SW, BL, BN and BW, where S and B indicate small and big, and L, N, and W indicate losers, neutral, and winners. The factor portfolios based on momentum ("Mom" in the table) is constructed as the equally-weighted average of WML_S=SW-SL and WML_B=BW-BL. For each given region, the return spread factor portfolios of locally-accessible stocks relative to the globally-accessible stocks are the differences in the respective factor portfolio returns for the set of locally-accessible stocks in the region and for the globally-accessible stocks. For example, for the size-related spread factor portfolio, we compute the return difference between the factor portfolio for the locally-accessible stocks (measured, in turn, as the difference between an equally-weighted average of the SG, SN, and SV portfolios and an equally-weighted average of the BG, BN, and BV portfolios) and the globally-accessible stocks (measured similarly). The value- and momentum-related spread factor portfolios are built in the same way. Unlike the whole sample, the B/M or C/P breakpoints for the spread portfolios are the 30^{th} and 70^{th} percentiles of B/M for the big stocks from the globally accessible sample for each given region. The globally accessible sample uses its own size and momentum breakpoints, and the locally-accessible sample uses regional size and momentum breakpoints.

All returns are in U.S. dollars. Market is the return on a value-weighted market portfolio globally or for the region minus the U.S. one month Treasury bill yield. Mean and Std Dev are the mean and standard deviation of the return, and t-Mean is the ratio of Mean to its standard error.

Table 2. Summary Statistics for Regression Tests of the Fama-French Three-Factor Model Using Monthly Excess Returns on 25 Size/B/M Portfolios, With (5×5) and Without (4×5) Microcap Stocks: November 1990 – December 2010.

Panel A: Kan, Robotti, and Shanken (2013) tests

	5×5 Size/B/M				4×5 Size/B/M			
	Global Benchmark	*Partial Segmentation*			*Global Benchmark*	*Partial Segmentation*		
	ρ^2	ρ^2	$\Delta\ \rho^2$	*p-value*	ρ^2	ρ^2	$\Delta\ \rho^2$	*p-value*
i.OLS								
Global	0.73	0.86	0.13	***(0.00)***	0.79	0.93	0.14	*(0.10)*
Developed Only	0.75	0.88	0.13	***(0.00)***	0.80	0.91	0.11	***(0.03)***
Global excl. NA	0.85	0.93	0.08	***(0.02)***	0.81	0.93	0.11	***(0.03)***
Developed only excl.NA	0.81	0.93	0.12	*(0.15)*	0.86	0.96	0.10	***(0.01)***
ii.GLS								
Global	0.21	0.47	0.25	***(0.03)***	0.20	0.65	0.45	***(0.05)***
Developed Only	0.26	0.46	0.20	***(0.03)***	0.24	0.54	0.30	***(0.08)***
Global excl. NA	0.46	0.58	0.12	*(0.38)*	0.51	0.69	0.18	*(0.26)*
Developed only excl.NA	0.30	0.53	0.23	***(0.09)***	0.36	0.67	0.31	***(0.06)***

Panel B: Estimates of Zero-Beta Rate, Risk Premia, and Prices of Covariance Risk using 5×5 Size/B/M portfolios (OLS Case)

	Global Benchmark				*Partial Segmentation*						
i. Risk Premia											
	$\hat{\gamma}_0^G$	$\hat{\gamma}_{vw}^G$	$\hat{\gamma}_{Size}^G$	$\hat{\gamma}_{B/M}^G$	$\hat{\gamma}_0^{PS}$	$\hat{\gamma}_{vw}^G$	$\hat{\gamma}_{Size}^G$	$\hat{\gamma}_{B/M}^G$	$\hat{\gamma}_{vw}^{\bar{A}-A}$	$\hat{\gamma}_{Size}^{\bar{A}-A}$	$\hat{\gamma}_{B/M}^{\bar{A}-A}$
Global	2.32*	-1.89*	0.22	0.53*	0.55	-0.07	0.15	0.54*	-0.07	0.31	0.38
Developed Only	1.98*	-1.51*	0.19	0.36	2.01*	-1.50	0.16	0.44*	-0.11	-0.19	0.82*
Global excl. NA	1.68*	-1.39	-0.06	0.75*	0.40	0.08	-0.13	0.66*	-0.29	0.47	0.02
Developed only excl.NA	1.10*	-0.86	-0.21	0.62*	0.76	-0.12	0.17	0.56*	-0.53	-0.31	0.28
ii. Prices of Covariance Risk											
	$\hat{\lambda}_0^G$	$\hat{\lambda}_{vw}^G$	$\hat{\lambda}_{Size}^G$	$\hat{\lambda}_{B/M}^G$	$\hat{\lambda}_0^{PS}$	$\hat{\lambda}_{vw}^G$	$\hat{\lambda}_{Size}^G$	$\hat{\lambda}_{B/M}^G$	$\hat{\lambda}_{vw}^{\bar{A}-A}$	$\hat{\lambda}_{Size}^{\bar{A}-A}$	$\hat{\lambda}_{B/M}^{\bar{A}-A}$
Global	2.32*	-9.18*	6.92*	5.46	0.55	4.62	10.42	11.94*	-7.02	13.37	14.12
Developed Only	1.98*	-7.48*	5.63	3.35	2.01*	-8.87	0.21	12.60*	3.49	-12.03	32.98*
Global excl. NA	1.68*	-5.79	1.69	9.62	0.40	5.27	7.09	13.79*	-6.13	9.81*	2.02
Developed only excl.NA	1.10*	-3.15	-1.64	8.15	0.76	-0.21	8.63	15.89*	-11.43*	-6.47	11.66

Panel C: Test Diagnostics

	5×5 Size/B/M					4×5 Size/B/M				
	R^2	GRS	$\lvert\alpha\rvert$	H-L α	*SR(α)*	R^2	GRS	$\lvert\alpha\rvert$	H-L α	*SR(α)*
i. Global Benchmark										
Global	0.92	3.12	0.16	1.13	0.62	0.94	1.74	0.11	0.39	0.41
Developed Only	0.89	2.67	0.16	0.77	0.57	0.90	1.62	0.13	0.43	0.39
Global excl. NA	0.83	1.27	0.24	0.80	0.39	0.83	1.24	0.25	0.68	0.34
Developed only excl.NA	0.77	1.58	0.34	0.81	0.44	0.78	1.51	0.35	0.69	0.38
ii. Partial Segmentation										
Global	0.93	2.30	0.10	0.84	0.57	0.95	1.16	0.06	0.37	0.36
Developed Only	0.93	2.06	0.13	0.61	0.54	0.94	1.17	0.10	0.43	0.36
Global excl. NA	0.88	0.84	0.16	1.11	0.34	0.89	0.67	0.15	0.73	0.27
Developed only excl.NA	0.91	1.01	0.14	0.46	0.37	0.92	0.76	0.12	0.24	0.29

Table 2, continued.

The regressions use the global Fama-French three-factor model and the partial segmentation Fama-French model to explain the returns on four sets of global portfolios formed on size and B/M. Here four sets of global portfolios include Global portfolios, Developed Markets portfolios, Global portfolios excluding North America, Developed Markets portfolios excluding North America. The 5×5 results include microcap portfolios, the 4×5 results exclude microcap portfolios. R^2 is the average time-series adjusted R^2; the GRS statistic tests whether all intercepts in a set of 25 (5×5) or 20 (4×5) regressions are zero; $|\alpha|$ is the average absolute intercepts; H-L α is the difference between the highest and lowest intercepts for a set of regressions; $SR(\alpha)$ is the Sharpe ratio for the intercepts. With 25 portfolios and 242 monthly returns, critical values of the GRS statistic for all models are: 90%: 1.41; 95%: 1.56; 97.5%: 1.69; 99%: 1.86 and 99.9%: 2.26. With 20 portfolios and 242 monthly returns, critical values of the GRS statistic for all models are: 90%: 1.45; 95%: 1.62; 97.5%: 1.78; 99%: 1.95 and 99.9%: 2.41.

Two classes of models are investigated:

Global Fama-French Model: $R_i - R_f = \alpha_i^G + \beta_i^G(R_m^G - R_f) + s_i^G F_{Size}^G + h_i^G F_{B/M}^G + \varepsilon_i$

Partial Segmentation Fama-French Model:
$$R_i - R_f = \alpha_i^{PS} + \beta_i^G(R_m^G - R_f) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^G F_{Size}^G + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A} + h_i^G F_{B/M}^G + h_i^{\bar{A}-A} F_{B/M}^{\bar{A}-A} + \varepsilon_i$$

The superscript "G" on the market and factor portfolios implies that they are constructed from all stocks around the world. The superscript "PS" denotes the intercept for the partial-segmentation model. The superscript "Ā-A" denotes a market or factor spread portfolio of the difference in the market or factor for locally-accessible stocks from the specific region (those not secondarily cross-listed overseas for which the test is performed) and that of the globally accessible stocks. The Main CL Tier is used here.

Panel A in the Table reports pairwise tests of equality of the OLS and GLS cross-sectional R^2s (Kan, Robotti, and Shanken, 2013) of the global benchmark and partial-segmentation models. The OLS and GLS cross-sectional R^2s (ρ^2 in the table) are reported, as well as the difference between the sample cross-sectional R^2s of the models ($\Delta\rho^2$ in the table) and the associated *p*-value for the test of H_0: $\Delta\rho^2 = 0$. The *p*-values are computed under the assumption that the models are potentially misspecified.

Panel B reports estimates of zero-beta Rate, risk premia, and prices of covariance risk under misspecified models. Here * denotes that the estimate is significant at 10% level, for example, the *t*-ratio of $\hat{\gamma}_0^G$ (or $\hat{\lambda}_0^G$) are for the test of the null hypothesis that the excess zero-beta rate is equal to zero.

Two forms of beta pricing models are studied: Let *f* be a *K*-vector of factors, *R* be a vector of returns on *N* test assets, and β be the $N \times K$ matrix of multiple regression betas of the *N* assets with respect to the *K* factors. The proposed *K*-factor beta pricing model specifies that asset expected returns are linear in β, that is,

$$\mu_R = X\gamma$$

where $X = [1_N, \beta]$, and γ is a vector consisting of the zero-beta rate and risk premia on the *K* factors. An alternative specification is considered in terms of the $N \times K$ matrix of V_{Rf} of covariances between returns and the factors, thus

$$\mu_R = C\lambda$$

where $C = [1_N, V_{Rf}]$, and λ is a vector consisting of the zero-beta rate and price of the covariance risk on the *K* factors.

Table 3. Summary Statistics for Regression Tests of the CAPM Model (5×5 Size/B/M Portfolios) and the Carhart Four-Factor Model (5×5 Size/ Momentum Portfolios): November 1990 – December 2010.

Panel A: Kan, Robotti, and Shanken (2013) tests

Test Assets	CAPM on 5×5 Size/B/M				Carhart on 5×5 Size/Momentum			
	Global Bench-mark	*Partial Segmentation*			*Global Bench-mark*	*Partial Segmentation*		
	ρ^2	ρ^2	$\Delta\ \rho^2$	*p-value*	ρ^2	ρ^2	$\Delta\ \rho^2$	*p-value*
i.OLS								
Global	0.37	0.65	0.29	***(0.06)***	0.61	0.90	0.28	***(0.00)***
Developed Only	0.49	0.70	0.21	*(0.11)*	0.63	0.92	0.29	***(0.05)***
Global excl. NA	0.60	0.62	0.02	*(0.61)*	0.53	0.90	0.37	***(0.00)***
Developed only excl.NA	0.57	0.62	0.06	*(0.35)*	0.49	0.92	0.43	***(0.01)***
ii.GLS								
Global	0.04	0.06	0.02	*(0.30)*	0.10	0.30	0.21	*(0.18)*
Developed Only	0.17	0.20	0.03	*(0.22)*	0.09	0.33	0.24	*(0.23)*
Global excl. NA	0.05	0.05	0.00	*(0.89)*	0.04	0.36	0.32	***(0.01)***
Developed only excl.NA	0.05	0.08	0.03	*(0.30)*	0.13	0.46	0.34	***(0.09)***

Panel B: Test Diagnostics

Test Assets	CAPM on 5×5 Size/B/M					Carhart on 5×5 Size/Momentum				
	R^2	GRS	$\|\alpha\|$	H-L α	$SR(\alpha)$	R^2	GRS	$\|\alpha\|$	H-L α	$SR(\alpha)$
i. Global Benchmark										
Global	0.79	2.74	0.27	1.38	0.56	0.89	2.19	0.20	1.18	0.53
Developed Only	0.80	3.29	0.23	1.22	0.62	0.88	2.72	0.16	0.97	0.59
Global excl. NA	0.68	1.68	0.26	1.27	0.44	0.80	1.88	0.26	1.05	0.49
Developed only excl.NA	0.69	2.12	0.25	1.21	0.50	0.75	1.56	0.31	0.95	0.44
ii. Partial Segmentation										
Global	0.84	3.23	0.35	1.57	0.62	0.90	1.92	0.19	1.06	0.52
Developed Only	0.86	3.45	0.30	1.22	0.64	0.92	2.40	0.21	1.03	0.58
Global excl. NA	0.80	1.75	0.36	1.33	0.46	0.86	1.81	0.25	1.06	0.50
Developed only excl.NA	0.85	1.97	0.29	1.13	0.48	0.91	1.81	0.21	1.06	0.51

Table 3, continued.

