



Emerging Markets Group

EMG Working Paper Series

WP-EMG-05-2009

***'Can Investor Heterogeneity be used to explain
the Cross-section of Average Stock Returns in
Emerging Markets?'***

Chan Shik Jung, Dong Wook Lee and Kyung Suh
Park

February 2009

Emerging Markets Group
Cass Business School
City University
106 Bunhill Row
London
EC1Y 8TZ
UK

www.cass.city.ac.uk/emg/

Can investor heterogeneity be used to explain the cross-section of average stock returns in emerging markets?

Chan Shik Jung ^a, Dong Wook Lee ^{b,*}, Kyung Suh Park ^c

Abstract

This paper examines whether investor heterogeneity can be used for asset-pricing purposes in emerging markets. We pose this question, since the lack of transparency and greater uncertainty, which are typical of those markets, render it more likely that investors will disagree with each other and hold different portfolios, resulting in a mean-variance *inefficient* market portfolio. Consequently, we examine whether a heterogeneity-based factor can sufficiently augment the market portfolio, so that the two can function as multivariate proxies for the tangency portfolio. We test this hypothesis in the Korean stock market in which the measures of heterogeneity such as foreign ownership and institutional holdings are available for a large number of stocks over an extended period of time. We find that the heterogeneity-augmented two-factor model outperforms the CAPM one-factor and the Fama-French three-factor models. Consistent with the greater severity of investor heterogeneity in emerging markets, a developed market with comparable data availability, namely, Japan, shows similar but weaker test results.

Keywords: investor heterogeneity; emerging market; multivariate proxies for tangency portfolio; factor model

JEL classification: G11; G12; G15

^a Korea University Business School, Seoul, Korea, 136-701

^b Korea University Business School, Seoul, Korea, 136-701

^c Korea University Business School, Seoul, Korea, 136-701

* Corresponding author: Tel.:+82.2.3290.2820; fax:+82.2.3290.1307; email:donglee@korea.ac.kr

Can investor heterogeneity be used to explain the cross-section of average stock returns in emerging markets?

Abstract

This paper examines whether investor heterogeneity can be used for asset-pricing purposes in emerging markets. We pose this question, since the lack of transparency and greater uncertainty, which are typical of those markets, render it more likely that investors will disagree with each other and hold different portfolios, resulting in a mean-variance *inefficient* market portfolio. Consequently, we examine whether a heterogeneity-based factor can sufficiently augment the market portfolio, so that the two can function as multivariate proxies for the tangency portfolio. We test this hypothesis in the Korean stock market in which the measures of heterogeneity such as foreign ownership and institutional holdings are available for a large number of stocks over an extended period of time. We find that the heterogeneity-augmented two-factor model outperforms the CAPM one-factor and the Fama-French three-factor models. Consistent with the greater severity of investor heterogeneity in emerging markets, a developed market with comparable data availability, namely, Japan, shows similar but weaker test results.

Keywords: investor heterogeneity; emerging market; multivariate proxies for tangency portfolio; factor model

JEL classification: G11; G12; G15

1. Introduction

Despite the massive financial integration over the past several decades, stock markets in different countries have yet to be fully integrated (Karolyi and Stulz, 2003). Furthermore, cross-country segmentation and in particular the distinction between emerging and developed markets are frequently attributed to rather time-invariant institutions, including political uncertainty, lack of transparency, and poor corporate governance (e.g., Nishiotis, 2004; Stulz, 2005; Bekaert, Harvey, Lundblad, and Siegel, 2007). Consequently, a different approach to emerging market asset pricing is warranted, one which takes into consideration its uniqueness. In this paper, we examine the role of investor heterogeneity in an attempt to develop such an alternative approach to explaining the cross-section of average stock returns in an emerging market.

Our interest in investor heterogeneity arises naturally, as the uncertain and opaque nature of emerging markets, coupled with the increased presence of foreign investors, maximizes the scope for disagreement among investors. More importantly, investor heterogeneity has an asset-pricing implication. Recall that the well-known failure of the CAPM is attributed to the mean-variance inefficiency of the market portfolio, or equivalently, its deviation from the mean-variance efficient tangency portfolio (Fama, 1976; Roll, 1977). As shown by Fama and French (2007), investor heterogeneity contributes to this wedge between the market portfolio and the tangency portfolio. Specifically, when heterogeneity exists among investors and one group of investors does not hold the tangency portfolio for some reason, the other group of investors will also deviate from the tangency portfolio to clear the market, thereby making the market portfolio different from the tangency portfolio. Consequently, risk-sharing within the market is limited, and an extra risk premium arises which is not associated with covariance with the market portfolio (Merton, 1987). In a market where this type of inefficiency is relevant, it is thus conceivable that the market portfolio can be augmented sufficiently by an additional factor representing the premium associated with the limited risk-sharing due to investor heterogeneity. Or equivalently,

as a model of multivariate proxies for the tangency portfolio, a heterogeneity-augmented two-factor model may more parsimoniously explain the cross-section of average stock returns.

To gauge empirically the feasibility of this two-factor model in an emerging market, we measure investor heterogeneity using foreign or institutional ownership on the grounds that the *composition* of the stock portfolio differs between locals and foreigners and between individuals and institutions (e.g., Falkenstein, 1996; Kang and Stulz, 1997; Cohen, 1999; Gompers and Metrick, 2001; Dahlquist and Robertsson, 2001; Giannetti and Simonov, 2003; Ahearne, Grier, and Warnock, 2004; Lins and Warnock, 2006).¹ Specifically, we construct the heterogeneity-augmenting factor using the hedged portfolio that is long in stocks with *low* foreign (or institutional) ownership and short in stocks with *high* foreign (or institutional) ownership. We then test the resultant two-factor (i.e., market portfolio + heterogeneity-augmenting factor) model in the Korean stock market in which both heterogeneity measures are available on a large number of firms for a reasonably long period of time, and then put the Korean results into perspective by comparing them with the test results for a developed market with similar data availability, namely, Japan.

Our test procedure is straightforward. In a given market, we examine the explanatory power of the two-factor model for the monthly returns on size- or book-to-market-ratio-sorted portfolios, and compare its performance with that of the CAPM one-factor and the Fama-French three-factor models. Our particular test portfolios are motivated by the fact that firm size and book-to-market

¹ Besides foreign or institutional ownership, we considered several other heterogeneity measures. However, few of them seem to be suited for our analysis, as they lack the needed asset pricing implications. For example, young and old investors may well differ in their stock holdings, but this difference is more likely to be about the allocation to stocks in their overall portfolio rather than about the composition of their stock holdings *per se*. This distinction is important because it is the latter that makes the market portfolio inefficient. For example, even if some investors allocate all their money to stocks while others invest only 10 percent of their wealth in stocks, the market portfolio can still be mean-variance efficient, as long as their stock portfolio compositions are the same. As an illustration, the former may invest exclusively in the stock market index, whereas the latter invest only 10 percent of their wealth in the *same* stock market index and put the remaining 90 percent in the money market fund. Since the mean-variance inefficiency of the market portfolio arises when some investors deviate from the tangency portfolio, a researcher can start with a proxy for informationally disadvantaged (Kang and Stulz, 1997) or institutionally constrained investors (Ross, 1989). Our choice of foreigners and institutions is motivated in this context.

ratio (BM, hereafter) are the two most important firm characteristics that are independently correlated with stock returns. In other words, a valid asset pricing model first must be capable of explaining the cross-sectional dispersion in average return along these two dimensions. However, we also utilize individual stocks as test assets to ensure the robustness of our portfolio results. The comparison with the Fama-French three-factor model is motivated by the fact that it is the most widely used asset pricing model specifically designed to explain the size- and BM-related stock return. In other words, we do not assume that the Fama-French three factor model is the best among the existing asset pricing models. Related, as we examine the two countries in which no momentum profit is found (e.g, Griffin, Ji, and Martin, 2003), we do not consider other models including the momentum factor.

We find that the heterogeneity-augmented two-factor model performs the best among the three competing models in the Korean market. Compared to the CAPM one-factor and the Fama-French three-factor models in the time-series regression context, our two-factor model significantly reduces the number of incidences of a significant regression intercept. The time-series regression intercept represents the average return on the test asset that is not explained by the suggested risk factor(s). Hence, this result indicates that the two-factor model explains the average stock return better than the other two models. We also confirm that the results are robust to using individual stocks as test assets.

The cross-section of average stock return is then examined by a joint test for the regression intercepts across test assets (Fama and French, 1993; Griffin, 2002). Both the Wald and the Gibbons, Ross, and Shanken (1989; GRS, hereafter) tests show that our two-factor model best explains the cross-section of average stock returns. As another cross-sectional analysis, we employ the Fama-MacBeth regression analysis, which first fits the cross-section of stock return using the factor loadings as the explanatory variables and then average their cross-sectional regression coefficients over time. We find that the estimated loading on the heterogeneity-

augmenting factor is more useful than the loadings on the size and BM factors in explaining stock returns cross-sectionally.

All these results are robust to different heterogeneity measures, as we use either foreign ownership (from July 1992 to December 2006) or institutional holdings (from July 1992 to June 2005) and obtain very similar results. The comparable results between the two heterogeneity measures demonstrate that our results are not limited to foreign investors but are driven by heterogeneity among investors in general. In this regard, our model is distinguished from another two-factor model containing both the domestic and foreign market indices (e.g., Foerster and Karolyi, 1999). In fact, we find that our foreign ownership-based model outperforms this alternative two-factor model.

The performance of the two-factor model in the Japanese market is, as might be expected, similar to but weaker than its performance in the Korean market. For the period from 1976 to 2004, the two-factor model outperforms the other two models by only a modest margin in the time-series regression analysis, whereas the dominance of the heterogeneity-augmenting factor over size and BM factors remains pronounced in the Fama-MacBeth regressions. Although making only two observations, the different results between the two markets are consistent with the larger role of investor heterogeneity in emerging market asset pricing. For example, the stronger foreign ownership-based results in Korea are consistent with the greater severity of the so-called home-bias in emerging markets (e.g., Ahearne, Grier, and Warnock, 2004).

In summary, our empirical results lend strong support to the idea of using investor heterogeneity for asset-pricing purposes. The results also suggest that this idea be useful especially for emerging markets in which the heterogeneity-driven inefficiency in the market portfolio is likely to be more severe. In drawing these implications, we stress that investor heterogeneity is not motivated as another firm characteristic relevant to asset pricing, besides firm

size and BM.² In other words, unlike a firm characteristic-based multifactor model, our model does not suggest a new priced risk. Recall that the characteristic-based approach typically starts with certain firm attributes that are already known to be correlated with average stock. Consequently, the resultant risk factors are frequently criticized as being post-selected but hard to identify the underlying risks (e.g., Ferson et al., 1999; Berk, Greene, and Naik, 1999; Daniel, Hirshleifer, and Subrahmanyam, 2005). In stark contrast, we begin by asking why the market portfolio cannot serve as the sole risk factor, and thus are motivated to use investor heterogeneity as an augmenting factor, so that the two can together function as multivariate proxies for the tangency portfolio.

