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# What Factors Drive Global Stock Returns?

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## Abstract

Using monthly returns for over 27,000 stocks from 49 countries over a three-decade period, we show that a multifactor model that includes factor-mimicking portfolios based on momentum and cash flow-to-price captures significant time series variation in global stock returns, and has lower pricing errors and fewer model rejections than the global CAPM or a popular model that uses size and book-to-market factors. We find reliable evidence that the global cash flow-to-price factor is related to a covariance risk model. In contrast, we reject the covariance risk model in favor of a characteristic model for size and book-to-market factors. (*JEL* F30, G14, G15)

## What Factors Drive Global Stock Returns?

The identification of sources of return comovement and, hence, of possible sources of portfolio risk is a primary pursuit of researchers in the field of asset pricing and one of central importance to investment practitioners, especially those involved in global financial markets. The seminal international asset pricing models of Solnik (1974), Grauer, Litzenberger, and Stehle (1976), Sercu (1980), Stulz (1981), and Errunza and Losq (1985) emphasize the importance of market-wide, consumption-based or currency factor risks. Nevertheless, there is a growing amount of evidence that stock returns are related to factors that are based on firm-level characteristics, such as size, book-to-market equity, cash flow-to-price, and momentum in the United States, and in developed and emerging markets around the world.[1]

However, there has been no comprehensive examination about which factors related to firm-level characteristics can explain the cross-sectional and time-series variation in global stock returns. The need for such an analysis is further increased by a number of controversies in the literature. One such controversy focuses on whether the explanatory power of these characteristics arises locally or globally. Some studies argue that only local, country-specific factors constructed from these firm-level characteristics matter for global stock returns (Griffin, 2002), while others perceive a more globally integrated market, and advocate models that incorporate both local and foreign components of factors built from firm characteristics (Fama and French, 1998; Bekaert, Hodrick and Zhang, 2009). A second major controversy stems from the interpretation of the evidence itself. Some believe that the premiums associated with these characteristics represent compensation for pervasive extra-market risk factors, in the spirit of a multifactor version of Merton’s (1973) Intertemporal Capital Asset Pricing Model (ICAPM) or Ross’s (1976) Arbitrage Pricing Theory (APT) (Fama and French, 1993, 1996; Davis, Fama, and French, 2000), whereas others attribute them to inefficiencies in the way markets incorporate information into prices (Lakonishok, Shleifer, and Vishny, 1994; Daniel and Titman, 1997; Daniel, Titman and Wei, 2001).

Motivated by these concerns, this study examines a large number of firm-level characteristics that might explain the cross-sectional and time-series variation in global stock returns. We evaluate size, dividend and earnings yields (D/P and E/P, respectively), cash flow-to-price (C/P), book-to-market equity (B/M), leverage, and momentum using monthly returns for over 27,000 individual stocks from 49 countries over three decades (1981 to 2003). We specifically seek answers to the following questions:

(a) Which firm-level characteristics offer the greatest explanatory power for the cross-sectional and time-series variation in global stock returns?

(b) Is the explanatory power of these characteristics driven by their local country-specific components, their non-local foreign components, or both?

(c) For those firm-level characteristics that best explain the variation in global stock returns, does their success arise from the explanatory power of the characteristics or from the covariance structure of returns related to those characteristics?

We undertake a number of new experiments to answer each of these questions and we uncover several important findings. First, using cross-sectional Fama-MacBeth (1973) tests of individual stock returns and time-series regression-based tests of multifactor models, we confirm the strong and reliable explanatory power of a value-based factor in global stock returns. However, this factor is based on C/P, and not on B/M, E/P, or D/P. In other words, different measures of the value-growth effect are not easily interchangeable, which is a surprising finding that challenges a key result in Fama and French (1998). The C/P characteristic is statistically reliable and economically important in the Fama-MacBeth cross-sectional regressions. Furthermore, in time-series tests, a global C/P factor-mimicking portfolio (constructed as a long-short portfolio that buys high-C/P stocks and sells short low-C/P stocks) can explain much of the return differences for country and industry test portfolios, and for a wide variety of characteristic-based global test portfolios. This is not the case for the B/M, E/P, and D/P characteristics and their respective factor-mimicking portfolios. The incremental explanatory power of a B/M factor-mimicking portfolio, over and above that based on C/P, is also negligible.

In addition, we show that medium-term stock-price momentum exists in international markets, as others have found (Rouwenhorst, 1998; Griffin, Ji and Martin, 2003), and that a factor portfolio constructed on the basis of this characteristic complements the explanatory power of the C/P-based factor portfolio in almost all tests. Of the various multifactor models combining different global factor-mimicking portfolios, a three-factor model that combines the C/P and momentum factor-mimicking portfolios with a global market portfolio not only captures strong common variation in global stock returns but also has the lowest pricing error and rejection rate (using *F*-tests of Gibbons, Ross and Shanken, 1989) for country, industry, and characteristic-based global test portfolios.

Our second experiment examines whether the empirical validity of the global factor-mimicking portfolios based on C/P, momentum, and other firm characteristics arises as a result of important country-specific components of those global portfolios rather than their foreign components. Whether securities are priced locally in segmented markets or globally in a single integrated market has been one of the enduring questions in international asset pricing (see Karolyi and Stulz, 2003). The liberalization of financial markets around the world has increased market accessibility for foreign investors but implicit barriers, such as political risk and differences in information quality, legal protection for private investors, and market regulations, can still inhibit full market integration. Most empirical tests focus on whether market or consumption risks are priced locally or globally, following predictions of international asset pricing models put forth by Solnik (1974), Grauer, Litzenberger, and Stehle (1976), Sercu (1980), Stulz (1981), and Errunza and Losq (1985). Recently, the focus has shifted to the role of firm characteristics in the pricing of securities in global markets. Of particular interest in this respect is Griffin's (2002) finding that the success of the global version of Fama and French's (1993) three-factor model, which includes a market factor, a size factor, and a book-to-market equity factor, arises from the domestic component of the factors for US, Canadian, UK, and Japanese stock returns. Griffin's study is important because it challenges Fama and French's original findings (1998), which demonstrate the applicability of the global version of their multifactor model to the US and twelve other developed markets.

We compare the relative success of global, local, and international (including separate local and foreign components) versions of various multifactor models in explaining the returns of industry and characteristic-sorted test portfolios within each country. Local and international versions of these multifactor models are found to have much lower pricing errors than global versions. This is especially true for emerging markets, which is not surprising as those countries are more likely to be segmented from global markets. We also show that the international version of the multifactor model with the market, C/P, and momentum factor-mimicking portfolios provides the lowest average pricing error and rejection rate of the various versions of competing multifactor models. Therefore, we find that foreign components of these factors are as important as local components for pricing.

In our third and final experiment, we investigate whether the cross-sectional explanatory power of our global factor-mimicking portfolios is directly related to the firm-level characteristics on which they are based - for such reasons as investor over- or under-reaction or illiquidity - or whether it derives from the covariance structure of returns that is related to these characteristics. To distinguish the "covariance" view from the "characteristics" view of these factor-mimicking portfolios, we follow Daniel and Titman (1997), Davis, Fama, and French (2000), and Daniel, Titman, and Wei (2001), and identify variation in covariance risk loadings that is independent of the corresponding characteristic. We then test whether this is associated with spreads in average returns. Specifically, we form portfolios by sequentially sorting stocks first on characteristics, such as size and B/M, and then on risk loadings associated with the factor-mimicking portfolios based on the same characteristics. If characteristics drive returns, there should be no relation between average returns and the risk loadings after controlling for the characteristics themselves. A finding of a relation between average returns and loadings on a factor-mimicking portfolio after controlling for the characteristic on which the factor portfolio is based would indicate that the characteristic of interest proxies for sensitivity to a covariance risk factor.

In our global experiments, we investigate the size, B/M, C/P, and momentum characteristics, and their corresponding factor risk loadings. We find reliable empirical evidence that C/P is related to a global covariance risk factor. In various empirical specifications, risk loadings on the C/P factor-mimicking portfolio are always associated with an economically large and statistically significant return premium of 42 to 48 basis points per month, even after controlling for variation in the C/P characteristic. Just as importantly, we demonstrate that this is not the case for risk loadings on the B/M factor-mimicking portfolio. This finding reinforces our earlier inference that these value-based characteristics are not readily interchangeable in terms of their importance for global stock returns. Not only do we reject the covariance risk explanation for B/M but we also reject it for size. We find mixed evidence that momentum is related to a covariance risk factor.

It is important to emphasize that our characteristic-versus-covariance experiment not only contributes to the literature on international asset pricing. By exploiting the wide breadth and scope of our global sample of stocks, it also adds to the domestic asset pricing literature. The sensitivity of the findings in Daniel and Titman (1997), Davis, Fama, and French (2000), and Daniel, Titman, and Wei (2001) to different subperiods and different countries emphasizes the importance of examining results for a sample large enough to allow the researcher to form diversified portfolios with enough independent cross-sectional variation in factor loadings and characteristics. This papers presents the most extensive implementation of such a test to date and, to the best of our knowledge, we are the first to provide reliable empirical evidence of a value-related factor (based on C/P) as a covariance risk factor.

Our paper offers useful guidance for the global asset management industry. The popularity of global factor models has grown rapidly – such models are extensively used for portfolio risk optimization, active-risk budgeting, performance evaluations, and style/attribution analyses. In addition to market, currency, macroeconomic, and industry-specific risk factors, models such as BARRA's Integrated Global Equity Model (Stefek, 2002; Senechal, 2003), Northfield's Global Equity Risk Model (Northfield, 2005), ITG's Global Equity Risk Model (ITG, 2003), and Smith Barney's Global Equity Risk Management Model (GRAM, Miller et al., 2002) all include what are referred to as "style," "fundamental," "financial-statement ratio," or "bottom-up" factors. All of these models rationalize their choice of factor model specifications on the basis of joint goals of robustness and parsimony. Our findings validate the use of some fundamental factors (C/P) in these models for risk-control purposes, and suggest that others (B/M and size) may be better indicators of profitable investment opportunities or, possibly, for implementation of cost control.

The next section outlines the data in detail and presents the summary statistics. Sections 2 through 4 present, respectively, the results of the experiments on the cross-sectional tests of individual stock returns and time-series tests of global multifactor models using global test portfolios; on the relative performance of the local, global, and international versions of multifactor models using country-specific test portfolios; and on the roles of characteristics versus covariances in explaining global stock returns. In Section 5, we outline our conclusions and discuss avenues for future research.

## 1. Data and Summary Statistics

Our sample construction begins with all publicly-traded firms included in the country lists and dead-firm lists provided by Datastream from July 1981 to December 2003.[2] From these lists, which contain over 50,000 stocks, we select those with sufficient information to calculate at least one of the following financial variables: book-to-market equity (B/M), cash flow-to-price (C/P), dividend-to-price (D/P), earnings-to-price (E/P), long-term debt-to-book equity (L/B), and market value of equity (*size*). These company-accounts items are obtained from the Worldscope database, which includes data on over 39,000 firms in more than 50 countries for the period 1981 to 2003. These firms represented approximately 95% of global market capitalization.[3] We then select common stocks that are traded on the country's major exchange(s), excluding preferred stocks, warrants, REITs, closed-end funds, exchange-traded funds, and depositary receipts. For most countries, the exchange with the largest number of traded stocks is selected. However, multiple exchanges are included for China (Shanghai and Shenzen exchanges), Japan (Osaka and Tokyo exchanges), and the United States (NYSE, AMEX, and NASDAQ). In addition, a stock must have had at least 12 monthly stock returns during the sample period to be included in the sample.

We apply several screening procedures for monthly returns, as suggested by Ince and Porter (2003) and others. First, any return above 300% that is reversed within one month is treated as missing. Specifically, if $R_t$ or $R_{t-1}$ is greater than 300%, and $(1+R_t) \times (1+R_{t-1}) - 1 < 50\%$, then both $R_t$ and $R_{t-1}$ are set to "missing". Second, in order to exclude remaining outliers in returns that cannot be identified as stock splits or mergers, we treat as missing the monthly returns that fall outside the 0.1% to 99.9% percentile range in each country. We cross-check (in results not reported) our return data for US firms with those from the CRSP database by matching their CUSIPs, and find that the average difference in monthly returns for all matched firms is less than 0.01%. In order to minimize potential biases arising from low-price and illiquid stocks, we also require a minimum price of $1 at the end of the previous month for a stock to be included in the analysis.

To ensure that the accounting ratios are known before the returns, we match the year-end financial statement data for year *t-1* with monthly returns from July of year *t* to June of year *t+1*. Of the accounting ratios, D/P (Worldscope data item WC09404), E/P (WC09204), and L/B (WC08226) are directly obtained from Worldscope. We use the inverse of the price-to-book ratio (WC09304) and the inverse of the price-to-cash flow ratio (WC09604) to calculate the B/M and C/P ratios, respectively. Appendix A provides a detailed description of the Worldscope construction of these variables. In addition, *size* is defined as the market value of equity at the end of June of year *t*, while momentum (*Mom*) for month *t* is the cumulative raw return from month *t-6* to month *t-2*, skipping month *t-1* to mitigate the impact of microstructure biases such as bid-ask bounce or non-synchronous trading. For some of the tests, we also employ betas with respect to the value-weighted global and country-portfolios to which a stock belongs. These betas are estimated annually for each stock at the end of June of each year, using the stock's previous 36 monthly returns (12-month minimum).

After imposing the sampling criteria described above, our final sample encompasses 27,488 common stocks from 49 countries and 34 industries.[4] Figure 1 exhibits the distribution of our sample stocks across the 49 countries over the entire period from 1981 to 2003. US firms constitute 36% of the sample population (9,840 stocks), followed by firms in Japan (10%), the UK (9%), Canada (4%), and France (4%). Several emerging markets – China, South Korea, Malaysia, Taiwan, Thailand, and South Africa – are well represented in the sample. Figure 2 shows the development of the sample over time – the data coverage improves significantly in the late 1980s, especially for emerging economies. This is partly because Worldscope began to include more firms in the database at that time but it did not backfill the data for those newly added firms.

Table 1 presents the summary statistics of monthly returns (denominated in US dollars) and other firm characteristics for the final sample. We report the time-series means of median (across stocks) returns (on a monthly basis) and other characteristics (on an annual basis) for each country. Many emerging markets have representation in relatively few (22 on average) FTSE industries, while the developed markets usually have representation in at least 30 of the 34 industries (30 on average). The median monthly return ranges from -0.69% for Brazil to 5.69% for Zimbabwe. The median firm size (market capitalization) ranges from

$44 million for Hungary to $892 million for Hong Kong. Table 1 also reports the time-series averages of median B/M, *Mom*, C/P, D/P, E/P, L/B, and betas with respect to value-weighted global and country portfolios. There is considerable cross-country variation in the median B/M and L/B, but much less variation for D/P, C/P, and E/P. For example, B/M ranges from as low as 0.26 (China) to as high as 2.04 (Russia).[5] In contrast, the median E/P ranges from a low of -0.02 (Zimbabwe) to a high of 0.26 (Russia). The median global betas are measurably smaller in magnitude than the country betas; global betas average 0.58 across countries and country-specific betas average 0.76.

## 2. What Factors Explain Global Stock Returns?

Our first experiment involves two types of asset-pricing tests and aims to determine the factors that best explain global stock returns. We employ the cross-sectional regression approach proposed by Fama and MacBeth (1973) using individual stocks.[6] Each month, the cross-section of individual stock returns is regressed on variables hypothesized to explain expected returns. The time-series means of the monthly regression slopes then provide standard tests of whether explanatory variables explain the cross-section of average returns.[7] The second test adopts the time-series regression approach of Black, Jensen, and Scholes (1972), which has been applied by Fama and French (1993, 1996) and others, in which returns on country, industry, and characteristic-sorted test portfolios are regressed on returns of various factor-mimicking portfolios. The time-series regression slopes in these regressions have natural interpretations as factor loadings, or factor sensitivities, which allow us to judge how well different combinations of factor-mimicking portfolios can explain average returns across a variety of test assets (with the *F*-test of Gibbons, Ross and Shanken, 1989).

### 2.1 Cross-sectional tests with individual stocks

**Table 2** reports the time-series averages of the slope coefficients (with associated *t*-statistics) from monthly Fama-MacBeth (FM) regressions of individual stock returns on betas and other firm-level characteristics.[8] We report results for "univariate" regressions involving only one independent variable per regression model and "multivariate" regressions involving multiple independent variables. For C/P, D/P, E/P, and L/B, we follow Fama and French (1992), and use dummy variables to separate firms with negative cash flows, no dividends, negative earnings, and no leverage from those with positive cash flows, dividends, earnings, and leverage. These dummy variables appear together with the positive level counterparts - designated as "(+)" in the acronym - in each FM regression. Panel A of Table 2 presents the regression results across all stocks from all countries. Panels B and C present the results for the US only, for developed (excluding US), and emerging markets separately, for separate subperiods, and for January versus other months in the year (to highlight the effects of seasonalities, as in Keim, 1983).

The univariate FM regressions across all countries show that global and country betas do not explain the cross-section of average stock returns. The average slopes are negative, although they are not reliably different from zero. In contrast, most other firm-level characteristics show reliable explanatory power. The slope coefficient for (log) *size* is -0.12% (*t*-statistic of -3.39), indicating that small firms earn higher returns, on average. Similarly, the coefficients on (log) B/M, *Mom*, C(+)/P, D(+)/P, and E(+)/P are all significant and positive, suggesting that stocks with high B/M, high *Mom*, high C/P, high D/P, or high E/P all achieve higher returns. The slope coefficient on L(+)/B, on the other hand, is insignificant. We do not include the poorly performing betas or the leverage ratio in the multivariate regression. Of those variables that are included, the slope coefficients for (log) *size*, (log) B/M, *Mom*, C(+)/P, D(+)/P, and E(+)/P, although smaller in magnitude, remain significant and maintain the same signs. On the other hand, the slope coefficients on C/P dummy, D/P dummy, and E/P dummy are all insignificant.

Panels B and C try to dissect these findings. The first supplemental set of tests focuses on US markets from 1981 to 2003 (Panel B). As Figure 1 indicates, the 9,840 US stocks constitute more than one-third of our final global sample. The univariate FM regression results for the US run in parallel to those for all countries (Panel A). We find that the slope coefficient for (log) *size* (-0.13%) remains almost unchanged. The slope coefficients for (log) B/M, *Mom*, C(+)/P, and E(+)/P are all slightly smaller in magnitude, although they are still reliably significant. The D(+)/P coefficient is much smaller and is indistinguishable from zero.

In the multivariate FM regressions, the coefficients on (log) *size*, *Mom*, C(+)/P, and, to a lesser extent, on (log) B/M remain significant, while those on E(+)/P and D(+)/P become insignificant.

The next series of supplemental tests (Panel C) show that the results obtained from all countries largely hold for stocks from developed markets outside the US, with the exceptions of the size and E/P effects. For emerging markets, only C(+)/P retains a significant slope coefficient (0.91%). The B/M effect is weaker in second half of our sample period (1992 to 2003) than in the first half (1981 to 1992), whereas the opposite is true for C/P, D/P, and E/P. The momentum effect is equally strong in both halves of the sample period, and the size effect is insignificant in both halves. Finally, the size effect is clearly concentrated in January, as expected, whereas the momentum effect reverses in January (-2.45% compared to 1.29% from February through December).