The regressions use the CAPM (*left in Panels A&B*) and the Carhart four-factor model (*right in Panels A&B*) to explain the returns on four sets of global portfolios formed on size and B/M (*left in Panels A&B*) and those on size and momentum (*right in Panels A&B*). Here four sets of global portfolios include Global portfolios, Developed Markets portfolios, Global portfolios excluding North America, Developed Markets portfolios excluding North America. R^2 is the average time-series adjusted R^2; the GRS statistic tests whether all intercepts in a set of 25 (5×5) regressions are zero; $|\alpha|$ is the average absolute intercepts; H-L α is the difference between the highest and lowest intercepts for a set of regressions; $SR(\alpha)$ is the Sharpe ratio for the intercepts. With 25 portfolios and 242 monthly returns, critical values of the GRS statistic for all models are: 90%: 1.41; 95%: 1.56; 97.5%: 1.69; 99%: 1.86 and 99.9%: 2.26.

Four classes of models are investigated:

Global CAPM:
$$R_i - R_f = \alpha_i^G + \beta_i^G\left(R_m^G - R_f\right) + \varepsilon_i$$

Partial Segmentation CAPM:
$$R_i - R_f = \alpha_i^{PS} + \beta_i^G\left(R_m^G - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + \varepsilon_i$$

Global Carhart Model:
$$R_i - R_f = \alpha_i^G + \beta_i^G\left(R_m^G - R_f\right) + s_i^G F_{Size}^G + h_i^G F_{B/M}^G + m_i^G F_{Mom}^G + \varepsilon_i$$

Partial Segmentation Carhart Model:
$$R_i - R_f = \alpha_i^{PS} + \beta_i^G\left(R_m^G - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^G F_{Size}^G + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A}$$
$$+ h_i^G F_{B/M}^G + h_i^{\bar{A}-A} F_{B/M}^{\bar{A}-A} + m_i^G F_{Mom}^G + m_i^{\bar{A}-A} F_{Mom}^{\bar{A}-A} + \varepsilon_i$$

The superscript "G" on the market and factor portfolios implies that they are constructed from all stocks around the world. The superscript "PS" denotes the intercept for the partial-segmentation model. The superscript "Ā-A" denotes a market or factor spread portfolio of the difference in the market or factor for locally-accessible stocks from the specific region (those not secondarily cross-listed overseas for which the test is performed) and that of the globally accessible stocks. The Main CL Tier is used here.

Panel A in the Table reports pairwise tests of equality of the OLS and GLS cross-sectional R^2s (Kan, Robotti, and Shanken, 2013) of the global benchmark and partial-segmentation models. The OLS and GLS cross-sectional R^2s (ρ^2 in the table) are reported, as well as the difference between the sample cross-sectional R^2s of the models ($\Delta\,\rho^2$in the table) and the associated p-value for the test of H_0: $\Delta\,\rho^2 = 0$. The p-values are computed under the assumption that the models are potentially misspecified.

Table 4. Summary Statistics for Regression Tests Using Monthly Excess Returns on 25 Size/B/M (Size/Momentum) Portfolios and Industry Portfolios: November 1990 – December 2010.

Panel A: Kan, Robotti, and Shanken (2013) tests

Test Assets	Fama-French *for* 5×5 Size/B/M + 10 industry				Carhart *for* 5×5 Size/Momentum + 10 industry			
	Global Bench-mark	*Partial Segmentation*			*Global Bench-mark*	*Partial Segmentation*		
	ρ^2	ρ^2	$\Delta\ \rho^2$	*p-value*	ρ^2	ρ^2	$\Delta\ \rho^2$	*p-value*
					i.OLS			
Global	0.33	0.82	0.50	***(0.00)***	0.48	0.79	0.31	***(0.00)***
Developed Only	0.29	0.67	0.38	***(0.00)***	0.35	0.65	0.30	*(0.20)*
Global excl. NA	0.50	0.81	0.31	***(0.00)***	0.25	0.71	0.47	***(0.00)***
Developed only excl.NA	0.56	0.74	0.18	*(0.27)*	0.02	0.62	0.60	***(0.06)***
					ii.GLS			
Global	0.13	0.40	0.27	***(0.00)***	0.04	0.22	0.18	***(0.02)***
Developed Only	0.12	0.29	0.17	***(0.01)***	0.03	0.16	0.13	***(0.03)***
Global excl. NA	0.17	0.38	0.21	***(0.01)***	0.01	0.18	0.17	***(0.01)***
Developed only excl.NA	0.13	0.23	0.10	*(0.15)*	0.01	0.09	0.08	*(0.18)*

Panel B: Test Diagnostics

Test Assets	Fama-French *for* 5×5 Size/B/M + 10 industry					Carhart *for* 5×5 Size/Momentum + 10 industry				
	R^2	GRS	$\|\alpha\|$	H-L α	$SR(\alpha)$	R^2	GRS	$\|\alpha\|$	H-L α	$SR(\alpha)$
i. Global Benchmark										
Global	0.87	3.28	0.18	1.13	0.77	0.79	2.68	0.29	1.63	0.69
Developed Only	0.85	2.66	0.18	1.07	0.69	0.78	2.90	0.28	1.50	0.72
Global excl. NA	0.80	1.84	0.24	1.01	0.58	0.74	2.52	0.32	1.63	0.67
Developed only excl.NA	0.75	2.24	0.31	1.23	0.63	0.69	2.16	0.34	1.61	0.62
ii. Partial Segmentation										
Global	0.88	2.30	0.11	0.84	0.68	0.81	1.85	0.17	1.28	0.61
Developed Only	0.88	2.05	0.15	0.92	0.65	0.82	2.19	0.20	1.56	0.67
Global excl. NA	0.84	1.53	0.16	1.11	0.55	0.79	2.22	0.25	1.32	0.67
Developed only excl.NA	0.86	1.95	0.19	1.71	0.63	0.82	2.22	0.24	1.91	0.67

Table 4, continued.

The regressions use the Fama-French three-factor model (*left in Panels A&B*) and the Carhart four-factor model (*right in Panels A&B*) to explain the returns on four sets of global portfolios. The models are estimated using monthly returns on the 25 Fama-French size and B/M ranked portfolios and ten industry portfolios (*left in Panels A&B*) and those on size and momentum and ten industry portfolios (*right in Panels A&B*). Here four sets of global portfolios include Global portfolios, Developed Markets portfolios, Global portfolios excluding North America, Developed Markets portfolios excluding North America. R^2 is the average time-series adjusted R^2; the GRS statistic tests whether all intercepts in a set of 35 (5×5+10) regressions are zero; $|\alpha|$ is the average absolute intercepts; H-L α is the difference between the highest and lowest intercepts for a set of regressions; $SR(\alpha)$ is the Sharpe ratio for the intercepts. With 35 portfolios and 242 monthly returns, critical values of the GRS statistic for all models are: 90%: 1.35; 95%: 1.48; 97.5%: 1.60; 99%: 1.73 and 99.9%: 2.05.

Four classes of models are investigated:

Global Fama-French Model:
$$R_i - R_f = \alpha_i^G + \beta_i^G\left(R_m^G - R_f\right) + s_i^G F_{Size}^G + h_i^G F_{B/M}^G + \varepsilon_i$$

Partial Segmentation Fama-French Model:
$$R_i - R_f = \alpha_i^{PS} + \beta_i^G\left(R_m^G - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^G F_{Size}^G + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A} + h_i^G F_{B/M}^G + h_i^{\bar{A}-A} F_{B/M}^{\bar{A}-A} + \varepsilon_i$$

Global Carhart Model:
$$R_i - R_f = \alpha_i^G + \beta_i^G\left(R_m^G - R_f\right) + s_i^G F_{Size}^G + h_i^G F_{B/M}^G + m_i^G F_{Mom}^G + \varepsilon_i$$

Partial Segmentation Carhart Model:
$$R_i - R_f = \alpha_i^{PS} + \beta_i^G\left(R_m^G - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^G F_{Size}^G + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A} + h_i^G F_{B/M}^G + h_i^{\bar{A}-A} F_{B/M}^{\bar{A}-A} + m_i^G F_{Mom}^G + m_i^{\bar{A}-A} F_{Mom}^{\bar{A}-A} + \varepsilon_i$$

The superscript "G" on the market and factor portfolios implies that they are constructed from all stocks around the world. The superscript "PS" denotes the intercept for the partial-segmentation model. The superscript "Ā-A" denotes a market or factor spread portfolio of the difference in the market or factor for locally-accessible stocks from the specific region (those not secondarily cross-listed overseas for which the test is performed) and that of the globally accessible stocks. The Main CL Tier is used here.

Panel A in the Table reports pairwise tests of equality of the OLS and GLS cross-sectional R^2s (Kan, Robotti, and Shanken, 2013) of the global benchmark and partial-segmentation models. The OLS and GLS cross-sectional R^2s (ρ^2 in the table) are reported, as well as the difference between the sample cross-sectional R^2s of the models ($\Delta\,\rho^2$in the table) and the associated *p*-value for the test of H_0: $\Delta\,\rho^2 = 0$. The *p*-values are computed under the assumption that the models are potentially misspecified.

Table 5. Over-identification Tests Using Only Globally Accessible Stocks as Test Assets.

Panel A: Kan, Robotti, and Shanken (2013) tests

Test Assets	OLS				GLS			
	Global Bench-mark	*Partial Segmentation*			*Global Bench-mark*	*Partial Segmentation*		
	ρ^2	ρ^2	$\Delta\ \rho^2$	*p-value*	ρ^2	ρ^2	$\Delta\ \rho^2$	*p-value*
Fama-French for 5×5 Size/B/M + 10 Industry								
Global	0.47	0.60	0.13	*(0.24)*	0.13	0.29	0.16	***(0.09)***
Developed Only	0.60	0.66	0.07	*(0.37)*	0.15	0.26	0.10	*(0.14)*
Global excl. NA	0.60	0.66	0.06	*(0.43)*	0.15	0.24	0.09	*(0.25)*
Developed only excl.NA	0.57	0.68	0.10	*(0.48)*	0.10	0.22	0.12	*(0.16)*
Carhart for 5×5 Size/Momentum + 10 Industry								
Global	0.61	0.75	0.11	***(0.05)***	0.06	0.28	0.21	***(0.05)***
Developed Only	0.63	0.71	0.15	*(0.35)*	0.08	0.16	0.08	*(0.36)*
Global excl. NA	0.51	0.65	0.28	*(0.13)*	0.10	0.28	0.18	***(0.05)***
Developed only excl.NA	0.38	0.52	0.08	*(0.41)*	0.08	0.13	0.06	*(0.64)*

Panel B: Test Diagnostics

Test Assets	*Global Benchmark*					*Partial-segmentation Model*				
	R^2	GRS	$\lvert\alpha\rvert$	H-L α	$SR(\alpha)$	R^2	GRS	$\lvert\alpha\rvert$	H-L α	$SR(\alpha)$
Fama-French for 5×5 Size/B/M + 10 Industry										
Global	0.81	2.61	0.26	1.06	0.68	0.84	1.62	0.15	0.76	0.58
Developed Only	0.80	2.42	0.25	1.08	0.66	0.81	1.63	0.20	0.81	0.58
Global excl. NA	0.76	2.09	0.18	0.83	0.61	0.77	1.74	0.15	1.05	0.59
Developed only excl.NA	0.74	1.89	0.18	0.81	0.58	0.76	1.61	0.22	1.41	0.57
Carhart for 5×5 Size/Momentum + 10 Industry										
Global	0.80	4.08	0.30	1.35	0.87	0.84	3.29	0.21	1.14	0.82
Developed Only	0.79	3.17	0.28	1.29	0.77	0.80	2.74	0.26	1.15	0.76
Global excl. NA	0.76	3.26	0.27	1.60	0.78	0.77	2.76	0.24	1.36	0.75
Developed only excl.NA	0.74	3.69	0.23	1.37	0.83	0.77	3.25	0.25	1.30	0.82

Table 5, continued.

The regressions use the global model and the partial-segmentation model to explain the returns on four sets of global portfolios. Here the portfolios include just globally accessible stocks. Four sets of global portfolios include Global portfolios, Developed Markets portfolios, Global portfolios excluding North America, Developed Markets portfolios excluding North America. Fama-French three-factor model (*top half of Panel A*) and the Carhart four-factor model (*bottom half of Panel A*) are estimated using monthly returns on the 25 Fama-French size and B/M ranked portfolios and ten industry portfolios (*top half of Panel A*) and those on size and momentum and ten industry portfolios (*bottom half, Panel A*). R^2 is the average time-series adjusted R^2; the GRS statistic tests whether all intercepts in a set of 35 (5×5+10) regressions are zero; $|\alpha|$ is the average absolute intercepts; H-L α is the difference between the highest and lowest intercepts for a set of regressions; $SR(\alpha)$ is the Sharpe ratio for the intercepts. With 35 portfolios and 242 monthly returns, critical values of the GRS statistic for all models are: 90%: 1.35; 95%: 1.48; 97.5%: 1.60; 99%: 1.73 and 99.9%: 2.05.

