Industry costs of equity: Evidence from frontier markets

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Abstract

Frontier markets are considered a good destination for international diversification due to their low level of integration with global markets. However, a diversification strategy into frontier markets with respect to country factors does not optimally capture their full diversification potential. Enhancing this strategy by simultaneously incorporating industry factors improves the ability to diversify portfolio risk. We investigate the industry costs of equity in frontier markets using five asset pricing models, taking into account the differences in five regions of frontier markets, namely, Africa, Eastern Europe, the Middle East, Latin America and Caribbean, and Asia. Additionally, we examine how well the explanatory factors of developed and emerging markets can explain industry returns in frontier markets. Our results precisely identified two industries in Africa, and two industries in Eastern Europe that exhibit segmentation from developed markets, and two industries in Africa and one industry in Asia show segmentation from emerging markets. However, we document the limited temporal variation in four regions of frontier markets indicating more precise estimates than US, UK, and European ones. Unlike previous studies, our findings show that the time-varying slopes in frontier markets follow a random-walk process. Consequently, the rolling regression of the five models could be of interest to fund managers and regulators.

Keywords: Asset pricing; frontier markets; cost of equity; industry; Fama and French

1. Introduction

Frontier markets are “emerging” emerging markets (Marshall et al., 2015), smaller and less accessible than the emerging markets (Berger et al., 2011). These markets have a low level of integration with global markets and offer international diversification benefits for investors (Speidell & Krohne, 2007). Berger et al. (2011) argue that investigating frontier markets provides an understanding of international diversification with respect to country factors (geographical diversification). However, if a country is segmented from world markets, its particular industries could be integrated with world markets due to industry-specific criteria such as foreign ownership and high volume exports, which implies that country segmentation (integration) does not preclude industry integration (segmentation) (Carrieri et al., 2004). Therefore, investment in frontier markets for international diversification based on country factors can be optimized if the investment strategy simultaneously considers diversification across industries. A diversification strategy at the industry level entails a better understanding of the performance of industry portfolios, which requires accurate costs of equity and a precise determination of the risk factors that significantly affect the industry returns.

The existing literature considers the industry cost of equity a crucial factor, because investors value potential investments based on it and policymakers use it to set the sale prices of utilities. Most of the textbooks raise the uncertainty issue of the cashflow, which is a consequence of the imprecise estimates of the cost of equity that has been used as a discount rate, and elaborate that the imprecise estimates of the cost of equity is caused by the time-varying risk loadings (Fama & French, 1997). The time-varying risk loadings can follow a mean reverting or random walk process, which significantly affect the model selection that produce the smallest forecast errors, and subsequently enhances the certainty of the cashflow and the revenue of the investment strategies. Previous studies investigate the cost of equity for industries in developed markets. For example, Fama and French (FF, 1997) use the capital asset pricing model (CAPM) and their three-factor models on 48 industry portfolios and find that the estimates of the cost of equity for industries in the United States are imprecise due to uncertainty about the true factor risk premium and the imprecise estimates of the industry’s loadings on risk factors. Gregory and Michou (2009) replicate FF's (1997) US analysis for UK industries, using four models on 35 industry portfolios. The authors conclude that similar to US industries, estimates of the UK industry's costs of equity are imprecise. More recently, Lutzenberger (2017) replicates FF's (1997) US analysis by using nine multifactor models on 117 industries from 16 European countries and concludes that these models provide imprecise estimates of the costs of equity due to large intertemporal variation of the risk factor slopes.

Although the findings of these three aforementioned studies indicate the impreciseness of the industry cost of equity, all of them favor using the static model for the long term-forecast of cost of equities, because it produces smaller forecast errors than the rolling and conditional models[1], implying that the time-varying risk loadings in these markets follow the mean-reverting process. To the best of our knowledge, the industry cost of equity in frontier markets has not been investigated in the literature. This gap, coupled with the findings of the previously mentioned studies of Speidell and Krohne (2007) and Carrieri et al. (2004), raises several research questions on optimizing the diversification strategy into frontier markets. To fill the gap, we focus on the following two research questions: i) whether the asset pricing models used in this study provide precise estimates of the cost of equity for industries in frontier markets and ii) whether industries in frontier markets differ in terms of asset pricing integration with developed and emerging markets.