We perform a number of additional robustness checks, although to conserve space, these results are not tabulated. For example, one might suggest that the uniform $1 price screen we apply is overly restrictive for stocks traded outside the US and that it may cause us to drop a disproportionately large number of international stocks from our analysis (the $1 price level corresponds to roughly the tenth percentile for US stocks and the twenty-fifth percentile for international stocks.) To address this concern, we remove the $1 price screen and re-estimate the cross-sectional regressions across all countries. We find that the coefficients on (log) B/M, C(+)/P, and *Mom* remain positive, while the coefficient on (log) *size* remains negative and significant in both the univariate and multivariate regressions. In a related check, we keep the $1 screen for US stocks but impose a less restrictive $0.20 screen for international stocks (which corresponds to approximately the tenth percentile). The results are very similar to those obtained when the $1 screen is applied to all countries.[9] Therefore, our key findings are not sensitive to the type of price screen employed.

Another potential concern is that the differences across countries in the treatment of certain accounting items and in accounting standards may influence our results. For example, prior to the early 1990s, many European companies did not provide consolidated financial statements, which could make accounting items, such as book equity, difficult to compare across countries. To investigate this issue, we drop firms (countries) that do not report consolidated statements or those that follow purely local accounting standards. We then repeat the cross-sectional regressions. We find that the premiums associated with size, B/M, C/P, and momentum are robust to the exclusion of these firms, which suggests that our results are not driven by differences in accounting rules and standards across countries.

Our cross-sectional tests indicate that alternative measures of the value-growth effect are not interchangeable, and that the selection and identification of the numerator of these “inverse-price” ratios (B/M, C/P, E/P, and D/P) is important. To corroborate this finding, we construct the inverse of price (1/P) in US dollars and investigate its explanatory power for the cross-section of average returns (unreported results). As this characteristic belies important differences in par value conventions across countries, it might pick up on important country-specific forces at work. Nevertheless, a statistically insignificant slope coefficient is found in both the univariate and multivariate tests.

One might also argue that the significant premiums from our cross-sectional regressions do not represent feasible trading strategies from the perspective of a global investor, as many emerging countries have restrictions on foreign ownership and, as a result, not all stocks in those countries are accessible to foreign investors. To this end, we utilize data from Standard & Poor’s Emerging Markets Database (EMDB) to screen stocks from emerging countries based on the extent to which they are accessible to foreign investors. The EMDB includes a variable called “degree open factor,” which is assigned a value of between zero (not investable) and one (fully investable) to reflect the investable weight of a stock that is accessible to foreigners. We find that the exclusion of stocks from emerging countries that have an investable weight below various cutoffs (0.25, 0.5, and 1) has virtually no effect on our inferences.

Finally, we replicate our US findings using the CRSP/Compustat database for the 1981 to 2003 sample period. This calibration exercise confirms that our results cannot be explained by differences in coverage between CRSP/Compustat and Datastream/Worldscope.

## 2.2 Constructing the factor-mimicking portfolios

The Fama-MacBeth tests offer a useful preliminary look at the role of firm characteristics in the cross-section of stock returns. Some characteristics, such as C/P and momentum, seem to do a good job of explaining average return differences for both developed and emerging markets, particularly in the more recent decade, but there unlikely to be enough power in the tests to distinguish them from size, B/M, E/P, and D/P. As L/B is not found to be particularly helpful, we do not carry it forward to the next set of experiments.

In order to further explore the characteristics that best account for the variation in global stock returns, we follow Fama and French (1993), and Chan, Karceski, and Lakonishok (1998), and construct proxy factors as returns on zero-investment portfolios that go long in stocks with high values for a certain characteristic (such as B/M) and short in stocks with low values for that characteristic. An examination of the return behavior of these proxy factors, referred to as factor-mimicking portfolios (hereafter, FMP), helps us to evaluate and interpret the underlying factors. When we find that a particular FMP exhibits significant time-series variation, then it is viewed as a candidate factor for capturing a substantial common component of return movements. A sizeable factor premium may also help to explain the cross-sectional variation of average stock returns. Ultimately, our goal is to employ the time-series regression approach of Black, Jensen, and Scholes (1972), which has been applied by Fama and French (1993, 1996) and others. In this approach, excess returns on test portfolios are regressed on returns of various candidate FMPs. The time-series slopes have natural interpretations as factor loadings or factor sensitivities, which enable us to judge how well different combinations of these FMPs can explain average returns across a wide variety of portfolios.

We proceed in two steps. In the first step, we construct an FMP for each firm-level characteristic and assess summary statistics of the FMPs, including their average premiums, volatility, autocorrelations, and cross-correlations. In the second step, we evaluate their explanatory power using time-series regressions.

For each of the characteristics, we form global quintile portfolios at the end of June of each year *t* and calculate the value-weighted returns of each portfolio from July of year *t* to June of *t*+1, as in Fama and French (1992, 1993).[10] We then compute the FMP returns as the highest-quintile returns minus the lowest-quintile returns, except for size FMP returns, which are calculated as the smallest size-quintile returns minus the largest size-quintile returns.[11] In addition, the momentum FMP is calculated following Jegadeesh and Titman's (1993) six-month/six-month strategy, whereby each month's return is an equal-weighted average of six individual strategies of buying the winner quintile and selling the loser quintile, rebalanced monthly.[12] In order to minimize the bid-ask bounce effect, we skip one month between ranking and holding periods when constructing the momentum FMP.

Table 3 reports the means, standard deviations, autocorrelations, and cross-correlations of monthly returns on various global FMPs. Of these, the market portfolio achieves an average excess return of 0.49% per month and, surprisingly, it is only marginally different from zero over the 270-month horizon (*t*-statistic of 1.87). The E/P, C/P, D/P, and momentum FMPs achieve the highest average monthly returns of 0.75%, 0.70%, 0.69%, and 0.63%, respectively, each with a *t*-statistic greater than two. The average returns for the size and B/M FMPs are considerably smaller: B/M achieves an average monthly return of 0.51% with a *t*-statistic of 2.10, while the size FMP produces an average monthly return of 0.55% with a *t*-statistic of 2.70.

While a small premium on a factor does not necessarily imply that it is unimportant for return comovement, low volatility might. The third column of Panel A, therefore, reports the standard deviation of the FMP returns. The value-weighted global market portfolio has a standard deviation of 4.31% per month, which highlights the fact that a factor that induces strong patterns of return comovement need not be associated with a large premium in returns. The E/P and D/P FMPs have the highest return volatilities (5.14% and 5.08%, respectively) followed by the momentum FMP at 4.52%. Although the B/M FMP has a relatively small premium, it is associated with substantial volatility (4.00% per month). In Panel B, we see that the autocorrelations for up to 12 lags of these FMPs are indistinguishable from zero.

Given the number of candidate factors, our approach must necessarily be selective. The correlations between the returns of the different FMPs provide one way of narrowing the field. If the returns on several FMPs are highly correlated with each other, then they are most likely picking up similar underlying factors. Therefore, all else equal, less information about return variation will be lost if we drop factors that are highly correlated with others. In Panel C, several of the FMPs associated with valuation ratios (C/P, B/M, E/P, and D/P) are shown to be positively correlated at around 0.80, which might be a basis for concern. The value-weighted market portfolio is negatively associated with these FMPs and the size FMP at around -0.40, and the momentum FMP appears to have low correlations (less than 0.20) with most of the other FMPs.

In sum, several candidate FMPs possess desirable statistical attributes for time-series asset-pricing tests. In addition to the market portfolio, we include the momentum factor, as it has a sizeable premium and volatility, and has relatively low correlations with any of the other factors we consider. FMPs based on the valuation ratios B/M, C/P, D/P, and E/P are good candidates, but there may be significant overlap among them.

### 2.3 Time-series regression tests with country, industry, and characteristic-sorted test portfolios

In Fama and French (1996), many of the CAPM average-return anomalies are shown to be captured by a parsimonious three-factor model proposed in Fama and French (1993). The model states that the expected return on a portfolio in excess of the risk-free rate, $E(R_i) - r_f$, is explained by the sensitivity of its returns to three factors: (i) the excess returns on a broad market portfolio ($R_m - r_f$); (ii) the difference between the returns on a portfolio of small stocks and the returns on a portfolio of large stocks (*SMB*); and (iii) the difference between the returns on a portfolio of high-B/M stocks and the returns on a portfolio of low-B/M stocks (*HML*). Specifically, the model defines:

$$E(R_i) - r_f = \beta_i \{E(R_m) - r_f\} + s_i E(SMB) + h_i E(HML), \tag{1}$$

where $\{E(R_m) - r_f\}$, $E(SMB)$, and $E(HML)$ are expected premiums. The factor sensitivities, or loadings, $\beta_i$, $s_i$, and $h_i$ are the slopes in the time-series regression:

$$R_{it} - r_{ft} = \alpha_i + \beta_i \{R_{mt} - r_{ft}\} + s_i SMB_t + h_i HML_t + \varepsilon_{it}. \tag{2}$$

Fama and French show that this three-factor model provides a reasonably accurate description of average returns of US test portfolios formed on size and B/M (Fama and French, 1993), and on single and various double-sorted portfolios formed on E/P, C/P, sales growth, and prior-five-year returns (Fama and French, 1996). This three-factor model is less appropriate for portfolios formed on momentum (Fama and French, 1996) and for industry portfolios (Fama and French, 1997). An international two-factor equivalent based on the market and B/M factor describes the returns on B/M-, E/P-, C/P-, and D/P-sorted portfolios for stocks in 12 developed markets taken from the Morgan Stanley Capital International universe (Fama and

French, 1998).

We follow a line of inquiry similar to Fama and French (1993, 1996) for global stock returns but we have no particular multifactor model in mind. Our effort is exploratory – we propose different combinations of FMPs based on our preliminary analysis. The "playing field" comprises different sets of test assets, including country portfolios, global industry portfolios, and decile portfolios based on each of the firm-level characteristics (size, B/M, momentum, C/P, D/P, and E/P). We judge each model based on its explanatory power and the magnitude of model pricing errors, and we model test rejections using the Gibbons, Ross, and Shanken (GRS) *F*-test statistic for the hypothesis that the intercepts are jointly equal to zero across the test assets of interest.[13] We use the global CAPM as a starting point for each set of test portfolios, and then add various combinations of FMPs to the global CAPM.

Table 4 reports the time-series regression results. The first two columns of Panel A give the raw excess return differences between the highest and lowest-return country (20 countries), between the highest and lowest-return industry (34 industries), and between the extreme decile portfolios for each characteristic (designated "H-L Ret") and the average absolute returns of the country, industry, and characteristic-sorted decile portfolios (designated "|Ret|").[14] Our first set of results is for the global CAPM model shown in columns three through six. We report the difference between the highest and lowest regression intercepts ("H-L $\alpha$"), the average absolute intercepts ("$|\alpha|$"), the average adjusted $R^2$ ("$R^2$"), and the GRS *F*-statistic (with an indication of its statistical significance at the 1%, 5%, and 10% levels). The average adjusted $R^2$ for the country test portfolios is relatively low at 35%, compared to those for the industry and characteristic-sorted test portfolios (both averaging above 60%). For each experiment (set of test portfolios), the difference between the extreme intercepts is always greater than the difference in raw excess returns, but the average absolute intercept is much smaller than the average absolute raw return, as we would expect given the reasonable explanatory power ($R^2$) of the model. However, the GRS *F*-statistics tell a clear story: in each experiment – except for the experiment related to country portfolios, which suffers from the low power of the test – the global CAPM model is easily rejected. The *F*-statistics have large values, especially for the characteristic-based portfolios. There is, therefore, an opportunity for multifactor models to pick up where the global CAPM leaves off. [15]

The remaining columns of Panel A in Table 4 evaluate the global version of the Fama-French model. The addition of the size and B/M FMPs in this extended model leads to one fewer model rejection and lower GRS *F*-statistics for some of the experiments. As with the CAPM model, we are unable to reject the Fama-French model for country test portfolios and the average pricing error (measured by the average absolute intercept) remains unchanged at 0.28%. We still reject the model for industry, size, momentum, C/P, D/P, and E/P test portfolios (although the average absolute intercept decreases in most cases relative to the CAPM model). Only in the experiment using B/M decile portfolios can we no longer reject the model. This improvement is noteworthy, as the average absolute intercept is 0.07%, which is much smaller than it is in the CAPM model (0.24%).

We need a logical process for building a parsimonious global factor model in order to pick up what the global CAPM and the global Fama-French model fail to explain. One approach to narrowing the list is to add the characteristic-based FMPs to the global market portfolio one at a time:

$$R_{it} - r_{ft} = \alpha_i + \beta_i \{R_{mt} - r_{ft}\} + f_i F_t + \varepsilon_{it}, \tag{3}$$

where $F_t$ is a characteristic-based FMP, and $f_i$ is the factor sensitivity or loading associated with it. Panel B of Table 4 presents the results of these alternative two-factor models. To conserve space, we report only the average absolute intercepts and the GRS *F*-statistics for each set of test assets.

As with the global CAPM, none of the models can be rejected for country test portfolios, except those that add the D/P or E/P FMP to the market portfolio. Furthermore, the average absolute intercepts are similar, ranging from 0.23% to 0.29%. All of these two-factor models are rejected at the 10% or lower level for industry, size, and C/P test portfolios. For industry portfolios, the addition of the D/P FMP to the market portfolio produces the lowest average absolute intercept (0.18%). For size and C/P test portfolios, the addition of the FMP based on the same sorting characteristic (size or C/P FMP) produces the lowest average absolute intercepts (0.18% and 0.09%, respectively). For B/M and momentum test portfolios, the addition of the FMP based on the same characteristic results in the lowest average absolute intercept (0.06% and 0.02%, respectively) and the GRS $F$-statistics are no longer significant. The same cannot be said about the D/P and E/P test portfolios. In fact, for both of these test portfolios, the addition of the C/P FMP, rather than the D/P or E/P FMP, produces the lowest average absolute intercepts (0.10% and 0.08%, respectively) and the only GRS $F$-statistics that are insignificant.

Finally, a comparison of the various two-factor models' performances for the entire range of test portfolios reveals that the model with the market portfolio plus the C/P FMP produces, by far, the fewest number of rejections and the lowest pricing error. We cannot reject it for country, B/M, D/P, and E/P test portfolios, and the average absolute intercept is 0.15% across all experiments. Models with the market and the D/P or E/P FMPs are rejected by all test portfolios except B/M test portfolios with an average absolute intercept of 0.17% for both models. The model with the market and the B/M FMP is rejected by all except for B/M and country test portfolios, and the average absolute intercept is 0.18%. Therefore, different value-related FMPs (B/M, C/P, D/P, and E/P) are not easily substitutable. The model with the market portfolio plus the momentum FMP is rejected for all portfolios, except the momentum and country portfolios, with an average absolute intercept of 0.24%. The model with the market portfolio plus the size FMP is rejected for all portfolios, except country test portfolios, with an average absolute intercept of 0.23% across all experiments.

What do we learn from these tests? The C/P FMP shows promise in terms of pricing test portfolios based on other value-based characteristics, whereas other value-related FMPs do not. The momentum FMP is the only FMP that has the capacity to explain momentum test portfolios. Consequently, we introduce a new three-factor model (which we denote as "HKK"; Panel C of Table 4) that includes C/P FMP ($F_{C/P,t}$) and momentum FMP ($F_{Mom,t}$) in addition to the market portfolio:

$$R_{it} - r_{ft} = \alpha_i + \beta_i \{R_{mt} - r_{ft}\} + c_i F_{C/P,t} + m_i F_{Mom,t} + \varepsilon_{it}, \tag{4}$$

where $c_i$ and $m_i$ are the respective factor loadings. Compared to the global CAPM and Fama-French model reported in Panel A, this model offers a significant improvement for industry, momentum, C/P, D/P, and E/P test portfolios in terms of higher average adjusted $R^2$ and lower average absolute intercepts. Furthermore, it is no worse for country and B/M test portfolios. In none of these seven experiments is the model rejected by the GRS $F$-statistic. This new three-factor model also shows a significant improvement in performance relative to the various two-factor models investigated in Panel B. If we take the best-performing of those models – the model with the market factor plus the C/P FMP – as the benchmark, the three-factor model is no longer rejected by industry, momentum, and C/P test portfolios (not the case for the two-factor model), and it further reduces the average absolute intercept across all experiments from 0.15% to 0.13%. The only weakness of the HKK model lies in its inability to explain the returns of the size test portfolios. The GRS *F*-statistic of 2.72 easily rejects the model at the 1% level, although the average absolute intercept of 0.17% is the smallest among all of the models we have considered thus far. Notably, none of these models can explain the returns for the size portfolios.

We perform two final tests in Panel C of Table 4. First, we replace the C/P FMP in the HKK model with the B/M FMP. The results show that such a model takes a distinct step backwards, as it is rejected not only by the size test portfolios, but also by industry, C/P, D/P, and E/P portfolios. Moreover, it raises the average absolute intercept to 0.15% across all experiments. The replacement of the C/P FMP with E/P or D/P FMPs leads to even worse performance. Second, we construct a composite five-factor model that nests both the HKK model and the Fama-French model. This model is again rejected by industry, size, and D/P test portfolios (two more rejections than HKK). It also fails to improve on the average pricing error (average absolute intercept of 0.13%) over HKK. Therefore, this composite model is not better than the more parsimonious HKK model and, in certain cases, its performance is considerably worse.

We further confirm the robustness of the HKK model by pitting it against other combinations of FMPs and using double-sorted, characteristic-based test portfolios, although to save space, these results are not reported. We also investigate the relative performance of the HKK model using test portfolios constructed within developed markets and within emerging markets, and find that we cannot reject the HKK model using any of the test portfolios from developed markets, including size portfolios. The inability of the HKK model to explain the globally-formed size portfolios stems from the emerging markets only, for which the model is easily rejected.

## 3. Country-Specific or Global Factors?

In an efficient and globally integrated equity market, there should be only one set of risk factors that describe the expected returns of stocks from all countries. However, the question of whether markets are locally segmented or globally integrated has been one of the most enduring issues in international asset pricing (Karolyi and Stulz, 2003). The liberalization of financial markets around the world has increased market accessibility for foreign investors but implicit barriers, such as political risks, differences in information quality, legal protection for private investors, and market regulations, can still segment markets (Bekaert, Harvey, Lundblad, and Siegel, 2010). Theoretical models, such as the one in Errunza and Losq (1985), allow for a form of hybrid structure or partial segmentation in which both local and foreign factors can impact returns. Empirically, these have shown promise (e.g., Bekaert and Harvey, 1995; Bekaert, Harvey, and Lumsdaine, 2002; Carrieri, Errunza, and Hogan, 2007).

Given our specific focus on factor models with FMPs built on firm characteristics, we pay particular attention to Griffin (2002), who shows that the success of the global version of Fama and French's (1993) three-factor model in explaining US, Canadian, UK, and Japanese stock returns arises exclusively from the domestic (local) component of the factors. This finding has important implications because the choice of a local rather than a global model can substantially affect expected returns, which, in turn, impacts cost-of-capital computations for valuations of international companies, and the risk control and performance evaluations made by asset managers with global mandates.

We compare the relative performance of global, local, and international (including local and foreign components) versions of different multifactor models that combine various FMPs in each country using industry and characteristic-sorted (size, B/M, Mom, C/P, D/P, and E/P) quintile test portfolios. For a given model, there are a total of 343 potential experiments that we can perform (7 sets of test portfolios × 49 countries). However, in order for a given country to qualify for an experiment involving characteristic-sorted test portfolios, it must have at least 20 firms with non-missing data on that characteristic for a minimum of 36 months. Furthermore, the industry experiment for a given country requires that there must be at least five industries in that country and a minimum of four firms within each of those industries (specific start dates for these experiments are available upon request).