Four classes of models are investigated:

Global Fama-French Model:
$$R_i - R_f = \alpha_i^G + \beta_i^G\left(R_m^G - R_f\right) + s_i^G F_{Size}^G + h_i^G F_{B/M}^G + \varepsilon_i$$

Partial Segmentation Fama-French Model:
$$R_i - R_f = \alpha_i^{PS} + \beta_i^G\left(R_m^G - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^G F_{Size}^G + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A} + h_i^G F_{B/M}^G + h_i^{\bar{A}-A} F_{B/M}^{\bar{A}-A} + \varepsilon_i$$

Global Carhart Model:
$$R_i - R_f = \alpha_i^G + \beta_i^G\left(R_m^G - R_f\right) + s_i^G F_{Size}^G + h_i^G F_{B/M}^G + m_i^G F_{Mom}^G + \varepsilon_i$$

Partial Segmentation Carhart Model:
$$R_i - R_f = \alpha_i^{PS} + \beta_i^G\left(R_m^G - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^G F_{Size}^G + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A} + h_i^G F_{B/M}^G + h_i^{\bar{A}-A} F_{B/M}^{\bar{A}-A} + m_i^G F_{Mom}^G + m_i^{\bar{A}-A} F_{Mom}^{\bar{A}-A} + \varepsilon_i$$

The superscript "G" on the market and factor portfolios implies that they are constructed from all stocks around the world. The superscript "PS" denotes the intercept for the partial-segmentation model. The superscript "Ā-A" denotes a market or factor spread portfolio of the difference in the market or factor for locally-accessible stocks from the specific region (those not secondarily cross-listed overseas for which the test is performed) and that of the globally accessible stocks. The Main CL Tier is used here.

Panel A in the Table reports pairwise tests of equality of the OLS and GLS cross-sectional R^2s (Kan, Robotti, and Shanken, 2013) of the global benchmark and partial-segmentation models. The OLS and GLS cross-sectional R^2s (ρ^2 in the table) are reported, as well as the difference between the sample cross-sectional R^2s of the models ($\Delta\rho^2$ in the table) and the associated p-value for the test of H_0: $\Delta\rho^2 = 0$. The p-values are computed under the assumption that the models are potentially misspecified.

Table 6. Summary Statistics for Regression Tests In the Regional Mandates Using Monthly Excess Returns on 25 Size/B/M (Size/Momentum) Portfolios and Industry Portfolios: November 1990 – December 2010.

Panel A: Kan, Robotti, and Shanken (2013) tests: Partial-segmentation model vs. Local Benchmark

Test Assets	Fama-French for 25 Size/B/M + 10 industry				Carhart for 25 Size/Momentum + 10 industry			
	OLS		*GLS*		*OLS*		*GLS*	
	$\Delta\,\rho^2$	*p-value*	$\Delta\,\rho^2$	*p-value*	$\Delta\,\rho^2$	*p-value*	$\Delta\,\rho^2$	*p-value*
North America	0.15	*(0.20)*	0.05	*(0.41)*	0.05	*(0.29)*	0.03	*(0.71)*
Europe	-0.02	*(0.85)*	0.01	*(0.91)*	0.34	***(0.00)***	0.23	*(0.11)*
Asia Pacific	0.06	*(0.45)*	0.06	*(0.58)*	0.03	*(0.64)*	0.11	*(0.42)*
Japan	0.04	*(0.83)*	0.05	*(0.73)*	0.10	*(0.38)*	0.05	*(0.56)*
Emerging Markets	0.12	*(0.39)*	0.06	*(0.37)*	0.16	*(0.17)*	0.17	*(0.12)*

Panel B: Estimates of Zero-Beta Rate, Risk Premia, and Prices of Covariance Risk using 5×5 Size/B/M portfolios + 10 industry portfolios (OLS Case)

	Local Benchmark				*Partial Segmentation*						
i. Risk Premia											
	$\hat{\gamma}_0^L$	$\hat{\gamma}_{vw}^L$	$\hat{\gamma}_{Size}^L$	$\hat{\gamma}_{B/M}^L$	$\hat{\gamma}_0^{PS}$	$\hat{\gamma}_{vw}^G$	$\hat{\gamma}_{Size}^G$	$\hat{\gamma}_{B/M}^G$	$\hat{\gamma}_{vw}^{\bar{A}-A}$	$\hat{\gamma}_{Size}^{\bar{A}-A}$	$\hat{\gamma}_{B/M}^{\bar{A}-A}$
North America	0.48	0.21	0.38	0.21	0.12	0.83	0.09	0.04	-0.10	-0.03	0.73*
Europe	0.18	0.44	-0.25	0.41*	0.03	0.60	-0.32	0.03	-0.15	-0.08	0.79*
Asia Pacific	1.11*	-0.43	0.19	0.66*	1.12*	-0.66	0.18	0.17	0.35	0.07	0.67
Japan	0.54*	-0.53	-0.23	0.34	0.69*	-0.12	0.44	0.09	-0.54	-0.64	0.42
Emerging Markets	1.07	-0.41	0.18	0.83*	1.55	-0.70	0.26	-0.01	-0.49	0.28	1.27*
ii. Prices of Covariance Risk											
	$\hat{\lambda}_0^L$	$\hat{\lambda}_{vw}^L$	$\hat{\lambda}_{Size}^L$	$\hat{\lambda}_{B/M}^L$	$\hat{\lambda}_0^{PS}$	$\hat{\lambda}_{vw}^G$	$\hat{\lambda}_{Size}^G$	$\hat{\lambda}_{B/M}^G$	$\hat{\lambda}_{vw}^{\bar{A}-A}$	$\hat{\lambda}_{Size}^{\bar{A}-A}$	$\hat{\lambda}_{B/M}^{\bar{A}-A}$
North America	0.48	0.70	4.26	3.27	0.12	5.42*	-0.73	2.42	0.96	1.41	19.05*
Europe	0.18	2.10	-4.13	6.20*	0.03	2.04	-8.24	2.60	1.61	-1.15	17.76*
Asia Pacific	1.11*	-1.22	1.48	6.38*	1.12*	-3.60	1.91	6.40	1.82	0.90	8.49*
Japan	0.54*	-0.57	-0.92	4.06	0.69*	-0.97	9.39	5.79	-1.55	-2.63	6.72
Emerging Markets	1.07	-1.26	3.01	5.58*	1.55	-5.52	9.16	0.90	-2.78	2.21	7.70*

Panel C: Test Diagnostics

Test Assets	Fama-French for 25 Size/B/M + 10 industry					Carhart for 25 Size/Momentum + 10 industry				
	R^2	GRS	$\|\alpha\|$	H-L α	$SR(\alpha)$	R^2	GRS	$\|\alpha\|$	H-L α	$SR(\alpha)$
Local Benchmark										
North America	0.83	1.83	0.15	0.78	0.57	0.83	1.79	0.15	1.07	0.57
Europe	0.86	1.99	0.15	0.83	0.60	0.86	3.08	0.23	1.28	0.77
Asia Pacific	0.78	1.56	0.30	2.03	0.54	0.80	2.52	0.26	1.26	0.70
Japan	0.85	0.86	0.12	0.71	0.39	0.85	1.59	0.20	0.89	0.53
Emerging Markets	0.62	1.79	0.45	1.23	0.56	0.61	2.13	0.62	1.44	0.62
Partial Segmentation										
North America	0.79	2.76	0.30	1.07	0.71	0.80	2.25	0.35	1.24	0.65
Europe	0.83	2.23	0.22	1.15	0.66	0.83	3.10	0.30	1.33	0.80
Asia Pacific	0.76	2.00	0.34	1.68	0.63	0.79	3.62	0.40	1.71	0.87
Japan	0.84	1.20	0.25	1.17	0.48	0.85	2.17	0.25	1.27	0.66
Emerging Markets	0.61	1.66	0.37	1.59	0.56	0.61	2.15	0.60	1.31	0.64

Table 6, continued.

The regressions use the Fama-French three-factor model (*left in Panels A&C*) and the Carhart four-factor model (*right in Panels A&C*) to explain the returns on fve sets of regional portfolios on North America ("NA" in the table), Europe, Japan, Asia Pacific (excluding Japan), and Emerging Markets. The models are estimated using monthly returns on the 25 Fama-French size and B/M ranked portfolios and ten industry portfolios (*left in Panels A&C*) and those on size and momentum and ten industry portfolios (*right in Panels A&C*). The table presents regression results of the local benchmark and the partial-segmentation model. R^2 is the average time-series adjusted R^2; the GRS statistic tests whether all intercepts in a set of 35 (5×5+10) regressions are zero; $|\alpha|$ is the average absolute intercepts; H-L α is the difference between the highest and lowest intercepts for a set of regressions; $SR(\alpha)$ is the Sharpe ratio for the intercepts. With 35 portfolios and 242 monthly returns, critical values of the GRS statistic for all models are: 90%: 1.35; 95%: 1.48; 97.5%: 1.60; 99%: 1.73 and 99.9%: 2.05.

Six classes of models are investigated:

Local Fama-French Model:
$$R_i - R_f = \alpha_i^L + \beta_i^L\left(R_m^L - R_f\right) + s_i^L F_{Size}^L + h_i^L F_{B/M}^L + \varepsilon_i$$

Partial Segmentation Fama-French Model:
$$R_i - R_f = \alpha_i^{PS} + \beta_i^G\left(R_m^G - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^G F_{Size}^G + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A} + h_i^G F_{B/M}^G + h_i^{\bar{A}-A} F_{B/M}^{\bar{A}-A} + \varepsilon_i$$

Local Carhart Model:
$$R_i - R_f = \alpha_i^L + \beta_i^L\left(R_m^L - R_f\right) + s_i^L F_{Size}^L + h_i^L F_{B/M}^L + m_i^L F_{Mom}^L + \varepsilon_i$$

Partial Segmentation Carhart Model:
$$R_i - R_f = \alpha_i^{PS} + \beta_i^G\left(R_m^G - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^G F_{Size}^G + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A} + h_i^G F_{B/M}^G + h_i^{\bar{A}-A} F_{B/M}^{\bar{A}-A} + m_i^G F_{Mom}^G + m_i^{\bar{A}-A} F_{Mom}^{\bar{A}-A} + \varepsilon_i$$

The superscript "G" on the market and factor portfolios implies that they are constructed from all stocks around the world.The superscript designation of "*L*" on the market and factor portfolios implies that they are constructed only from local - or regional, in our experiments – stocks. The superscript "PS" denotes the intercept for the partial-segmentation model. The superscript "Ā-A" denotes a market or factor spread portfolio of the difference in the market or factor for locally-accessible stocks from the specific region (those not secondarily cross-listed overseas for which the test is performed) and that of the globally accessible stocks. The Main CL Tier is used here.

Panel A in the Table reports pairwise tests of equality of the OLS and GLS cross-sectional R^2s (Kan, Robotti, and Shanken, 2013) of the local benchmark and partial-segmentation models. The difference between the sample cross-sectional R^2s of the models ($\Delta\,\rho^2$in the table) is reported, as well as the associated *p*-value for the test of H_0: $\Delta\,\rho^2 = 0$. The *p*-values are computed under the assumption that the models are potentially misspecified.

Panel B reports estimates of zero-beta Rate, risk premia, and prices of covariance risk under misspecified models. Here * denotes that the estimate is significant at 10% level, for example, the *t*-ratio of $\hat{\gamma}_0^G$ (or $\hat{\lambda}_0^G$) are for the test of the null hypothesis that the excess zero-beta rate is equal to zero.

Two forms of beta pricing models are studied: Let *f* be a *K*-vector of factors, *R* be a vector of returns on *N* test assets, and β be the *N*×*K* matrix of multiple regression betas of the *N* assets with respect to the *K* factors. The proposed *K*-factor beta pricing model specifies that asset expected returns are linear in β, that is,

$$\mu_R = X\gamma$$

where $X = [1_N, \beta]$, and γ is a vector consisting of the zero-beta rate and risk premia on the *K* factors. An alternative specification is considered in terms of the *N*×*K* matrix of V_{Rf} of covariances between returns and the factors, thus

$$\mu_R = C\lambda$$

where $C = [1_N, V_{Rf}]$, and λ is a vector consisting of the zero-beta rate and price of the covariance risk on the *K* factors.

Table 7. Summary Statistics for Regression Tests on Europe and Emerging Markets Using Monthly Excess Returns on 25 Size/Momentum Portfolios and Industry Portfolios: November 1990 – December 2010.