We also emphasize that our two-factor model is not designed to capture the return commonalities caused by the demand shock to stocks preferred by foreigners or institutions. Although it is possible that those investor groups create a common demand shock to stocks with certain characteristics and hence their return comovement, the resulting “premium” cannot be persistent and will be subsequently reversed when the demand shocks disappear (Gompers and Metrick, 2001). For this reason, we are careful to construct our heterogeneity-augmenting factor using the *subsequent* stock return (see Section 3 for details). Consequently, this additional factor, which is based on a hedged portfolio that is *long* in stocks with *low* foreign (institutional) ownership and *short* in stocks with *high* foreign (institutional) ownership, has a *positive* average return.

This paper proceeds as follows. In the next section, we motivate our two-factor model in a more theoretical context. Section 3 describes the sample and data, and Section 4 reports the empirical results for the Korean stock market. Section 5 provides an array of robustness checks including the tests using the Japanese data. Finally, Section 6 concludes the paper.

2. Heterogeneity-augmented factor model

² For studies searching for other price-relevant firm characteristics, see, e.g., Hou, Karolyi, and Kho (2007).

In this section, we motivate our two-factor model in a more theoretical context. We do so by beginning with the empirical inadequacy of the CAPM that has given rise to a variety of multi-factor models (see, e.g., Fama and French, 1992, 1993). As mentioned in the introduction, the failure of the CAPM, or equivalently, the insufficiency of the market portfolio as the sole risk factor is simply due to the fact that the market portfolio is not mean-variance efficient (see, e.g., Fama, 1976; Roll, 1977).³ As a result, the subsequent studies have focused on the question as to what other factor(s) can best complement the inefficient market portfolio.

2.1. Firm characteristics-based factor model

A typical approach to complementing the inefficient market portfolio begins with the empirical observation that certain firm characteristics, besides the covariance with the market portfolio, are correlated with the cross-section of average stock returns. They include the market value of equity, the ratio of book value of equity to its market value (or book-to-market ratio), the price-to-earnings ratio, and leverage, to name a few. Fama and French (1992) find that the book-to-market ratio and market capitalization subsume other variables in explaining the cross-section of average stock returns in the U.S. market. Fama and French (1993) then create factor-mimicking portfolios based on the two variables, and show that the size and book-to-market effects disappear once the loadings on these two additional factor-mimicking portfolios, as well as the one on the market portfolio, are taken into consideration. The authors also provide international evidence for the characteristic-based factor-mimicking portfolios, especially the one based on book-to-market ratio (Fama and French 1998).

In their later study, Fama and French (2007) clarify the possible sources of the wedge between the market portfolio and the tangency portfolio. Specifically, they show that the market portfolio is mean-variance inefficient when: (1) investors disagree and hold different portfolios of

³ In the same spirit, Fama and French (1996) mention that what an asset pricing test is up to is whether the suggested explanatory portfolio is the mean-variance efficient portfolio using those assets to be explained.

risky assets, (2) investors hold risky assets for reasons besides their expected returns, and (3) investors hold risky assets to hedge against unexpected changes in investment and consumption opportunity sets (i.e., state variable risks). However, since it is difficult to disentangle the three sources of the inefficiency (and as a matter of fact, they are not mutually exclusive), the authors suggest being “agnostic about whether the tangency portfolio is not the market portfolio because of disagreement, tastes for assets as consumption goods, state variable risks, or an amalgam of the three. (p. 685)” In fact, the authors further suggest that “One approach to capturing T [mean-variance efficient tangency portfolio] is to form a set of diversified portfolios that seem to cover observed differences in average returns related to common factors in returns. If these portfolios span T , they can be used (along with the risk-free rate) to describe differences in expected asset returns. (pp. 684-685)”

2.2. Investor heterogeneity-based factor model

A closer examination of the three sources suggests that investor heterogeneity is at the heart of the mean-variance inefficiency of the market portfolio. For example, if investors have different expectations about the probability distribution of future asset returns owing to different access to information or different degrees of rationality (which thus correspond to the first two sources), then some investors may well hold a non-tangency portfolio and thus make the overall market portfolio deviate from the tangency portfolio. Alternatively, heterogeneity in other dimensions can also cause the market portfolio to be different from the tangency portfolio even if investors completely agree on the probability distribution of future asset returns. For example, investors residing in different countries will perceive different risks even if they have the same expectations about foreign exchange rate changes. If investors use stocks to hedge against their own state variable risks in addition to holding the common tangency portfolio, their portfolios and thus the aggregate market portfolio will differ from the tangency portfolio (see Merton, 1973; Fama, 1996).

The deviation of the market portfolio from the tangency portfolio implies that there is an additional risk premium that is not related to the covariance with the market portfolio. This extra risk premium arises from the imperfect risk-sharing within the market in the spirit of Merton (1987). Recall that heterogeneity causes a certain group of investors to prefer only a subset of stocks in the market or hold stocks in different proportions than in the tangency portfolio. As long as this group of investors is not driven out of the market, their preference for certain stocks in a particular proportion will force other investors to clear the market by holding the remaining proportion in addition to their own optimal portfolio. Since this additional holding is costly, those other investors need to be rewarded. The reward is provided in the form of a lower purchasing price, so that an extra return premium subsequently accrues. This premium is effectively the outcome of the imperfect risk-sharing due to investor heterogeneity, and corresponds directly to the inefficiency of the market portfolio.

To the extent that this type of inefficiency is economically significant, a two-factor model can be motivated in which the market portfolio is augmented by an additional factor that captures the premium associated with the limited risk-sharing due to investor heterogeneity. In other words, the market portfolio and a heterogeneity-augmenting factor combined can function as a proxy for the tangency portfolio. This idea appears to be most suited for emerging markets, since these markets suffer from political uncertainty, lack of accounting transparency, various corporate governance problems, and the like, all of which maximize the degree of investor heterogeneity and thus the extent of this type of limited risk-sharing.

To gauge empirically the feasibility of this idea, we must measure investor heterogeneity. We first consider foreign ownership. It is well documented in the international finance literature that foreign investors selectively hold domestic stocks with certain characteristics (see, e.g., Kang and Stulz, 1997; Dahlquist and Robertsson, 2001; Giannetti and Simonov, 2003; Ahearne, Grierer,

and Warnock, 2004; Lins and Warnock, 2006).⁴ Even with such selective demand, foreigners will not be driven out of the domestic market, because they need some domestic stocks for global diversification or other benefits.⁵ This selective demand of foreign investors will induce domestic investors to deviate from their optimal tangency portfolio by underweighting stocks preferred by foreigners and by overweighting the stocks they avoid. In equilibrium, domestic investors will do so while receiving a reward in the form of the lower purchase prices of those stocks avoided by foreigners and their higher return in the future. Thus, we expect the return on the portfolio long in stocks with *lowest* foreign ownership and short in stocks with *highest* foreign ownership to serve as the heterogeneity-augmenting factor in the two-factor model.

Alternatively, we use institutional holdings to measure investor heterogeneity. The difference in portfolio composition between individuals and institutions is also well established in the literature (e.g., Falkenstein, 1996; Cohen, 1999; Gompers and Metrick, 2001). In addition, this alternative measure is instructive for us to understand the extent to which our results are unique to foreign investors rather than investor heterogeneity in general. Since the mean-variance inefficiency of the market portfolio arises when some investors deviate from the tangency portfolio, a good heterogeneity measure should be a proxy for informationally disadvantaged (Kang and Stulz, 1997) or institutionally constrained investors (Ross, 1989). Our two measures are motivated in this context.

2.3. *Alternative interpretations*

There is an alternative way to look at our two-factor model. Focusing on foreign ownership, the additional factor is feasible only in a market in which foreigners can invest. Hence, our model is closely related to international asset pricing models. A number of international asset pricing

⁴ Earlier studies on this “home-bias” include French and Poterba (1991), Lewis (1991), Cooper and Kaplanis (1994), and Tesar and Werner (1995).

⁵ Stulz and Wasserfallen (1995) model and empirically show that the demand of foreign investors for domestic stocks is *inelastic* compared to that of domestic investors. See also Bailey and Jagtiani (1994) and Domowitz, Glenn, and Madhavan (1997) for a downward-sloping demand curve of foreign investors.

models show that when a stock market moves from complete segmentation to full integration, the relevant asset pricing model changes from the domestic version of the CAPM to the world CAPM. In other words, the relevant tangency portfolio is not the domestic market portfolio but the world market portfolio (see, e.g., Errunza and Losq, 1985; Alexander, Eun, and Janakiramanan, 1987; Stulz, 1999). As the majority of economies are characterized as partially integrated (or partially segmented), however, a more realistic asset pricing model is in the spirit of a two-factor model containing both the domestic and foreign risk factors (e.g., Foerster and Karolyi, 1999, Morck, Yeung, and Yu, 2000). Our two-factor model can be viewed as the one in which the foreign ownership-based heterogeneity-augmenting factor represents the foreign factor. Based on the actual stock holdings of foreign investors, however, our heterogeneity-augmenting factor is expected to better capture the extent of the global risk-sharing between domestic and foreign investors, and the loading on this factor is likely to prove more informative.⁶

Another interpretation of our two-factor model has to do with the correlation of foreign or institutional ownership with various firm characteristics, including firm size, liquidity, leverage, governance, transparency, riskiness, and past stock returns (see, e.g., Kansg and Stulz, 1997; Cohen, 1999; Dahlquist and Robertsson, 2001; Gompers and Metrick, 2001; Giannetti and Simonov, 2003; Ahearne, Grier, and Warnock, 2004; Lins and Warnock, 2006). Since those firm characteristics are themselves correlated with the cross-section of average stock returns, foreign or institutional ownership can be viewed as a “catch-all” variable for many of those price-relevant firm characteristics. It then follows that our heterogeneity-augmenting factor can subsume the firm characteristic-based factors. Although not correctly revealing the theoretical background of our two-factor model – namely, a model of the multivariate proxies for the tangency portfolio –, this alternative interpretation clarifies the improvement that our model is making in terms of parsimony.

⁶ In an unreported result, we confirmed that this foreign index-based two-factor model produces a similar but weaker result compared to our foreign ownership-based two-factor model. This result is available from the authors upon request.

3. Sample and data

Our main sample consists of all common stocks listed on the Korean Stock Exchange. Their monthly stock returns (including dividends) are from the Korean Securities Research Institute and the monthly market capitalization data are from the FnGuide. Annual accounting information including ownership data is from TS2000, a database provided by the Korea Listed Companies Association. The sample period is from July 1992 to December 2006, since prior to 1992, there is no adequate cross-sectional dispersion in foreign ownership.⁷ Institutional ownership, as measured by one minus the ownership of domestic individual investors, is available for a shorter period ending in June 2005.⁸

As a proxy for the market portfolio, we use the KOSPI index. The ownership-based heterogeneity-augmenting factor is constructed with sample stocks whose foreign or institutional ownership data are available. Fama and French's SMB and HML, as well as the test portfolios, are constructed using sample stocks whose book value of equity is positive. Finally, the risk-free rate is the monthly yield on the one-year Monetary Stabilization Bonds.

The Japanese sample contains all common stocks listed on both sections of the Tokyo Stock Exchange. Both the monthly stock returns (including dividends) and market capitalization data are from the PACAP database. Annual accounting information including foreign and institutional ownership data is also from PACAP. Unlike Korea, the sample period starts in October, not in July, since the fiscal year for most Japanese companies ends in March (see, e.g., Daniel, Titman, and Wei, 2001). Specifically, the sample period is from October 1976 to December 2004. The TOPIX index is used as a proxy for the market portfolio. The risk-free rate is, as in Daniel,

⁷ The opening of the Korean stock market is generally dated to the early 1990s. See, for example, Bekaert and Harvey (2000).