Therefore, to provide insights into better country–industry diversification into frontier markets, this study investigates the cost of equity for industries in frontier markets, particularly in terms of the uncertainty surrounding the risk loadings using the CAPM, the three-factor model of FF (1993), Carhart's (1997) model, the five-factor model of FF (2015), and FF's (2018) six-factor model, taking into consideration the differentiation between five regions of frontier markets in Africa, Eastern Europe, Middle East, Latin America and Caribbean (LAC). Additionally, we examine the extent to which developed and emerging markets' risk factors can explain industry returns in frontier markets and precisely identify the industries that show segmentation with developed and emerging markets. We follow FF (1997) to estimate the models. Our sample consists of common stocks listed on the stock exchanges of 29 countries categorized by Standard & Poor's (S&P) as frontier markets from 2010 to 2021.

[1] This is true for the European markets if the manager wants to stick to the CAPM, otherwise, the conditional FF three-factor model is preferable for long-term forecast (Lutzenberger, 2017).

This study contributes to the literature in several ways. First, we investigate the preciseness of the estimates of the costs of equity for industries in frontier markets, taking into account the variation across the five regions. Previous studies examining the costs of equity for industries have focused primarily on the developed markets (e.g. FF (1997), Gregory and Michou (2009), and Lutzenberger (2017) investigate the US, UK, and European cost of industries, respectively), and all of them favor using the static regression for the long term-forecast of cost of equities because it produces smaller forecast errors, as a result of the mean-reverting process of the time-varying risk loadings. To the best of our knowledge, this is the first study that analyses the asset pricing dynamics at the industry level in frontier markets, and the findings support the premise that what happens in developed markets should not be copied in other markets. Unlike previous studies, our findings show that the time-varying risk loading in frontier markets follows a random walk process instead of a mean-reverting process. Second, this study contributes to the literature on frontier markets by extending the integration analysis to the industry level. Previous studies on frontier markets examine integration at the country level (Blackburn & Cakici, 2017; Zaremba & Maydybura, 2019). Asset pricing integration has been investigated in the literature by examining the power of the risk factors of developed markets in explaining equity returns in emerging and frontier markets. However, this is the first time this method is applied to industry portfolios. We precisely identify four industries and their relevant locations that exhibit asset pricing segmentation from developed markets and three industries and their relevant locations that exhibit segmentation from emerging markets. Third, this study offers important implications for fund managers. The findings show that the rolling CAPM and rolling FF three-factor model produce the smallest forecast errors for the short and long-term forecast horizon and, therefore, should be considered by fund managers for investment valuation.

The remainder of this paper is organized as follows. Section 2 reviews the literature on industry returns and frontier markets. Section 3 describes the data and methodology. Section 4 presents the results. Section 5 discusses the findings. Section 6 draws the conclusions.

2. Literature review

2.1 Industry portfolio

In terms of the industry costs of equity, FF (1997), Gregory and Michou (2009), and Lutzenberger (2017) investigate the industry costs of equity in the US, UK, and European markets, respectively. They document temporal variation of risk loadings across industries, making the cost of equity imprecise. On the other hand, Moskowitz and Grinblatt (1999) conclude that an industry momentum strategy (buying past industry winners and selling past industry losers) is more profitable than an individual stock momentum strategy, even after controlling for firm characteristics. The reason is that industry momentum always absorbs the momentum of individual stock, whereas the opposite is not the case. Chou et al. (2012) argue that asset pricing anomalies such as those pertaining to size, value, and momentum are associated with industry classification. Therefore, the authors conclude that the small size effect is significant only for firms whose capitalization is below their industry average. Additionally, the authors contend that the value effect is an intra-industry phenomenon, that the one-year momentum is an inter-industry phenomenon, and that the optimal asset pricing model should include interactions of the industry classification with rational and mispricing components. Hou and Robinson (2006) suggest that the asset pricing model should include features of the product market as a return factor, because their analysis shows that such features as industry concentration contribute to equity returns. The authors argue that distress risk is a proxy for industry concentration that is very sensitive to the business cycle and that firms in highly concentrated industries underperform firms in less concentrated industries, even after controlling for size, book-to-market, and momentum factors.

Bai and Green (2010) decompose the risk factor in emerging markets into country and industry components and conclude that the country effects before 2004 are stronger than the industry effects, but, from 2004 onward, the industry effects increase remarkably and surpass the country effects. The authors conclude that the increase in the importance of industry effects is greater for beta than for returns, with a one-year lead for the effect on beta over that on the return. Bai and Green (2020) later link the industry and country components to the performance of asset pricing models (specifically the local and global CAPMs) in emerging markets. They find that, before 1996, the country factor is an independent factor that explains the cross-sectional returns of stocks and, after 1996, when partial integration prevails, the country and industry factors become independent factors that explain stock returns. Therefore, the authors strongly recommend diversification across countries and industries simultaneously. Similarly, Umutlu and Bengitöz (2020) find that industry-based alphas are higher than stock-based alphas and therefore recommend using country–industry indexes to enhance international diversification strategies.