Panel A: Europe

Test Assets	Test Diagnostic					Kan, Robotti, and Shanken (2013) tests			
	R^2	GRS	$\|\alpha\|$	H-L α	*SR(α)*	$OLS\ \rho^2$	$\Delta\ \rho^2$	$GLS\ \rho^2$	$\Delta\ \rho^2$
i) EuroZone Membership									
						Local Benchmark			
Eurozone	0.82	2.43	0.22	1.25	0.69	0.63		0.09	
- before 1999	*0.81*	*1.68*	*0.29*	*2.68*	*1.06*	*0.56*		*0.20*	
- after 1999	*0.83*	*1.67*	*0.33*	*1.78*	*0.80*	*0.53*		*0.08*	
Non Eurozone	0.80	4.42	0.26	1.26	0.91	0.49		0.05	
						Partial Segmentation			
Eurozone	0.79	2.29	0.30	1.30	0.69	0.86	0.24*	0.27	0.17
- before 1999	*0.74*	*2.24*	*0.52*	*3.10*	*1.27*	*0.71*	*0.15*	*0.28*	*0.08*
- after 1999	*0.83*	*1.10*	*0.36*	*2.58*	*0.70*	*0.83*	*0.29*	*0.41*	*0.32**
Non Eurozone	0.76	4.04	0.35	1.24	0.90	0.61	0.13	0.14	0.10
ii) EU Membership									
						Local Benchmark			
EU Members	0.84	3.10	0.23	1.81	0.77	0.52		0.07	
- excluding U.K.	0.84	2.48	0.23	1.21	0.69	0.61		0.10	
Non EU Members	0.63	1.67	0.28	1.36	0.56	0.63		0.29	
						Partial Segmentation			
EU Members	0.81	3.24	0.31	1.63	0.81	0.82	0.30*	0.28	0.21
- excluding U.K.	0.81	2.48	0.30	1.24	0.71	0.84	0.24*	0.24	0.14
Non EU Members	0.60	1.41	0.32	1.46	0.53	0.78	0.15	0.49	0.20

Panel B: Emerging Markets

Test Assets	Test Diagnostic					Kan, Robotti, and Shanken (2013) tests			
	R^2	GRS	$\|\alpha\|$	H-L α	*SR(α)*	$OLS\ \rho^2$	$\Delta\ \rho^2$	$GLS\ \rho^2$	$\Delta\ \rho^2$
						Local Benchmark			
EEMEA	0.44	2.72	0.86	2.51	0.70	0.70		0.13	
Latin America	0.55	1.91	0.49	4.36	0.57	0.90		0.07	
Southeast Asia	0.72	2.39	0.42	1.12	0.65	0.77		0.11	
						Partial Segmentation			
EEMEA	0.48	2.07	0.73	2.19	0.63	0.80	0.10	0.23	0.10
Latin America	0.50	1.49	0.48	2.05	0.53	0.94	0.04	0.21	0.14
Southeast Asia	0.74	2.41	0.44	1.44	0.67	0.84	0.07	0.27	0.16

Table 7, continued.

The regressions use the Carhart four-factor model to explain the returns on Europe (Panel A) and Emerging Markets (Panel B). EEMEA denotes those countries in Eastern Europe, Middle East, and Africa. The test asset portfolios include 25 size and momentum ranked portfolios and ten industry portfolios. The table presents regression results of the local benchmark and the partial-segmentation model. R^2 is the average time-series adjusted R^2; the GRS statistic tests whether all intercepts in a set of 35 (5×5+10) regressions are zero; $|\alpha|$ is the average absolute intercepts; H-L α is the difference between the highest and lowest intercepts for a set of regressions; $SR(\alpha)$ is the Sharpe ratio for the intercepts. With 35 portfolios and 242 monthly returns, critical values of the GRS statistic for all models are: 90%: 1.35; 95%: 1.48; 97.5%: 1.60; 99%: 1.73 and 99.9%: 2.05.

Two classes of models are investigated:

Local Carhart Model:

$$R_i - R_f = \alpha_i^L + \beta_i^L\left(R_m^L - R_f\right) + s_i^L F_{Size}^L + h_i^L F_{B/M}^L + m_i^L F_{Mom}^L + \varepsilon_i$$

Partial Segmentation Carhart Model:

$$R_i - R_f = \alpha_i^{PS} + \beta_i^G\left(R_m^G - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^G F_{Size}^G + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A} + h_i^G F_{B/M}^G + h_i^{\bar{A}-A} F_{B/M}^{\bar{A}-A} + m_i^G F_{Mom}^G + m_i^{\bar{A}-A} F_{Mom}^{\bar{A}-A} + \varepsilon_i$$

The superscript designation of "L" on the market and factor portfolios implies that they are constructed only from local - or regional, in our experiments – stocks. The superscript "PS" denotes the intercept for the partial-segmentation model. The superscript "G" on the market and factor portfolios implies that they are constructed from all stocks around the world. The superscript "Ā-A" denotes a market or factor spread portfolio of the difference in the market or factor for locally-accessible stocks from the specific region (those not secondarily cross-listed overseas for which the test is performed) and that of the globally accessible stocks. The Main CL Tier is used here.

On the right side of Panels A and B in the Table, it reports pairwise tests of equality of the OLS and GLS cross-sectional R^2s (Kan, Robotti, and Shanken, 2013) of the local benchmark and partial-segmentation models. The difference between the sample cross-sectional R^2s of the models ($\Delta\,\rho^2$ in the table) is reported, as well as the associated *p*-value for the test of H_0: $\Delta\,\rho^2 = 0$. The *p*-values are computed under the assumption that the models are potentially misspecified.

Table 8. Summary Statistics for Regression Tests of the Partial Segmentation Version of the Fama-French Three-Factor Model Using Monthly Excess Returns on 25 Size/B/M Portfolios and Industry Portfolios When Different CL Samples are Used to Construct the Local Spread Factors: November 1990 – December 2010.

Panel A: Kan, Robotti, and Shanken (2013) tests

Test Assets	Global Benchmark	Partial Segmentation											
		Main CL Tier			*CL1st Tier*			*CL 2nd Tier*			*CL 3rd Tier*		
	ρ^2	ρ^2	$\Delta\rho^2$	*p-value*	ρ^2	$\Delta\rho^2$	*p-value*	ρ^2	$\Delta\rho^2$	*p-value*	ρ^2	$\Delta\rho^2$	*p-value*
i.OLS													
Global	0.33	0.82	0.50	***(0.00)***	0.77	0.45	***(0.00)***	0.76	0.43	***(0.00)***	0.81	0.48	***(0.00)***
Developed Only	0.29	0.67	0.38	***(0.00)***	0.61	0.32	***(0.08)***	0.52	0.23	*(0.24)*	0.60	0.31	***(0.01)***
Global excl. NA	0.50	0.81	0.31	***(0.00)***	0.79	0.29	***(0.00)***	0.76	0.26	***(0.00)***	0.82	0.33	***(0.00)***
Developed only excl.NA	0.56	0.74	0.18	*(0.27)*	0.76	0.21	*(0.14)*	0.69	0.13	*(0.50)*	0.76	0.20	*(0.17)*
ii.GLS													
Global	0.13	0.40	0.27	***(0.00)***	0.33	0.19	***(0.01)***	0.30	0.17	***(0.01)***	0.39	0.26	***(0.00)***
Developed Only	0.12	0.29	0.17	***(0.01)***	0.25	0.13	***(0.02)***	0.17	0.05	*(0.46)*	0.28	0.16	***(0.01)***
Global excl. NA	0.17	0.38	0.21	***(0.01)***	0.31	0.14	***(0.08)***	0.28	0.11	*(0.15)*	0.41	0.23	***(0.01)***
Developed only excl.NA	0.13	0.23	0.10	*(0.15)*	0.25	0.12	*(0.10)*	0.15	0.02	*(0.75)*	0.20	0.07	*(0.26)*

Panel B: Test Diagnostics

Test Assets	Global Benchmark	Partial Segmentation											
		Main CL Tier			*CL1st Tier*			*CL 2nd Tier*			*CL 3rd Tier*		
	R^2	R^2	GRS	$\lvert\alpha\rvert$	R^2	GRS	$\lvert\alpha\rvert$	R^2	GRS	$\lvert\alpha\rvert$	R^2	GRS	$\lvert\alpha\rvert$
Global	0.87	0.88	2.30	0.11	0.88	2.75	0.12	0.88	3.02	0.14	0.88	2.37	0.13
Developed Only	0.85	0.88	2.05	0.15	0.87	2.34	0.20	0.86	2.42	0.15	0.87	2.11	0.16
Global excl. NA	0.80	0.84	1.53	0.16	0.84	1.63	0.14	0.84	1.68	0.13	0.83	1.50	0.15
Developed only excl.NA	0.75	0.86	1.95	0.19	0.86	1.98	0.23	0.85	2.07	0.14	0.86	1.89	0.16

Table 8, continued.

The regressions use the partial-segmentation Fama-French three-factor model to explain the returns on four sets of global portfolios. The models are estimated using monthly returns on the 25 Fama-French size and B/M ranked portfolios and ten industry portfolios. Four sets of global portfolios include Global portfolios, Developed Markets portfolios, Global portfolios excluding North America, Developed Markets portfolios excluding North America. Four different set of globally-accessible stocks are considered, where the Main CL Tier refers to the sample with two relative viability constraints, CL 1st Tier refers to the sample without viability constraints, CL 2nd Tier is the sample with absolute viable constraint, CL 3rd is the sample where more stringent screenings are imposed on the two viability constraints. Note that the regression results for the Main CL Tier and the global benchmark are repeated from Table 3 for comparison. The selection criteria are described in the Appendix C. R^2 is the average time-series adjusted R^2; the GRS statistic tests whether all intercepts in a set of 35 (5×5+10) regressions are zero; $|\alpha|$ is the average absolute intercepts. With 35 portfolios and 242 monthly returns, critical values of the GRS statistic for all models are: 90%: 1.35; 95%: 1.48; 97.5%: 1.60; 99%: 1.73 and 99.9%: 2.05.

Two classes of models are investigated:

Global Fama-French Model: $$R_i - R_f = \alpha_i^G + \beta_i^G\left(R_m^G - R_f\right) + s_i^G F_{Size}^G + h_i^G F_{B/M}^G + \varepsilon_i$$

Partial Segmentation Fama-French Model: $$R_i - R_f = \alpha_i^{PS} + \beta_i^G\left(R_m^G - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^G F_{Size}^G + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A} + h_i^G F_{B/M}^G + h_i^{\bar{A}-A} F_{B/M}^{\bar{A}-A} + \varepsilon_i$$

The superscript "G" on the market and factor portfolios implies that they are constructed from all stocks around the world. The superscript "PS" denotes the intercept for the partial-segmentation model. The superscript "Ā-A" denotes a market or factor spread portfolio of the difference in the market or factor for locally-accessible stocks from the specific region (those not secondarily cross-listed overseas for which the test is performed) and that of the globally accessible stocks.

Panel A in the Table reports pairwise tests of equality of the OLS and GLS cross-sectional R^2s (Kan, Robotti, and Shanken, 2013) of the global benchmark and partial-segmentation models. The OLS and GLS cross-sectional R^2s (ρ^2 in the table) are reported, as well as the difference between the sample cross-sectional R^2s of the models ($\Delta\,\rho^2$ in the table) and the associated p-value for the test of H_0: $\Delta\,\rho^2 = 0$. The p-values are computed under the assumption that the models are potentially misspecified.

Table 9. Placebo Tests of Alternative Models Using Monthly Excess Returns on 25 Size/B/M Portfolios and Industry Portfolios: November 1990 – December 2010.

Panel A: Kan, Robotti, and Shanken (2013) tests

Test Assets	Global Bench-mark	Partial Segmentation											
		Main CL Tier			*Placebo Tests*								
					Size			Liquidity			PCA		
	ρ^2	ρ^2	$\Delta\ \rho^2$	*p-value*	ρ^2	$\Delta\ \rho^2$	*p-value*	ρ^2	$\Delta\ \rho^2$	*p-value*	ρ^2	$\Delta\ \rho^2$	*p-value*
i.OLS													
Global	0.33	0.82	0.50	***(0.00)***	0.61	0.28	***(0.00)***	0.65	0.32	***(0.02)***	0.35	0.03	*(0.95)*
Developed Only	0.29	0.67	0.38	***(0.00)***	0.35	0.06	*(0.76)*	0.50	0.21	*(0.19)*	0.52	0.23	*(0.10)*
Global excl. NA	0.50	0.81	0.31	***(0.00)***	0.80	0.30	***(0.00)***	0.61	0.11	*(0.32)*	0.65	0.15	*(0.19)*
Developed only excl.NA	0.56	0.74	0.18	*(0.27)*	0.73	0.17	*(0.27)*	0.63	0.08	*(0.77)*	0.77	0.22	*(0.27)*
ii.GLS													
Global	0.13	0.40	0.27	***(0.00)***	0.15	0.02	*(0.69)*	0.18	0.05	*(0.40)*	0.14	0.00	*(0.97)*
Developed Only	0.12	0.29	0.17	***(0.01)***	0.17	0.05	*(0.46)*	0.21	0.09	*(0.19)*	0.15	0.03	*(0.73)*
Global excl. NA	0.17	0.38	0.21	***(0.01)***	0.45	0.27	***(0.01)***	0.21	0.03	*(0.76)*	0.33	0.16	***(0.08)***
Developed only excl.NA	0.13	0.23	0.10	*(0.15)*	0.22	0.09	*(0.18)*	0.14	0.01	*(0.89)*	0.34	0.21	***(0.07)***

Panel B: Test Diagnostics

Test Assets	Global Bench-mark	Partial Segmentation											
		Main CL Tier			*Placebo Tests*								
					Size			Liquidity			PCA		
	R^2	R^2	GRS	$\|\alpha\|$	R^2	GRS	$\|\alpha\|$	R^2	GRS	$\|\alpha\|$	R^2	GRS	$\|\alpha\|$
Global	0.87	0.88	2.30	0.11	0.87	2.98	0.20	0.87	3.36	0.17	0.87	3.25	0.18
Developed Only	0.85	0.88	2.05	0.15	0.88	3.00	0.22	0.85	2.50	0.18	0.85	2.66	0.18
Global excl. NA	0.80	0.84	1.53	0.16	0.83	1.52	0.19	0.81	1.64	0.18	0.80	1.92	0.25
Developed only excl.NA	0.75	0.86	1.95	0.19	0.86	2.08	0.22	0.79	2.01	0.16	0.80	2.42	0.35

Table 9, continued.