⁸ It is on the grounds that foreign investors are almost always institutions. See, e.g., Choe, Kho, and Stulz (2005).

Titman, and Wei (2001), the call money rate (from October 1976 to November 1977) or the 30-day Gensaki (repo) rate (from December 1977 to December 2004).

4. Empirical results – Korean stock market

4.1. Heterogeneity-augmenting factor

To construct the heterogeneity-augmenting factor, we sort our sample stocks into five groups at the end of June in year t by one of our heterogeneity measures from the most recent fiscal year (i.e., $t-1$), and use the resultant quintile rankings from July of year t to June of year $t+1$. An equally weighted portfolio is constructed within each quintile, and the heterogeneity-augmenting factor is the return on the portfolio long in the lowest quintile portfolio and short in the highest quintile portfolio.

Table 1 reports the quintile points of foreign and institutional ownership over time. Panel A shows that foreign ownership in the Korean stock market has increased significantly over time but, at the same time, the dispersion remains sizable. For example, while the 60th percentile increased from 0.02 percent to 7.67 percent, the 20th percentile seldom changed: it changed from 0 percent to 0.17 percent. This wide and time-persistent dispersion suggests that foreign ownership is a useful measure for heterogeneity among investor.⁹ A similar pattern is observed with institutional ownership in Panel B: institutions hold stocks selectively and this selective stock holding behavior also persists over time.

[Insert Table 1 about here]

Table 2 reports the summary statistics of the foreign or institutional ownership-based heterogeneity-augmenting factor (FOF and IOF, respectively) and other factor-mimicking

⁹ Panel A also shows that at the beginning of the sample period, both the 20th and 40th foreign ownership percentiles are zero, so both quintile groups are used to construct the heterogeneity-augmenting factor.

portfolios. For the period from July 1992 to December 2006, the average return on the market portfolio in excess of the risk-free rate is 0.3 percent per month, which translates to an annual market risk premium of approximately 3.7 percent. This number seems small and is also statistically insignificant. We suspect that this is partly attributable to the high interest rates during the Asian crisis period. In an unreported result, we excluded the crisis period of July 1997 to June 1998, and found that the average monthly return on the market portfolio increases to 0.8 percent. Similar to the market risk premium, the premium for SMB is negative during the full sample period but turns positive once the crisis period is excluded. The premium for HML, on the other hand, is sizable (0.7 percent per month) and appears to be reliably different from zero (t -statistic = 1.744).¹⁰

[Insert Table 2 about here]

We find that FOF commands a sizable premium: it is estimated to be 0.9 percent during the sample period. A positive return premium for FOF makes sense since, as the return difference between the *low* foreign ownership stock portfolio and the *high* foreign ownership stock portfolio, it represents the compensation for domestic investors who hold the stocks avoided by foreigners in addition to their own optimal portfolio. Similarly, IOF has the average return of 1.2 percent per month with the t -statistic of 2.128 during the shorter period ending in June 2005.

The correlation coefficients of the heterogeneity-augmenting factors with other factor-mimicking portfolios are given in the second panel of Table 2. Both FOF and IOF are correlated

¹⁰ The different return premiums for SMB and HML may have to do with the way that they are constructed. As in Fama and French (1993), HML is based on the 30th and 70th percentiles while SMB is based on the median. Fama and French choose this specification because the book-to-market ratio is shown to be more relevant for average stock returns compared to firm size in their earlier study (1992). This finding may not carry over to other markets like Korea, but the Fama-French specification seems to be accepted as a norm even in non-U.S. markets.

positively with SMB, since foreigners and institutions are known to avoid small stocks. However, their correlation with the market portfolio or with HML is statistically insignificant.

4.2. Time-series regression analysis

To examine how well an asset pricing model explains the cross-section of average stock return, we first employ the time-series regression of an asset's return on the realization of the suggested risk factors. As noted by Fama and French (1993) and Griffin (2002), the intercept from this regression represents the average return on the test asset that is not explained by the risk factors. Hence, the explanatory power of an asset pricing model for the cross-section of average stock return can be judged by a joint test for the intercepts across test assets. In this setup, portfolios are often used as test assets to minimize the measurement error and to keep the number of test assets manageable.¹¹ Thus, we first follow this convention and later supplement the portfolio results with individual stocks (Section 4.3). In the subsequent analysis, we employ another cross-sectional analysis method, namely, the Fama-MacBeth regressions (Section 4.4).

As test portfolios, we use the size- or BM-sorted decile portfolios. They are motivated by the fact that firm size and book-to-market ratio are the two most important firm characteristics correlated independently with average stock returns. Each portfolio is equally weighted and based either on the end-of-June market capitalization (for size-sorted portfolios) or on the end-of-December book-to-market ratio (previous fiscal year's book value divided by the end-of-December market capitalization; for book-to-market-ratio-sorted portfolios).

The first lines of Panels A and B in Table 3 report the average return on these test portfolios over the period during which foreign ownership is available.¹² They confirm the existence of the size and BM effects in the Korean market. We recognize that grouping stocks into portfolios

¹¹ The joint test for the regression intercepts lacks power as the number of test assets increases. See, e.g., Gibbons, Ross, and Shanken (1989). When the number of test assets is greater than the number of time-series observations, the test becomes infeasible.

¹² Note that since foreign ownership is available for a longer period, we use FOF first and later repeat the analysis by replacing FOF with IOF.

causes a loss of information regarding the cross-sectional pattern in stock returns. However, as the test portfolios are sorted by the firm characteristics correlated with stock returns, they still provide a meaningful cross-section for which different asset pricing models can compete. For example, whereas the average stock return on 10 size-sorted portfolios ranges from 0.9 percent to 4.4 percent (Panel A), we found that the average monthly return on 248 (!) individual stocks whose returns are available over the same period ranges only between 0.4 percent and 5.4 percent. It is because the much larger and more volatile returns on individual stocks are largely averaged away over time.

[Insert Table 3 about here]

Table 3 then reports the results of the following time-series regressions:

$$R_{p,t} - r_f = \alpha_p + \beta_{p,1}(R_{mkt,t} - r_f) + \varepsilon_{p,t}, \quad (1)$$

$$R_{p,t} - r_f = \alpha_p + \beta_{p,1}(R_{mkt,t} - r_f) + \beta_{p,2}FOF_t + \varepsilon_{p,t}, \quad (2)$$

$$R_{p,t} - r_f = \alpha_p + \beta_{p,1}(R_{mkt,t} - r_f) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \varepsilon_{p,t}, \quad (3)$$

where $R_{p,t}$ is the return on test portfolio p , r_f is the monthly risk-free rate, $R_{mkt,t}$ is the return on the market portfolio proxy, and FOF_t , SMB_t , and HML_t are respectively the returns on the already-defined factor-mimicking portfolios. For the reason mentioned above, we focus our attention principally on the regression intercept and discuss the implications of the R-squared later.

When the 10 size-sorted portfolios are regressed on the market portfolio return alone, the estimated regression intercepts are economically and statistically significant for two of the 10 portfolios. They are the two smallest size decile portfolios, and thus the size effect that is not explained by the market beta difference is confirmed. Our two-factor model mitigates this problem. Among the ten test portfolios, only the smallest decile portfolio has a significant regression intercept. Moreover, the magnitude of its intercept is reduced from 3.5 percent for the

CAPM one-factor model to 2.2 percent for the two-factor model. None of the other nine portfolios has a regression intercept whose t -statistic is greater than 1.8. The Fama-French three-factor model, although specifically devised to explain the size effect (and the value effect), performs poorly in the Korean stock market. The estimated regression intercepts are both economically and statistically significant for three of the 10 portfolios. The smallest decile portfolio has an intercept of 3.2 percent, and is similar in magnitude to the 3.5 percent estimated by the one-factor model. The second and third smallest portfolios, respectively, have 1.7 percent and 0.9 percent as the intercept estimate, and both have a t -statistic greater than 3.7.

The joint test for all the 10 intercepts lends further support to the two-factor model. Whereas the one-factor model has only slightly higher test statistics (38.96 vs. 36.87 for the Wald statistic; 3.65 vs. 3.43 for the GRS F -statistic), the two test statistics make a clear comparison between the two-factor and the Fama-French three-factor models. Both the Wald and the GRS F -statistics increase by almost 50 percent from the two-factor to the three-factor models (36.87 vs. 60.62 for the Wald statistic; 3.43 vs. 5.61 for the GRS F -statistic).¹³

Panel B reports the results when the BM-sorted portfolios are used as test assets. Consistent with the size-sorted portfolio results, the two-factor model best explains the average returns on the BM-sorted portfolios and their cross-sectional variation. Specifically, the one-factor model yields three regression intercepts whose t -statistics are greater than 2. They are the three value stock portfolios (i.e., three highest book-to-market ratio portfolios), and thus confirm the value stock effect that is not explained by the market beta differences. With the two-factor model, only one regression intercept for the value stock portfolio is statistically significant (t -statistic = 2.54). Finally, the three-factor model yields as many as six regression intercepts that are statistically significant. The joint tests for the intercepts also confirm the superiority of the two-factor model.

¹³ For the Wald statistic, we estimate the ten regressions a system using the seemingly unrelated regression method. For the GRS F statistic, we refer to Campbell, Lo, and MacKinlay (1997, p.247). The GRS F -statistic compares the squared Sharpe Ratio of the factor-mimicking portfolios in question with the ex-post maximum squared Sharpe Ratio.

Both the Wald and the GRS F statistics are greater for the one-factor model than for the two-factor model (24.86 vs. 21.48 for the Wald statistic; 2.33 vs. 2.00 for the GRS F -statistic). More strikingly, both statistics almost double when the three-factor model.

Regression R-squared can also be used to compare the three models, although this statistics is more about the common variation in stock return and hence does not speak directly to the cross-section of average stock returns. For the smallest decile portfolio, the R-squared of the one-factor model is only 26 percent and, similar to the case in the U.S., they increase in firm size and reach a satisfactory level only for several large stock portfolios (e.g., Fama and French, 1993). This pattern in the R-squared disappears when the FOF augments the market portfolio. The addition of FOF improves the R-squared for the smallest decile portfolio from 26 percent to 71 percent. The second smallest portfolio experiences similar improvement in the R-squares from 36 percent to 72 percent, and the third smallest portfolio from 49 percent to 75 percent. As a consequence, there is little pattern in the R-squared in relation to firm size. The R-squares are the highest when the Fama-French three-factor model is used, but the improvement from the two-factor model is rather marginal. We also note the decreasing pattern in the R-squared of the one-factor model with the book-to-market ratio, and that this pattern disappears when the market portfolio is complemented by FOF. Although the R-squared remains the highest when the three-factor model is estimated, the R-squared of the two-factor model appears satisfactory ranging from 69 to 84 percent.

We now switch to institutional ownership that is applicable only to the period ending in June 2005. With the IOF-based model, we pay attention exclusively to the regression intercept. After confirming the size and BM effects during this shorter period (reported in the first lines of Panels A and B), Table 4 shows that the two-factor model based on institutional holdings continues to outperform the other two models. Among the size-sorted decile portfolios, only the smallest portfolio has a significant intercept when it is regressed on IOF along with the market portfolio (t -statistic = 2.197). The intercepts of the other nine portfolios are all statistically insignificant with

a noticeably small magnitude. The one-factor and three-factor models, however, generate a larger and more significant regression intercept with greater frequency. The GRS F -tests confirm further that the two-factor model performs the best with the smallest test statistic of 2.95; the F -statistics of the one-factor and three-factor models are 3.36 and 5.07, respectively.