For each country and each set of test portfolios, we estimate the global, local, and international versions of the CAPM, the Fama-French three-factor model, and the HKK three-factor model. We report the results in Table 5.[16] The local, global and international versions of the CAPM are, respectively:

$$R_{it} - r_{ft} \;=\; \alpha_i + \beta_i^L \{R_{mt}^L - r_{ft}\} + \varepsilon_{it}, \tag{5a}$$

$$R_{it} - r_{ft} \;=\; \alpha_i + \beta_i^W \{R_{mt}^W - r_{ft}\} + \varepsilon_{it}, \text{ and} \tag{5b}$$

$$R_{it} - r_{ft} \;=\; \alpha_i + \beta_i^L \{R_{mt}^L - r_{ft}\} + \beta_i^F \{R_{mt}^F - r_{ft}\} + \varepsilon_{it}, \tag{5c}$$

where the "*L*" superscript denotes a local, country-specific market portfolio, the "*W*" superscript denotes the global market portfolio, and the "*F*" superscript denotes a foreign market portfolio, which is constructed from global stocks *excluding* those from the country of interest in the tests.[17] The three versions of the Fama-French model are, respectively:

$$R_{it} - r_{ft} \;=\; \alpha_i + \beta_i^L \{R_{mt}^L - r_{ft}\} + \mathrm{s}_i^L F_{Size,t}^L + h_i^L F_{B/M,t}^L + \varepsilon_{it}, \tag{6a}$$

$$R_{it} - r_{ft} \;=\; \alpha_i + \beta_i^W \{R_{mt}^W - r_{ft}\} + \mathrm{s}_i^W F_{Size,t}^W + h_i^W F_{B/M,t}^W + \varepsilon_{it}, \text{ and} \tag{6b}$$

$$R_{it} - r_{ft} \;=\; \alpha_i + \beta_i^L \{R_{mt}^L - r_{ft}\} + \beta_i^F \{R_{mt}^F - r_{ft}\} + \mathrm{s}_i^L F_{Size,t}^L + \mathrm{s}_i^F F_{Size,t}^F + h_i^L F_{B/M,t}^L + h_i^F F_{B/M,t}^F + \varepsilon_{it}, \tag{6c}$$

and those for the HKK three-factor model are, respectively:

$$R_{it} - r_{ft} \;=\; \alpha_i + \beta_i^L \{R_{mt}^L - r_{ft}\} + c_i^L F_{C/P,t}^L + m_i^L F_{Mom,t}^L + \varepsilon_{it}, \tag{7a}$$

$$R_{it} - r_{ft} \;=\; \alpha_i + \beta_i^W \{R_{mt}^W - r_{ft}\} + c_i^W F_{C/P,t}^W + m_i^W F_{Mom,t}^W + \varepsilon_{it}, \text{ and} \tag{7b}$$

$$R_{it} - r_{ft} \;=\; \alpha_i + \beta_i^L \{R_{mt}^L - r_{ft}\} + \beta_i^F \{R_{mt}^F - r_{ft}\} + c_i^L F_{C/P,t}^L + c_i^F F_{C/P,t}^F + m_i^L F_{Mom,t}^L + m_i^F F_{Mom,t}^F + \varepsilon_{it}. \tag{7c}$$

Figure 3 shows the average returns of the local market portfolios and the local characteristic-based FMPs for each country. A positive market premium is evident for each country (top figure) and, for the majority of the countries, the local FMPs based on various characteristics also show positive premiums. We see substantial variation in FMP returns across countries for some characteristics, while they are not as evident for others. For example, the average return for the local C/P FMP ranges from around 3% per month for Brazil to less than -1% for Israel. In contrast, the size FMP reaches its highest return for Poland at just about 1% and its lowest return for Mexico at around -0.5%.

For each country, each set of test portfolios, and each version of a model, we compute the average absolute intercepts, the average adjusted $R^2$, and the GRS *F*-statistic for the hypothesis that all regression intercepts are jointly equal to zero. Table 5 reports the number of countries for which we perform the tests (denoted “Exp” for experiments), the number of experiments for which the null is rejected at the 5% significance level for each version of a model (denoted “Rej”), the average absolute intercepts across countries, and the average adjusted $R^2$ across countries. The results are reported separately for each type of test portfolio, across all types of test portfolios, for all countries, for developed countries, and for emerging countries. We are particularly interested in the comparison between developed and emerging markets, as our prior is that the global versions of the various multifactor models are likely to underperform the local or international versions in emerging markets. Those countries only liberalized their markets slowly through the 1990s and many indirect barriers to investments by global investors most likely still exist.

Panel A reports the results for the global, local, and international versions of the CAPM. For the 258 experiments across all countries and all types of test portfolios, 71, or 28%, reject the global version of the CAPM. This rejection rate is lower than for the local version of the CAPM (82 rejections, 32%), or for the international version with both local and foreign market portfolios (84 rejections, 33%). However, this is partly attributable to the fact that the GRS *F*-tests involving the global CAPM lack power. The global CAPM produces a much lower average $R^2$ (23%) than the local and international CAPM (both at 72%), and a much higher average pricing error (average absolute intercept of 0.57% vs. 0.35% for the other two models). In terms of specific test portfolios, we see that the differences in performance across the three versions of the CAPM for momentum and value-based (B/M, C/P, D/P, and E/P) test portfolios are similar to the overall differences. On the other hand, for industry and size test portfolios, the global CAPM exhibits not only higher average pricing error and lower $R^2$ but also a higher rejection rate. For example, with respect to industry test portfolios, the global CAPM is rejected in five out of 24 countries (21% rate) with an average $R^2$ of 19% and an average absolute intercept of 0.40%, while the local CAPM is rejected in two countries (8%)

with an average $R^2$ of 56% and an average absolute intercept of 0.25%, and the international CAPM is rejected in only one country (4%) with an average $R^2$ of 56% and an average absolute intercept of 0.26%.

Our prior is that the relative poor performance of the global CAPM arises primarily from the experiments in emerging markets, which we find to be the case. Of the 114 experiments performed in emerging markets, the global CAPM is rejected 15 times (13% rate) compared to 22 rejections (19%) for the local CAPM and for the international CAPM. However, the average $R^2$ for the global CAPM is considerably lower (14% compared to 73% for the local and international CAPM) and the average absolute intercept is considerably higher (0.72% compared to 0.45% for the local CAPM and 0.46% for the international CAPM). For developed markets, the performance difference is relatively limited. For example, the difference in the average $R^2$ between the global CAPM (30%) and the international CAPM (72%) is about two-thirds of the difference for emerging markets, and the difference in the average absolute intercepts between the global CAPM (0.45%) and the international CAPM (0.27%) is also two-thirds of the difference for emerging markets.

Our analysis includes a large number of multifactor models, but we only report the results for the HKK model (Panel B) and the Fama-French model (Panel C). Relative to each of the three versions of the CAPM, the corresponding HKK model significantly reduces the number of model rejections and the average model pricing error, while it also moderately increases the model explanatory power. For example, of the 258 experiments across countries and test portfolios, the international version of the HKK model is rejected in only 21 instances (8% rate), which is one-quarter of the rejection rate for the international CAPM. The average absolute intercept declines from 0.35% to 0.26% for the international CAPM, while the corresponding average $R^2$ increases from 72% to 77%. This improvement of the HKK model over the corresponding CAPM model is mainly driven by momentum and value-based (B/M, C/P, D/P, and E/P) test portfolios, whereas there are only marginal differences between the two for industry and size test portfolios.

When we compare the different versions of the HKK model, we find that the international model performs best, as it achieves the lowest rejection rate and pricing error, and has the highest explanatory power. In comparison with the global model, the international model has only one fewer rejection (21 versus

22) but it offers a much lower absolute intercept (0.26% versus 0.44%) and a much higher average $R^2$ (77% versus 27%). The local model offers the same average absolute intercept (0.26%) and a marginally lower average $R^2$ (76% versus 77%) than the international model but it produces ten more model rejections (31 versus 21). When we further distinguish between developed and emerging market experiments, we find that the advantage of the international model over the global model stems primarily from emerging markets. The incremental improvement of the international model over the local model can be mostly attributed to developed markets.

Panel C shows that the global Fama-French model produces a lower rejection rate but a higher average pricing error and lower $R^2$ than the local or international Fama-French models. As with the HKK model, the Fama-French model, in each of its three versions, significantly improves on the performance of the corresponding CAPM model. However, it is not as successful as the HKK model in doing so. Although the Fama-French model offers comparable pricing errors and model explanatory power, it is always associated with a much higher model rejection rate. For example, the global version of the Fama-French model is rejected in 33 out of 258 experiments (13%), which is 11 more rejections than the global HKK model. The model pricing errors are similar (average absolute intercepts of 0.46% and 0.44%, respectively) as are the average $R^2$ (28% and 27%, respectively). The difference in rejection rates increases for the local models and rises even more for the international models. The international Fama-French model is rejected in 60 experiments (23% rate), which is almost three times the number of rejections associated with the international HKK model. Not surprisingly, the Fama-French model, in all three versions, produces lower pricing errors and shows higher explanatory power for test portfolios based on size and B/M (although rejection rates are not necessarily lower). However, the HKK model shows much better performance on all metrics for industry, momentum, and other value-based (C/P, D/P, E/P) test portfolios. The better overall performance of the HKK model relative to the Fama-French model arises from both developed and emerging markets.

In summary, our experiments on the relative importance of country-specific factor models versus global factor models indicate that the local and international versions of the models (which include both local and foreign factors) typically outperform the purely global versions in explaining the variation in local stock returns in most countries. Local factors are important for reducing model rejections and model pricing errors, and for increasing model explanatory power, but there are also measurable benefits to extending the multifactor models, such as the HKK model, to an international context. In particular, the international version of the HKK model, which adds local and foreign components of momentum and C/P FMPs to the market portfolio, achieves the lowest rejection rate and pricing error, and ranks near the top in terms of model explanatory power of all the different versions of the multifactor models that we examine.

## 4. Characteristics, Covariances, and Global Stock Returns

In a series of influential studies, Fama and French (1993, 1996, and 1998) argue that the return premiums associated with their size and B/M factors represent compensation for systematic risks in the economy, as described in the multifactor version of Merton's (1973) ICAPM or Ross's (1976) APT. Daniel and Titman (1997) counter that Fama and French's tests of their three-factor model lack power against an alternative – the "characteristic model." In the characteristic model, expected returns are linked directly to firm-level characteristics due to investors' behavioral biases and they are specifically not determined by the covariance structure of returns.

Daniel and Titman (1997) reject the Fama-French "covariance risk" factor model in favor of the characteristics model using US stock returns between 1973 and 1993. They use a novel approach to identify independent variation in risk loadings that are uncorrelated with characteristics. Specifically, they form portfolios by sequentially sorting stocks first on characteristics, such as size and B/M, and then on risk loadings associated with the FMPs based on the same characteristics, such as those for size and B/M. If characteristics drive returns, there should be no relation between average returns and the risk loadings after controlling for the characteristics themselves. However, any relation between average returns and risk loadings on an FMP after controlling for the characteristic on which the FMP is based would indicate that the characteristic of interest proxies for sensitivity to a risk factor. Daniel and Titman (1997) confirm the relation between B/M and average returns but find no relation between B/M risk loadings and returns after controlling for the B/M characteristic. Davis, Fama, and French (2000), in turn, extend the investigation back to 1925 to show that Daniel and Titman's findings are specific to the 1973 to 1993 period. However, Daniel, Titman, and Wei (2001) establish further support for the characteristics model in Japan for the 1975 to 1997 period.

In our global experiment, we investigate the FMPs based on size, B/M, C/P, and momentum, and their corresponding factor risk loadings. Our primary goal is to understand whether the success of the C/P and momentum FMPs in the HKK model in terms of explaining the returns of global test portfolios (Section 2) stems from the C/P and momentum characteristics, or from their potential roles as global covariance risk factors.[18] One major advantage of our analysis is that our characteristic-versus-covariance tests have significant power because we use a large, global sample of stocks to form diversified portfolios with sufficient independent variations in factor loadings and characteristics.

The tests proceed in two steps. First, we sort global stocks at the end of June of each year *t* into three size groups (small, S; medium, M; and big, B) based on their market capitalization at the end of June. We also sort them into three groups by C/P or B/M (low, L; medium, M; and high, H) based on the value of C/P or B/M from year *t-1*. Nine portfolios (S/L, S/M, S/H, M/L, M/M, M/H, B/L, B/M, and B/H) are formed as the intersections of the three size and the three C/P or B/M groups. Each of the nine portfolios is then subdivided into three portfolios (L, M, and H) using pre-formation C/P or B/M factor loadings estimated with monthly returns over the previous 36 months (12-month minimum) using the global HKK model or the Fama-French model.[19] Value-weighted monthly returns on these 27 triple-sorted portfolios are calculated from July of year *t* to June of year *t+1*.

In the second step, we construct a zero-cost "characteristic-balanced" portfolio for each of the nine size and C/P (B/M) categories by taking a long position on the high-C/P (B/M) loading portfolio and taking an equivalent short position on the low-C/P (B/M) loading portfolio, which has similar size and C/P (B/M) characteristics. The average returns on these characteristic-balanced portfolios (denoted "H – L"), therefore, reflect the isolated effect of varying C/P (B/M) factor loadings. To maximize power in an overall test, we combine the nine characteristic-balanced portfolios to form one equally-weighted portfolio. We then estimate regressions of the returns of the nine characteristic-balanced portfolios and the combined portfolio on the HKK factors (Fama-French factors). We also perform characteristic-versus-covariance tests on the momentum characteristic and on the momentum factor loading using a similar triple-sorting procedure. However, instead of sorting at the end of June of each year, we sort monthly to be consistent with conventions in the momentum literature.[20]

Under the null hypothesis of the covariance risk factor models, average returns are determined by factor risk loadings, which should continue to predict returns even after controlling for variation in characteristics. This hypothesis implies that characteristic-balanced portfolios should have positive average returns due to their positive factor loadings and zero intercepts when their returns are regressed on the relevant factors. In contrast, the alternative characteristic model maintains that average returns are determined by characteristics irrespective of factor loadings and that, therefore, factor loadings should have no incremental predictive power for returns after controlling for variation in characteristics. Those characteristic-balanced portfolios should have average returns that are equal to zero. The regression of their returns on the relevant factors should produce negative intercepts to compensate for the positive expected returns implied by the product of positive factor loadings and the factors' positive premiums.

### 4.1 C/P characteristic versus C/P factor loading

Table 6 presents the results of first sorting on size and C/P characteristics and then on pre-formation C/P factor loadings. In Panel A, we report the summary statistics of the 27 triple-sorted portfolios as well as the results of the global HKK model regressions. In Panel B, we report the average returns and the HKK model regression results for the nine characteristic-balanced portfolios (denoted "Hc – Lc") formed within each size-C/P group and for the combined characteristic-balanced portfolio.

Panel A confirms that the three-dimensional sort effectively achieves considerable variation in C/P factor loadings, which is unrelated to size and C/P characteristics. Within each of the nine size-C/P groups, the third-dimensional sort on pre-formation C/P factor loadings produces a large spread in post-formation loadings ("$c_i^W$" coefficients) while leaving the size and C/P characteristics approximately constant. For example, within the big-size, medium-C/P group, the three C/P loading portfolios (B/M/Lc, B/M/Mc, and B/M/Hc) report similar value-weighted average size of $3,534 million, $3,657 million, and $3,398 million, respectively, and all report a value-weighted C/P of 0.12. However, their post-formation loadings on the C/P FMP increase monotonically from 0.01 to 0.59. The average returns reported in Panel A offer some initial evidence in favor of the covariance risk model. Within each of the nine size-C/P groups, average returns increase monotonically with C/P factor loadings. The difference in average returns between the low-loading portfolio and the high-loading portfolio ranges from 0.28% (small size, medium C/P) to 0.76% (big size, low C/P) per month.

Like Daniel and Titman (1997), Davis, Fama, and French (2000), and Daniel, Titman, and Wei (2001), we formally test the covariance risk model against the characteristic model by examining the average returns and HKK model intercepts of the characteristic-balanced portfolios. Panel B of Table 6 shows that all nine characteristic-balanced portfolios have positive average returns, and four (two) of them are significant at the 10% (5%) level. Most importantly, the combined characteristics-balanced portfolio has an average return of 0.42% per month (*t*-statistic of 2.12), which is both economically large and reliably different from zero. Since the characteristic-balanced portfolios are neutral with respect to the size and C/P characteristics, this finding suggests that independent variation in C/P factor loadings is associated with significant spreads in average returns. Therefore, the test based on the average returns rejects the characteristic model in favor of the covariance risk model.

Turning to the regression intercepts of the characteristic-balanced portfolios, the covariance risk model predicts that the intercepts should be zero, while the characteristic model predicts negative intercepts. Only three of the nine characteristic-balanced portfolios produce negative intercepts, and none of them are statistically significant at the 10% level (the other six intercepts are all positive but insignificant). Furthermore, the combined portfolio has an intercept of 0.04% per month (*t*-statistic of 0.25), which is statistically and economically insignificant. The evidence from the intercepts, therefore, is consistent with the covariance risk model. In short, our characteristic-versus-covariance test cannot reject the hypothesis that C/P is related to a global covariance risk factor in favor of the alternative characteristic interpretation. The covariance risk model under-predicts the average characteristic-balanced return by only 0.04% per month (*t*-statistic of 0.25), while the characteristic model under-predicts the return by 0.42% per month (*t*-statistic of 2.12).

### 4.2 Momentum, B/M, and size characteristics versus corresponding factor loadings

Table **7** presents the results of characteristics-versus-covariances tests for momentum, size, and B/M characteristics, and their corresponding factor loadings. The experiments are conducted using the same triple-sorting procedure as in Table 6. To conserve space, we only report the average returns and regression results for the characteristic-balanced portfolios for a given characteristic of interest (the equivalent of Panel B of Table 6 in each case).

In the first experiment, we investigate whether the explanatory power of the global momentum FMP uncovered in Section 2 stems from the momentum characteristic or from its role as a global covariance risk factor, like the C/P FMP. Panel A reports the results of the characteristic-balanced portfolios formed by sorting stocks first based on size and momentum and then, within each size-momentum category, by pre-formation loadings on the momentum FMP in the global HKK model. The second column of Panel A shows that eight of the nine characteristic-balanced portfolios have positive average returns but only three of them are statistically significant at the 10% level. More importantly, the combined portfolio also has an insignificant average return (0.23% per month, *t*-statistic of 1.26). As a result, we cannot reject the characteristic model. On the other hand, the positive sign of the average combined return matches the direction predicted by the covariance risk model. It is, therefore, useful to examine whether the data could also be consistent with the risk model. The HKK model regression results show that only one of the nine characteristic-balanced portfolios produces a negative intercept (-0.09%) and that it is statistically insignificant (*t*-statistic of -0.25). The combined portfolio has an intercept of 0.24% per month, which is statistically not different from the zero value predicted by the covariance risk model (*t*-statistic of 1.32). Therefore, the test based on regression intercepts suggests that we cannot reject the risk model.

In summary, our test does not have enough power to distinguish the covariance risk model from the characteristic model for momentum. Furthermore, we find only mixed support for momentum as a global covariance risk factor.