The regressions use the alternative models to explain the returns on four sets of global portfolios. The models are estimated using monthly returns on the 25 Fama-French size and B/M ranked portfolios and ten industry portfolios. Four sets of global portfolios include Global portfolios, Developed Markets portfolios, Global portfolios excluding North America, Developed Markets portfolios excluding North America. Here alternative models are built on only size screening, only liquidity screening, and principal component analysis (PCA). For the size screening, the globally accessible stocks are those among those stocks in the top 75% of market capitalization for the market. For the liquidity screening, the liquidity is measured by the proportion of zero daily returns (ZR) observed over the relevant month for each market, followed by Lesmond, Ogden and Trzcinka (1999) and Lesmond (2005); the globally accessible stocks are those in the bottom 75% percentile of ZR for each country. The local factors in the PCA-based alternative model is constructed as follow: first orthogonalize the stock returns for the specific region for which the test is performed relative to the global factors, next identify up to three principal components of the residuals, then the local factor portfolios are determined by the extracted principal factors, with portfolio weights given by the scaled eigenvector. The PCA-based alternative model therefore consists of three global factors and three "local" principal component factors. Note that the regression results for the Main CL Tier and the global benchmark are repeated from Table 3 for comparison. R^2 is the average time-series adjusted R^2; the GRS statistic tests whether all intercepts in a set of 35 (5×5+10) regressions are zero; $|\alpha|$ is the average absolute intercepts. With 35 portfolios and 242 monthly returns, critical values of the GRS statistic for all models are: 90%: 1.35; 95%: 1.48; 97.5%: 1.60; 99%: 1.73 and 99.9%: 2.05.

Two classes of models are investigated:

Global Fama-French Model: $R_i - R_f = \alpha_i^G + \beta_i^G\left(R_m^G - R_f\right) + s_i^G F_{Size}^G + h_i^G F_{B/M}^G + \varepsilon_i$

Partial Segmentation Fama-French Model: $R_i - R_f = \alpha_i^{PS} + \beta_i^G\left(R_m^G - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^G F_{Size}^G + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A} + h_i^G F_{B/M}^G + h_i^{\bar{A}-A} F_{B/M}^{\bar{A}-A} + \varepsilon_i$

The superscript "G" on the market and factor portfolios implies that they are constructed from all stocks around the world. The superscript "PS" denotes the intercept for the partial-segmentation model. The superscript "Ā-A" denotes a market or factor spread portfolio of the difference in the market or factor for locally-accessible stocks from the specific region (those not secondarily cross-listed overseas for which the test is performed) and that of the globally accessible stocks.

Panel A in the Table reports pairwise tests of equality of the OLS and GLS cross-sectional R^2s (Kan, Robotti, and Shanken, 2013) of the global benchmark and partial-segmentation models. The OLS and GLS cross-sectional R^2s (ρ^2 in the table) are reported, as well as the difference between the sample cross-sectional R^2s of the models ($\Delta\,\rho^2$in the table) and the associated *p*-value for the test of H_0: $\Delta\,\rho^2 = 0$. The *p*-values are computed under the assumption that the models are potentially misspecified.

Figure 1a.
Global Equity Universe, reported by Total Market Capitalization, 1990-2010.

The figure shows the distribution of the global equity universe by region. Beside each region name is the time series average market capitalization from that region that qualifies for analysis, which is in U.S. dollars trillion, and its percentage of global market capitalization. The sample selection criteria are described in Appendix B.

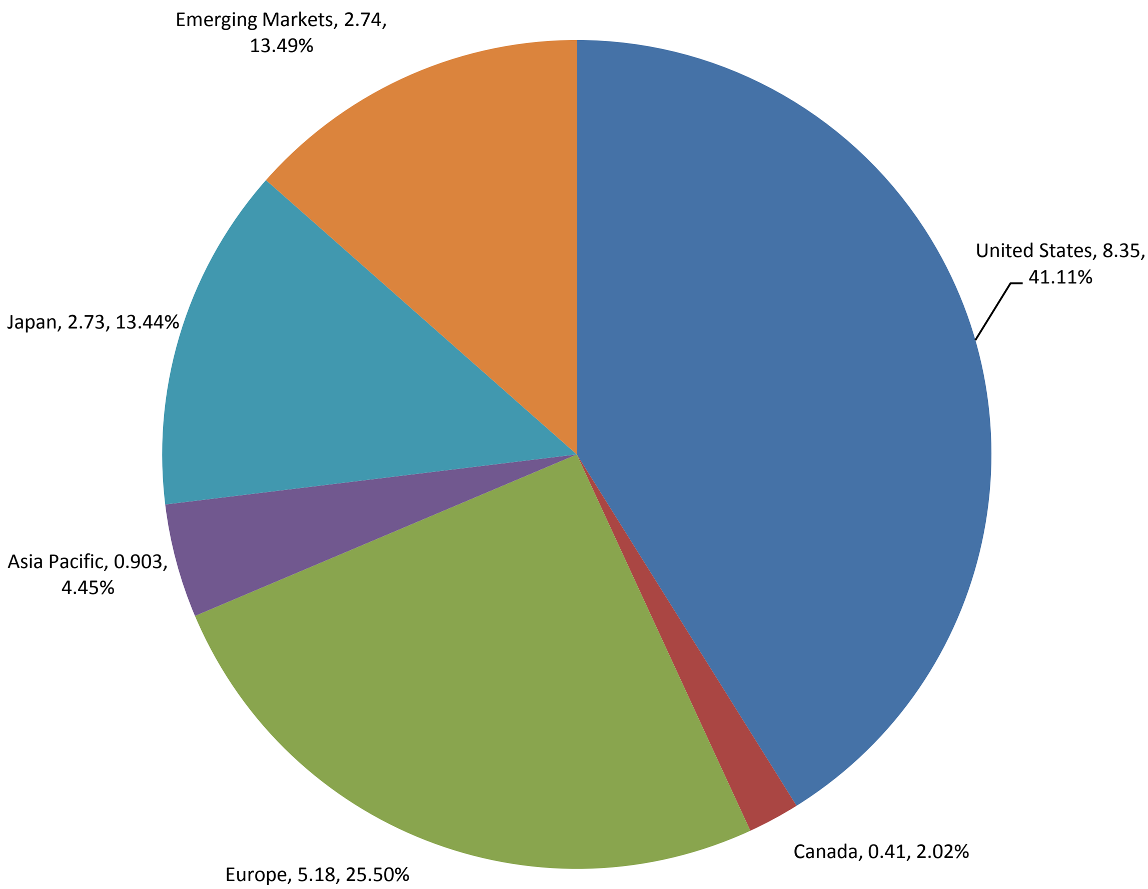
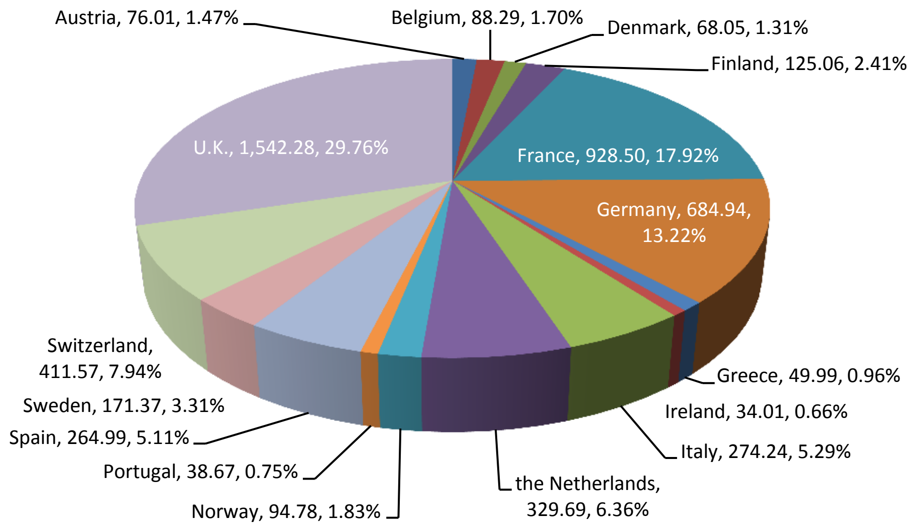
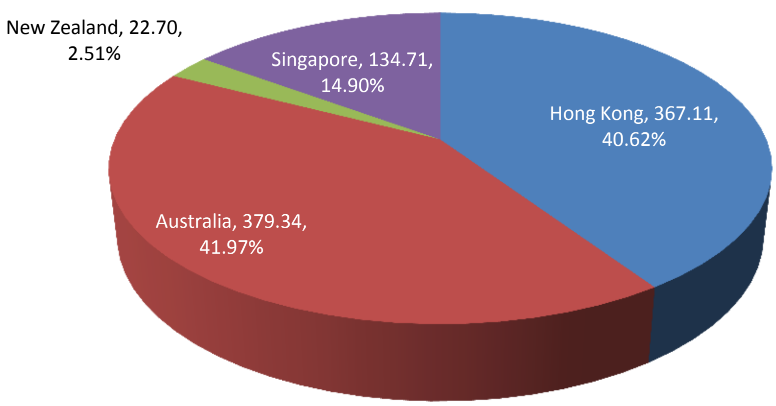


Figure 1a, continued.

Global Equity Universe, reported by Total Market Capitalization, 1990-2010.

The figures show the distributions of Europe, Asia Pacific and Emerging Markets equity universes by country. Beside each country name is the average market capitalization from that country, which is in U.S. dollars billion, and the percentage of regional market capitalization. The sample selection criteria are described in Appendix B.





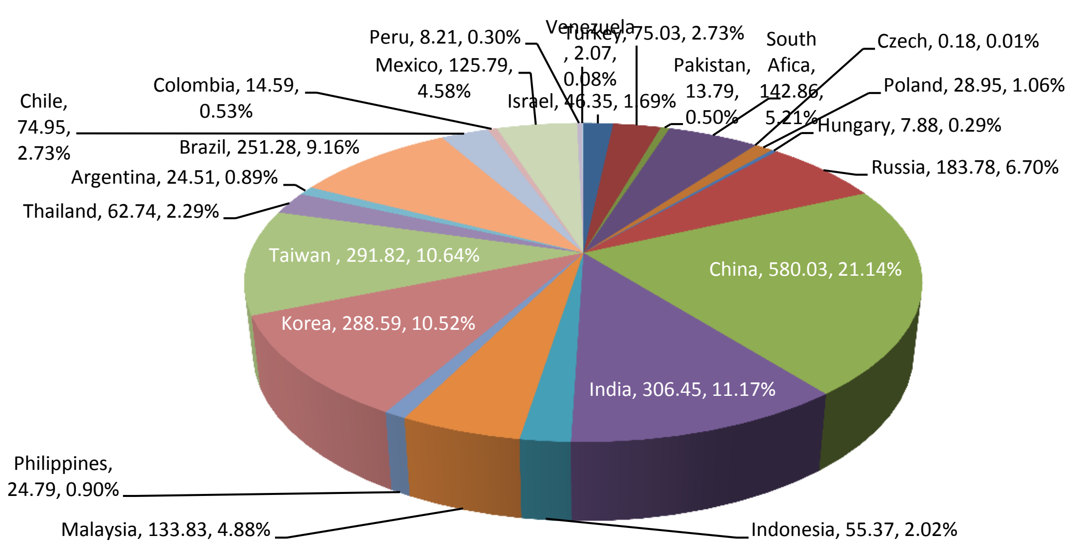


Figure 1b.
Global Equity Universe by Year, reported by Total Number of Stocks, 1990-2010.
The figures show the distribution of our sample stocks from each region by year. The sample selection criteria are described in Appendix B.