[Insert Table 4 about here]

The BM-sorted portfolios reveal a similar or even stronger performance of the two-factor model. The return on the value portfolio can now be better explained, as its regression intercept has a t -statistic of 1.905, compared to the t -statistic of 2.544 for the FOF-based two-factor model. However, the relatively poor performance of the growth portfolio is more pronounced (t -statistic = -2.017) with the IOF-based two-factor model. The CAPM one-factor and especially the Fama-French three-factor models continue to show the inferior test results. The GRS F -statistic for the one-factor model is 1.96, and that of the three-factor model is 3.30, both of which are greater than the two-factor model's F -statistic of 1.78.

4.3. Time-series regression analysis – alternative specifications

To ensure the robustness of our portfolio results in the preceding sub-section, we adopt two alternative specifications. First, we employ individual stocks as test assets. This alternative specification is readily motivated, since grouping stocks into portfolios causes a loss of information regarding the cross-section of stock returns. To utilize the full information while containing the measurement error associated with the use of individual stock returns, only those stocks with a certain minimum number of monthly returns are used for the analysis. We estimate equations (1), (2), and (3) for each of those stocks, and examine the absolute value of the regression intercepts and the absolute value of the accompanying t -statistics, both averaged across

the stocks. Note that the joint test for the regression intercepts is infeasible, since the number of test assets exceeds the number of time-series observations.

Panel A of Table 5 shows that the superior performance of the two-factor model is robust to using individual stocks as test assets. For the period from July 1992 to December 2006, the FOF-based two-factor model has both the lowest average absolute intercept and the lowest average absolute t -statistic for the intercept. This result is consistent across three different samples created by different minimum numbers of monthly returns (i.e., 60, 100, or the full time-series of 174 months). Since IOF is available for a shorter period, the analysis is repeated for this period with IOF in place of FOF. We find that the IOF-based two-factor model continues to outperform the other two models, except for the sample of stocks with at least 60 monthly returns.

[Insert Table 5 about here]

As the second alternative specification, we use the factor-mimicking portfolios themselves as test assets (one at a time). It is based on the concept that the average return on a factor-mimicking portfolio is the estimated premium of the underlying risk factor. Hence, by regressing one factor-mimicking portfolio on others, one can determine whether the hypothesized risk factor (i.e., the one used as the dependent variable) is indeed independent of other risk factors (i.e., the ones used as the explanatory variables). Specifically, the following equations are estimated:

$$OF_t = \alpha + \beta_1 (R_{mkt,t} - r_f) + \beta_2 SMB + \beta_3 HML + \varepsilon_{i,t}, \quad (4)$$

$$SMB_t = \alpha + \beta_1 (R_{mkt,t} - r_f) + \beta_2 OF + \varepsilon_{i,t}, \text{ and} \quad (5)$$

$$HML_t = \alpha + \beta_1 (R_{mkt,t} - r_f) + \beta_2 OF + \varepsilon_{i,t}, \quad (6)$$

where OF is either FOF or IOF.

Panel B of Table 5 shows that when FOF is regressed on the three factors in the Fama-French model, the intercept is estimated to be 0.010 (i.e., average monthly return of 1 percent) and it is

highly significant (t -statistic = 2.60). On the other hand, neither SMB nor HML have a significant alpha when regressed on the market portfolio and FOF, meaning that they do not command a return premium on their own once FOF is controlled for. However, it is worth noting that the regression of HML on the market portfolio and FOF has remarkably low adjusted R-squares (0.001). This implies that HML has its own variation that is useful in explaining the common variation in stock returns. Results are quite similar when FOF is replaced by IOF for the shorter period from July 1992 to June 2005.

4.4. Fama-MacBeth regression analysis

Thus far, we have utilized the time-series regressions to examine the explanatory power of an asset pricing model for the cross-section of average stock returns. Another approach to evaluating an asset pricing model is to see how well the risk factors suggested by the model fit the cross-section of stock returns on average. To this end, we use the two-step Fama-MacBeth (1973) regressions. Specifically, we estimate the loadings of a test asset on the suggested risk factors (e.g., CAPM β) via the time-series regressions, and use the resultant loadings estimates as the explanatory variables for the cross-section of returns across test assets. Finally, the cross-sectional regression coefficients are averaged over time to examine how those factor loadings are related, on average, to the cross-section of returns on the test assets. To minimize the errors-in-variables problem, we use 25 portfolios independently sorted by size and BM (i.e., intersections of five size- and BM-sorted quintile portfolios) as test assets.¹⁴ Sorted along the two firm characteristics, our test portfolios guarantee that the loadings on the size and BM factors are sufficiently dispersed, further raising the bar for our two-factor model. Since the available time-series is relatively short (156 or 174 months), we estimate the factor loadings over the entire sample period as in Fama and French (1992).

¹⁴ Results based on individual stocks are discussed later in this sub-section.

Panel A of Table 6 reports the loadings on the market portfolio, FOF, SMB, and HML estimated over the period from July 1992 to December 2006 (174 months). The 25 test portfolios show the well-dispersed loadings on SMB and HML. Although the cross-sectional variation in the market portfolio beta is somewhat limited, the loading on FOF with adequate cross-sectional dispersion ensures the power of our test. Panel B of Table 6 reports the results of the Fama-MacBeth regressions. With the exception of the CAPM beta, each of the factor loadings is significantly related to stock returns cross-sectionally, although the significance of the loading on HML is rather marginal. When those factor-loading estimates are together in one regression (Model (5)), the loading on FOF dominates others in explaining the cross-section of stock return on the test portfolios. Panels C and D show that the results remain virtually identical when FOF is replaced by IOF for the shorter period ending in June 2005 (156 months). In an unreported result, we utilized individual stocks in this cross-sectional regression framework. However, we found that none of the factor loadings are significant, probably owing to the noise inherent in the loadings estimates.

[Insert Table 6 about here]

5. Robustness

In this section, we provide several robustness checks for the Korean results. Since foreign ownership is available for a longer period, we use it for these checks. We then analyze the Japanese data to put the Korean results into perspective.

5.1. Additional tests with the Korean data

5.1.1. FOF based on changes in foreign ownership

In the preceding analysis, we have used FOF based on the level of foreign ownership. We believe that using the ownership level is the correct way to construct the heterogeneity-

augmenting factor, since it is different portfolio holdings that cause the market portfolio to deviate from the tangency portfolio. However, one may argue that changes in ownership can better speak to the disagreement among investors. One difficulty with this argument is that some of the trades are motivated by liquidity needs or portfolio rebalancing purposes, and are thus not necessarily an outcome of disagreement with other investors. However, we repeated our analysis by replacing the foreign ownership level measured at the end of year t with its changes during that year. As before, we use the rankings based on the foreign ownership changes for the stock returns from July of year $t+1$ to June of year $t+2$.

Even with this alternative specification for FOF, we found that our two-factor model outperforms the CAPM one-factor and the Fama-French three-factor models. To save space, we report only the test statistics here without tabulating the entire results. Against the size-sorted test portfolios, the GRS F -statistics are 3.65, 3.45, and 5.61 respectively for the one-factor, two-factor, and three-factor models. With the BM-sorted portfolios, the GRS F -statistic for the two-factor model is 1.85 and is again lower than the F -statistics for the one-factor or the three-factor model, which are 2.33 and 3.93, respectively.

5.1.2. Sub-period analysis

Some may wonder about how the foreign ownership restrictions influence our results. Those restrictions seem to be a binding constraint for foreign investors, since their ownership in the domestic market has been increasing with the lowering of the restrictions over time (Panel A of Table 1). However, so long as there is no substantial cross-sectional dispersion in those restrictions, the *year-by-year* foreign ownership rankings will provide useful information about the cross-section of average stock returns. In addition, the IOF-based two-factor model already confirmed that our results are not solely driven by foreign investors. Still, it is possible that foreign ownership restrictions truncate some of the observed foreign ownership and introduce a bias to our results. Hence, we repeated our analysis for the sub-period beginning in July 1998 on

the grounds that the Korean stock market eliminated the foreign ownership restrictions after the 1997 financial crisis.

We found that during the post-crisis period, the two-factor model continues to outperform the other two models. With the size-sorted portfolios, the GRS F -statistic for our two-factor model is 1.81, which is lower than 2.27 for the one-factor model and 3.18 for the three-factor model. Using the BM-sorted portfolios as test assets, we found that the GRS F -statistic of the two-factor model is 1.89, whereas the statistics for the one-factor and the three-factor models are 2.34 and 3.69, respectively.

5.1.3. Herding?

What if one group of investors follows other investors? With such herding behavior, would there be any point in distinguishing among investors, for example, between domestic and foreign investors? We believe that this type of herding behavior actually reinforces the effect of investor heterogeneity. Suppose that domestic investors purchase stocks that foreigners are known to have bought. This herding will create a price pressure not only on the stocks in demand but also other stocks that are initially avoided by foreigners and subsequently by domestic investors. Hence, the prices of the demanded (avoided) stocks will be higher (lower) than they would otherwise be. Initially, those demanded (avoided) stocks have a higher (lower) realized return due to the price pressure, but unless such demand shocks are present at all times, the higher (lower) prices will result in a lower (higher) average return in the subsequent period.

We verify the above conjecture by modifying the specification of the change-based FOF (which was employed in Section 5.1.1). Specifically, to examine the effect of using contemporaneous – as opposed to subsequent – return, we associated the rankings based on the foreign ownership changes during year t with the stock returns from January to December of year t (instead of the stock return from July of year $t+1$ to June of year $t+2$). We found that this alternative change-based FOF has an average monthly return of -1.7 percent with a t -statistic of -

5.17. We have already seen that once we use the subsequent returns (i.e., from July of year $t+1$ to June of year $t+2$), the average return on FOF is a *positive* 0.7 percent and the two-factor model using this version of FOF outperforms the other models. In a nutshell, the negative average return on the change-based FOF using the contemporaneous stock return indicates that the stocks purchased by foreign investors do, indeed, experience a price increase. At the same time, the positive average return on the change-based FOF using the subsequent stock return, as well as on the level-based FOF, suggests that such demand shocks are not present at all times but are transient and that stock prices are adjusted back to their equilibrium level after the demand shocks vanish.

5.1.4. Using foreign equity capital flows

We now approach the demand shock story in the previous sub-section from a different angle. As recognized by Gompers and Metrick (2001), a factor model using the ownership of a certain investor group can be empirically successful simply because it picks up the return commonalities caused by the demand of that investor group for stocks with certain characteristics, rather than the model capturing the commonalities due to their similar exposure to the priced risk factor(s). To address this possibility, we identified and excluded the months with very large (either top 10 or 20 percentiles) net foreign equity capital inflows from our analysis, since they may correspond to greater demand for domestic stocks by foreign investors. The reader should, however, be cautioned that to the extent that the foreign equity capital flows are correlated with the macroeconomic shocks, this approach reduces the power of the test.

Without the top 10 percent months, we find that the GRS F -statistics for the size-sorted portfolios are 3.91, 4.07, and 6.47 respectively for the one-factor, two-factor, and three-factor models. With the BM-sorted portfolios, the statistics are 2.90, 2.66, and 4.00 respectively for the three models. When the 20 percentile is used as a cutoff, the results remain similar. Although the GRS F -tests are not conclusive between the one-factor and two-factor models, the magnitudes of

the regression intercepts for the size-sorted portfolios and the incidences of the statistically significant intercept clearly favor the two-factor model. We do not tabulate those results to save space, but they are available from the authors upon request.