2.2 The frontier market context

More than 30 years since Morgan Stanley first introduced emerging markets in 1984, these markets have now actually emerged. Simultaneously, another group of markets, called frontier markets, has taken their place (Speidell & Krohne, 2007). Frontier markets are increasingly known as emerging emerging markets (Marshall et al., 2015) and are spread throughout Europe, Africa, Latin America, Asia, and the Middle East (Speidell & Krohne, 2007). Berger et al. (2011, P. 227) define frontier markets as "smaller, less accessible yet still investable countries in the developing world."

Recently, frontier markets have been recognized as a good destination for international diversification, but the number of studies focusing on these markets is limited. Speidell and Krohne (2007), Berger et al. (2011), and Samarakoon (2011) conclude that the correlation between frontier markets and world markets is low. Berger et al. (2011) argue that developed and emerging markets have a high correlation with world markets, with integration increasing over time, whereas frontier markets have a low correlation with world markets, with no variation in integration over time. Therefore, frontier markets offer diversification benefits in the form of risk reduction. For instance, US investors can reduce risk levels and achieve higher returns by diversifying their portfolios into emerging and frontier markets (Jayasuriya & Shambora, 2009).

Nevertheless, the interdependence between frontier and US markets during regular times is lower in magnitude during crisis time, and the US financial crisis was more contagious to frontier markets than to emerging markets (L. P. Samarakoon, 2011). Moreover, frontier markets from different regions do not have similar relationships with the leading markets; macro- and microeconomic factors in both frontier and leading markets affect the integration, which was, in its turn, affected by the financial crisis (Chen et al., 2014). Diversification into frontier markets has consistently been more beneficial to US investors compared to Australian investors, due to the difference in the economic structures of the US and Australian economics and the lower correlation between frontier and US markets compared to that between frontier and Australian markets (Sukumaran et al., 2015). Diversifying into frontier markets thus raises several concerns, such as liquidity levels, transaction costs, and volatility. Marshall et al. (2015) find that transaction costs are two and a half to three times greater than those in the US market; however, if the rebalancing frequency is not high, then investors can take advantage of diversification into frontier markets. Recently, Patel et al. (2022) have conducted a meta-literature review on financial market integration from 1981 to 2021 and find several papers indicating that frontier markets are the least integrated with global markets, which signals the importance of investigating asset allocation across different markets for portfolio diversification.

Regarding the explanatory power of asset pricing models in frontier markets, De Groot et al. (2012) conduct an analysis using the individual stocks of S&P Broad market index in 24 frontier markets and conclude that value, momentum, and local size effects exist in frontier markets, even after transaction costs are incorporated, and they are similar to those found in developed and emerging markets. However, the authors note that global risk factors cannot explain these effects and are not driven by country exposure or downside risk. Zaremba et al. (2019) use seven asset pricing models to investigate equity anomalies in 23 frontier markets based on the MSCI country classification and conclude that the anomalies in these markets are weak compared to those in developed markets. Moreover, the authors conclude that the Carhart model best explains the anomaly return, compared to other models, adding profitability and investment factors do not improve the model's explanatory power. Zaremba (2020) points out that performance persistence in frontier markets is driven by past short-term momentum and long-term cross-sectional variation.

Although much of the empirical asset pricing literature on equity returns pays particular attention to the decomposition of returns into industry and country components, the body of literature concerned with the cost of equity for industries is relatively small, and the relevant studies focus only on developed markets. Given that the adequate cost of equity estimations improves firms' valuation and diversification strategies, this study aims to investigate the industry costs of equity in frontier markets by using five asset pricing models on 10 industry portfolios returns.

Additionally, we identify the industries that show asset pricing integration with developed and emerging markets for diversification purposes.

3. Data and methodology

3.1. Sample selection

This study utilizes a data set of 29 equity markets that S&P has classified as frontier markets: namely, Argentina, Bahrain, Bangladesh, Botswana, Bulgaria, Ivory Coast, Croatia, Cyprus, Estonia, Ghana, Jamaica, Jordan, Kazakhstan, Kenya, Latvia, Lithuania, Mauritius, Morocco, Namibia, Nigeria, Oman, Panama, Romania, Slovenia, Sri Lanka, Trinidad and Tobago, Tunisia, Vietnam, and Zambia. S&P (2021) classifies these 29 countries as frontier markets based on several factors, such as macroeconomic conditions, political stability, legal property rights, trading, and settlement processes and conditions, therefore, these countries have similar risk profiles. We source the data from 2010 to 2021 from Bloomberg. Following FF (1996), we include only common stocks in the analysis, excluding preferred stocks, mutual funds, exchange-traded funds, trusts, real estate investment trusts, units, and foreign stocks. Additionally, we exclude financial firms, due to their high level of leverage, which is considered normal for financial firms but indicates financial distress for nonfinancial firms (FF, 1992). We retrieve the data in US dollars, and the total monthly returns are in percentages and adjusted for dividends and stock splits. Finally, we apply data screening to detect abnormal returns representing potential data errors, by excluding returns over 500% a month and below -98% a month (Zaremba et al., 2019). We exclude 74 observations and include delisted firms in the analysis to avoid survivorship bias.