In Panels B and C of Table 7, we repeat our two experiments on C/P and momentum, except that we first sort stocks based on C/P and momentum characteristics. Panel B examines the incremental effect of C/P factor loadings on average returns after controlling for C/P and momentum characteristics, whereas Panel C studies the effect of momentum factor loadings. The results are quantitatively similar to those reported in Table 6 and in Panel A of Table 7. The evidence from the test on average returns and on regression intercepts favors the covariance risk model over the characteristic model for C/P. As above, we fail to reject either the risk model or the characteristic model for momentum and are, therefore, unable to distinguish between the two explanations. [21]

The final two panels report the results on characteristic-versus-covariance tests with respect to size and B/M. We add these tests to facilitate comparisons with Daniel and Titman (1997), Davis, Fama, and French (2000), and Daniel, Titman, and Wei (2001), and to extend their results to our global sample. In Panel D, we sort the global stocks first by size and B/M characteristics, and then by pre-formation loadings on the B/M FMP in the global Fama-French three-factor model. We see that only one of the nine characteristic-balanced portfolios has a positive average return (0.08% per month) and that it is statistically insignificant (*t*-statistic of 0.22). Furthermore, the combined characteristic-balanced portfolio has an average return of -0.14% (*t*-statistic of -0.66), which is insignificant. Therefore, we cannot reject the characteristic model, which predicts a zero-return spread related to B/M factor loadings after controlling for the B/M characteristic. On the other hand, the Fama-French model regression intercepts appear to reject the covariance risk model. All nine characteristic-balanced portfolios produce negative intercepts. The combined intercept of -0.37% per month is marginally significant at the 5% level (*t*-statistic of -1.95).

We conclude that the evidence favors the characteristic model over the covariance risk interpretation of B/M, a conclusion that is consistent with Daniel and Titman (1997) and Daniel, Titman, and Wei (2001). Even more importantly, through a direct comparison with our findings in Table 6, we show that B/M and C/P

– both of which are value-related characteristics – play different roles in global stock returns. We are unable to reject C/P as being related to a covariance risk factor, while we are able to do so for B/M.

In the last panel (Panel E) of Table 7, we replace the B/M factor loadings in the third-dimensional sort with size factor loadings to examine the latter's contribution to average returns after controlling for size and B/M characteristics. The results are largely similar to those for B/M loadings reported in Panel D. In particular, the combined characteristic-balanced portfolio based on size factor loadings has an average return that is close to zero (0.11% per month, *t*-statistic of 0.59), and the Fama-French model intercept is negative and marginally significant at the 5% level (-0.30% per month, t-statistic of -1.91). Consequently, we are able to reject the covariance risk model in favor of the characteristic model for size, as is the case for B/M.

## 5. Conclusions and Future Work

Our study provides the most comprehensive examination to date of the firm-level characteristics that could explain cross-sectional and time-series variation in global stock returns. We evaluate size, dividend yield, earnings yield, cash-flow-to-price, book-to-market equity, leverage, and momentum using monthly returns for over 27,000 individual stocks from 49 countries from 1981 to 2003. Our work is motivated by one open question and by two major debates that still linger in the asset pricing literature.

The major unanswered question focuses on which characteristics and associated factor portfolios offer the greatest explanatory power for the variation in global stock returns. We perform a number of tests and uncover several important findings. First, using cross-sectional Fama-MacBeth (1973) regressions of individual stock returns and time-series regressions of multifactor models, we confirm the strong and reliable explanatory power of a value-based factor in global stock returns. However, this factor is based specifically on C/P, and not based on B/M, E/P, or D/P. The C/P characteristic is statistically reliable and economically important in the Fama-MacBeth cross-sectional regressions. Furthermore, in time-series tests, a global C/P factor-mimicking portfolio (constructed as a long-short portfolio that buys high-C/P stocks and sells short low-C/P stocks) captures significant return differences in country, industry, and a wide variety of characteristic-sorted global test portfolios. This is not the case for B/M, E/P, or D/P characteristics and their respective factor-mimicking portfolios. We also show that medium-term stock-price momentum not only exists in international equity markets, but that a factor portfolio constructed on the basis of this characteristic also complements the explanatory power of the value-based C/P factor portfolio. A three-factor model that includes the C/P and momentum factor-mimicking portfolios, in addition to the global market factor, captures strong common variation in global stock returns. It also produces the lowest pricing error and the lowest rejection rate of the various global multifactor models we consider.

The first debate to which we contribute concerns the relative importance of global and local, country-specific factors in explaining local stock returns. Inspired by the predictions of the international asset pricing models of Solnik (1974), Grauer, Litzenberger, and Stehle (1976), Sercu (1980), Stulz (1981), and Errunza and Losq (1985), and by the rapid pace of financial market liberalization around the world, researchers have provided evidence that global market and macroeconomic factors matter for the pricing of local stocks. Recently, however, the focus of this literature has shifted to the role of firm-level characteristics in pricing securities in global markets, and researchers have shown that local, country-specific components of these characteristic-based factors matter more than their global counterparts. We compare the relative ability of global, local, and international (including both local and foreign components) versions of various multifactor models to explain the returns of industry and characteristic-sorted test portfolios in each country. We find that the local and international versions of these multifactor models have lower pricing errors than their purely global counterparts, especially for emerging markets. We also show that the international version of the multifactor model that includes the market, C/P, and momentum factor-mimicking portfolios provides the lowest model pricing error and the lowest rejection rate of the competing models.

The second debate concerns the sources of the explanatory power of these characteristics and their corresponding factor-mimicking portfolios. One group of explanations argues that the return predictabilities represent anomalies arising from systematic market under and over-reactions caused by investors' behavioral biases. The other group attributes the predictive power to pervasive extra-market covariance risk factors. In our global experiment, we conduct tests used by Daniel and Titman (1997), Davis, Fama, and French (2000), and Daniel, Titman, and Wei (2001) on several different characteristics to evaluate the covariance risk explanation and the alternative characteristic-based mispricing explanation. We find reliable empirical evidence that C/P is related to a global covariance risk factor. Risk loadings on the C/P factor-mimicking portfolio are associated with an economically large, statistically significant return premium of 42 to 48 basis points per month after controlling for the C/P characteristic. Just as importantly, this is not the case for risk loadings on the B/M factor-mimicking portfolio, which supports our finding that these value-based characteristics are not readily interchangeable in terms of their importance for global stock returns. Finally, the evidence on whether momentum is related to a covariance risk factor appears to be mixed.

This paper supports the notion that there are important benefits to building multifactor models of global stock returns using certain firm-specific characteristics, such as the cash flow-to-price ratio and stock-price momentum. Furthermore, our findings indicate that both local and foreign components of these characteristic-based factors matter, and that these characteristics appear to matter as global risk factors and not just as characteristics. Our findings are important not only for researchers of international asset pricing but also for practitioners interested in cost-of-capital calculations, risk control, and performance evaluations of global portfolios.

There are many possible avenues for future work. First, one might explore whether or how our characteristic-based factors are linked to global and country-specific macroeconomic factors, in the spirit of Liew and Vassalou (2000), Vassalou (2003), Brennan, Wang, and Xia (2004), and Petkova (2006). Second, one could study the effect of exchange rate risks on the relative performance of our characteristic-based factors. All of our returns are US-dollar denominated at prevailing exchange rates. In this respect, a key contribution of Solnik's (1974) seminal international asset pricing model is that currency risk can be priced. There is also growing evidence that the magnitude of currency-risk exposure can be quite large (Dumas and Solnik, 1995; DeSantis and Gerard, 1997, 1998; Griffin and Stulz, 2001). Third, there are a number of firm-level characteristics that we do not consider, such as liquidity, net stock issues, investment, and asset growth (Chen, Novy-Marx, and Zhang, 2010). A study of liquidity is likely to be particularly promising, as several new studies have documented strong cross-sectional and time-series relations between returns and various liquidity proxies, especially in emerging markets (Rouwenhorst, 1999; Lesmond, 2005; Bekaert, Harvey and Lundblad, 2008; Lee, 2011).

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**Table 1**
**Summary statistics by country, July 1981 - December 2003**

| Country | Start date | Total number of stocks | Total number of industries | Monthly returns (%) | Global beta | Country beta | Size (US$ mills.) | Book-to-market (B/M) | Mom-entum (*Mom*) | Cash flow -to-price (C/P) | Dividend -to-price (D/P) | Earnings -to-price (E/P) | Leverage (L/B) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Developed Markets** | | | | | | | | | | | | | |
| Australia | 1981/07 | 704 | 34 | 0.53 | 0.64 | 0.79 | 216.47 | 0.73 | 4.87 | 0.14 | 0.05 | 0.08 | 0.30 |
| Austria | 1981/07 | 125 | 24 | 0.46 | 0.31 | 0.71 | 80.45 | 0.65 | 2.90 | 0.16 | 0.02 | 0.04 | 0.36 |
| Belgium | 1981/07 | 145 | 31 | 0.83 | 0.55 | 0.74 | 66.98 | 0.99 | 5.36 | 0.23 | 0.03 | 0.09 | 0.30 |
| Canada | 1981/07 | 1,185 | 34 | 0.15 | 0.74 | 0.82 | 124.85 | 0.69 | 2.97 | 0.14 | 0.01 | 0.06 | 0.42 |
| Denmark | 1981/07 | 256 | 27 | 0.70 | 0.43 | 0.70 | 61.10 | 1.02 | 4.43 | 0.17 | 0.02 | 0.08 | 0.31 |
| Finland | 1987/02 | 171 | 28 | 0.45 | 0.67 | 0.72 | 140.08 | 0.90 | 3.15 | 0.16 | 0.03 | 0.06 | 0.84 |
| France | 1981/07 | 1160 | 34 | 0.71 | 0.70 | 0.76 | 160.77 | 0.78 | 4.53 | 0.18 | 0.02 | 0.07 | 0.44 |
| Germany | 1981/07 | 882 | 31 | 0.26 | 0.52 | 0.69 | 176.85 | 0.53 | 2.51 | 0.15 | 0.02 | 0.04 | 0.18 |
| Hong Kong | 1981/07 | 197 | 24 | 0.60 | 0.95 | 0.87 | 892.04 | 0.59 | 6.93 | 0.10 | 0.04 | 0.09 | 0.09 |
| Ireland | 1981/07 | 70 | 25 | 0.86 | 0.72 | 0.73 | 131.24 | 0.75 | 7.07 | 0.17 | 0.04 | 0.10 | 0.34 |
| Italy | 1981/07 | 378 | 32 | 0.19 | 0.69 | 0.78 | 209.57 | 0.71 | 2.59 | 0.17 | 0.02 | 0.05 | 0.23 |
| Japan | 1981/07 | 2,844 | 33 | 0.07 | 1.04 | 0.87 | 352.96 | 0.59 | 2.41 | 0.08 | 0.01 | 0.03 | 0.30 |
| Luxembourg | 1991/04 | 28 | 14 | 0.17 | 0.44 | 0.44 | 131.38 | 0.79 | 1.93 | 0.13 | 0.03 | 0.05 | 0.37 |
| Netherlands | 1981/07 | 263 | 31 | 0.83 | 0.62 | 0.77 | 110.98 | 0.99 | 5.72 | 0.24 | 0.04 | 0.10 | 0.36 |
| New Zealand | 1986/02 | 97 | 30 | 1.13 | 0.56 | 0.84 | 182.70 | 0.64 | 8.90 | 0.12 | 0.05 | 0.08 | 0.39 |
| Norway | 1981/07 | 266 | 30 | 0.41 | 0.56 | 0.69 | 65.78 | 0.80 | 3.89 | 0.17 | 0.02 | 0.07 | 1.45 |
| Singapore | 1981/07 | 191 | 29 | 0.07 | 1.01 | 0.91 | 251.10 | 0.68 | 5.21 | 0.07 | 0.02 | 0.05 | 0.06 |
| Spain | 1986/02 | 188 | 32 | 0.56 | 0.92 | 0.83 | 364.49 | 0.79 | 4.06 | 0.15 | 0.03 | 0.07 | 0.23 |
| Sweden | 1982/02 | 422 | 33 | 0.59 | 0.67 | 0.73 | 109.34 | 0.62 | 4.48 | 0.14 | 0.02 | 0.06 | 0.61 |
| Switzerland | 1981/07 | 257 | 29 | 0.33 | 0.55 | 0.81 | 103.89 | 0.79 | 2.65 | 0.14 | 0.03 | 0.06 | 0.49 |
| UK | 1981/07 | 2,460 | 34 | 0.43 | 0.70 | 0.78 | 119.81 | 0.63 | 4.80 | 0.12 | 0.03 | 0.08 | 0.17 |
| US | 1981/07 | 9,840 | 34 | 0.48 | 0.79 | 0.90 | 130.27 | 0.63 | 4.31 | 0.12 | 0.01 | 0.06 | 0.29 |
| Total Developed | | 22,129 | | | | | | | | | | | |
| **Panel B: Emerging Markets** | | | | | | | | | | | | | |
| Argentina | 1988/02 | 77 | 25 | 2.05 | 0.24 | 0.75 | 191.42 | 0.93 | 18.72 | 0.29 | 0.01 | 0.04 | 0.23 |
| Brazil | 1990/02 | 50 | 20 | -0.69 | 0.65 | 0.69 | 66.75 | 1.76 | -0.26 | 0.20 | 0.04 | 0.05 | 0.13 |
| Chile | 1989/08 | 103 | 26 | 0.67 | 0.26 | 0.64 | 162.69 | 0.66 | 7.43 | 0.14 | 0.05 | 0.09 | 0.21 |
| China | 1991/02 | 820 | 31 | 0.22 | -0.13 | 0.99 | 198.36 | 0.26 | 12.93 | 0.03 | 0.22 | 0.03 | 0.01 |
| Colombia | 1992/02 | 25 | 13 | 0.14 | 0.21 | 0.93 | 286.51 | 1.05 | 2.74 | 0.15 | 0.05 | 0.09 | 0.17 |
| Czech Republic | 1993/08 | 67 | 22 | 0.17 | 0.26 | 0.63 | 63.10 | 1.54 | 1.31 | 0.29 | 0.01 | 0.09 | 0.10 |
| Greece | 1988/02 | 324 | 32 | 0.27 | 0.36 | 0.87 | 57.16 | 0.54 | 6.39 | 0.10 | 0.03 | 0.06 | 0.04 |
| Hungary | 1991/02 | 40 | 18 | -0.41 | 0.88 | 0.66 | 44.73 | 0.81 | -1.68 | 0.14 | 0.02 | 0.08 | 0.03 |
| India | 1990/02 | 306 | 27 | 0.29 | 0.10 | 0.84 | 115.86 | 0.48 | 4.43 | 0.11 | 0.02 | 0.07 | 0.43 |
| Indonesia | 1990/05 | 212 | 29 | -0.60 | 0.59 | 0.58 | 64.66 | 0.48 | 2.28 | 0.13 | 0.04 | 0.09 | 0.07 |
| Israel | 1986/02 | 78 | 23 | 0.60 | 0.85 | 0.90 | 204.63 | 0.75 | 4.24 | 0.11 | 0.01 | 0.05 | 0.36 |
| Korea, South | 1981/07 | 766 | 30 | -0.15 | 0.52 | 0.78 | 54.22 | 1.12 | 2.63 | 0.22 | 0.02 | 0.06 | 0.68 |
| Malaysia | 1981/07 | 521 | 33 | -0.18 | 0.87 | 0.87 | 172.03 | 0.47 | 5.40 | 0.08 | 0.02 | 0.05 | 0.02 |
| Mexico | 1988/02 | 122 | 25 | 0.77 | 0.83 | 0.76 | 450.19 | 0.80 | 7.33 | 0.16 | 0.01 | 0.08 | 0.26 |
| Pakistan | 1991/02 | 71 | 19 | 0.29 | 0.18 | 0.45 | 50.50 | 0.49 | 5.80 | 0.15 | 0.05 | 0.11 | 0.11 |
| Peru | 1991/02 | 51 | 16 | 0.84 | 0.55 | 0.66 | 94.22 | 0.52 | 9.75 | 0.14 | 0.02 | 0.08 | 0.09 |
| Philippines | 1987/10 | 65 | 19 | -0.09 | 0.35 | 0.33 | 165.71 | 0.65 | 3.89 | 0.15 | 0.01 | 0.10 | 0.40 |
| Poland | 1992/03 | 71 | 22 | -0.68 | 0.84 | 0.75 | 126.66 | 0.68 | -1.57 | 0.12 | 0.01 | 0.06 | 0.09 |
| Portugal | 1988/02 | 121 | 26 | -0.09 | 0.47 | 0.67 | 60.45 | 0.84 | 0.33 | 0.13 | 0.02 | 0.06 | 0.31 |
| Russian Federation | 1995/10 | 37 | 13 | 0.52 | 1.59 | 0.76 | 443.35 | 2.04 | 13.76 | 0.42 | 0.01 | 0.26 | 0.10 |
| South Africa | 1981/07 | 406 | 30 | 0.42 | 0.67 | 0.81 | 283.61 | 0.58 | 3.91 | 0.15 | 0.04 | 0.10 | 0.10 |
| Sri Lanka | 1987/07 | 18 | 9 | 1.24 | 0.18 | 0.91 | 51.85 | 1.04 | 13.04 | 0.18 | 0.03 | 0.11 | 0.45 |
| Taiwan | 1987/10 | 466 | 27 | -0.08 | 0.98 | 0.95 | 491.18 | 0.32 | 6.12 | 0.06 | 0.01 | 0.05 | 0.08 |
| Thailand | 1987/02 | 412 | 31 | -0.10 | 0.88 | 0.69 | 70.38 | 0.73 | 6.40 | 0.16 | 0.07 | 0.10 | 0.12 |
| Turkey | 1988/02 | 107 | 23 | -0.05 | 0.01 | 0.93 | 176.94 | 0.30 | 15.61 | 0.22 | 0.09 | 0.13 | 0.43 |
| Venezuela | 1990/02 | 16 | 9 | 1.28 | 0.36 | 0.95 | 480.40 | 1.27 | 11.44 | 0.28 | 0.06 | 0.12 | 0.10 |
| Zimbabwe | 1988/09 | 7 | 5 | 5.69 | -0.06 | . | 329.60 | 1.04 | 77.93 | 0.28 | 0.09 | -0.02 | 0.03 |
| Total Emerging | | 5,359 | | | | | | | | | | | |
| Total All | | 27,488 | | | | | | | | | | | |

The table shows summary statistics of our sample stocks for each country over the July 1981 to December 2003 sample period. To be included in the analysis, each stock has to have at least 12 monthly returns, be listed on its country's major exchange(s), and have sufficient information to calculate at least one of the following characteristics: market value of equity (*size*), book-to-market (B/M), cash flow-to-price (C/P), dividend-to-price (D/P), earnings-to-price (E/P), or long-term debt-to-book equity (L/B). We also apply several screening procedures for Datastream data errors in monthly returns, as suggested by Ince and Porter (2003) and others. These are discussed in the text. In order to minimize potential biases arising from low-price and illiquid stocks, we require a minimum price of $1 at previous month-end for a stock to be included in the analysis. The beginning date for each country is as shown. The total numbers of unique stocks and industries are reported for each country. The industry classifications follow the FTSE Level 4 definitions (34 industries). The monthly return (%) for each country is the time-series average of the median monthly US dollar-denominated individual stock returns. *Mom* is the time series average of the median past six months' returns (skipping the most recent month). The time-series average of annual medians for size, B/M, C/P, D/P, E/P, L/B, and betas are also reported with respect to value-weighted global and country portfolios estimated annually for each stock at the end of June each year using its previous 36 months returns (12-month minimum).