5.2. Tests using Japanese data

We now utilize the Japanese data. The test procedure is identical to the one used for Korea, but whenever a different procedure is warranted, we follow Daniel, Titman, and Wei (2001) (e.g., portfolio rebalancing at the end of September rather than June; see Section 3 for details).

5.2.1. Summary statistics of factor-mimicking portfolios

We provide the summary statistics of the Japanese FOF (or IOF) and other factor-mimicking portfolios in Table 7. Although the premiums for the factor-mimicking portfolios are smaller than those for the Korean market, they are all positive. In particular, the premiums for FOF and IOF, both estimated to be 0.4 percent per month, seem to be reliably different from zero with the t -statistics of 2.029 and 2.849, respectively. As in the Korean stock market, both FOF and IOF are significantly positively correlated with the SMB.

[Insert Table 7 about here]

One concern is a large negative value for HML (i.e., a minimum of -1.250). Due to this extreme value, the premium for HML is estimated to be as low as 0.4 percent per month with a t -statistic of 0.930. Excluding this outlier, the premium increases to 0.7 percent per month with a t -statistic of 4.76. In the subsequent analysis, we thus investigate the effects of this extreme value for HML on our results and inferences.

5.2.2. Time-series regression analysis

The size effect manifests itself in the first line of Panel A, Table 8. We note that the magnitude is smaller than the one observed in the Korean market (1.3 percent per month in the Japanese market vs. 3 percent per month in the Korean market). To investigate this issue further, we estimated the size effect in both markets during the same estimation period from July 1992 to December 2004, and found that the Korean size effect is 2.7 percent per month and is therefore greater than the Japanese size effect of 1.2 percent. This pattern suggests that the Japanese stock market allows for smaller room for additional factor(s) besides the market portfolio.

[Insert Table 8 about here]

As shown in the remainder of the first panel, the time-series regression results show virtually the same pattern as those for Korea. Most importantly, the two-factor model (based either on FOF or on IOF) renders all the regression intercepts insignificant except for the one for the smallest portfolio. A significant regression intercept is found more frequently with the one-factor model (3 times) and the three-factor model (2 times). Finally, both the Wald statistic and the GRS F -statistic favor the two-factor model over the other two models. For example, the GRS F -statistics are 3.16, 2.88, 2.34, and 2.94 respectively for the one-factor, the FOF-based two-factor, the IOF-based two-factor, and the three-factor models.

The second panel of Table 8 shows the results when the BM-sorted portfolios are used as test portfolios. The first line reports the value effect in the Japanese market. Its magnitude is 1.3 percent per month and is again smaller than the value effect of 2.5 percent per month in the Korean market. The difference continues to be observed during the same estimation period: it is 2.3 percent for Korea vs. 1.4 percent for Japan. Again, the need for additional factor(s) seems to be smaller in the Japanese stock market.

The time-series regression results continue to show that the two-factor model performs the best. In terms of the number of incidences of a significant regression intercept, the one-factor

model is inarguably the worst, with six such incidences. However, between the two-factor and the three-factor models, both have three significant regression intercepts for one growth and two value portfolios. The Wald and GRS tests point to the two-factor model as the front-runner, but the difference between the two models is rather modest.

In an unreported result, we repeated the analysis without the month when HML has a very negative value of -1.250. With the remaining 338 months, the Fama-French three-factor model performs much better for the BM-sorted portfolios. However, the IOF-based two-factor model still outperforms the three-factor model against the size-sorted portfolios.

5.2.3. Time-series regression analysis – alternative specifications

To utilize individual stock returns, we again require that a certain number of monthly returns be available of each stock. Panel A of Table 9 shows that the two-factor model best explains the cross-section of average monthly return on individual stocks. Consistent with the portfolio results, however, its outperformance relative to the three-factor model is not as pronounced as in the Korean market. For example, with 1,583 stocks having at least 60 monthly returns, the two-factor model yields the lowest average absolute t -statistic for the intercept, but the average absolute value of the intercept itself is slightly greater than that of the three-factor model. With the smaller sample of 1,216 stocks meeting the minimum requirement of 200 monthly returns, the two-factor model is definitely better than the three-factor model, but the comparison again becomes inconclusive in the third sample of stocks whose returns are available over the entire sample period. However, it is also instructive that our two-factor model best performs unanimously when the month with the extreme HML value is excluded. Both the average absolute values of the regression intercept and its t -statistic are the lowest with the two-factor model, and this finding is robust to the three different samples and the two different heterogeneity measures.

[Insert Table 9 about here]

With the second alternative specification in which one of the factor-mimicking portfolios is used as a test asset (Panel B), we find that no model emerges as the front-runner. Interestingly, one consistent pattern across the two markets is that a large fraction of HML's variation is not explained by other factor-mimicking portfolios, since the regression R-squared is only 2.3 percent by the FOF-based two-factor model and 3.6 percent by the IOF-based two-factor model. Recall that the corresponding R-squared for the Korean market was even smaller (Table 5). This result confirms the earlier conjecture that HML is useful in capturing the commonalities in individual stock returns that do not necessarily command a premium.

5.2.4. Fama-MacBeth regression analysis

Finally, we examine the Japanese market using the Fama-MacBeth regressions. As shown in Table 10, the loading on FOF (or IOF) clearly dominates the loading on SMB. However, the loading on HML remains significant even together with the loading on FOF (or IOF) in the same regression. These results remain robust when we exclude the month with a large negative value for HML of -1.250. The stronger explanatory power of HML in the Japanese market as compared to the Korean market is consistent with earlier studies such as Daniel, Titman, Wei (2002). All in all, the Fama-MacBeth regressions in the Japanese market lend support to our heterogeneity-augmented two-factor model, but its superiority, particularly to the Fama-French three-factor model, is not as obvious as in the Korean market.

[Insert Table 10 about here]

6. Conclusions

In this paper, we examine whether investor heterogeneity can be used to explain the cross-section of average stock returns. The idea of using investor heterogeneity for asset-pricing

purposes is motivated by the fact that the inefficiency of the market portfolio is caused by heterogeneity. In other words, our idea is to augment the inefficient market portfolio by directly addressing the source of its inefficiency, so that we can obtain a satisfactory *multivariate* proxy for the tangency portfolio. We further conjecture that this heterogeneity-augmented asset pricing model is particularly useful for emerging markets where investor heterogeneity is expected to be more severe and thus the heterogeneity-driven inefficiency in the market portfolio is economically more crucial. Our approach is, therefore, in sharp contrast to the traditional firm characteristic-based multifactor models that hypothesize additional priced risks.

We verify empirically the feasibility of this idea using a heterogeneity-augmenting factor mimicked by the portfolio long in low foreign (institutional) ownership stocks and short in high foreign (institutional) ownership stocks. Specifically, in the Korean stock market where both heterogeneity measures are available on a large number of firms for a reasonably long period of time, we find that the two-factor (i.e., market portfolio + heterogeneity-augmenting factor) model outperforms both the CAPM one-factor model and the Fama-French three-factor model. We also examine a developed country with similar data availability, namely, Japan, and find that the two-factor model continues to outperform the one-factor and the three-factor models. However, the superiority of the two-factor model in the Japanese market is not as obvious as in the Korean market. The stronger performance of the two-factor model in the Korean stock market confirms that investor heterogeneity is useful particularly for emerging market asset pricing.

We are grateful to an anonymous referee, Bok Hyeon Baik, Sang Kyung Jeon, Jinho Jeong, Aneel Keswani, Woojin Kim, Sang Woo Lee, Eliza Wu, and Lu Zhang for comments and suggestions. We also thank the seminar participants and discussants at Korea University Business School, Seoul National University, the 2007 Korean FMA meetings at Seoul, the 2008 KSA meetings at Seoul, the 2008 EMG conference on emerging markets finance at London, the 2008 CICF meetings at Dalian, the 2008 Asian FA/NFA meetings at Yokohama, and the 2008 FMA meetings at Dallas for comments. This paper was started when Dong Wook Lee was at the University of Kentucky. Financial support from Korea University is gratefully acknowledged (Kyung Suh Park).

References

- Ahearne, A., Grier, W., Warnock, F., 2004. Information costs and home bias: An analysis of U.S. holdings of foreign equities. *Journal of International Economics*, 313-336.
- Alexander, G., Eun, C., Janakiraman, S., 1987. Asset pricing and dual listing on foreign capital markets: A Note. *Journal of Finance*, 151-158.
- Bailey, W., Jagtiani, J., 1994. Foreign ownership restrictions and stock prices in the Thai capital market. *Journal of Financial Economics*, 57-87.
- Bekaert, G., Harvey, C., 2000. Foreign speculators and emerging equity markets. *Journal of Finance*, 565-613.
- Bekaert, G., Harvey, C., Lundblad, C., Siegel, S., 2007. What segments equity markets? Unpublished working paper. Columbia University, New York.
- Berk, J., Greene, R., Naik, V., 1999. Optimal investment, growth options, and security returns. *Journal of Finance* 1553-1607.
- Campbell, J., Lo, A., MacKinlay, C., 1997. *The econometrics of financial markets*. Princeton University Press, New Jersey.
- Choe, H., Kho, B., Stulz, R., 2005. Do domestic investors have an edge? The trading experience of foreign investors in Korea. *Review of Financial Studies*, 795-829.
- Cohen, R., 1999. Asset allocation decisions of individuals and institutions. Unpublished working paper. Harvard Business School, Boston.
- Cooper, I., Kaplanis, E., 1994. Home Bias in Equity Portfolios, Inflation Hedging, and International Capital Market Equilibrium. *Review of Financial Studies* 7, 45-60.
- Dahlquist, M., Robertsson, G., 2001. Direct foreign ownership, institutional investors, and firm characteristics. *Journal of Financial Economics*, 413-440.
- Daniel, K., Hirshleifer, D., Subrahmanyam, A., 2005. Investor psychology and tests of factor pricing models. Unpublished working paper. The Ohio State University, Columbus.
- Daniel, K., Titman, S., Wei, J., 2001. Explaining the cross-section of stock returns in Japan: Factors or characteristics? *Journal of Finance*, 743-766.
- Domowitz, I., Glenn, J., Madhavan, A., 1997. Market segmentation and stock prices: Evidence from an emerging market. *Journal of Finance*, 1059-1085.
- Errunza, V., Losq, E., 1985. International Asset Pricing Under Mild Segmentation: Theory And Test. *Journal of Finance*, 105-124.
- Falkenstein, E., 1996. Preferences for stock characteristics as revealed by mutual fund portfolio holdings. *Journal of Finance*, 111-136.