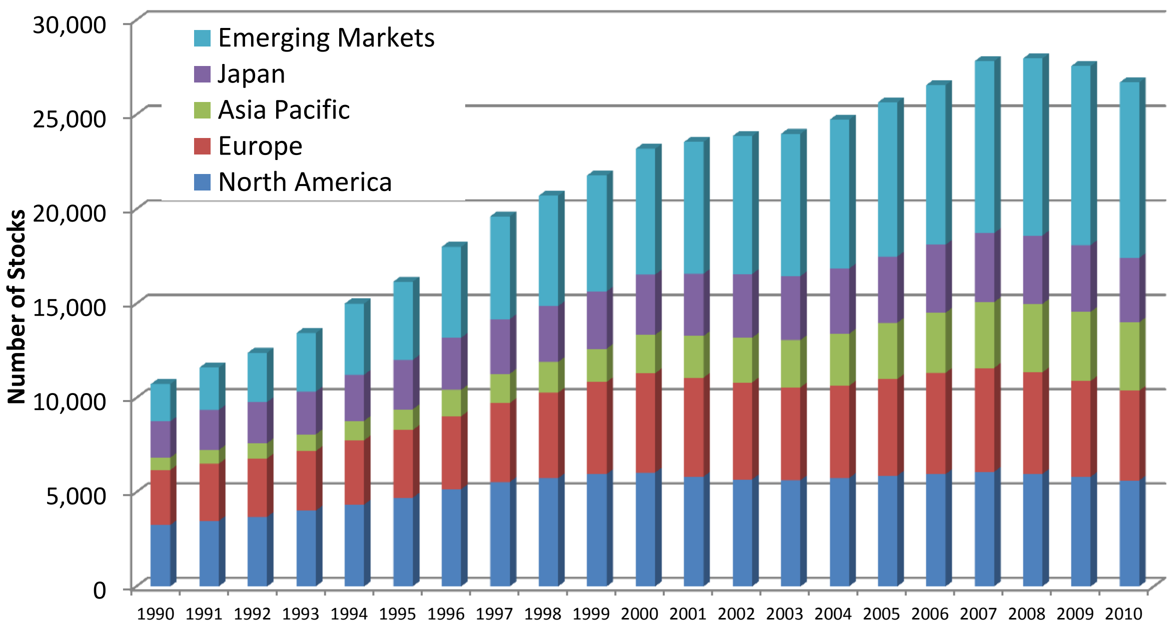


Figure 2a.
Globally Accessible Sample, reported by Total Market Capitalization, 1990-2010.
The figure shows the distribution of the globally accessible sample by region. Beside each region name is the average market capitalization from that region, which is in U.S. dollars trillion, and its percentage of market capitalization. Here the sample is represented by the Main CL Tier and the sample selection criteria are described in the Appendix C.

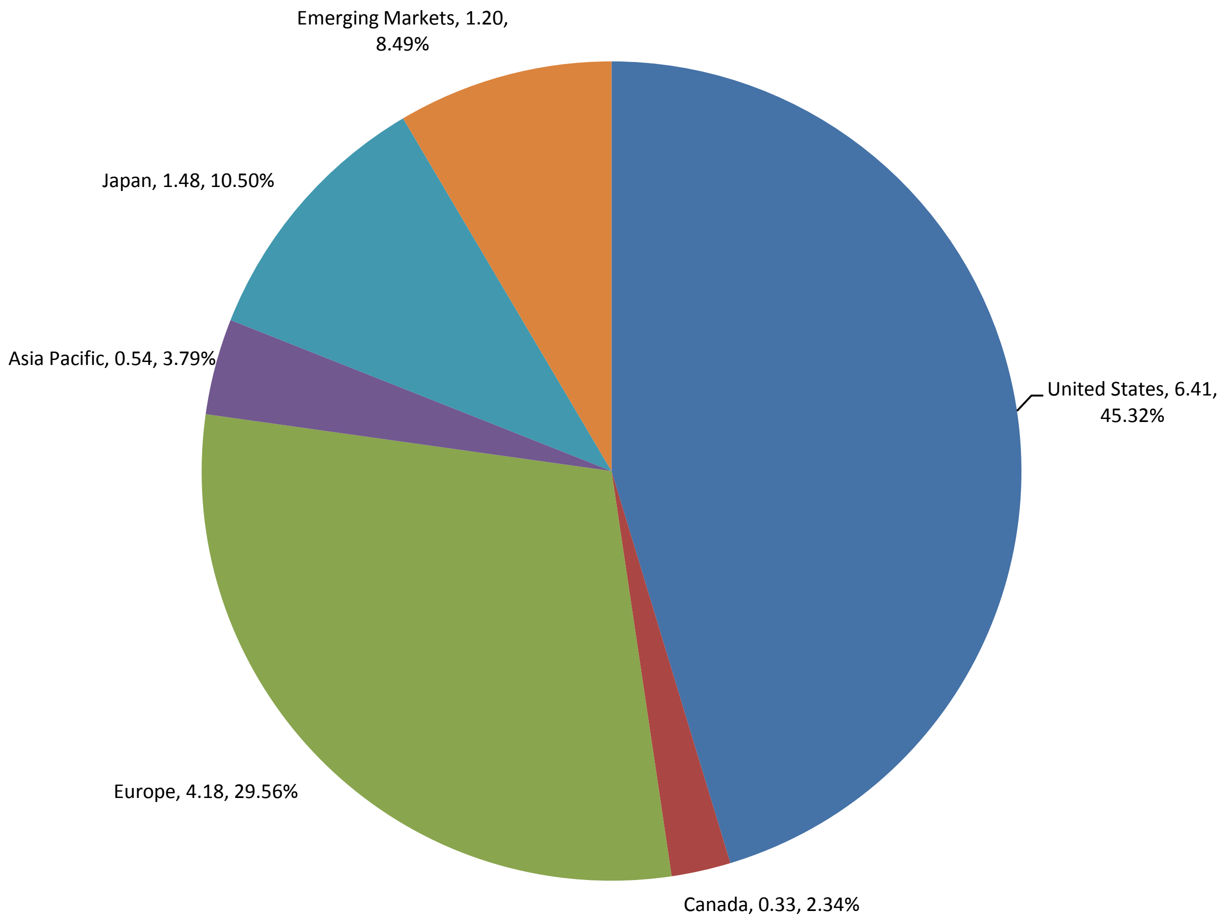
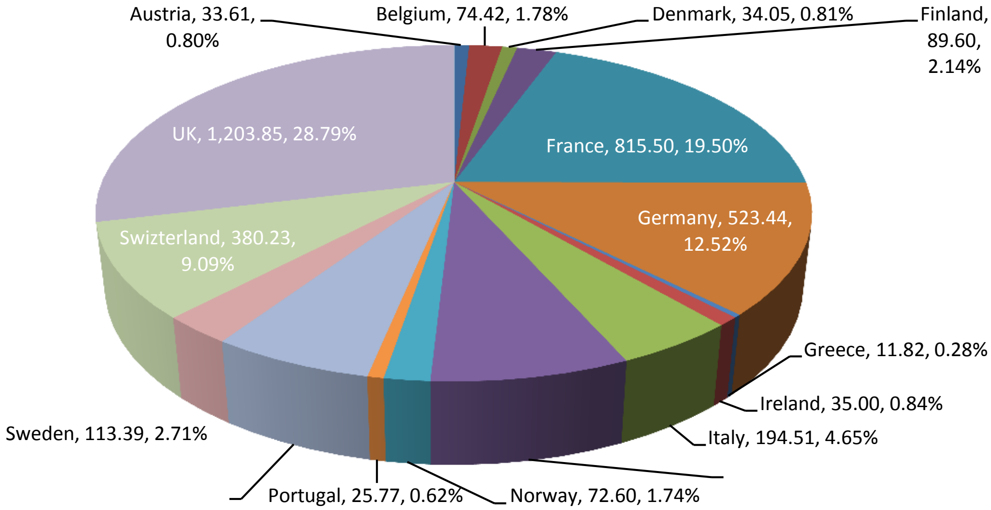
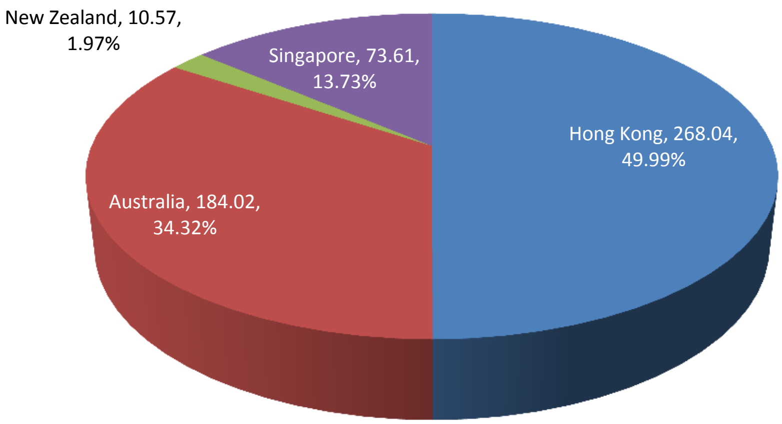


Figure 2a, continued.

Globally Accessible Sample, reported by Total Market Capitalization, 1990-2010.

The figures show the distributions of Europe, Asia Pacific and Emerging Markets globally accessible samples by country. Beside each country name is the average market capitalization from that country, which is in U.S. dollars billion, and its percentage of market capitalization. Here the sample is represented by the Main CL Tier and the selection criteria are described in the Appendix C.





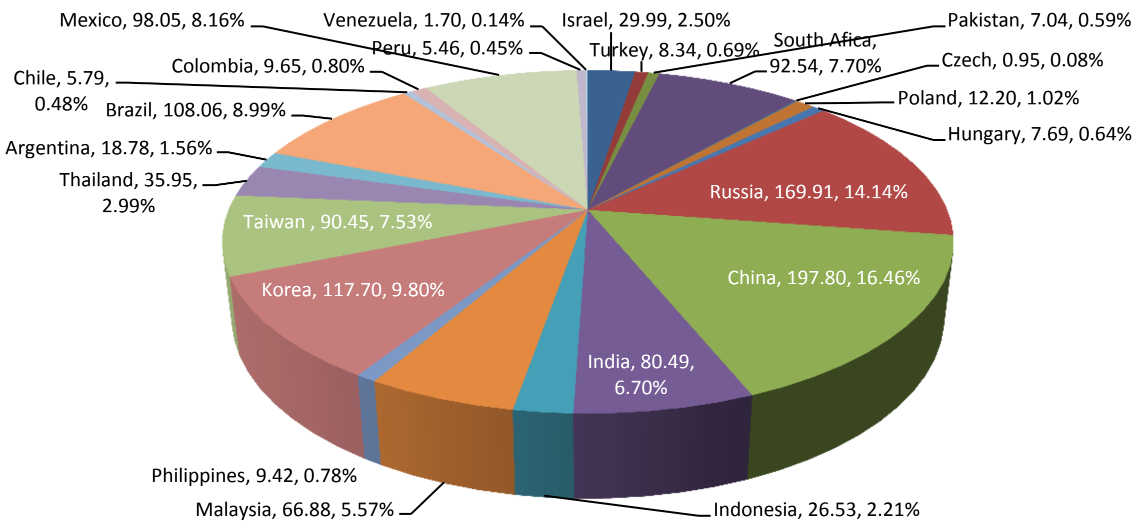
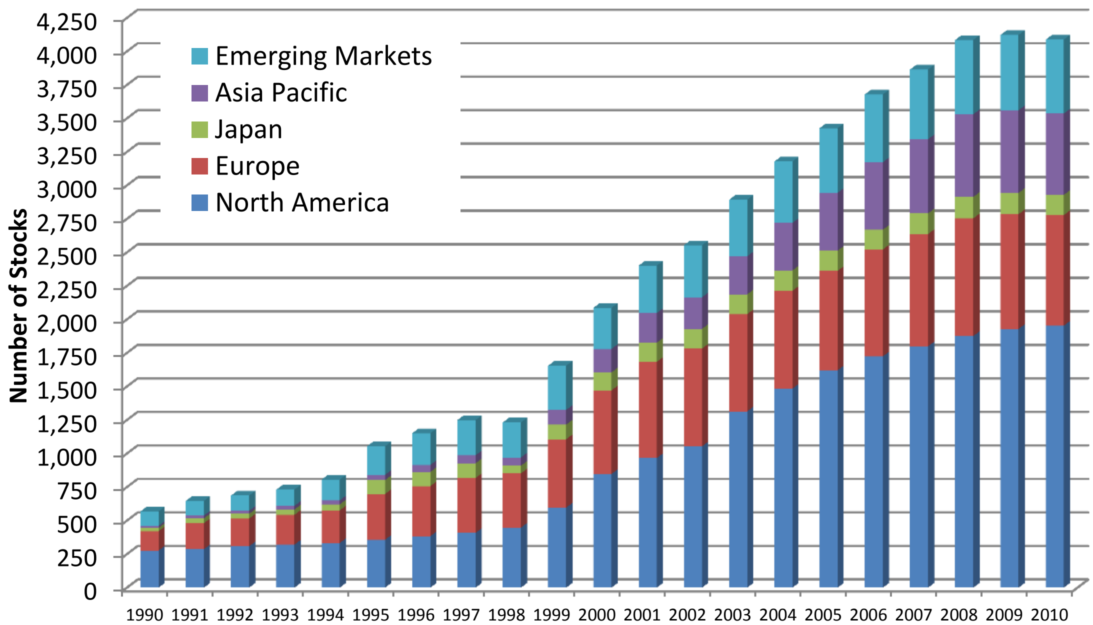
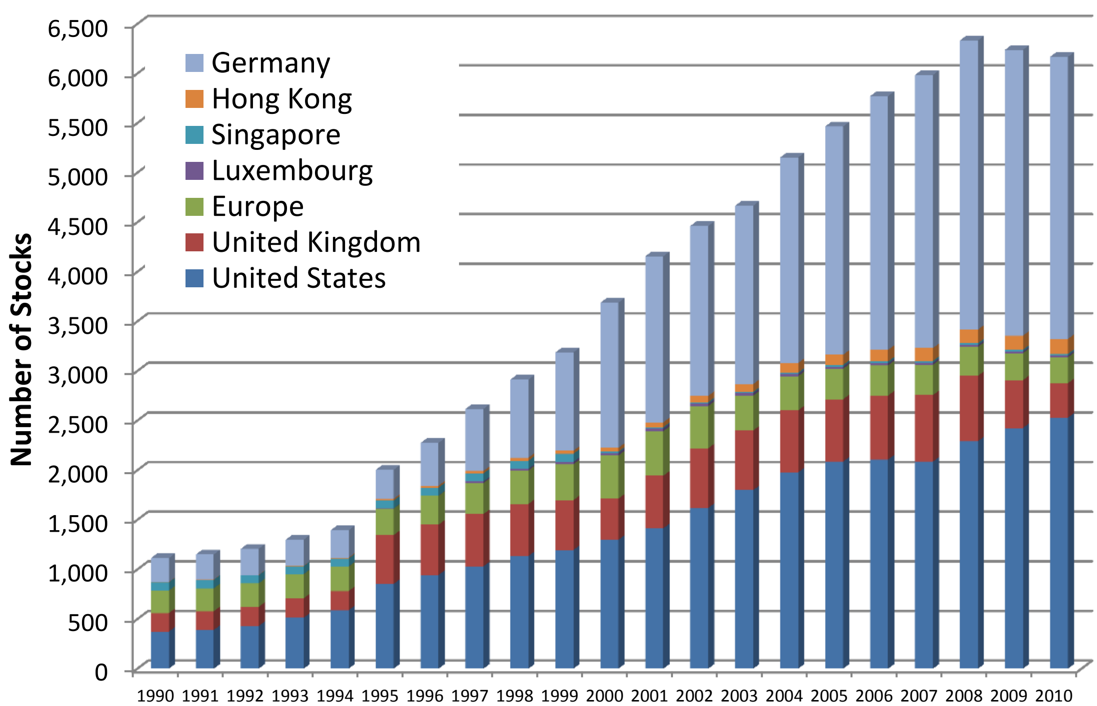