**Table 2**

**Fama-MacBeth monthly cross-sectional regressions of individual stock returns on various firm-level characteristics, July 1981 - December 2003**

| | Characteristics | Global β | Country β | ln(Size) | ln(B/M) | Mom | C(+)/P | C/P dummy | D(+)/P | D/P dummy | E(+)/P | E/P dummy | L(+)/B | L/B dummy |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Individual stocks from all countries | | | | | | | | | | | | | | |
| | Univariate | -0.17 | -0.11 | -0.12$^{***}$ | 0.36$^{***}$ | 1.08$^{***}$ | 1.34$^{***}$ | 0.03 | 10.18$^{***}$ | 0.50$^{***}$ | 4.49$^{***}$ | 0.31 | 0.00 | 0.07 |
| | | *(-1.26)* | *(-0.73)* | *( -3.39)* | *(4.25)* | *(3.87)* | *(5.85)* | *(0.15)* | *(4.00)* | *(2.26)* | *(5.00)* | *(1.58)* | *(-0.15)* | *(0.89)* |
| | Multivariate | | | -0.06$^{**}$ | 0.18$^{***}$ | 0.99$^{***}$ | 0.51$^{***}$ | -0.15 | 4.36$^{**}$ | 0.33$^{*}$ | 1.51$^{***}$ | -0.08 | | |
| | | | | *(-1.99)* | *(2.76)* | *(3.85)* | *(2.90)* | *(-1.31)* | *(2.13)* | *(1.78)* | *(2.29)* | *(-0.79)* | | |
| Panel B: Individual stocks from US only | | | | | | | | | | | | | | |
| | Univariate | -0.07 | -0.04 | -0.13$^{***}$ | 0.28$^{***}$ | 0.91$^{***}$ | 1.02$^{***}$ | 0.01 | 1.31 | 0.23 | 2.87$^{***}$ | 0.24 | -0.01 | 0.08 |
| | | *(-0.47)* | *(-0.27)* | *(-2.65)* | *(2.70)* | *(3.15)* | *(3.57)* | *(0.05)* | *(0.51)* | *(1.03)* | *(2.58)* | *(0.99)* | *(-0.68)* | *(0.68)* |
| | Multivariate | | | -0.09$^{**}$ | 0.14$^{*}$ | 0.80$^{***}$ | 0.34$^{**}$ | -0.15 | -1.85 | 0.08 | 0.92 | -0.05 | | |
| | | | | *(-2.07)* | *(1.91)* | *(3.24)* | *(2.03)* | *(-1.01)* | *(-0.85)* | *(0.53)* | *(1.46)* | *(-0.34)* | | |
| Panel C: Subsample robustness tests | | | | | | | | | | | | | | |
| Developed (excl. US) only | Multivariate | | | -0.04 | 0.22$^{***}$ | 1.09$^{***}$ | 0.55$^{***}$ | -0.13 | 5.52$^{**}$ | 0.02 | 1.25 | 0.07 | | |
| | | | | *(-1.16)* | *(3.14)* | *(3.57)* | *(3.37)* | *(-1.20)* | *(2.04)* | *(0.12)* | *(1.58)* | *(0.56)* | | |
| Emerging only | Multivariate | | | -0.12 | 0.13 | -0.07 | 0.91$^{***}$ | 0.17 | 6.27 | 0.16 | -1.16 | 0.09 | | |
| | | | | *(-1.46)* | *(0.73)* | *(-0.10)* | *(2.37)* | *(0.34)* | *(1.56)* | *(0.51)* | *(-0.62)* | *(0.25)* | | |
| 07/1981-06/1992 | Multivariate | | | -0.07 | 0.21$^{***}$ | 1.00$^{***}$ | 0.27 | -0.28$^{**}$ | 2.25 | 0.04 | 1.06 | -0.14 | | |
| | | | | *(-1.60)* | *(2.30)* | *(2.71)* | *(1.43)* | *(-2.10)* | *(0.86)* | *(0.16)* | *(1.18)* | *(-0.82)* | | |
| 07/1992-12/2003 | Multivariate | | | -0.06 | 0.16$^{*}$ | 0.98$^{***}$ | 0.73$^{***}$ | -0.02 | 6.37$^{**}$ | 0.61$^{**}$ | 1.94$^{**}$ | -0.03 | | |
| | | | | *(-1.22)* | *(1.65)* | *(2.72)* | *(2.53)* | *(-0.11)* | *(2.05)* | *(2.12)* | *(2.02)* | *(-0.24)* | | |
| January only | Multivariate | | | -0.46$^{***}$ | 0.34 | -2.45$^{**}$ | 2.26$^{***}$ | 1.41$^{***}$ | 5.44 | 2.28$^{***}$ | 2.16 | 1.82$^{***}$ | | |
| | | | | *(-4.02)* | *(1.05)* | *(-2.00)* | *(2.91)* | *(3.27)* | *(0.76)* | *(2.76)* | *(0.79)* | *(5.32)* | | |
| February – December only | Multivariate | | | -0.03 | 0.17$^{***}$ | 1.29$^{***}$ | 0.35$^{**}$ | -0.29$^{***}$ | 4.26$^{**}$ | 0.16 | 1.45$^{**}$ | -0.25$^{***}$ | | |
| | | | | *(-0.89)* | *(2.55)* | *(5.18)* | *(2.02)* | *(-2.53)* | *(2.00)* | *(0.84)* | *(2.14)* | *(-2.42)* | | |

This table reports the time series average coefficients and their t-statistics (*in italics in parentheses*) from monthly Fama-MacBeth (FM, 1973) cross-sectional regressions of individual stock returns on various firm-level characteristics. Global β and Country β are loadings from market model regressions on constructed global and country-specific value-weighted market indexes, respectively, estimated annually for individual stocks at the end of June of each year using its previous 36 monthly returns (12-month minimum). Variable definitions are from Table 1. If cash flow is positive, C(+)/P is C/P and the C/P dummy is 0. If cash flow is not positive, C(+)/P is 0 and the C/P dummy is 1. If dividend is positive, D(+)/P is D/P and the D/P dummy is 0. If dividend is 0, D(+)/P is 0 and the D/P dummy is 1. If earnings are positive, E(+)/P is E/P and the E/P dummy is 0. If earnings are not positive, E(+)/P is 0 and the E/P dummy is 1. If L/B is positive, L(+)/B is L/B and the L/B dummy is 0. If L/B is 0, L(+)/B is 0 and the L/B dummy is 1. The rows labeled "Univariate" present individual results from FM regressions of returns on each characteristic. The dummy variables (C/P dummy, D/P dummy, E/P dummy, and L/B dummy) are combined with their corresponding level variables (C(+)/P, D(+)/P, E(+)/P, and L(+)/B) in a univariate regression. Therefore, there are nine separate univariate regressions reported in a single row. The rows labeled "Multivariate" report multivariate regressions in which multiple characteristics are simultaneously included as independent variables. $^{***}$, $^{**}$ and $^{*}$ indicate significance at the 1%, 5%, and 10% levels, respectively.

**Table 3**
**Summary statistics of global factor-mimicking portfolio returns, July 1981 - December 2003**

Panel A: Returns distributions of factor-mimicking portfolios

| Attributes | Mean Return (%) | *t*-statistic | Standard Deviation (%) | Average Number of Stocks | Number of Months |
|---|---|---|---|---|---|
| Market | 0.49 | 1.87 | 4.31 | 10,823 | 270 |
| Size | 0.55 | 2.70 | 3.35 | 2,165 | 270 |
| B/M | 0.51 | 2.10 | 4.00 | 1,636 | 270 |
| Mom | 0.63 | 2.29 | 4.52 | 2,165 | 270 |
| C/P | 0.70 | 3.12 | 3.70 | 1,378 | 270 |
| D/P | 0.69 | 2.23 | 5.08 | 1,165 | 270 |
| E/P | 0.75 | 2.40 | 5.14 | 1,383 | 270 |

Panel B: Autocorrelations of factor-mimicking portfolio returns

| | Monthly Autocorrelations | | | |
|---|---|---|---|---|
| Attributes | Lag 1 | Lag 2 | Lag 3 | Lag 12 |
| Market | 0.05 | -0.05 | 0.00 | -0.01 |
| Size | 0.04 | -0.05 | -0.11 | 0.22 |
| B/M | 0.06 | 0.09 | 0.09 | 0.03 |
| Mom | 0.03 | -0.09 | 0.00 | 0.02 |
| C/P | 0.06 | 0.04 | 0.11 | -0.04 |
| D/P | 0.02 | 0.00 | 0.11 | -0.02 |
| E/P | 0.04 | 0.02 | 0.09 | -0.03 |

Panel C: Correlations of factor-mimicking portfolio returns

| Attributes | Market | Size | B/M | Mom | C/P | D/P | E/P |
|---|---|---|---|---|---|---|---|
| Market | 1.00 | | | | | | |
| Size | -0.46 | 1.00 | | | | | |
| B/M | -0.33 | 0.53 | 1.00 | | | | |
| Mom | -0.22 | 0.16 | 0.12 | 1.00 | | | |
| C/P | -0.42 | 0.42 | 0.81 | 0.19 | 1.00 | | |
| D/P | -0.52 | 0.42 | 0.66 | 0.22 | 0.84 | 1.00 | |
| E/P | -0.41 | 0.45 | 0.70 | 0.19 | 0.87 | 0.92 | 1.00 |

The table reports summary statistics for value-weighted global factor-mimicking portfolios (FMPs). At the end of June of each year, stocks are sorted into quintile portfolios based on end-of-June market cap (*size*), previous year-end book-to-market (B/M), cash flow-to-price (C/P), dividend-to-price (D/P), or earnings-to-price (E/P). The factor-mimicking portfolio (FMP) returns are then calculated over the next 12 months as the highest-quintile value-weighted returns minus the lowest-quintile returns, except for the size FMP returns, which are calculated as the smallest-quintile returns minus the biggest-quintile returns. The momentum FMP returns (Mom) are calculated based on Jegadeesh and Titman's (1993) six-month/six-month strategy (with one month skipped), which are long in the quintile of winners and short in the quintile of losers, held for six months and rebalanced every month. "Market" is the monthly US dollar-denominated return in excess of the one-month US Treasury bill yield for the global value-weighted market portfolio.

**Table 4**
**Time-series regression tests of global CAPM and multifactor models using monthly excess returns of country, global industry, and global characteristic-sorted decile portfolios, July 1981 - December 2003**

Panel A: Raw portfolio returns, global CAPM, and Fama-French model

| | Raw Returns | | Global CAPM | | | | Global Fama-French ("FF") Model | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Test Assets | H-L Ret | \|Ret\| | H–L α | \|α\| | GRS | $R^2$ | H–L α | \|α\| | GRS | $R^2$ |
| Country | 0.84 | 0.60 | 0.91 | 0.28 | 1.39 | 0.35 | 1.32 | 0.28 | 1.21 | 0.38 |
| Industry | 0.95 | 0.59 | 1.21 | 0.21 | 2.07*** | 0.60 | 1.29 | 0.28 | 3.00*** | 0.62 |
| Size | 0.88 | 0.69 | 1.08 | 0.29 | 5.97*** | 0.73 | 0.63 | 0.20 | 11.51*** | 0.94 |
| B/M | 0.74 | 0.64 | 0.89 | 0.24 | 4.84*** | 0.82 | 0.21 | 0.07 | 1.27 | 0.93 |
| Mom | 0.78 | 0.48 | 0.92 | 0.23 | 4.43*** | 0.86 | 0.84 | 0.20 | 3.22*** | 0.87 |
| C/P | 0.91 | 0.61 | 1.13 | 0.32 | 8.78*** | 0.82 | 0.64 | 0.19 | 4.98*** | 0.88 |
| D/P | 0.81 | 0.64 | 1.17 | 0.35 | 8.04*** | 0.73 | 0.72 | 0.20 | 4.62*** | 0.80 |
| E/P | 1.00 | 0.66 | 1.26 | 0.39 | 8.56*** | 0.77 | 0.69 | 0.20 | 3.60*** | 0.84 |

Panel B: Global market + single characteristic FMP models

| | GCAPM + Single Characteristic FMP Model | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Size Factor | | B/M Factor | | Mom Factor | | C/P Factor | | D/P Factor | | E/P Factor | |
| Test Assets | \|α\| | GRS | \|α\| | GRS | \|α\| | GRS | \|α\| | GRS | \|α\| | GRS | \|α\| | GRS |
| Country | 0.27 | 1.19 | 0.23 | 1.00 | 0.25 | 1.04 | 0.25 | 0.89 | 0.28 | 1.73** | 0.29 | 1.58** |
| Industry | 0.28 | 3.07*** | 0.23 | 2.00*** | 0.19 | 1.58** | 0.20 | 1.50** | 0.18 | 1.36* | 0.19 | 1.54** |
| Size | 0.18 | 9.36*** | 0.19 | 3.42*** | 0.29 | 5.49*** | 0.18 | 2.96*** | 0.21 | 3.56*** | 0.18 | 3.25*** |
| B/M | 0.14 | 1.79* | 0.06 | 0.96 | 0.23 | 4.11*** | 0.06 | 0.79 | 0.09 | 1.04 | 0.08 | 0.89 |
| Mom | 0.21 | 3.38*** | 0.21 | 3.76*** | 0.02 | 0.27 | 0.20 | 3.17*** | 0.19 | 3.04*** | 0.20 | 3.09*** |
| C/P | 0.25 | 5.27*** | 0.17 | 4.13*** | 0.29 | 7.15*** | 0.09 | 1.90** | 0.14 | 2.85*** | 0.15 | 3.42*** |
| D/P | 0.27 | 5.16*** | 0.17 | 3.60*** | 0.31 | 6.52*** | 0.10 | 1.27 | 0.13 | 2.53*** | 0.13 | 2.47*** |
| E/P | 0.26 | 4.48*** | 0.19 | 3.51*** | 0.34 | 6.76*** | 0.08 | 0.98 | 0.11 | 2.29** | 0.10 | 2.28** |

Panel C: Global multifactor models

| | Global Market + C/P + Mom ("HKK") | | | | Global Market + B/M + Mom | | | | Global HKK + FF Factors | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Test Assets | H–L α | \|α\| | GRS | $R^2$ | H–L α | \|α\| | GRS | $R^2$ | H–L α | \|α\| | GRS | $R^2$ |
| Country | 1.26 | 0.25 | 0.81 | 0.38 | 0.92 | 0.22 | 0.80 | 0.38 | 1.29 | 0.28 | 1.24 | 0.40 |
| Industry | 0.98 | 0.18 | 1.22 | 0.62 | 1.07 | 0.21 | 1.55** | 0.62 | 1.03 | 0.21 | 1.77*** | 0.64 |
| Size | 0.88 | 0.17 | 2.72*** | 0.74 | 0.90 | 0.17 | 2.97*** | 0.78 | 0.51 | 0.14 | 7.10*** | 0.94 |
| B/M | 0.27 | 0.06 | 0.83 | 0.89 | 0.20 | 0.06 | 0.99 | 0.92 | 0.21 | 0.06 | 0.86 | 0.93 |
| Mom | 0.26 | 0.08 | 1.41 | 0.95 | 0.12 | 0.04 | 0.62 | 0.94 | 0.12 | 0.04 | 0.59 | 0.95 |
| C/P | 0.35 | 0.08 | 1.40 | 0.91 | 0.49 | 0.15 | 3.12*** | 0.88 | 0.38 | 0.08 | 1.56 | 0.91 |
| D/P | 0.42 | 0.11 | 1.32 | 0.84 | 0.60 | 0.15 | 2.93*** | 0.80 | 0.45 | 0.14 | 1.97** | 0.85 |
| E/P | 0.32 | 0.08 | 0.87 | 0.88 | 0.58 | 0.16 | 2.62*** | 0.84 | 0.39 | 0.08 | 1.08 | 0.88 |

Value-weighted monthly US dollar-denominated returns in excess of the one-month US Treasury bill rate ($R_i – R_f$) on country, global industry portfolios as well as on global size, book-to-market (B/M), momentum (Mom), cash-flow-to-price (C/P), dividend yield (D/P), and earnings yield (E/P) decile portfolios are regressed on the excess return of the global value-weighted market portfolio ($R_M$ - $R_f$) and returns on various global factor-mimicking portfolios (FMP). Six classes of models are investigated:

Global CAPM (GCAPM): $R_i - R_f = \alpha_i + \beta_i (R_M - R_f) + \varepsilon_i$,
Global Fama-French ("FF") Model: $R_i - R_f = \alpha_i + \beta_i (R_M - R_f) + s_i F_{Size} + h_i F_{B/M} + \varepsilon_i$,
Global Market + Single Characteristic FMP Model: $R_i - R_f = \alpha_i + \beta_i (R_M - R_f) + f_i F_k + \varepsilon_i$,
Global Market + C/P + Momentum ("HKK") Model: $R_i - R_f = \alpha_i + \beta_i (R_M - R_f) + c_i F_{C/P} + m_i F_{Mom} + \varepsilon_i$,
Global Market + B/M + Momentum Model: $R_i - R_f = \alpha_i + \beta_i (R_M - R_f) + h_i F_{B/M} + m_i F_{Mom} + \varepsilon_i$, and
Global HKK + FF Factor Model: $R_i - R_f = \alpha_i + \beta_i (R_M - R_f) + c_i F_{C/P} + m_i F_{Mom} + s_i F_{Size} + h_i F_{B/M} ++ \varepsilon_i$.

$F_k$ is the factor-mimicking portfolio associated with firm-level characteristic k. Its construction is detailed in the notes to Table 3. The high minus low portfolio return ("H-L Ret.") is the difference in the average return between the highest-ranked characteristic decile (smallest for size) and the lowest-ranked decile (largest for size) portfolios, or between the highest and lowest extremes among the country and global industry portfolios. We also report the average absolute mean return for each set of test portfolios ("|Ret.|"). Reported regression results include the difference between the highest and lowest intercepts ("H-L α"), the average absolute intercept ("|α|"), the average adjusted $R^2$ ("$R^2$"), and the Gibbons, Ross, and Shanken (1989) F-statistic for the null hypothesis that the regression intercepts for a set of test portfolios are jointly equal to zero ("GRS"). ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. Tests on country portfolios are conducted using 20 of the 49 countries for which there are complete time series from July 1981 to December 2003. Tests on industry portfolios are conducted using the 34 global industry portfolios.