- Fama, E., 1996. Multifactor portfolio efficiency and multifactor asset pricing. *Journal of Financial and Quantitative Analysis*, 441-465.
- Fama, E., 1976. *Foundations of Finance*. Basic Books, New York.
- Fama, E., French, K., 2007. Disagreement, tastes, and asset prices. *Journal of Financial Economics*, 667-689.
- Fama, E., French, K., 1998. Value versus Growth: The international evidence. *Journal of Finance*, 1975-1999.
- Fama, E., French, K., 1996. Multifactor explanations of asset pricing anomalies. *Journal of Finance*, 55-84.
- Fama, E., French, K., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3-56.
- Fama, E., French, K., 1992. The cross-section of expected stock returns. *Journal of Finance* 47, 427-466.
- Fama, E., MacBeth, J., 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 71, 607-636.
- Ferson, W., Sarkissian, S., Simin, T., 1990. The alpha factor asset pricing model: A parable. *Journal of Financial Markets* 2, 49-68.
- Foerster, S., Karolyi, A., 1999. The effects of market segmentation and investor recognition on asset prices: Evidence from foreign stocks listing in the United States. *Journal of Finance*, 981-1013.
- French, K., Poterba, R., 1991. Investor Diversification and International Equity Markets. *American Economic Review* 81, 222-226.
- Giannetti, M., Simonov, A., 2003. Which investors fear expropriation? CEPR Working Paper no. 3843.
- Gibbons, M., Ross, S., Shanken, J., 1989. A test of the efficiency of a given portfolio. *Econometrica*, 1121-1152.
- Gompers, P., Metrick, A., 2001. Institutional investors and equity price. *Quarterly Journal of Economics*, 229-259.
- Griffin, John, 2002. Are the Fama and French factors global or country specific?, *Review of Financial Studies*, 783-803.
- Griffin, J., Ji, S., Martin, S., 2003. Momentum investing and business cycle risk: Evidence from Pole to Pole. *Journal of Finance*, 2515-2547.
- Hou, K., Karolyi, A., Kho, B., 2007. What factors drive global stock returns? Unpublished working paper. The Ohio State University, Columbus.

- Kang, J., Stulz, R., 1997. Why is there a home bias? An analysis of foreign portfolio equity ownership in Japan. *Journal of Financial Economics* 46, 2-28.
- Karolyi, A, Stulz, R., 2003. Are assets priced locally or globally. In: Constantinides, G., Harris, M., Stulz, R. (Eds.), *The Handbook of the Economics of Finance*. North Holland.
- Lewis, K., 1999. Trying to Explain Home Bias in Equities and Consumption. *Journal of Economic Literature* 37, 571-608.
- Lins, K., Warnock, F., 2006. Do foreigners invest less in poorly governed firms? NBER Working Paper no. 12222.
- Merton, R., 1973. An intertemporal capital asset pricing model. *Econometrica*, 867-888.
- Merton, R., 1987. A simple model of capital market equilibrium with incomplete information. *Journal of Finance*, 483-510.
- Morck, R., Yeung, B., Yu, W., 2000. The information content of stock markets: Why do emerging markets have synchronous stock price movements? *Journal of Financial Economics*, 215-260.
- Nishiotis, G., 2004. Do indirect investment barriers contribute to capital market segmentation? *Journal of Financial and Quantitative Analysis*, 613-630.
- Roll, R., 1977. A critique of the asset pricing theory's test: Part I: On past and potential testability of the theory. *Journal of Financial Economics*, 129-176.
- Ross, S., 1989. Institutional markets, financial marketing, and financial innovation. *Journal of Finance* 44, 541-556.
- Stulz, R., Wasserfallen, W., 1995. Foreign equity investment restrictions, capital flight, and shareholder wealth maximization: Theory and evidence. *Review of Financial Studies*, 1019-1057.
- Stulz, R., 1999. Globalization of equity markets and the cost of capital. NYSE Working Paper no. 99-02.
- Stulz, R., 2005. The limits of financial globalization. *Journal of Finance* 60, 1595-1638.
- Tesar, L., Werner, I., 1995. Home bias and high turnover. *Journal of International Money and Finance*, 467-493.

Table 1. Time-series quintile of foreign and institutional ownership in Korea

This table reports various quintiles of foreign ownership (Panel A) and institutional ownership (Panel B) in the Korean stock market. P20 represents the 20th percentile, P40 stands for the 40th percentile, and so forth. The ownership information is measured at the end of year t-1 and is associated with stock returns from July of year t to June of year t+1. Years in the table represent year t.

Year	P20	P40	P60	P80	P100
<i>Panel A. Foreign ownership</i>					
1992	0.00	0.00	0.02	1.56	64.40
1993	0.00	0.02	1.05	4.81	65.15
1994	0.01	1.37	4.85	9.97	63.83
1995	0.00	1.79	5.31	9.89	85.56
1996	0.04	1.20	4.02	11.09	77.34
1997	0.00	0.83	3.21	9.97	58.78
1998	0.00	0.33	2.07	7.77	91.58
1999	0.00	0.10	1.37	7.70	78.80
2000	0.00	0.18	2.10	8.97	99.02
2001	0.00	0.09	1.02	7.02	85.95
2002	0.00	0.11	0.97	7.83	82.94
2003	0.01	0.17	1.28	10.63	86.06
2004	0.02	0.35	3.02	18.51	92.43
2005	0.02	0.43	4.90	22.80	94.11
2006	0.17	1.41	7.67	23.50	85.47
<i>Panel B. Institutional ownership</i>					
1992	18.05	29.98	44.24	60.01	99.89
1993	20.60	33.13	45.94	61.03	99.98
1994	21.22	34.40	45.94	61.66	95.87
1995	19.13	32.39	46.32	61.63	100
1996	19.18	33.40	46.93	61.76	100
1997	20.07	33.23	47.52	62.67	99.79
1998	18.50	31.80	44.85	61.50	100
1999	13.48	24.20	37.73	55.24	99.99
2000	10.90	23.44	38.92	59.97	100
2001	10.11	22.73	39.38	63.14	100
2002	11.68	27.21	44.23	64.87	100
2003	13.30	28.57	44.89	66.31	100
2004	13.91	29.28	46.97	68.37	100

Table 2. Summary statistics of heterogeneity-augmenting factor and other factor-mimicking portfolios

This table reports the summary statistics of foreign ownership-based or institutional ownership-based heterogeneity-augmenting factors (FOF and IOF, respectively) and other factor-mimicking portfolios. MKTrf is the monthly KOSPI index return, a proxy for the domestic market portfolio return, less the monthly yield on one-year Monetary Stabilization Bonds, a proxy for the risk-free rate. SMB and HML are the factor-mimicking portfolios in the Fama-French three-factor model. FOF (IOF) is the foreign (institutional) ownership-based factor-mimicking portfolio, which is the difference between the returns on the lowest foreign (institutional) ownership quintile portfolio minus the returns on the highest foreign (institutional) ownership quintile portfolio. The numbers in parentheses of the first panel are the t -statistics of the test for the zero mean. The numbers in parentheses of the second panel are the p -values of the test for the zero correlation coefficient.

	N	Min	Q1	Median	Q3	Max	Mean	Std
MKTrf	174	-0.283	-0.059	-0.006	0.055	0.495	0.003 (0.355)	0.096
SMB	174	-0.296	-0.044	0.000	0.043	0.259	-0.001 (-0.098)	0.076
HML	174	-0.164	-0.022	0.003	0.032	0.329	0.007 (1.744)	0.054
FOF	174	-0.243	-0.034	0.006	0.042	0.317	0.009 (1.682)	0.071
IOF	156	-0.178	-0.031	0.011	0.049	0.273	0.012 (2.128)	0.069

Correlation coefficients between factor-mimicking portfolios

	MKTrf	SMB	HML
SMB	-0.201 (0.008)		
HML	0.054 (0.476)	0.201 (0.008)	
FOF	-0.111 (0.146)	0.714 (0.000)	0.090 (0.237)
IOF	-0.120 (0.136)	0.724 (0.000)	-0.003 (0.966)

Table 3. Time-series regressions using FOF: 199207~200612

This table reports the average monthly returns on the test portfolios (sorted either by size or by BM) and the time-series regression intercept (α) and the adjusted R^2 . Size-sorted portfolios are equally weighted and are based on end-of-June market capitalization. BM-sorted portfolios are equally weighted and based on end-of-December book-to-market ratio. Factor-mimicking portfolios used as the explanatory variables in the regressions are defined in Table 2.

<i>Panel A. Size-sorted decile portfolios as test assets</i>										
	small	pf 2	pf 3	pf 4	pf 5	pf 6	pf 7	pf 8	pf 9	large
average return	0.044	0.028	0.020	0.015	0.016	0.015	0.009	0.009	0.012	0.014

One-Factor: MKTrf										
α	0.035	0.019	0.011	0.006	0.006	0.005	-0.001	-0.001	0.002	0.004
(<i>t</i> -stat)	(3.576)	(2.474)	(1.688)	(0.941)	(1.068)	(0.842)	(-0.190)	(-0.157)	(0.591)	(1.261)
MKTrf	0.803	0.777	0.864	0.860	0.918	0.929	0.873	0.950	0.987	1.030
(<i>t</i> -stat)	(7.91)	(9.94)	(12.86)	(13.20)	(16.17)	(15.09)	(18.78)	(21.35)	(29.30)	(28.28)
adj. R^2	0.263	0.361	0.487	0.500	0.601	0.567	0.670	0.724	0.832	0.822
Wald-Statistic=38.96 (p-val: 0.000) GRS F=3.650 (p-val: 0.000)										

Two-Factor: MKTrf, FOF										
α	0.022	0.009	0.003	-0.001	0.000	-0.000	-0.005	-0.004	0.001	0.006
(<i>t</i> -stat)	(3.519)	(1.763)	(0.636)	(-0.304)	(0.095)	(-0.096)	(-1.150)	(-0.904)	(0.189)	(1.646)
MKTrf	0.919	0.863	0.935	0.925	0.965	0.978	0.906	0.976	0.999	1.018
(<i>t</i> -stat)	(14.31)	(16.60)	(19.83)	(19.10)	(20.56)	(18.63)	(22.01)	(23.67)	(30.22)	(28.36)
FOF	1.417	1.052	0.866	0.790	0.582	0.591	0.401	0.315	0.142	-0.138
(<i>t</i> -stat)	(16.25)	(14.92)	(13.53)	(12.01)	(9.14)	(8.29)	(7.17)	(5.63)	(3.16)	(-2.84)
adj. R^2	0.708	0.721	0.751	0.727	0.730	0.690	0.745	0.766	0.840	0.829
Wald-Statistic=36.87 (p-val: 0.000) GRS F=3.433 (p-val: 0.000)										

Three-Factor: MKTrf, SMB, HML										
α	0.032	0.017	0.009	0.004	0.004	0.002	-0.003	-0.003	-0.001	0.003
(<i>t</i> -stat)	(5.337)	(4.982)	(3.771)	(1.681)	(1.856)	(0.640)	(-1.429)	(-1.088)	(-0.253)	(0.784)
MKTrf	0.988	0.949	1.013	1.003	1.040	1.030	0.949	1.012	1.011	1.016
(<i>t</i> -stat)	(15.77)	(26.26)	(40.27)	(41.13)	(45.05)	(26.02)	(37.11)	(33.64)	(38.93)	(28.19)
SMB	1.255	1.131	0.993	0.956	0.820	0.709	0.550	0.456	0.222	-0.036
(<i>t</i> -stat)	(15.55)	(24.29)	(30.63)	(30.44)	(27.59)	(13.90)	(16.68)	(11.77)	(6.63)	(-0.77)
HML	0.488	0.242	0.294	0.304	0.267	0.379	0.378	0.350	0.360	0.243
(<i>t</i> -stat)	(4.41)	(3.79)	(6.60)	(7.06)	(6.54)	(5.41)	(8.35)	(6.59)	(7.85)	(3.81)
adj. R^2	0.733	0.870	0.932	0.934	0.937	0.830	0.905	0.880	0.905	0.834
Wald-Statistic=60.62 (p-val: 0.000) GRS F=5.609 (p-val: 0.000)										

Table 3. cont.