Figure 2b.

Globally Accessible Sample by Year, reported by Total Number of Stocks, 1990-2010.

The figures show the distribution of globally accessible sample from each region (above) and from each target markets (below) by year. Here the sample is represented by the Main CL Tier and the sample selection criteria are described in the Appendix C.





Appendix A. Kan, Robotti, and Shanken (2013) Model Comparison Tests.

Kan, Robotti, and Shanken (2013) develop a test of model comparison based on the sample cross-sectional regression (CSR) R^2, taking into account the impact of model misspecification on the variability of the CSR estimates. They derive the asymptotic distribution of the difference between the sample R^2s of two beta pricing models under the null hypothesis that the population values are the same is derived. They show that the distribution depends on whether the two models are nested or non-nested and whether the models are correctly specified.

More specifically, they consider two competing beta pricing models. Let f_1, f_2, and f_3 be three sets of distinct factors, where f_i is of dimension $K_i \times 1$, i=1,2,3. Assume that model$A$ uses f_1 and f_2, while model B uses f_1 and f_3 as factors. Therefore, model A requires that the expected returns on the test assets, μ_R, be linear in the betas or covariances with respect to f_1 and f_2 , that is,

$$\mu_R = 1_N\lambda_{A,0} + Cov[R, f_1']\lambda_{A,1} + Cov[R, f_2']\lambda_{A,2} = C_A\lambda_A$$

where $C_A = \left[1_N, Cov[R, f_1'], Cov[R, f_2']\right]$ and $\lambda_A = [\lambda_{A,0}, \lambda_{A,1}', \lambda_{A,2}']'$. Model B requires that the expected returns be linear in the betas or covariances with respect to f_1 and f_3 , that is,

$$\mu_R = 1_N\lambda_{B,0} + Cov[R, f_1']\lambda_{B,1} + Cov[R, f_3']\lambda_{B,3} = C_B\lambda_B$$

where $C_B = \left[1_N, Cov[R, f_1'], Cov[R, f_3']\right]$ and $\lambda_B = [\lambda_{B,0}, \lambda_{B,1}', \lambda_{B,3}']'$.

A. Nested Models

Without loss of generality, K_3=0 is assumed so that model A nests model B. They show that when the models are misspecified, $R^2_A=R^2_B$ if and only if $\lambda_{A,2} = 0_{K_2}$. There are two equivalent ways to test whether the models have the same R^2. One can simply perform a Wald test of $H_0\colon \lambda_{A,2} = 0_{K_2}$ based on the CSR estimate and its misspecification-robust covariance matrix. Alternatively, in keeping with the common practice of comparing cross-sectional R^2s, one can use the asymptotic distribution of $\hat{R}^2_A = \hat{R}^2_B$ to perform the weighted chi-squared test H_0: $R^2_A=R^2_B$. Results on both of the tests are consistent in the empirical applications.

In this paper, because the partial-segmentation model nests the global model, we conduct both tests to investigate the statistical significance of the differences between the sample cross-sectional R^2s for this pair of nested model. In the empirical evidence, we report the Wald test in the tables; results for the weighted chi-squared test are consistent with those shown in the tables.

B. Non-Nested Models

Under H_0: $R^2_A=R^2_B$, there are three possible asymptotic distribution for $\hat{R}^2_A - \hat{R}^2_B$, depending on why the two models have the same cross-sectional R^2s. One possibility is that the factors that are not common to the two non-nested models are irrelevant for explaining expected returns. In other words, the models have the same stochastic discounted factors and therefore the same pricing errors as well as identical population R^2s. Alternatively, the two models may produce different pricing errors but still have the same overall goodness of fit. It is then theoretically possible for two models to both be correctly specified (that is, $R^2_A=R^2_B=1$) even though their factors differ. Another possibility, a more general case, is that one model might do a good job of pricing some assets that the other prices poorly and vise versa, such that the aggregation of pricing errors is the same across the two models ($0<R^2_A= R^2_B<1$).

Given the three distinct cases described above, testing H_0: $R^2_A=R^2_B$ for non-nested models entails a sequential test. Another approach is to simply perform the normal test of H_0: $0<R^2_A= R^2_B<1$. Kan, Robotti, and Shanken (2013) conduct both the sequential test and the normal test when comparing non-nested models, and focus mainly on the normal test because, as they point out, the test is more powerful insofar as the simplifying assumptions are valid.

When comparing the partial-segmentation model and the local model in this paper, we follow Kan, Robotti, and Shanken (2013), conduct both of the tests, and report mainly on the normal tests.

Appendix B. Procedure for Constructing the Globally Equity Universe.

We require each firm's home country to be clearly identified in the database. Financial firms are excluded from the study due to their different characteristics. We also exclude depositary receipts (DRs), real estate investment trusts (REITs), preferred stocks, and other stocks with special features.[26] For most countries, we restrict the sample to stocks from major exchanges, which we define as the exchanges on which the majority of stocks in that country are listed. However, multiple exchanges are included in samples for China (Shanghai Stock Exchange and Shenzhen Stock Exchange), Japan (Osaka Stock Exchange, Tokyo Stock Exchange, and JASDAQ), Russia (MICEX and Russian Trading System), South Korea (Korea Stock Exchange and KOSDAQ), Canada (Toronto Stock Exchange and TSX Ventures Exchange), and U.S.(NYSE, AMEX and NASDAQ). To limit the effect of survivorship bias, we include dead stocks in the sample.

To reduce errors in Datastream, we follow several screening procedures for monthly returns as suggested by Ince and Porter (2006) and HKK (2011). First, any return above 300% that is reversed within one month is set to missing. Specifically, if R_t or R_{t-1} is greater than 300%, and if $(1+ R_t) \times (1+ R_{t-1}) - 1 \leq 50\%$, then both R_t and R_{t-1} are set to missing. Second, in order to exclude remaining outliers in returns that cannot be identified as stock splits or mergers, we treat as missing the monthly returns that fall out of the 0.1% and 99.9% percentile ranges in each country. Third, included firms are required to have at least 12 monthly returns during the sample period.

Additionally, we require the availability of the following financial variables for at least one firm-year observation: market value of equity ("Size" hereafter), B/M, and cash flow to price ("C/P" hereafter). To make sure that the accounting ratios are known before the returns, we match the financial statement data for fiscal year-end in year *t-1* with monthly returns from July of year *t* to June of year *t+1*. We take the inverse of the price-to-book ratio (item WC09304) and the price-to-cash flow ratio (item WC09604) to calculate the ratios of B/M and C/P, respectively. We do not use negative B/M (or C/P) stocks when calculating the breakpoints for B/M (or C/P) or when forming the size/B/M (or size/C/P) portfolios.

Figure 1a exhibits the distribution of our global equity universe across regions over the period from 1990 to 2010, reported by total market capitalization. On average, North America, Europe, Japan, Asia Pacific, and the Emerging Markets account for 43.13%, 25.50%, 13.44%, 4.45%, and 13.49% of global market capitalization. However, by the total number of stocks (not shown, but available), North America only constitutes one-quarter of the sample population, higher than Europe (23.08%), Japan (11.50%), and Asia Pacific (10.47%), but lower than the Emerging Markets (29.72%). Proportionally more large-cap stocks are concentrated in North America, especially the U.S. In contrast, proportionally more of the stocks from Asia Pacific and Emerging Markets are small cap stocks. In addition, among the countries in Europe, the average size of stocks in the Netherlands, Spain, and Switzerland are larger than those in Greece, Sweden, and the U.K. Hong Kong accounts for 40.62% of all market capitalization in Asia Pacific but only constitutes 24.96% of the sample population in the region. Most of the stocks in Emerging Markets are from Asia, either by count or by total market capitalization. The average size of stocks varies substantially across emerging market countries, with greater values for Mexico, Brazil, Russia, and China.

Figure 1b shows the sample over time and breaks it down by regions. The counts steadily increase from around 10,000 in 1990 to a peak of almost 28,000 in 2008. Most notably, the count in Emerging Markets has jumped from less than 2,000 in 1990 to nearly 9,500 in 2009. In contrast to these counts, global market capitalization has less steady growth (not shown, but available). It rises from US$7 trillion in 1990 to a peak of US$26 trillion in 2000. It falls after 2000 before reaching another peak of almost US$40 trillion in 2007. In the most recent two years, it rises again to US$34 trillion.

[26] We drop stocks with name including "REIT", "REAL EST", "GDR", "PF", "PREF", or "PRF" as these terms may represent REITs, GDRs, or preferred stocks. We drop stocks with name including "ADS", "CERTIFICATES", "RESPT", "Rights", "Paid in", "UNIT", and a host of others due to various special features. Additional country-specific screening rules are applied.

Appendix C. Procedure for Constructing the Globally Accessible Sample.

	Target Market	U.S.	U.K.	Europe	Germany	Luxembourg	Singapore	Hong Kong
	Target Exchanges	NYSE/AMEX, NASDAQ, Non NASDAQ OTC New York, NASDAQ/NMS, NYSE Arca	London London OTC London Plus Market SEAQ International	Euronext Amsterdam Brussels Lisbon Paris Easdaq	Frankfurt	Luxembourg	Singapore Catalist Singapore OTC Singapore	Hong Kong
Exclusion Criteria	• *Non domestic stocks only*	9,632	4,114	5,165	14,542	430	300	314
	• *Target market currency denominated only*	9,585	4,114	5,165	14,542	430	215	284
	• *ADRs, GDRs, or equity only*	8,900	3,112	4,212	13,899	404	212	246
	• *Available records of home market only*	9,181	3,086	4,205	13,873	363	212	246
	• *Qualified records of parent code only*	8,857	3,078	4,205	12,591	363	211	246
	• *Available RI records only*	7,586	2,413	2,997	12,186	143	179	216
	• *Exclude dual record in one target market*	6,421	1,995	2,217	11,463	133	171	212
	• *Qualified countries only*	6,320	1,791	2,165	11,292	126	170	210
	• *Available records from Worldscope only*	5,080	1,517	1,058	9,986	101	160	201
	• *Non-financial stocks only*	4,392	1,283	690	8,680	82	120	175
	• *Exclude special cases*	4,354	1,273	689	8,622	81	120	175
	• *Total across regions*				11,319			
	• *Additional domestic stocks included*	11,335						
	• *Qualified stocks only*	CL 1st Tier			11,057			
	• *Viability Constraints*	Main CL Tier			5,747		• *Relative viability constraints (I or II)*	
		CL 2nd Tier			9,605		• *Absolute viability constraint*	
		CL 3rd Tier			4,058		• *Stringent Relative viability constraints (I or II)*	

Appendix C, continued.

This table shows the procedure on how to construct the globally accessible sample and the total number of stocks is reported for each step. The list of target exchanges is as shown and each exclusion criterion is explained in the table below. To be included in the global accessible sample, each stock has to be cross listed in any of the 7 target markets with the types of ADRs, GDRs or equity, has sufficient information to identify its home market and parent codes, has at least one monthly returns, has sufficient information to calculate at least one of the characteristics including Size, B/M and C/P. "CL" stands for cross-listing.