**Table 5**

**Time-series regression tests of global, local, and international versions of the CAPM and multifactor models using monthly excess returns on country-specific industry and characteristic-sorted quintile portfolios, July 1981 - December 2003**

Panel A: Global, local, and international versions of CAPM

| Test Assets | All Countries | | | | | | | | | | Developed Countries Only | | | | | | | | | | Emerging Countries Only | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Global | | | Local | | | International | | | | Global | | | Local | | | International | | | | Global | | | Local | | | International | | |
| | Exp | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ | Exp | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ | Exp | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ |
| Industry | 24 | 5 | 0.40 | 0.19 | 2 | 0.25 | 0.56 | 1 | 0.26 | 0.56 | 18 | 5 | 0.38 | 0.23 | 1 | 0.23 | 0.53 | 1 | 0.24 | 0.54 | 6 | 0 | 0.47 | 0.07 | 1 | 0.30 | 0.63 | 0 | 0.31 | 0.64 |
| Size | 39 | 8 | 0.52 | 0.21 | 6 | 0.29 | 0.71 | 6 | 0.30 | 0.71 | 21 | 6 | 0.37 | 0.28 | 4 | 0.18 | 0.72 | 4 | 0.18 | 0.72 | 18 | 2 | 0.72 | 0.12 | 2 | 0.43 | 0.70 | 2 | 0.44 | 0.70 |
| B/M | 39 | 14 | 0.66 | 0.25 | 16 | 0.39 | 0.74 | 16 | 0.39 | 0.75 | 21 | 10 | 0.50 | 0.31 | 12 | 0.31 | 0.75 | 12 | 0.31 | 0.75 | 18 | 4 | 0.85 | 0.16 | 4 | 0.49 | 0.74 | 4 | 0.49 | 0.74 |
| Mom | 39 | 9 | 0.42 | 0.25 | 14 | 0.27 | 0.85 | 15 | 0.27 | 0.85 | 21 | 8 | 0.36 | 0.34 | 11 | 0.22 | 0.84 | 12 | 0.22 | 0.85 | 18 | 1 | 0.50 | 0.15 | 3 | 0.33 | 0.86 | 3 | 0.33 | 0.87 |
| C/P | 39 | 11 | 0.65 | 0.25 | 16 | 0.40 | 0.74 | 17 | 0.40 | 0.75 | 21 | 8 | 0.50 | 0.32 | 12 | 0.32 | 0.75 | 12 | 0.32 | 0.75 | 18 | 3 | 0.86 | 0.17 | 4 | 0.51 | 0.74 | 5 | 0.51 | 0.74 |
| D/P | 39 | 11 | 0.64 | 0.23 | 11 | 0.41 | 0.71 | 12 | 0.41 | 0.72 | 21 | 9 | 0.52 | 0.30 | 9 | 0.31 | 0.72 | 10 | 0.31 | 0.73 | 18 | 2 | 0.80 | 0.14 | 2 | 0.53 | 0.70 | 2 | 0.53 | 0.70 |
| E/P | 39 | 13 | 0.66 | 0.25 | 17 | 0.44 | 0.74 | 17 | 0.44 | 0.74 | 21 | 10 | 0.50 | 0.31 | 11 | 0.31 | 0.74 | 11 | 0.32 | 0.74 | 18 | 3 | 0.86 | 0.16 | 6 | 0.59 | 0.73 | 6 | 0.60 | 0.74 |
| Total | 258 | 71 | 0.57 | 0.23 | 82 | 0.35 | 0.72 | 84 | 0.35 | 0.72 | 144 | 56 | 0.45 | 0.30 | 60 | 0.27 | 0.72 | 62 | 0.27 | 0.72 | 114 | 15 | 0.72 | 0.14 | 22 | 0.45 | 0.73 | 22 | 0.46 | 0.73 |

Panel B: Global, local, and international versions of HKK model of market plus C/P and momentum factors

| Test Assets | All Countries | | | | | | | | | | Developed Countries Only | | | | | | | | | | Emerging Countries Only | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Global | | | Local | | | International | | | | Global | | | Local | | | International | | | | Global | | | Local | | | International | | |
| | Exp | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ | Exp | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ | Exp | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ |
| Industry | 24 | 2 | 0.38 | 0.24 | 1 | 0.25 | 0.58 | 1 | 0.27 | 0.60 | 18 | 2 | 0.33 | 0.29 | 0 | 0.23 | 0.56 | 1 | 0.25 | 0.57 | 6 | 0 | 0.52 | 0.10 | 1 | 0.33 | 0.65 | 0 | 0.36 | 0.66 |
| Size | 39 | 4 | 0.40 | 0.23 | 4 | 0.27 | 0.72 | 4 | 0.29 | 0.73 | 21 | 3 | 0.25 | 0.31 | 2 | 0.17 | 0.73 | 1 | 0.16 | 0.73 | 18 | 1 | 0.61 | 0.13 | 2 | 0.39 | 0.71 | 3 | 0.45 | 0.72 |
| B/M | 39 | 3 | 0.49 | 0.29 | 6 | 0.30 | 0.78 | 3 | 0.28 | 0.78 | 21 | 2 | 0.28 | 0.37 | 5 | 0.21 | 0.79 | 1 | 0.18 | 0.79 | 18 | 1 | 0.76 | 0.18 | 1 | 0.42 | 0.77 | 2 | 0.44 | 0.78 |
| Mom | 39 | 2 | 0.32 | 0.29 | 5 | 0.14 | 0.92 | 4 | 0.13 | 0.92 | 21 | 2 | 0.23 | 0.39 | 3 | 0.11 | 0.92 | 2 | 0.11 | 0.92 | 18 | 0 | 0.44 | 0.17 | 2 | 0.18 | 0.92 | 2 | 0.16 | 0.93 |
| C/P | 39 | 3 | 0.50 | 0.29 | 4 | 0.24 | 0.83 | 3 | 0.25 | 0.83 | 21 | 2 | 0.30 | 0.37 | 3 | 0.17 | 0.83 | 2 | 0.16 | 0.83 | 18 | 1 | 0.78 | 0.19 | 1 | 0.33 | 0.82 | 1 | 0.35 | 0.83 |
| D/P | 39 | 4 | 0.48 | 0.28 | 5 | 0.32 | 0.74 | 4 | 0.32 | 0.75 | 21 | 2 | 0.28 | 0.36 | 4 | 0.22 | 0.76 | 3 | 0.20 | 0.77 | 18 | 2 | 0.74 | 0.17 | 1 | 0.45 | 0.72 | 1 | 0.47 | 0.73 |
| E/P | 39 | 4 | 0.49 | 0.29 | 6 | 0.32 | 0.77 | 2 | 0.30 | 0.78 | 21 | 1 | 0.28 | 0.37 | 3 | 0.22 | 0.77 | 0 | 0.18 | 0.78 | 18 | 3 | 0.77 | 0.18 | 3 | 0.45 | 0.77 | 2 | 0.46 | 0.77 |
| Total | 258 | 22 | 0.44 | 0.27 | 31 | 0.26 | 0.76 | 21 | 0.26 | 0.77 | 144 | 14 | 0.28 | 0.35 | 20 | 0.19 | 0.76 | 10 | 0.18 | 0.77 | 114 | 8 | 0.66 | 0.16 | 11 | 0.37 | 0.77 | 11 | 0.38 | 0.77 |

Panel C: Global, local, and international versions of Fama-French model of market plus size and B/M factors

| Test Assets | All Countries | | | | | | | | | | Developed Countries Only | | | | | | | | | | Emerging Countries Only | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Global | | | Local | | | International | | | | Global | | | Local | | | International | | | | Global | | | Local | | | International | | |
| | Exp | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ | Exp | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ | Exp | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ | Rej | \| α \| | $R^2$ |
| Industry | 24 | 4 | 0.36 | 0.24 | 7 | 0.28 | 0.61 | 9 | 0.30 | 0.63 | 18 | 4 | 0.35 | 0.28 | 6 | 0.26 | 0.59 | 9 | 0.29 | 0.60 | 6 | 0 | 0.40 | 0.12 | 1 | 0.37 | 0.69 | 0 | 0.33 | 0.70 |
| Size | 39 | 4 | 0.40 | 0.26 | 13 | 0.18 | 0.89 | 14 | 0.19 | 0.89 | 21 | 3 | 0.25 | 0.34 | 8 | 0.13 | 0.89 | 9 | 0.14 | 0.89 | 18 | 1 | 0.60 | 0.16 | 5 | 0.26 | 0.88 | 5 | 0.26 | 0.88 |
| B/M | 39 | 6 | 0.51 | 0.29 | 4 | 0.24 | 0.84 | 2 | 0.24 | 0.84 | 21 | 5 | 0.34 | 0.35 | 4 | 0.17 | 0.84 | 2 | 0.17 | 0.84 | 18 | 1 | 0.74 | 0.21 | 0 | 0.34 | 0.84 | 0 | 0.34 | 0.84 |
| Mom | 39 | 5 | 0.34 | 0.29 | 12 | 0.27 | 0.86 | 12 | 0.25 | 0.87 | 21 | 5 | 0.28 | 0.37 | 9 | 0.22 | 0.85 | 9 | 0.21 | 0.86 | 18 | 0 | 0.42 | 0.19 | 3 | 0.33 | 0.88 | 3 | 0.31 | 0.88 |
| C/P | 39 | 3 | 0.54 | 0.30 | 5 | 0.32 | 0.78 | 8 | 0.34 | 0.79 | 21 | 3 | 0.37 | 0.35 | 2 | 0.23 | 0.78 | 5 | 0.23 | 0.79 | 18 | 0 | 0.76 | 0.22 | 3 | 0.45 | 0.78 | 3 | 0.47 | 0.78 |
| D/P | 39 | 6 | 0.52 | 0.27 | 7 | 0.36 | 0.75 | 7 | 0.37 | 0.75 | 21 | 6 | 0.38 | 0.34 | 4 | 0.24 | 0.76 | 4 | 0.25 | 0.77 | 18 | 0 | 0.71 | 0.19 | 3 | 0.52 | 0.73 | 3 | 0.53 | 0.73 |
| E/P | 39 | 5 | 0.51 | 0.29 | 9 | 0.36 | 0.77 | 8 | 0.34 | 0.77 | 21 | 5 | 0.36 | 0.35 | 5 | 0.25 | 0.77 | 6 | 0.25 | 0.77 | 18 | 0 | 0.71 | 0.21 | 4 | 0.51 | 0.77 | 2 | 0.46 | 0.77 |
| Total | 258 | 33 | 0.46 | 0.28 | 57 | 0.29 | 0.79 | 60 | 0.29 | 0.79 | 144 | 31 | 0.33 | 0.34 | 38 | 0.21 | 0.78 | 44 | 0.22 | 0.79 | 114 | 2 | 0.62 | 0.19 | 19 | 0.39 | 0.79 | 16 | 0.39 | 0.80 |

**Table 5 (continued)**

Value-weighted monthly US dollar-denominated returns in excess of the one-month US Treasury bill rate ($R_i – R_f$) on industry and characteristic-sorted quintile portfolios for each country are used to test the global, local, and international versions of the CAPM, HKK, and Fama-French models:

Global CAPM: $R_i - R_f = \alpha_i + \beta_i^W (R_M^W - R_f) + \varepsilon_i$
Global HKK Model: $R_i - R_f = \alpha_i + \beta_i^W (R_M^W - R_f) + c_i^W F_{C/P}^W + m_i^W F_{Mom}^W + \varepsilon_i$
Global Fama-French Model: $R_i - R_f = \alpha_i + \beta_i^W (R_M^W - R_f) + s_i^W F_{Size}^W + h_i^W F_{B/M}^W + \varepsilon_i$

Local CAPM: $R_i - R_f = \alpha_i + \beta_i^L (R_M^L - R_f) + \varepsilon_i$
Local HKK Model: $R_i - R_f = \alpha_i + \beta_i^L (R_M^L - R_f) + c_i^L F_{C/P}^L + m_i^L F_{Mom}^L + \varepsilon_i$
Local Fama-French Model: $R_i - R_f = \alpha_i + \beta_i^L (R_M^L - R_f) + s_i^L F_{Size}^L + h_i^L F_{B/M}^L + \varepsilon_i$

International CAPM: $R_i - R_f = \alpha_i + \beta_i^L (R_M^L - R_f) + \beta_i^F (R_M^F - R_f) + \varepsilon_i$
International HKK Model: $R_i - R_f = \alpha_i + \beta_i^L (R_M^L - R_f) + \beta_i^F (R_M^F - R_f) + c_i^L F_{C/P}^L + c_i^F F_{C/P}^F + m_i^L F_{Mom}^L + m_i^F F_{Mom}^F + \varepsilon_i$
International Fama-French Model: $R_i - R_f = \alpha_i + \beta_i^L (R_M^L - R_f) + \beta_i^F (R_M^F - R_f) + s_i^L F_{Size}^L + s_i^F F_{Size}^F + h_i^L F_{B/M}^L + h_i^F F_{B/M}^F + \varepsilon_i$.

A “W” superscript denotes a globally constructed market portfolio or factor-mimicking portfolio. An “L” superscript denotes a locally constructed market portfolio or factor-mimicking portfolio, and an “F” superscript denotes a foreign market portfolio or factor-mimicking portfolio in which the portfolio is constructed from global stocks *excluding* those from the specific country for which the test is performed. A country qualifies for a test if it has at least 20 firms for a given firm-specific characteristic and if the returns series for the test assets are at least 36 months in length. The starting date for each country is then the first month for which the country has at least 20 firms for that firm characteristic. The industry test for a given country requires at least five industries and at least four firms in each industry with the selection of the starting date based on an appropriate number of test assets and an appropriate testing period length (specific starting dates for each country are available upon request). For each country/test asset/model combination, we compute the Gibbons, Ross, and Shanken (1989) F-statistic for the null hypothesis that the regression intercepts for the test portfolios are jointly equal to zero. We report the number of experiments across countries (“Exp”), the number of experiments across countries that are rejected at the 5% significance level (“Rej”), the average absolute intercept (“$|\alpha|$”), and the average adjusted $R^2$ (“$R^2$”). The results are also reported for developing and emerging countries separately.

**Table 6**

**Multifactor model time-series regressions for global portfolios formed from sorts on size, cash flow-to-price (C/P), and C/P factor loading, July 1983 - December 2003**

Panel A: Summary statistics and regression results for portfolios formed from sorts on size, C/P, and C/P factor loading

| | | | | | | Regression Slope Coefficients | | | | *t*-statistics for Slope Coefficients | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Portfolio | Size | C/P | C/P Loading | Return | *t*-statistic | $\alpha_i^W$ | $\beta_i^W$ | $c_i^W$ | $m_i^W$ | $t(\alpha_i^W)$ | $t(\beta_i^W)$ | $t(c_i^W)$ | $t(m_i^W)$ | Adj $R^2$ |
| S/L/Lc | 35.16 | 0.05 | -1.12 | 0.34 | 0.86 | 0.20 | 0.97 | 0.07 | -0.06 | 0.69 | 13.53 | 0.81 | -0.91 | 0.49 |
| S/L/Mc | 33.79 | 0.05 | 0.04 | 0.61 | 2.36 | 0.42 | 0.73 | 0.32 | -0.01 | 2.23 | 15.83 | 5.99 | -0.15 | 0.52 |
| S/L/Hc | 36.16 | 0.05 | 1.11 | 0.69 | 2.21 | 0.36 | 0.88 | 0.39 | 0.00 | 1.59 | 15.92 | 6.22 | -0.01 | 0.52 |
| S/M/Lc | 34.55 | 0.12 | -0.83 | 0.75 | 2.55 | 0.59 | 0.83 | 0.21 | -0.04 | 2.94 | 16.87 | 3.78 | -1.02 | 0.57 |
| S/M/Mc | 35.58 | 0.12 | 0.10 | 0.95 | 4.02 | 0.75 | 0.70 | 0.32 | 0.02 | 4.61 | 17.33 | 7.02 | 0.61 | 0.56 |
| S/M/Hc | 36.85 | 0.12 | 1.00 | 1.03 | 3.70 | 0.67 | 0.85 | 0.41 | 0.05 | 3.67 | 19.03 | 8.08 | 1.24 | 0.61 |
| S/H/Lc | 30.50 | 0.52 | -0.82 | 1.19 | 4.28 | 1.00 | 0.80 | 0.33 | -0.07 | 5.24 | 17.07 | 6.10 | -1.67 | 0.57 |
| S/H/Mc | 31.94 | 0.50 | 0.15 | 1.28 | 5.34 | 1.04 | 0.73 | 0.37 | 0.02 | 6.58 | 18.86 | 8.35 | 0.47 | 0.61 |
| S/H/Hc | 33.06 | 0.49 | 1.09 | 1.48 | 5.05 | 1.07 | 0.89 | 0.52 | -0.01 | 5.60 | 19.03 | 9.71 | -0.17 | 0.61 |
| M/L/Lc | 184.21 | 0.05 | -1.22 | 0.09 | 0.20 | 0.16 | 1.08 | -0.15 | -0.23 | 0.55 | 15.38 | -1.85 | -3.84 | 0.62 |
| M/L/Mc | 180.82 | 0.06 | 0.03 | 0.27 | 0.99 | -0.01 | 0.90 | 0.30 | 0.00 | -0.07 | 23.40 | 6.81 | 0.09 | 0.71 |
| M/L/Hc | 184.48 | 0.05 | 1.04 | 0.46 | 1.43 | 0.04 | 1.03 | 0.39 | 0.01 | 0.22 | 21.45 | 7.18 | 0.17 | 0.67 |
| M/M/Lc | 171.35 | 0.12 | -0.73 | 0.54 | 1.85 | 0.33 | 0.90 | 0.28 | -0.08 | 1.85 | 20.67 | 5.71 | -2.06 | 0.67 |
| M/M/Mc | 174.43 | 0.12 | 0.15 | 0.76 | 3.17 | 0.47 | 0.80 | 0.38 | 0.02 | 3.64 | 25.38 | 10.62 | 0.64 | 0.74 |
| M/M/Hc | 179.58 | 0.12 | 0.95 | 0.95 | 3.30 | 0.47 | 0.96 | 0.54 | 0.00 | 3.10 | 25.85 | 12.76 | 0.13 | 0.75 |
| M/H/Lc | 165.96 | 0.44 | -0.61 | 0.91 | 3.20 | 0.67 | 0.86 | 0.34 | -0.07 | 3.73 | 19.67 | 6.85 | -1.79 | 0.64 |
| M/H/Mc | 166.49 | 0.37 | 0.23 | 0.98 | 4.01 | 0.66 | 0.82 | 0.44 | 0.00 | 4.98 | 25.12 | 11.87 | -0.03 | 0.73 |
| M/H/Hc | 171.66 | 0.40 | 1.09 | 1.23 | 4.11 | 0.70 | 1.00 | 0.61 | -0.02 | 4.55 | 26.46 | 14.07 | -0.48 | 0.76 |
| B/L/Lc | 4,926.99 | 0.05 | -1.24 | 0.01 | 0.02 | 0.44 | 1.12 | -0.89 | -0.10 | 2.52 | 26.39 | -18.27 | -2.74 | 0.89 |
| B/L/Mc | 5,009.80 | 0.06 | -0.06 | 0.59 | 2.06 | 0.46 | 0.93 | 0.05 | -0.02 | 3.77 | 31.18 | 1.52 | -0.64 | 0.84 |
| B/L/Hc | 3,853.52 | 0.06 | 0.88 | 0.77 | 2.53 | 0.32 | 1.05 | 0.38 | 0.04 | 2.15 | 28.62 | 9.04 | 1.34 | 0.78 |
| B/M/Lc | 3,533.55 | 0.12 | -0.62 | 0.36 | 1.17 | 0.25 | 1.00 | 0.01 | -0.06 | 2.03 | 33.28 | 0.38 | -2.24 | 0.86 |
| B/M/Mc | 3,657.29 | 0.12 | 0.24 | 0.77 | 2.87 | 0.36 | 0.95 | 0.44 | 0.01 | 3.00 | 32.39 | 13.12 | 0.60 | 0.82 |
| B/M/Hc | 3,398.18 | 0.12 | 0.96 | 1.02 | 3.36 | 0.47 | 1.08 | 0.59 | -0.02 | 3.63 | 34.04 | 16.23 | -0.79 | 0.84 |
| B/H/Lc | 2,826.67 | 0.36 | -0.45 | 0.78 | 2.67 | 0.55 | 0.96 | 0.12 | 0.04 | 3.83 | 27.54 | 3.08 | 1.41 | 0.79 |
| B/H/Mc | 3,049.42 | 0.37 | 0.34 | 0.94 | 3.70 | 0.45 | 0.94 | 0.55 | 0.04 | 4.91 | 41.57 | 21.22 | 2.14 | 0.88 |
| B/H/Hc | 3,159.17 | 0.33 | 1.10 | 1.11 | 3.61 | 0.45 | 1.10 | 0.68 | 0.01 | 3.77 | 37.32 | 20.26 | 0.60 | 0.86 |