<i>Panel B. BM-sorted decile portfolios as test assets</i>										
	growth	pf 2	pf 3	pf 4	pf 5	pf 6	pf 7	pf 8	pf 9	value
average return	0.008	0.012	0.015	0.015	0.018	0.016	0.019	0.023	0.023	0.033

One-Factor: MKTrf										
α	-0.001	0.002	0.006	0.005	0.009	0.006	0.010	0.013	0.013	0.023
(<i>t</i> -stat)	(-0.300)	(0.439)	(1.100)	(1.120)	(1.633)	(1.160)	(1.769)	(2.401)	(2.123)	(3.088)
MKTrf	0.920	0.802	0.953	0.919	0.901	0.893	0.891	0.877	0.880	0.951
(<i>t</i> -stat)	(18.97)	(14.23)	(18.09)	(18.16)	(16.36)	(16.63)	(15.69)	(15.48)	(13.58)	(12.33)
adj. <i>R</i> ²	0.675	0.538	0.654	0.655	0.607	0.614	0.586	0.580	0.515	0.466
Wald-Statistic=24.86 (p-val: 0.006) GRS F=2.329 (p-val: 0.014)										

Two-Factor: MKTrf, FOF										
α	-0.006	-0.002	0.001	0.000	0.003	0.001	0.004	0.007	0.007	0.015
(<i>t</i> -stat)	(-1.512)	(-0.480)	(0.145)	(0.041)	(0.731)	(0.283)	(0.908)	(1.660)	(1.369)	(2.544)
MKTrf	0.960	0.843	0.997	0.965	0.950	0.935	0.942	0.933	0.934	1.021
(<i>t</i> -stat)	(23.69)	(17.10)	(22.79)	(24.39)	(21.51)	(20.38)	(20.54)	(21.90)	(17.45)	(16.68)
FOF	0.487	0.503	0.536	0.572	0.598	0.512	0.611	0.677	0.665	0.854
(<i>t</i> -stat)	(8.86)	(7.52)	(9.03)	(10.65)	(9.98)	(8.23)	(9.82)	(11.71)	(9.16)	(10.28)
adj. <i>R</i> ²	0.776	0.651	0.764	0.791	0.750	0.722	0.734	0.765	0.672	0.668
Wald-Statistic=21.48 (p-val: 0.018) GRS F=2.000 (p-val: 0.036)										

Three-Factor: MKTrf, SMB, HML										
α	-0.001	0.003	0.005	0.005	0.007	0.003	0.006	0.010	0.008	0.017
(<i>t</i> -stat)	(-0.228)	(0.841)	(1.769)	(2.027)	(2.383)	(1.190)	(2.471)	(3.917)	(3.312)	(4.369)
MKTrf	1.021	0.916	1.065	1.032	1.007	0.986	0.985	0.977	0.968	1.052
(<i>t</i> -stat)	(30.21)	(22.74)	(33.76)	(39.41)	(32.96)	(34.72)	(38.40)	(36.47)	(40.24)	(25.66)
SMB	0.615	0.699	0.715	0.725	0.720	0.660	0.692	0.713	0.712	0.802
(<i>t</i> -stat)	(14.14)	(13.48)	(17.59)	(21.52)	(18.29)	(18.04)	(20.96)	(20.69)	(23.01)	(15.19)
HML	-0.078	-0.097	0.060	0.079	0.265	0.409	0.532	0.461	0.816	0.858
(<i>t</i> -stat)	(-1.30)	(-1.37)	(1.08)	(1.71)	(4.91)	(8.17)	(11.74)	(9.75)	(19.20)	(11.85)
adj. <i>R</i> ²	0.850	0.776	0.882	0.912	0.885	0.898	0.920	0.911	0.936	0.857
Wald-Statistic=42.45 (p-val: 0.000) GRS F=3.928 (p-val: 0.000)										

Table 4. Time-series regressions using IOF: 199207~200506

This table reports the average monthly returns on the test portfolios (sorted either by size or by BM) and the time-series regression intercept (α). The augmenting factor in the two-factor model is based on institutional ownership. Other variables (i.e., test portfolios and factor-mimicking portfolios) are the same as in Tables 2 and 3.

<i>Panel A. Size-sorted decile portfolios as test assets</i>										
	smallest	pf 2	pf 3	pf 4	pf 5	pf 6	pf 7	pf 8	pf 9	largest
average return	0.043	0.027	0.020	0.014	0.014	0.013	0.007	0.008	0.010	0.013

One-Factor: MKTrf										
α	0.031	0.015	0.009	0.003	0.004	0.004	-0.004	-0.001	0.001	0.005
(<i>t</i> -stat)	(2.870)	(1.780)	(1.246)	(0.442)	(0.668)	(0.596)	(-0.793)	(-0.315)	(0.235)	(1.164)
Wald-Statistic=36.19 (p-val: 0.000) GRS F=3.364 (p-val: 0.001)										

Two-Factor: MKTrf, IOF										
α	0.016	0.003	-0.001	-0.006	-0.003	-0.002	-0.008	-0.005	0.000	0.006
(<i>t</i> -stat)	(2.197)	(0.551)	(-0.130)	(-1.087)	(-0.508)	(-0.345)	(-1.787)	(-1.097)	(-0.124)	(1.393)
Wald-Statistic=31.94 (p-val: 0.000) GRS F=2.948 (p-val: 0.002)										

Three-Factor: MKTrf, SMB, HML										
α	0.032	0.016	0.010	0.004	0.005	0.003	-0.005	-0.002	-0.001	0.003
(<i>t</i> -stat)	(4.855)	(4.338)	(3.776)	(1.502)	(1.935)	(0.859)	(-1.788)	(-0.763)	(-0.266)	(0.800)
Wald-Statistic=55.27 (p-val: 0.000) GRS F=5.066 (p-val: 0.000)										

<i>Panel B. BM-sorted decile portfolios as test assets</i>										
	growth	pf 2	pf 3	pf 4	pf 5	pf 6	pf 7	pf 8	pf 9	value
average return	0.009	0.012	0.015	0.015	0.018	0.016	0.020	0.022	0.023	0.033

One-Factor: MKTrf										
α	-0.002	-0.001	0.005	0.005	0.005	0.004	0.008	0.011	0.010	0.022
(<i>t</i> -stat)	(-0.401)	(-0.125)	(0.868)	(0.857)	(0.913)	(0.658)	(1.374)	(1.728)	(1.401)	(2.647)
Wald-Statistic=21.13 (p-val: 0.020) GRS F=1.964 (p-val: 0.041)										

Two-Factor: MKTrf, IOF										
α	-0.008	-0.007	-0.001	-0.002	-0.001	-0.001	0.002	0.003	0.003	0.013
(<i>t</i> -stat)	(-2.017)	(-1.437)	(-0.296)	(-0.544)	(-0.180)	(-0.286)	(0.336)	(0.702)	(0.462)	(1.905)
Wald-Statistic=19.30 (p-val: 0.037) GRS F=1.781 (p-val: 0.070)										

Three-Factor: MKTrf, SMB, HML										
α	0.000	0.002	0.007	0.006	0.006	0.003	0.007	0.010	0.007	0.019
(<i>t</i> -stat)	(-0.003)	(0.388)	(1.998)	(2.300)	(1.855)	(1.030)	(2.633)	(3.506)	(2.753)	(4.391)
Wald-Statistic=36.00 (p-val: 0.000) GRS F=3.30 (p-val: 0.001)										

Table 5. Alternative specifications for time-series regressions

Panel A of this table reports the average absolute values of the time-series regression intercept and of its t -statistic using individual stocks as test asset. To be included in the analysis, individual stocks are required to have a certain minimum number of monthly returns. Panel B of this table reports the time-series regression results using one of the factor-mimicking portfolios as test asset.

Panel A. Individual stocks as test assets

	Stocks with a minimum of 60 monthly returns (n=763 with FOF; n=733 with IOF)		Stocks with a minimum of 100 monthly returns (n=602 with FOF; n=529 with IOF)		Stocks with monthly returns over the entire sample period (n=248 with FOF; n=268 with IOF)	
	avg. $ \alpha $	avg. $ t $	avg. $ \alpha $	avg. $ t $	avg. $ \alpha $	avg. $ t $
Results using FOF (1992.07 ~ 2006.12)						
One-Factor	0.0128	0.780	0.0123	0.791	0.0113	0.933
Two-Factor (FOF)	0.0117	0.727	0.0103	0.681	0.0083	0.725
Three-Factor	0.0120	0.764	0.0112	0.751	0.0097	0.836
Results using IOF (1992.07 ~ 2005.06)						
One-Factor	0.0128	0.737	0.0124	0.764	0.0111	0.844
Two-Factor (IOF)	0.0128	0.747	0.0109	0.698	0.0083	0.682
Three-Factor	0.0121	0.744	0.0115	0.760	0.0100	0.808

Panel B. Other factor-mimicking portfolios as test assets

dependent variable	intercept	MKTrf	FOF (IOF)	SMB	HML	adj. R^2
Results using FOF (1992.07 ~ 2006.12)						
FOF	0.010 (2.599)	0.030 (0.731)		0.684 (13.142)	-0.078 (-1.087)	0.506
SMB	-0.007 (-1.763)	-0.098 (-2.329)	0.753 (13.213)			0.520
HML	0.006 (1.543)	0.037 (0.852)	0.075 (1.273)			0.001
Results using IOF (1992.07 ~ 2005.06)						
IOF	0.013 (3.490)	0.031 (0.851)		0.662 (13.461)	-0.202 (-2.923)	0.542
SMB	-0.011 (-2.483)	-0.093 (-2.199)	0.822 (12.828)			0.533
HML	0.006 (1.251)	0.029 (0.670)	0.002 (0.038)			-0.010

Table 6. Fama-MacBeth regressions using 25 size/BM-sorted portfolios

This table reports the Fama-MacBeth regression results. Panel A reports the loadings on the factor-mimicking portfolios estimated over the entire sample period for each of the 25 test portfolios sorted independently by size and BM. Panel B reports the results of the month-by-month cross-sectional regressions of the test portfolios monthly return on the estimated factor loadings, averaged over the sample period. Numbers in parentheses are the t -statistics for the average regression coefficients.