More specifically, our sample construction begins with all non-domestic stocks listed in the target exchanges. From the list containing over 30,000 stocks, we select those that meet a number of selection criteria, for instance, available records of home market trading, a parent code in the database to verify the matching records, and stocks whose Return Index (RI) records are available in the database.[27] Similar to the global equity universe, we exclude financial firms and confine the sample to firms from 46 countries and with available company account items from Worldscope. This leaves 11,319 stocks secondarily cross-listed on at least one of the target markets. We then add domestic stocks from the seven target markets as long as three criteria are satisfied: they are among those stocks in the top 75% of market capitalization for the market; they have a minimum price of U.S. $5 and equivalent levels in terms of percentile rank for non-U.S. markets; and, they are among those stocks with a minimum 75% public float for listed stocks. These filters leave 11,057 qualified stocks, which we label as "CL 1st Tier" to denote the most all-encompassing group of cross-listed (CL) stocks.

To construct our final sample, we impose additional restrictions on how actively the secondarily cross-listed shares are traded, which we call our "viability" constraints. We drop cross-listed stocks for which trading in the target markets is too limited to be viably accessible for global investors. For each secondarily cross-listed stock in the CL 1st Tier, we compare (a) its monthly trading in the target markets with the total trading of all secondarily cross-listed stocks from the same home country (using VA, turnover by value, from Datastream) and (b) its monthly trading volume (VO, turnover by volume, from Datastream) in the target markets relative to that of the same stock in the home market. The first viability constraint evaluates the annual percentage of its trading in target markets relative to all secondarily cross-listed stocks from the same country trading there. If the time-series average of the annual percentages during the sample period is required to be at least 0.5%, there are nearly 900 stocks that qualify, many of which are the most popularly traded stocks for global investors. For the stocks that fail to meet our first viability criterion, we use a second one based on the annual percentage of its own global trading volume in any of the target markets (Baruch, Karolyi, & Lemmon, 2007). If the time-series average of these annual percentages during the sample period is required to be at least 0.1%, there are around 5,300 stocks left in the sample. Merging these two cross-listed sets of stocks and qualified domestic set of stocks from the target markets leaves 5,747 stocks, which we refer to as the "Main CL Tier."

Figure 2a presents its distribution across regions over the period from 1990 to 2010, reported by total market capitalization. On average, North America (47.66%) and Europe (29.56%) constitute the bulk of the total market capitalization in the Main CL Tier, followed by Japan (10.50%), Emerging Markets (8.49%), and Asia Pacific (3.79%). The cross-listed stocks constitute a significant fraction of the overall market capitalization in each home region (compare with Figure 1). By count, North America, Europe, Japan, Asia Pacific, and Emerging Markets represent 44.95%, 23.56%, 3.43%, 13.66%, and 14.41% of the sample population, respectively (not shown, but available). Figure 2a also exhibits the distribution of Main CL Tier stocks across countries within each region. In Europe, stocks from France, Germany, the Netherlands, and Switzerland are more likely to have shares secondarily cross-listed overseas but stocks from Austria, Greece, and the U.K. tend to stay in their home markets. In Asia Pacific, Hong Kong stocks are over-represented in the Main CL Tier relative to the global equity universe. Among emerging market countries, equities from China, India, and Taiwan are more likely to stay at home. On the other hand, equities from Russia, Mexico, and South Africa tend to go abroad.

[27] To limit the effect of survivorship bias, we include dead stocks in the sample. For both dead and active stocks, we confirm their effective ending months according to two criteria: (i) consecutive constant return index records (RIs) from the month until the end of the period, December 2010; and, (ii) zero trading volume from the month until the end of the period. If a given stock reports the same month for its base month and ending month, the stock is excluded from the sample.

Figure 2b illustrates the total market capitalization of the Main CL Tier, and breaks them down by regions and by year. The total count increases from less than 1,000 in the early 1990s to a peak of 4,123 in 2009 and then falls to 4,088 in 2010. In contrast to the counts, total market capitalization, as well as the market capitalizations from each region, has experienced more volatility over the period, reaching peaks in 2000 and 2007 (not shown, but available).

Figure 2b also shows the distribution of Main CL Tier stocks by each target market and by year. Most notably, the U.S. as a target market for internationally cross-listed stocks is more resilient than those in the U.K., Europe, and Germany, either by count or by market capitalization. Annual counts in the U.K. reach a peak of 670 in 2007 and decrease steadily to 347 in 2010. For Europe, the number of cross-listed stocks never goes up above 450 and it decreases steadily from 450 in 2001 to 261 in 2010. For the Frankfurt Stock Exchange, the annual count increases significantly from less than 270 in the early 1990s to 2,917 in 2008, but it falls during the most recent two years until down to 2,845 in 2010. Distinct from these markets, NYSE/AMEX, Nasdaq and the Non-Nasdaq OTC markets have attracted more foreign stocks cross-listed. Even after the 2008 financial crisis, the count is steadily rising from 2,087 in 2007 to 2,529 in 2010 (Iliev, Miller, and Roth, 2011). Although all target markets have shrunk in size around 2008, the cross-listed market capitalization in the U.S. drops by 28.01% from 2007 to 2009, much less than the 61.09% in the U.K., 48.31% in Europe, and 30.66% in Germany.

In addition to the Main CL Tier, we construct and evaluate two other definitions for the globally accessible sample, together with CL 1st Tier, to ensure the reliability of the partial-segmentation model we propose. First, we introduce an absolute viability constraint: for each stock in CL 1st Tier in a given year, if there is at least one month of non-zero trading in the target markets, the stock is included in the globally accessible sample for that year. The resulting sample has 9,605 stocks and is labeled the "CL 2nd Tier." Second, we consider more stringent screening on the two viability constraints: we raise the screening ratios up to 5% for the first relative viability constraint and 1% for the second one. Another new sample, denoted the "CL 3rd Tier," then contains 4,058 stocks. For each globally accessible sample, we group the stocks left in each respective region as the locally-accessible set. Summary statistics on total counts and firm-level characteristics for the Main CL Tier are not shown but available.

Appendix C, continued.

Definitions of Exclusion Criteria

Exclusion Criteria	Description
• *Non domestic stocks only*	If one stock is only listed in its home market, it is excluded from the sample. And these stocks are excluded as follow, ▪ Stocks are from U.S. and only listed in the target exchanges within the U.S.; ▪ Stocks are from U.K. and only listed in the target exchanges within the U.K.; ▪ Stocks are from Portugal and only listed in Euronext Lisbon; ▪ Stocks are from France and only listed in Euronext Paris; ▪ Stocks are from Netherland and only listed in Euronext Amsterdam; ▪ Stocks are from Luxembourg and only listed in Luxembourg; ▪ Stocks are from Singapore and only listed in the target exchanges within Singapore; ▪ Stocks are from Hong Kong and only listed in Hong Kong Stock Exchange
• *Target market currency denomination only*	If one stock is denominated with a currency other than that of the host market, it is excluded from the sample. This exclusion criterion only applies to stocks cross-listed in the U.S., Singapore and Hong Kong.
• *ADRs, GDRs, or equity only*	If one stock is recorded as other instrument types than ADRs, GDRs or equity from Datastream, it is excluded from the sample.
• *Available records of home market only*	If one stock has no available records of home market from Datastream, it is excluded from the sample.
• *Qualified records of parent code only*	If one stock has no available records of parent code in each major exchange from Datastream, it is excluded from the sample.
• *Available RI records only*	If one stock has no available Return Index (RI) from Datastream, it is excluded from the sample.
• *Exclude dual record case in one target market*	If one stock is cross listed on more than one target exchange within one given target market, it is counted as only one stock in the sample.
• *Qualified countries only*	If one stock is from countries other than the country list in Table 1, it is excluded from the sample.
• *Available records from Worldscope only*	If one stock has no available company account item from Worldscope, it is excluded from the sample.
• *Non-financial stocks only*	If one stock is financial stock, it is excluded from the sample.
• *Exclude special cases*	Special cases include but is not limited to that the ADR (or GDR), instead of the home equity, is primary quoted in Datastream.
• *Total across regions*	If one stock is listed in more than one target market, it is counted as only one stock in the sample.
• *Additional domestic stocks included*	Domestic stocks from the seven target markets are included as long as three criteria are satisfied: a. size (in the top 75% of market cap for the market); b. liquidity (a minimum price of $5 for U.S. and equivalent levels in terms of percentile rank for non U.S. markets); and c. float (a minimum 75% public float for listed stocks)
• *Qualified stocks only*	If one stock has less than 12 monthly returns, it is excluded from the sample.
• *Viability Constraints*	Viability constraints are evaluated by the Turnover (VO) from Datastream and it includes records in the home market and those in the target markets.
• *Relative viability constraint I*	For each cross-listed stock in the sample, there should be at least 0.5% of annual oversea trading value relative to all secondarily cross-listed stock trading from its country of domicile
• *Relative viability constraint II*	For each cross-listed stock in the sample, there should be at least 0.1% of annual global trading volume occurred in any of the target markets on average during the sample period
• *Absolute viability constraint*	For each cross-listed stock in the sample in a given year, if there is at least one month of non-zero trading occurred in the target markets, the stock is included in the sample for that year
• *Stringent Relative viability constraints(I or II)*	The screening ratios are 5% for relative viability constraint I or 1% for relative viability constraint II.

Appendix D. Constructions of Factor Portfolios and Testing Assets.

A. Building Factor Portfolios

Our first asset pricing tests are for 5×5 size/B/M portfolios and the explanatory returns are for 2×3 portfolios sorted on size and B/M. At the end of each June from 1990 to 2010, we allocate stocks in one region to two size groups – small stocks and big stocks. Big stocks are those in the top 90% of market capitalization for the region, and small stocks are those in the bottom 10%. The only difference between our sorting breakpoints and those of Fama and French (2012) is related to the B/M breakpoints. Fama and French (2012) use the 30th and 70th percentiles of B/M for the big stocks in each given region to avoid too much weight on micro-cap stocks. Value stocks are those with B/M ratios at or above the 70th percentile, growth stocks, those with B/M ratios at or below the 30th percentile, and the rest are neutral stocks. However, there are still differences in terms of accounting rule across countries within any one region. Given the fact that our globally accessible stocks are more likely to accept global standards for reporting that can be comparable across countries, we use B/M breakpoints based on the big stocks in the globally accessible sample from each region to avoid sorts that are dominated by the less comparable and tiny stocks in the region.

The global explanatory returns are constructed from the globally accessible sample. We use a universal size breakpoint, but use each region's B/M breakpoints to allocate the globally accessible stocks. Beyond the global factor returns, the partial-segmentation model includes local factor returns that are based on the locally-accessible stocks from the region for which the test is performed relative to the globally accessible stocks. Fama and French (2008, 2012) document that microcap stocks pose a challenge for asset pricing models and suggest factor returns should not be dominated by small stocks. Small stocks constitute the major component of the locally-accessible samples. So, if the size breakpoint is the bottom 10th percentile of market capitalization of the locally-accessible sample for each region, either the size factor or the value factor will be dominated by small stocks. Thus we use regional size cutoffs for the locally-accessible portfolios. In addition, we adopt the same regional B/M breaks as in the globally accessible portfolios to avoid the microcap effect. Then, for each given region, the return spread factor portfolios of locally-accessible stocks relative to the globally-accessible stocks are the differences in the respective factor portfolio returns for the set of locally-accessible stocks in the region and for the globally-accessible stocks. For example, for the size-related spread factor portfolio, we compute the return difference between the factor portfolio for the locally-accessible stocks (measured, in turn, as the difference between an equally-weighted average of the small-growth, small-neutral, and small-value portfolios and an equally-weighted average of the big-growth, big-neutral, and big-value portfolios) and the globally-accessible stocks (measured similarly). The value- and momentum-related spread factor portfolios are built in the same way. The spread factor portfolios vary by region because the set of locally-accessible stocks from which they are built changes.

Another set of explanatory returns are 2×3 factor portfolios returns sorted on size and momentum, which will be introduced in our second asset pricing tests on size/momentum portfolios. The momentum factor, WML, is formed using a 12-month/2-month strategy where each month's return is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. Similar to the size/B/M portfolios, the momentum breakpoints for the global explanatory returns are the 30th and 70th percentiles for the big stocks in the globally accessible sample from each region. And we use the regional momentum cutoffs based on big stocks for the given region when forming local explanatory returns. The momentum breakpoints from each region are employed in forming global portfolios. In our third set of tests on size/C/P portfolios, we build the set of explanatory returns that are for 2×3 portfolios sorted on size and C/P. The explanatory return associated with C/P is constructed by the same way as that associated with B/M.

B. Building Test Assets

Our first set of asset pricing tests evaluates 5×5 size/B/M portfolios. The size breakpoints for a region are the 3rd, 7th, 13th, and 25th percentiles of the region's aggregate market capitalization. The B/M breakpoints are defined by the 20th, 40th, 60th, and 80th percentiles for big stocks in the region. Appendix Table 6 displays the average excess returns and standard deviations for each set of 5×5 size/B/M test assets by global and regional experiment. Our results confirm the finding in Fama and French (2012) that the size pattern in value premiums poses a challenge for asset pricing models. The next two test assets are 5×5 size/momentum portfolios and 5×5 size/C/P portfolios. For the sake of brevity, average excess returns for these two types of test asset portfolios are reported in an appendix.