Panel B: Average returns and regression results for high loading – low loading (Hc – Lc) spread portfolios formed from sorts on size, C/P, and C/P factor loading

| | | | Regression Slope Coefficients | | | | *t*-statistics for Slope Coefficients | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Portfolio | Average Returns | *t*-statistic | $\alpha_i^W$ | $\beta_i^W$ | $c_i^W$ | $m_i^W$ | $t(\alpha_i^W)$ | $t(\beta_i^W)$ | $t(c_i^W)$ | $t(m_i^W)$ | Adj $R^2$ |
| S/L Hc-Lc | 0.35 | 1.32 | 0.16 | -0.09 | 0.33 | 0.06 | 0.59 | -1.45 | 4.43 | 1.01 | 0.13 |
| S/M Hc-Lc | 0.28 | 1.43 | 0.08 | 0.02 | 0.20 | 0.09 | 0.39 | 0.36 | 3.61 | 2.19 | 0.08 |
| S/H Hc-Lc | 0.29 | 1.54 | 0.07 | 0.09 | 0.19 | 0.06 | 0.37 | 1.96 | 3.54 | 1.47 | 0.05 |
| M/L Hc-Lc | 0.37 | 1.16 | -0.11 | -0.05 | 0.54 | 0.24 | -0.39 | -0.76 | 6.66 | 3.91 | 0.28 |
| M/M Hc-Lc | 0.41 | 2.05 | 0.14 | 0.07 | 0.26 | 0.08 | 0.72 | 1.40 | 4.69 | 1.94 | 0.10 |
| M/H Hc-Lc | 0.32 | 1.79 | 0.03 | 0.14 | 0.27 | 0.05 | 0.20 | 3.20 | 5.31 | 1.38 | 0.11 |
| B/L Hc-Lc | 0.76 | 1.75 | -0.11 | -0.07 | 1.27 | 0.14 | -0.39 | -0.97 | 15.48 | 2.31 | 0.59 |
| B/M Hc-Lc | 0.66 | 2.85 | 0.22 | 0.08 | 0.57 | 0.04 | 1.12 | 1.57 | 10.45 | 0.88 | 0.35 |
| B/H Hc-Lc | 0.33 | 1.32 | -0.09 | 0.14 | 0.56 | -0.03 | -0.41 | 2.50 | 8.94 | -0.58 | 0.25 |
| Combined | 0.42 | 2.12 | 0.04 | 0.04 | 0.46 | 0.08 | 0.25 | 0.86 | 9.94 | 2.31 | 0.36 |

**Table 6 (continued)**

At the end of June of each year *t* (1983 to 2003), we sort all global stocks (with at least 12 months of return data in the previous 36 months) independently into three size groups (small, medium or big; S, M, or B, respectively) and into three C/P groups (low, medium, or high; L, M, or H, respectively) based on the 33rd and 67th percentile breakpoints. Size is measured at the end of June of year *t* and C/P is measured at the end of year *t*-1. Nine portfolios (S/L, S/M, S/H, M/L, M/M, M/H, B/L, B/M, and B/H) are formed as the intersections of the three size groups and three C/P groups. The nine portfolios are then each subdivided into three portfolios (Lc, Mc, or Hc) based on pre-formation C/P factor loadings estimated with monthly returns over the previous 36 months (12-month minimum) using the following model:

Global HKK Model: $R_i - R_f = \alpha_i + \beta_i^W (R_M^W - R_f) + c_i^W F_{C/P}^W + m_i^W F_{Mom}^W + \varepsilon_i$.

The C/P factor loadings are orthogonalized with respect to the momentum factor loadings using a cross-sectional regression. Panel A reports value-weighted averages of size, C/P, pre-formation C/P loading, mean excess returns, and *t*-statistics for each of the 27 portfolios, as well as of the slope coefficients, associated *t*-statistics, and adjusted $R^2$ from regressing the value-weighted excess returns on $R_M^W$ - $R_f$, $F_{C/P}^W$, and $F_{Mom}^W$. Panel B reports average returns and regression statistics for a spread portfolio of high and low-C/P factor loadings (“Hc – Lc”) within each size and C/P group as well as for an equally weighted portfolio of the nine spread portfolios (“Combined”).

**Table 7**
**Multifactor model time-series regressions for global spread portfolios formed from sorts on various characteristics and factor loadings, July 1983 - December 2003**

Panel A: Average returns and regression results for high loading – low loading (Hm – Lm) spread portfolios formed from sorts on size, momentum, and momentum factor loading

| Size/Mom Portfolio | Average Returns | *t*-statistic | $\alpha_i^W$ | $\beta_i^W$ | $c_i^W$ | $m_i^W$ | $t(\alpha_i^W)$ | $t(\beta_i^W)$ | $t(c_i^W)$ | $t(m_i^W)$ | Adj $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Regression Slope Coefficients | | | | *t*-statistics for Slope Coefficients | | | | |
| S/L Hm-Lm | 0.12 | 0.54 | 0.14 | -0.08 | -0.19 | 0.20 | 0.63 | -1.44 | -3.01 | 4.25 | 0.09 |
| S/M Hm-Lm | 0.13 | 0.81 | 0.23 | -0.12 | -0.13 | 0.07 | 1.35 | -2.76 | -2.74 | 2.10 | 0.05 |
| S/H Hm-Lm | 0.00 | 0.00 | 0.05 | -0.09 | -0.22 | 0.19 | 0.22 | -1.53 | -3.09 | 3.63 | 0.07 |
| M/L Hm-Lm | 0.12 | 0.43 | 0.00 | -0.02 | -0.09 | 0.26 | 0.01 | -0.31 | -1.09 | 4.30 | 0.07 |
| M/M Hm-Lm | 0.40 | 2.14 | 0.38 | -0.07 | -0.04 | 0.13 | 1.94 | -1.40 | -0.82 | 3.20 | 0.05 |
| M/H Hm-Lm | 0.47 | 1.95 | 0.60 | -0.14 | -0.28 | 0.17 | 2.51 | -2.37 | -4.21 | 3.50 | 0.10 |
| B/L Hm-Lm | 0.03 | 0.09 | -0.09 | -0.09 | -0.11 | 0.34 | -0.25 | -1.02 | -1.07 | 4.40 | 0.08 |
| B/M Hm-Lm | 0.44 | 1.63 | 0.38 | -0.07 | -0.19 | 0.29 | 1.45 | -1.07 | -2.49 | 5.23 | 0.11 |
| B/H Hm-Lm | 0.39 | 1.29 | 0.42 | 0.01 | -0.48 | 0.37 | 1.49 | 0.11 | -6.01 | 6.33 | 0.22 |
| Combined | 0.23 | 1.26 | 0.24 | -0.07 | -0.19 | 0.22 | 1.32 | -1.70 | -3.83 | 6.05 | 0.16 |

Panel B: Average returns and regression results for high loading – low loading (Hc – Lc) spread portfolios formed from sorts on C/P, momentum, and C/P factor loading

| C/P / Mom Portfolio | Average Returns | *t*-statistic | $\alpha_i^W$ | $\beta_i^W$ | $c_i^W$ | $m_i^W$ | $t(\alpha_i^W)$ | $t(\beta_i^W)$ | $t(c_i^W)$ | $t(m_i^W)$ | Adj $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Regression Slope Coefficients | | | | *t*-statistics for Slope Coefficients | | | | |
| L/L Hc-Lc | 0.32 | 0.68 | -0.72 | 0.05 | 1.12 | 0.41 | -1.97 | 0.50 | 10.90 | 5.34 | 0.46 |
| L/M Hc-Lc | 0.94 | 2.58 | 0.30 | 0.00 | 0.88 | 0.10 | 1.00 | 0.01 | 10.55 | 1.56 | 0.39 |
| L/H Hc-Lc | 0.65 | 1.66 | 0.19 | -0.03 | 0.92 | -0.17 | 0.58 | -0.31 | 9.84 | -2.45 | 0.33 |
| M/L Hc-Lc | 0.67 | 1.92 | 0.00 | 0.11 | 0.68 | 0.24 | -0.01 | 1.40 | 7.73 | 3.74 | 0.28 |
| M/M Hc-Lc | 0.60 | 2.49 | 0.22 | 0.09 | 0.48 | 0.03 | 0.97 | 1.62 | 7.67 | 0.63 | 0.21 |
| M/H Hc-Lc | 0.42 | 1.75 | 0.15 | 0.10 | 0.44 | -0.08 | 0.63 | 1.79 | 6.68 | -1.71 | 0.16 |
| H/L Hc-Lc | 0.44 | 1.11 | -0.16 | 0.13 | 0.66 | 0.15 | -0.43 | 1.35 | 6.19 | 1.85 | 0.17 |
| H/M Hc-Lc | 0.17 | 0.68 | -0.14 | 0.05 | 0.42 | 0.01 | -0.54 | 0.85 | 5.96 | 0.29 | 0.14 |
| H/H Hc-Lc | 0.14 | 0.50 | -0.25 | 0.21 | 0.50 | -0.07 | -0.92 | 3.20 | 6.54 | -1.24 | 0.15 |
| Combined | 0.48 | 2.01 | -0.05 | 0.08 | 0.68 | 0.07 | -0.26 | 1.75 | 13.11 | 1.79 | 0.47 |

Panel C: Average returns and regression results for high loading – low loading (Hm – Lm) spread portfolios formed from sorts on C/P, momentum, and momentum factor loadings

| C/P / Mom Portfolio | Average Returns | *t*-statistic | $\alpha_i^W$ | $\beta_i^W$ | $c_i^W$ | $m_i^W$ | $t(\alpha_i^W)$ | $t(\beta_i^W)$ | $t(c_i^W)$ | $t(m_i^W)$ | Adj $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Regression Slope Coefficients | | | | *t*-statistics for Slope Coefficients | | | | |
| L/L Hm-Lm | -0.21 | -0.50 | -0.46 | -0.10 | -0.07 | 0.47 | -1.09 | -0.98 | -0.60 | 5.47 | 0.12 |
| L/M Hm-Lm | 0.47 | 1.40 | 0.41 | -0.04 | -0.26 | 0.34 | 1.24 | -0.52 | -2.80 | 4.82 | 0.10 |
| L/H Hm-Lm | 0.47 | 1.29 | 0.54 | 0.01 | -0.51 | 0.34 | 1.55 | 0.16 | -5.26 | 4.68 | 0.16 |
| M/L Hm-Lm | 0.17 | 0.53 | 0.10 | -0.10 | -0.02 | 0.18 | 0.31 | -1.22 | -0.16 | 2.64 | 0.03 |
| M/M Hm-Lm | 0.28 | 1.21 | 0.23 | -0.02 | -0.05 | 0.13 | 0.96 | -0.34 | -0.81 | 2.58 | 0.02 |
| M/H Hm-Lm | 0.15 | 0.61 | 0.13 | 0.00 | -0.26 | 0.25 | 0.53 | 0.01 | -3.70 | 4.91 | 0.12 |
| H/L Hm-Lm | 0.47 | 1.30 | 0.35 | -0.09 | -0.10 | 0.32 | 0.96 | -1.04 | -0.98 | 4.22 | 0.07 |
| H/M Hm-Lm | 0.14 | 0.57 | 0.07 | -0.04 | -0.09 | 0.20 | 0.28 | -0.58 | -1.36 | 3.96 | 0.06 |
| H/H Hm-Lm | 0.16 | 0.57 | 0.25 | -0.11 | -0.24 | 0.17 | 0.85 | -1.55 | -2.87 | 2.85 | 0.05 |
| Combined | 0.23 | 1.04 | 0.18 | -0.05 | -0.18 | 0.27 | 0.83 | -1.01 | -2.91 | 5.89 | 0.14 |

Panel D: Average returns and regression results for high loading – low loading (Hh – Lh) spread portfolios formed from sorts on size, B/M, and B/M factor loadings

| Size / B/M Portfolio | Average Returns | *t*-statistic | $\alpha_i^W$ | $\beta_i^W$ | $s_i^W$ | $h_i^W$ | $t(\alpha_i^W)$ | $t(\beta_i^W)$ | $t(s_i^W)$ | $t(h_i^W)$ | Adj $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Regression Slope Coefficients | | | | *t*-statistics for Slope Coefficients | | | | |
| S/L Hh-Lh | -0.27 | -0.94 | -0.25 | -0.15 | -0.24 | 0.40 | -0.88 | -2.04 | -2.39 | 4.95 | 0.12 |
| S/M Hh-Lh | -0.05 | -0.24 | -0.18 | 0.07 | -0.02 | 0.23 | -0.91 | 1.45 | -0.32 | 4.07 | 0.07 |
| S/H Hh-Lh | -0.01 | -0.04 | -0.24 | 0.22 | 0.00 | 0.24 | -1.05 | 3.75 | -0.05 | 3.72 | 0.09 |
| M/L Hh-Lh | -0.25 | -0.71 | -0.42 | -0.21 | -0.03 | 0.67 | -1.40 | -2.76 | -0.25 | 7.89 | 0.33 |
| M/M Hh-Lh | -0.45 | -1.76 | -0.70 | 0.09 | 0.21 | 0.22 | -2.79 | 1.43 | 2.28 | 3.14 | 0.10 |
| M/H Hh-Lh | -0.09 | -0.41 | -0.38 | 0.22 | 0.18 | 0.17 | -1.76 | 4.10 | 2.28 | 2.78 | 0.10 |
| B/L Hh-Lh | 0.08 | 0.22 | -0.34 | -0.02 | 0.21 | 0.73 | -1.16 | -0.26 | 1.98 | 8.80 | 0.39 |
| B/M Hh-Lh | -0.13 | -0.44 | -0.44 | 0.01 | 0.28 | 0.39 | -1.69 | 0.11 | 2.96 | 5.24 | 0.25 |
| B/H Hh-Lh | -0.08 | -0.33 | -0.41 | 0.22 | 0.34 | 0.09 | -1.74 | 3.64 | 4.00 | 1.39 | 0.11 |
| Combined | -0.14 | -0.66 | -0.37 | 0.05 | 0.10 | 0.35 | -1.95 | 1.05 | 1.47 | 6.43 | 0.23 |

**Table 7 (continued)**

Panel E: Average returns and regression results for high loading – low loading (Hs – Ls) spread portfolios formed from sorts on size, B/M, and size factor loadings

| Size / B/M | Average | | Regression Slope Coefficients | | | | *t*-statistics for Slope Coefficients | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Portfolio | Returns | *t*-statistic | $\alpha_i^W$ | $\beta_i^W$ | $s_i^W$ | $h_i^W$ | $t(\alpha_i^W)$ | $t(\beta_i^W)$ | $t(s_i^W)$ | $t(h_i^W)$ | Adj $R^2$ |
| S/L Hs-Ls | 0.24 | 0.83 | -0.22 | 0.45 | 0.76 | -0.36 | -0.85 | 6.90 | 8.13 | -4.87 | 0.28 |
| S/M Hs-Ls | 0.17 | 0.76 | -0.30 | 0.48 | 0.60 | -0.22 | -1.70 | 10.73 | 9.48 | -4.38 | 0.40 |
| S/H Hs-Ls | 0.24 | 1.10 | -0.21 | 0.40 | 0.52 | -0.09 | -1.10 | 8.41 | 7.74 | -1.66 | 0.29 |
| M/L Hs-Ls | -0.23 | -0.79 | -0.64 | 0.30 | 0.51 | -0.01 | -2.30 | 4.22 | 5.11 | -0.11 | 0.12 |
| M/M Hs-Ls | 0.02 | 0.10 | -0.29 | 0.26 | 0.35 | -0.03 | -1.58 | 5.66 | 5.41 | -0.55 | 0.16 |
| M/H Hs-Ls | -0.08 | -0.44 | -0.48 | 0.37 | 0.35 | 0.03 | -2.84 | 8.74 | 5.76 | 0.61 | 0.26 |
| B/L Hs-Ls | 0.18 | 0.56 | -0.32 | 0.29 | 0.56 | 0.16 | -1.06 | 3.75 | 5.07 | 1.79 | 0.16 |
| B/M Hs-Ls | 0.31 | 1.45 | -0.02 | 0.17 | 0.35 | 0.15 | -0.13 | 3.37 | 4.93 | 2.58 | 0.18 |
| B/H Hs-Ls | 0.14 | 0.60 | -0.26 | 0.29 | 0.38 | 0.10 | -1.21 | 5.43 | 4.91 | 1.63 | 0.17 |
| Combined | 0.11 | 0.59 | -0.30 | 0.34 | 0.49 | -0.03 | -1.91 | 8.27 | 8.46 | -0.67 | 0.31 |

At the end of June of each year *t* (1983 to 2003), we sort all global stocks (with at least 12 months of return data in the previous 36 months) independently into three groups based on the first characteristic and into three groups based on the second characteristic. Nine portfolios are formed as the intersections of the two-way sorts. The nine portfolios are then each subdivided into three portfolios (Lc, Mc, or Hc) based on pre-formation factor loadings estimated using monthly returns over the previous 36 months (12 months minimum) as follows:

| | First Sorting Characteristic | Second Sorting Characteristic | Factor Loading Sort | Regression Model |
|---|---|---|---|---|
| Panel A | Size (S, M, or B) | Mom (L, M, or H) | Mom Loading (Hm–Lm) | Global HKK |
| Panel B | C/P (L, M, or H) | Mom (L, M, or H) | C/P Loading (Hc-Lc) | Global HKK |
| Panel C | C/P (L, M, or H) | Mom (L, M, or H) | Mom Loading (Hm-Lm) | Global HKK |
| Panel D | Size (S, M, or B) | B/M (L, M, or H) | B/M Loading (Hh-Lh) | Global Fama-French |
| Panel E | Size (S, M, or B) | B/M (L, M, or H) | Size Loading (Hs-Ls) | Global Fama-French |

The multifactor time-series regression models include:

Global HKK Model: $R_i - R_f = \alpha_i + \beta_i^W (R_M^W - R_f) + c_i^W F_{C/P}^W + m_i^W F_{Mom}^W + \varepsilon_i$, and
Global Fama-French Model: $R_i - R_f = \alpha_i + \beta_i^W (R_M^W - R_f) + s_i^W F_{Size}^W + h_i^W F_{B/M}^W + \varepsilon_i$.

For tests involving momentum and momentum factor loading, the sorting is done monthly as opposed to annually for other characteristics and factor loadings. The C/P and Mom factor loadings are orthogonalized with respect to one another using a cross-sectional regression. Similarly, the size and B/M factor loadings are orthogonalized with respect to one another. We report average returns and regression statistics for a spread portfolio of high and low factor loadings within each two-way sorted group, as well as for an equally weighted portfolio of the nine spread portfolios ("Combined").