Panel A. Summary statistics of the estimated factor loadings (1992.07 ~ 2006.12)

Estimated loadings on	n	mean	stdev	median	min	max
MKTrf (β)	25	0.901	0.099	0.891	0.703	1.087
FOF (f)	25	0.617	0.426	0.558	-0.082	1.405
SMB (s)	25	0.714	0.405	0.755	0.053	1.376
HML (h)	25	0.331	0.357	0.319	-0.336	0.902

Panel A. Fama-MacBeth regression results using FOF (1992.07 ~ 2006.12)

Model	intercept	β	f	s	h	adj. R^2	# of obs.
(1)	0.046 (1.90)	-0.038 (-1.59)				0.161	174
(2)	0.001 (0.08)		0.017 (2.63)			0.229	174
(3)	0.001 (0.15)			0.014 (2.08)		0.233	174
(4)	0.009 (1.04)				0.008 (1.65)	0.071	174
(5)	-0.016 (-0.89)	0.021 (1.14)	0.066 (4.64)	-0.048 (-3.43)	0.004 (0.77)	0.359	174

Table 6. cont.**Panel C. Summary statistics of the estimated factor loadings (1992.07 ~ 2005.06)**

Estimated loadings on	n	mean	stdev	median	min	max
MKTrf (β)	25	0.893	0.103	0.876	0.676	1.096
IOF (i)	25	0.639	0.461	0.567	-0.023	1.514
SMB (s)	25	0.716	0.404	0.759	0.053	1.364
HML (h)	25	0.327	0.363	0.273	-0.330	0.942

Panel D. Fama-MacBeth regression results using IOF (1992.07 ~ 2005.06)

Model	intercept	β	i	s	h	adj. R^2	# of obs.
(1)	0.049 (1.91)	-0.045 -(1.73)				0.178	156
(2)	-0.001 -(0.14)		0.016 (2.48)			0.252	156
(3)	-0.002 -(0.23)			0.016 (2.15)		0.253	156
(4)	0.007 (0.81)				0.006 (1.15)	0.073	156
(5)	-0.036 -(1.91)	0.037 (1.83)	0.060 (4.05)	-0.041 -(2.73)	0.010 (1.77)	0.380	156

Table 7. Summary statistics of heterogeneity-augmenting factors and other factor-mimicking portfolios in Japanese market

This table reports the summary statistics of foreign ownership-based augmenting factor (FOF), institutional ownership-based augmenting factor (IOF) and other factor-mimicking portfolios in the Japanese stock market. MKTrf is the monthly TOPIX Index return, a proxy for the domestic market portfolio return, less the combined series of the call money rate (from October 1976 to November 1977) and the 30-day Gensaki (repo) rate (from December 1977 to December 2004) converted to the monthly yield, a proxy for the risk-free rate. SMB and HML are the factor-mimicking portfolio in the Fama-French three-factor model. FOF (IOF) is the foreign (institutional) ownership-based factor-mimicking portfolio, which is the difference between the returns on the lowest foreign (institutional) ownership quintile portfolio minus the returns on the highest foreign (institutional) ownership quintile portfolio. The numbers in parentheses of the first panel are the t-statistics of the test for the zero mean. The numbers in parentheses of the second panel are the p-values of the test for the zero correlation coefficient.

	N	Min	Q1	Median	Q3	Max	Mean	Std
MKTrf	339	-0.202	-0.024	0.003	0.035	0.173	0.003 (1.013)	0.051
SMB	339	-0.146	-0.023	0.001	0.031	0.829	0.004 (1.202)	0.061
HML	339	-1.250	-0.010	0.006	0.022	0.136	0.004 (0.930)	0.074
FOF	339	-0.115	-0.020	0.002	0.028	0.193	0.004 (2.029)	0.040
IOF	339	-0.093	-0.014	0.004	0.019	0.169	0.004 (2.849)	0.028

Correlation coefficients between factor-mimicking portfolios

	MKTrf	SMB	HML
SMB	0.018 (0.738)	1.0000	
HML	-0.110 (0.043)	-0.641 (0.000)	1.0000
FOF	-0.035 (0.526)	0.434 (0.000)	0.135 (0.013)
IOF	0.038 (0.481)	0.426 (0.000)	0.168 (0.002)

Table 8. Time-series regressions using Japanese data: 197610~200412

This table reports the average monthly returns on the test portfolios (sorted either by size or by BM) and the time-series regression intercept (α). Size-sorted portfolios are equally weighted and are based on end-of-September market capitalization. BM-sorted portfolios are equally weighted and based on end-of-March book-to-market ratio. Factor-mimicking portfolios used as the explanatory variables in the regressions are defined in Table 7.

	smallest	pf 2	pf 3	pf 4	pf 5	pf 6	pf 7	pf 8	pf 9	largest
average return	0.019	0.014	0.011	0.010	0.008	0.008	0.007	0.007	0.007	0.006

One-Factor: MKTrf										
α	0.013	0.008	0.006	0.005	0.003	0.003	0.002	0.001	0.001	0.001
(<i>t</i> -stat)	(3.684)	(2.793)	(2.103)	(1.983)	(1.158)	(1.233)	(1.065)	(0.975)	(0.855)	(1.093)
Wald-Statistic=32.61 (p-val: 0.000) GRS F=3.155 (p-val: 0.001)										

Two-Factor: MKTrf, FOF										
α	0.008	0.004	0.002	0.002	0.000	0.001	0.001	0.001	0.001	0.001
(<i>t</i> -stat)	(3.171)	(1.883)	(1.026)	(0.935)	(0.070)	(0.334)	(0.330)	(0.401)	(0.730)	(1.753)
Wald-Statistic=29.81 (p-val: 0.001) GRS F=2.876 (p-val: 0.002)										

Two-Factor: MKTrf, IOF										
α	0.006	0.003	0.001	0.001	-0.001	0.000	0.000	0.000	0.001	0.002
(<i>t</i> -stat)	(2.360)	(1.185)	(0.350)	(0.283)	(-0.517)	(-0.159)	(-0.084)	(0.181)	(0.536)	(1.938)
Wald-Statistic=24.23 (p-val: 0.007) GRS F=2.337 (p-val: 0.011)										

Three-Factor: MKTrf, SMB, HML										
α	0.005	0.001	-0.001	-0.001	-0.003	-0.002	-0.002	-0.001	-0.000	0.001
(<i>t</i> -stat)	(2.885)	(1.207)	(-0.643)	(-0.931)	(-2.543)	(-1.732)	(-1.423)	(-1.041)	(-0.461)	(1.716)
Wald-Statistic=30.60 (p-val: 0.001) GRS F=2.942 (p-val: 0.001)										

Table 8. cont.**Panel B. BM-sorted decile portfolios as test assets**

	growth	pf 2	pf 3	pf 4	pf 5	pf 6	pf 7	pf 8	pf 9	value
avg return	0.004	0.007	0.008	0.009	0.010	0.010	0.011	0.012	0.014	0.017

One-Factor: MKTrf										
α	-0.002	0.001	0.002	0.003	0.004	0.005	0.005	0.005	0.008	0.011
(t-stat)	(-0.950)	(0.535)	(0.918)	(1.791)	(2.245)	(2.523)	(2.620)	(2.724)	(3.551)	(3.801)
Wald-Statistic=37.18 (p-val: 0.000) GRS F=3.597 (p-val: 0.000)										

Two-Factor: MKTrf, FOF										
α	-0.004	-0.001	0.000	0.002	0.002	0.003	0.003	0.003	0.005	0.007
(t-stat)	(-2.144)	(-0.313)	(0.008)	(0.945)	(1.468)	(1.656)	(1.746)	(1.849)	(2.887)	(3.192)
Wald-Statistic=32.56 (p-val: 0.000) GRS F=3.140 (p-val: 0.001)										

Two-Factor: MKTrf, IOF										
α	-0.005	-0.001	-0.001	0.001	0.002	0.002	0.002	0.002	0.004	0.005
(t-stat)	(-2.472)	(-0.660)	(-0.331)	(0.559)	(1.058)	(1.133)	(1.148)	(1.281)	(2.201)	(2.537)
Wald-Statistic=28.84 (p-val: 0.001) GRS F=2.782 (p-val: 0.003)										

Three-Factor: MKTrf, SMB, HML										
α	-0.006	-0.002	-0.002	-0.001	0.000	0.001	0.001	0.001	0.003	0.004
(t-stat)	(-3.467)	(-1.701)	(-1.585)	(-0.448)	(0.244)	(0.589)	(0.703)	(0.923)	(3.183)	(3.238)
Wald-Statistic=34.07 (p-val: 0.000) GRS F=3.276 (p-val: 0.000)										

Table 9. Alternative specifications for time-series regressions using Japanese data

Panel A of this table reports the average absolute values of the time-series regression intercept and of its t -statistic using individual stocks as test asset. To be included in the analysis, individual stocks are required to have a certain minimum number of monthly returns. Panel B of this table reports the time-series regression results using one of the factor-mimicking portfolios as test asset.

Panel A. Individual stocks as test assets

	Stocks with a minimum of 60 monthly returns (n=1,583)		Stocks with a minimum of 200 monthly returns (n=1,216)		Stocks with monthly returns over the entire sample period (n=746)	
	avg. $ \alpha $	avg. $ t $	avg. $ \alpha $	avg. $ t $	avg. $ \alpha $	avg. $ t $
One-Factor	0.0050	0.706	0.0043	0.723	0.0042	0.732
Two-Factor (FOF)	0.0041	0.587	0.0031	0.558	0.0029	0.554
Two-Factor (IOF)	0.0041	0.591	0.0031	0.567	0.0029	0.553
Three-Factor	0.0040	0.605	0.0031	0.579	0.0028	0.563

Panel B. Other factor-mimicking portfolios as test assets

dependent variable	intercept	MKT _{trf}	FOF (IOF)	SMB	HML	adj. R^2
Results using FOF						
FOF	0.001 (0.380)	0.021 (0.679)		0.576 (17.220)	0.379 (13.633)	0.475
SMB	0.001 (0.313)	0.040 (0.678)	0.671 (8.866)			0.185
HML	0.003 (0.774)	-0.153 (-1.964)	0.244 (2.433)			0.023
Results using IOF						
IOF	0.001 (1.320)	0.059 (2.792)		0.425 (18.582)	0.294 (15.479)	0.519
SMB	0.000 (-0.013)	0.002 (0.039)	0.917 (8.613)			0.176
HML	0.002 (0.558)	-0.169 (-2.186)	0.451 (3.236)			0.036

Table 10. Fama-MacBeth regressions using 25 size/BM-sorted portfolios in Japanese market

This table reports the Fama-MacBeth regression results. Panel A reports the loadings on the factor-mimicking portfolios estimated over the entire sample period for each of the 25 test portfolios sorted independently by size and BM. Panel B reports the results of the month-by-month cross-sectional regressions of the test portfolios monthly return on the estimated factor loadings, averaged over the sample period. Numbers in parentheses are the *t*-statistics for the average regression coefficients.

Panel A. Summary statistics of the estimated factor loadings (1976.10 ~ 2004.12)

Estimated loadings on	n	mean	stdev	median	min	max
MKTrf (β)	25	0.897	0.054	0.900	0.802	0.977
FOF (f)	25	0.522	0.373	0.501	-0.132	1.174
IOF (i)	25	0.762	0.522	0.752	-0.168	1.632
SMB (s)	25	0.682	0.351	0.761	-0.011	1.208
HML (h)	25	0.432	0.216	0.476	-0.054	0.769

Panel B. Fama-MacBeth regression results using (1976.10 ~ 2004.12)

Model	intercept	β	f	i	s	h	adj. R^2	# of obs.
(1)	0.033 (3.65)	-0.028 (-2.98)					0.041	339
(2)	0.003 (1.06)		0.008 (2.93)				0.284	339
(3)	0.003 (0.97)			0.006 (2.99)			0.282	339
(4)	0.002 (0.86)				0.007 (2.34)		0.287	339
(5)	0.001 (0.38)					0.014 (3.09)	0.263	339
(6)	0.011 (1.35)	-0.006 (-0.63)	0.022 (3.39)		-0.045 (-3.08)	0.048 (2.68)	0.494	339
(7)	0.015 (1.85)	-0.010 (-1.01)		0.020 (3.75)	-0.044 (-3.15)	0.037 (2.07)	0.496	339