**Figure 1**
**Global equity market firm sample by country, 1981-2003**

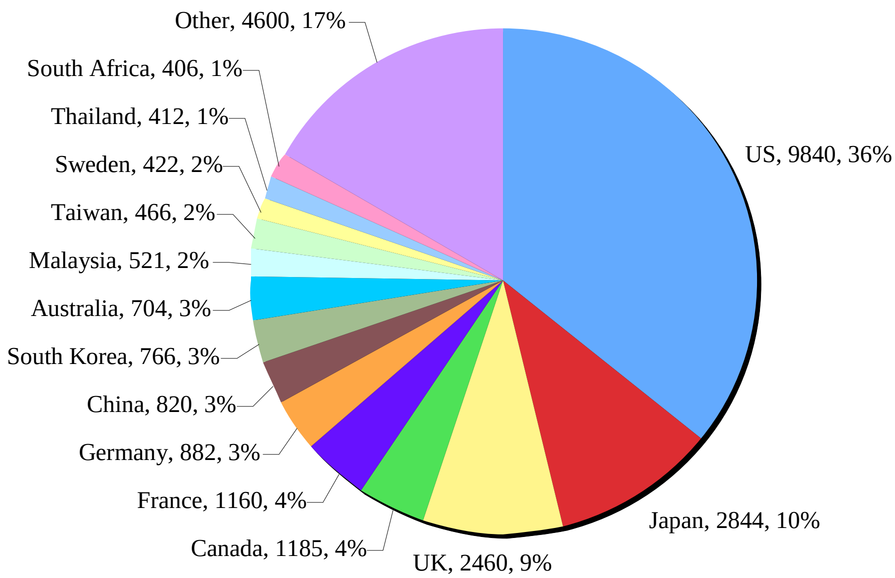

**Figure 1**
**Global equity market firm sample by country, 1981-2003**

The figure shows the distribution of our sample stocks by country. Next to each country name is the total number of sample stocks from that country that qualifies for analysis and the percentage of the total number of stocks in that country that this count represents. The sample selection criteria are described in Table 1.

**Figure 2**
**Global equity market firm sample by year, 1981 - 2003**

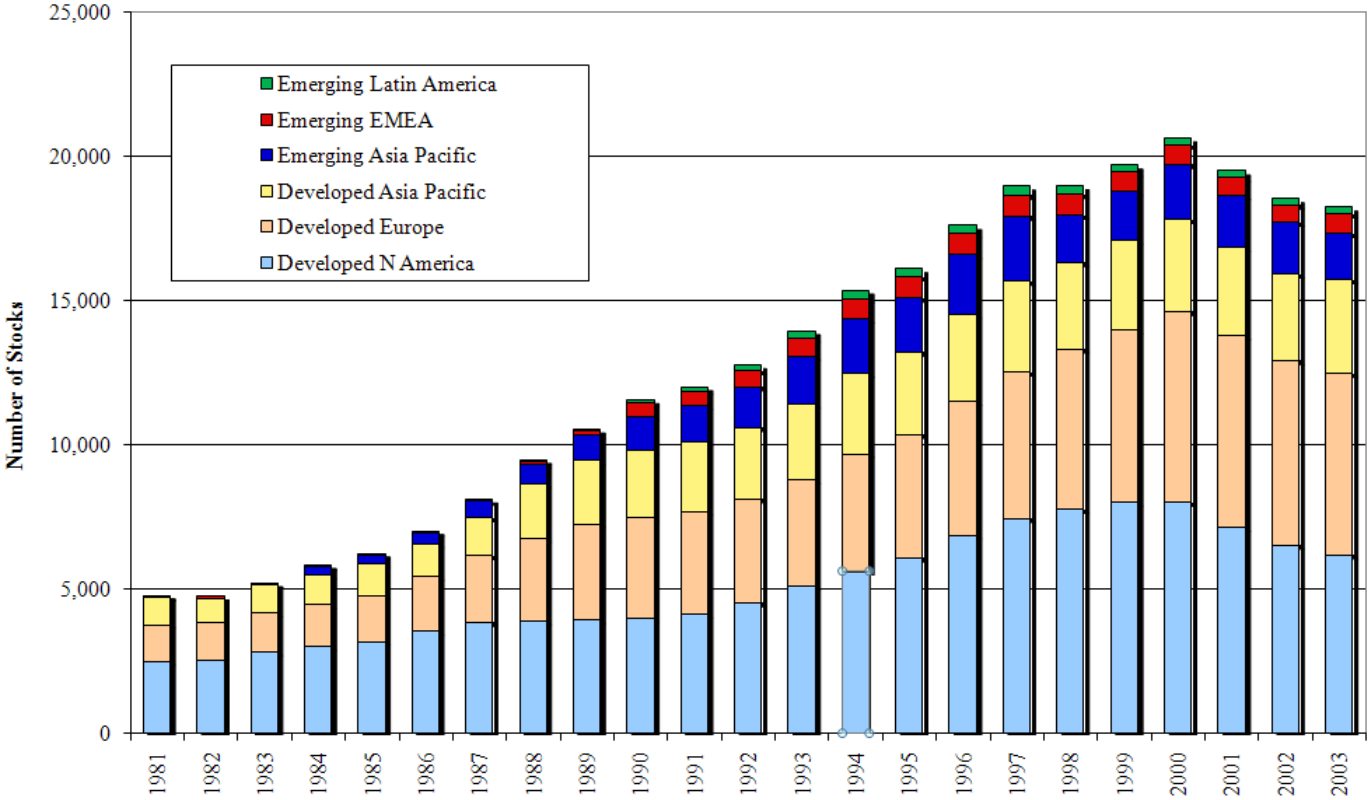

**Figure 2**
**Global equity market firm sample by year, 1981 - 2003**

The figure shows the distribution of our sample stocks by region and year. The sample selection criteria are described in Table 1. Six global regions are defined, including three emerging market regions (EMEA constitutes Europe, the Middle East, and Africa) and three developed market regions.

**Figure 3**
**Characteristic-based factor-mimicking portfolios sorted by country, July 1981 – December 2003**

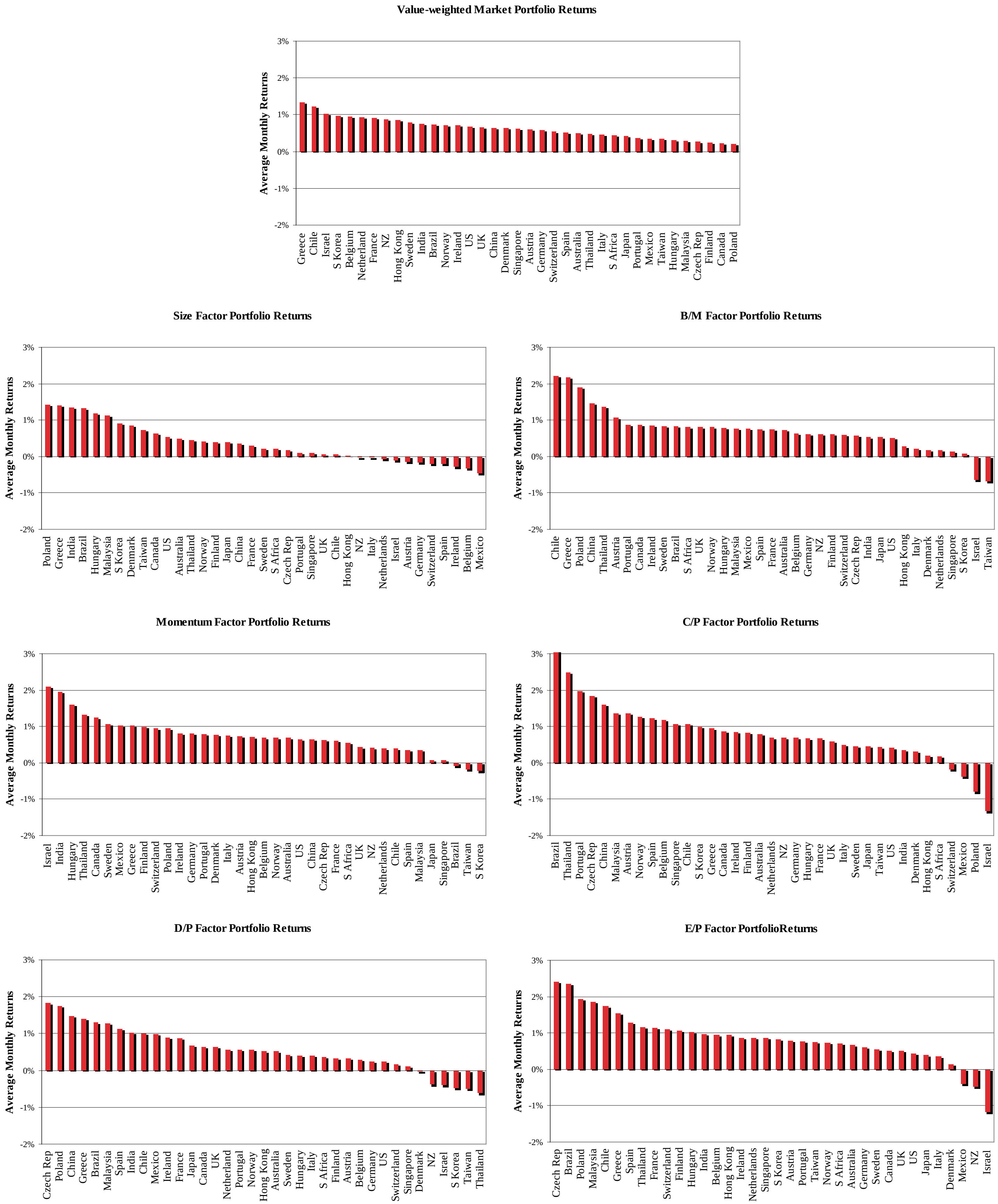

**Figure 3**
**Characteristic-based factor-mimicking portfolios sorted by country, July 1981 – December 2003**

The figure shows average returns on value-weighted country-specific factor-mimicking portfolios (FMPs). At the end of June of each year, stocks from each country are sorted into quintile portfolios based on end-of-June market cap (*size*), previous year-end book-to-market (B/M), cash flow-to-price (C/P), dividend-to-price (D/P), and earnings-to-price (E/P). The factor-mimicking portfolio (FMP) returns are then calculated over the next 12 months as the highest-quintile value-weighted returns minus the lowest-quintile returns, except for the size FMP returns, which are calculated as the smallest-quintile returns minus the biggest-quintile returns. The momentum FMP returns (*Mom*) are calculated based on Jegadeesh and Titman's (1993) six-month/six-month strategy (with one month skipped), which are long in the quintile of winners and short in the quintile of losers, held for six months and rebalanced every month. "Market" is the monthly US dollar-denominated return in excess of the one-month US Treasury bill yield for the country-specific value-weighted market portfolio.

**Appendix A**
**Worldscope Variables Definitions**

Worldscope presents all price and per share data on a calendar year-end basis for US firms and on a fiscal year-end basis for non-US firms. This timing convention applies to the construction of the variables detailed below.

| Variable | Definition | Datatype |
|---|---|---|
| Price/Book Value Ratio | This is the market price at year-end (WC05001) divided by the book value per share (WC05476). We take the inverse of this ratio to obtain the B/M ratio used in the analysis. The market price at year-end represents the closing price of the company's stocks on December 31 for US firms and at fiscal year-end for non-US firms. The book value per share represents the book value (proportioned common equity divided by outstanding shares) as of December 31 for US firms and at fiscal year-end for non-US firms. | WC09304 |
| Price/Cash Flow Ratio | This is the market price at year-end (WC05001) divided by cash flow per share (WC05501). We take the inverse of this ratio to obtain the C/P ratio used in the analysis. The cash flow per share represents the cash earnings per share of the company before all non-cash charges or credits, such as depreciation, amortization, deferred taxes, and provisions. | WC09604 |
| Dividend Yield | This is the dividend per share (WC05101) divided by the market price at year-end (WC05001). The dividend per share represents total dividends (including extra dividends and before normal withholding tax is deducted at the country's basic rate, but excluding the special tax credit available in some countries) per share declared during the calendar year for US firms and during the fiscal year for non-US firms. | WC09404 |
| Earnings Yield | This is the earnings per share (WC05201) divided by the market price at year-end (WC05001). Preferred stocks are included in the share base if they participate along with the common shares in the profits of the company. | WC09204 |
| Long-Term Debt/ Common Equity | This is the long-term debt (WC03251) divided by the common equity (WC03501). The long-term debt represents all interest-bearing financial obligations, excluding those due within one year, and is reported net of premiums or discounts. The common equity represents common shareholders' investments in a company. | WC08226 |

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**Footnotes**

[1] For size-related research, see Banz (1981), Reinganum (1981), Keim (1983), and, for global markets, Kato and Schallheim (1985), Heston, Rouwenhorst, and Wessels (1995), Hawawini and Keim (1999), and, most recently, Fama and French (2010). For research on value-related characteristics, see Fama and French (1992, 1996), Lakonishok, Shleifer, and Vishny (1994), and, for global markets, Capaul, Rowley, and Sharpe (1993), Chui and Wei (1998), Fama and French (1998, 2010), Achour, Harvey, Hopkins, and Lang (1999a, 1999b), and Estrada and Serra (2005). For momentum-related research, see Jegadeesh and Titman (1993, 2001), Carhart (1997), and, for global markets, Rouwenhorst (1998), Chan, Hameed, and Tong (2000), Chui, Titman, and Wei (2003), Griffin, Ji, and Martin (2003), and Fama and French (2010).

[2] Many recent studies use data from Datastream International due to its broad and deep coverage, e.g., Griffin (2002), Griffin, Ji, and Martin (2003), Lesmond (2005), and Lee (2011).

[3] Note that the Worldscope database carries only one representative type of share for each firm based on trading intensity and availability for foreign investors, while the Datastream International database carries more than one type of share for a given firm. In addition, Worldscope uses standard data definitions for financial accounting items in an attempt to minimize differences in accounting terminology and treatment across countries. The data is collected from corporate documents, such as annual reports and press releases, exchange and regulatory agency filings, and newswires. See www.thomsonreuters.com, "Worldscope Fundamentals", for more details. Worldscope incorporates data from its merger with Compact Disclosure, which occurred in June 1995 between Worldscope and Datastream's original holding company, Primark Corporation. This was prior to Worldscope's June 2000 acquisition by Thomson Financial.

[4] The industry classifications follow FTSE's Global Classification system (www.ftse.com) Level 4 groupings.

[5] The median US B/M ratio of 0.63 compares favorably with the 0.65 of the CRSP/Compustat US sample during the same period.

[6] See Ang, Liu, and Schwarz (2008) for a useful discussion of the importance of conducting tests at the firm level to limit losses of efficiency due to portfolio aggregation.

[7] Each coefficient in the cross-sectional regression can be considered as the return to a zero-cost minimum-variance portfolio with a weighted average of the corresponding regressor equal to one and weighted averages of all other regressors equal to zero. The weights are tilted towards firms with more volatile returns.

[8] We are concerned about overweighting extreme observations in the cross-sectional regressions. To mitigate exposure to such influential observations, we winsorize the cross-sectional sample at the top and bottom 0.5% of observations on B/M, C/P, D/P, E/P, and L/B. Observations beyond the extreme percentiles are set equal to the values of the ratios at those percentiles.

[9] We also experiment with a uniform price screen at the tenth percentile for each country (which represents, for example, $0.001 for the Philippines, $0.23 for the UK, $1 for the US, $14 for Denmark, and $64 for Switzerland) and find almost identical results.

[10] We do not use negative B/M, C/P, E/P, or zero D/P firms in forming the quintile portfolios.

[11] We offer a note of caution about direct comparisons of our size and B/M FMPs with Fama and French's (1993, 1996) SMB or HML. Fama and French break their US sample into two size groups (small and big) based on the median size of NYSE stocks, and into three book-to-market groups based on NYSE breakpoints for the bottom 30% (low), middle 40%, and top 30% (high). Their HML is then the return difference between the simple averages of the small and big of the high book-to-market category, and the simple averages of the small and big of the low book-to-market category. The goal is to

minimize the correlation between the SMB and HML factors. At this point, we have no strong priors as to which combinations of FMPs will rise to the challenge, so we consistently construct them based on quintile extremes for each variable.

[12] For example, the momentum FMP return for January 2001 is 1/6 of the return spread between the winners and losers from July 2000 through November 2000, 1/6 of the return spread between the winners and losers from June 2000 through October 2000, 1/6 of the return spread between the winners and losers from May 2000 through September 2000, 1/6 of the return spread between the winners and losers from April 2000 through August 2000, 1/6 of the return spread between the winners and losers from March 2000 through July 2000, and 1/6 of the return spread between the winners and losers from February 2000 through June 2000.

[13] An important limitation of this methodology is that it is unconditional and ignores the potential time variation in the premiums. We also ignore the fact that the slope coefficients may vary over time. Important conditional tests of international asset pricing models include Harvey (1991), Chan, Karolyi and Stulz (1992), Ferson and Harvey (1993, 1994), Dumas and Solnik (1995), Zhang (2006), and many others.

[14] Our country experiment includes only 20 countries for which the time series of returns extends for the full period of analysis. We also examine larger sets of country portfolios with shorter time horizons and obtain similar results. The construction of the characteristic-sorted decile portfolios is analogous to that of the quintile portfolios used to form the FMPs.

[15] Prior tests of the global CAPM with country portfolios have rejected the null hypothesis that the model is adequate in explaining country returns (Harvey, 1991, Table VII) but that is not always the case when investigated in unconditional form (see Dumas and Solnik, 1995, Table III). De Moor and Sercu (2005) evaluate 39 country test portfolios (their Table 35) and their Wald tests do not reject the null hypothesis at the 5% level. We reach a similar conclusion with our 20 country test portfolios.

[16] Our analysis extends beyond these three models and includes many of the models considered in the previous section and in Table 4. To save space, these robustness results are not reported.

[17] All of our tests are performed without weighting the two market portfolios in (5c) using their respective market capitalizations. Griffin (2002) performs similar tests for the US, the UK, Japan, and Canada with and without the market cap weightings, and finds that the results are consistent.

[18] We also test size and B/M against their corresponding factor loadings to calibrate our results with Daniel and Titman (1997), Davis, Fama, and French (2000), and Daniel, Titman, and Wei (2001) but for our global sample and for the period 1981 to 2003.

[19] To focus on the return spread that is uniquely associated with the C/P (B/M) factor loading, we orthogonalize the pre-formation C/P (B/M) factor loadings with respect to the momentum (size) factor loadings obtained from the same HKK (Fama-French) model regressions using a cross-sectional regression. All of our results in this section remain robust when we use the raw pre-formation factor loadings instead of the orthogonalized factor loadings in the third-dimension sort.

[20] In supplementary tests, we construct "covariance-balanced" portfolios in addition to the "characteristics-balanced" portfolios. That is, we run the portfolio sort first on the factor loadings and then on the characteristics, and then evaluate the average returns on the "H-L" characteristic spread portfolios within each factor loading group and in a combined manner across different factor loading groups (hence, "covariance-balanced"). The inferences from these covariance-balanced portfolios regarding the relevant characteristics versus their corresponding factor loadings are consistent with those obtained from the "characteristics-balanced" portfolios.

[21] In supplemental experiments, we repeat the global characteristics-versus-covariance experiment on C/P and momentum separately for three individual countries for which we feel the number of stocks is large enough to continue with portfolio sorting in a reliable way: the US, the UK, and Japan. For the US alone, the characteristics-balanced and covariance-balanced portfolios for both C/P and momentum cannot deliver a clear verdict in favor of either the covariance risk model or the characteristic model. For both Japan and the UK, momentum again produces mixed results but C/P shows positive evidence in favor of the covariance risk model.