To increase the power of our test, we incorporate the assumption of integration into the analysis. Therefore, we split the 29 frontier markets into five regions: Africa, Eastern Europe, the Middle East, Latin America and the Caribbean (LAC), and Asia, and subsequently, we allocate each region's stocks to 10 industry portfolios. Africa region includes Botswana, Ivory Coast, Ghana, Kenya, Mauritius, Morocco, Namibia, Nigeria, Tunisia, and Zambia. Eastern Europe includes Bulgaria, Cyprus, Croatia, Estonia, Lithuania, Latvia, Romania, and Slovenia. Middle East region includes, Jordan, Bahrain, and Oman. Latin America and Caribbean (LAC) region includes Argentina, Jamaica, Panama, and Trinidad and Tobago. Asia includes Bangladesh, Kazakhstan, Sri lanka, and Vietnam. In addition, it seems reasonable to assume regional integration with the formation and operation of regional trade agreements. For instance, the integration between African countries is reasonable due to the African continental free trade area agreement (AfcFTA) (Fofack, 2020). Similarly, the assumption of integration between the eastern European countries is reasonable as all of them are members of the European Economic Area (EEA). The Asia-pacific countries are also increasingly more connected within each other and with other economies (Didier et al., 2017). The Middle East region in our sample consists of three countries, two of them (Bahrain and Oman) are members of the gulf cooperation council (GCC), therefore, the integration assumption is rational. In addition, the intra-regional trade agreement boosts the integration between the Latin American and Caribbean countries (LAC) (World Bank, 2019).

Regarding industry portfolios, S&P has developed and uses the Global Industry Classification Standards (GICS), which classifies companies based on their business activities. We conduct our analysis based on the GICS sector level, which consists of 11 sectors (hereafter denoted as industries), to ensure having a reasonable number of stocks in each industry portfolio and a realistic level of diversification. These industry portfolios are communications, consumer discretionary, consumer staples, energy, health care, industrials, materials, real estate, utilities, and technology.

Table 1 presents the sample decomposition by country, industry, and region. Specifically, Panel A shows the sample decomposition by country. Our sample consists of data from 29 countries, allowing for broader geographical coverage than the work of Zaremba et al. (2019), which covers 23 countries, and of Blackburn and Cakici (2017), which covers 21 countries classified by MSCI as frontier markets. The total number of firms in 2021 is therefore 1,913. Panel B shows the sample decomposition by industry. We split our sample into 10 industry portfolios (after excluding the financial firms), compared to the 48 industry portfolios of FF (1997), the 35 industry portfolios of Gregory and Michou (2009), and the 117 industry portfolios of Lutzenberger (2017).

Panel C shows the sample decomposition by regions/industries. Most of the previous studies on frontier markets perform their analysis on all the combined stocks listed on the stock exchanges of the frontier markets (Berger et al., 2011; Samarakoon, 2011; Blackburn & Cakici, 2017; Zaremba *et al.*, 2019; Cagliesi & Guidi, 2021), except Blackburn and Cakici (2017) split the frontier markets into four regions (Europe, Africa, the Middle east, and Asia). In this study, and to increase the power of our analysis, we split our sample into five regions and split each region portfolio into 10 industry portfolios.

<Insert Table 1 near here>

3.2. Variables

We follow FF (2015) and collect the accounting variables for capitalization, the book-to-market ratio, operating profitability, and total assets to compute the breakpoints of firm characteristics such as size, value, profitability, and investment in June of each year. We employ the market capitalization value of June in year *t* to compute the size breakpoints and the book-to-market ratio to compute the value breakpoints (FF, 1993). The book-to-market ratio is equal to the book equity value for the last fiscal year ending in year t - 1 divided by the market value, which equals the number of shares outstanding multiplied by the share price in December of year t - 1. We exclude firms with a negative book equity value for the last fiscal year.

Due to the limited availability of several accounting variables, we follow Zaremba et al. (2019) and use net profit divided by the book equity value for the last fiscal year ending in year t - 1 as a proxy for operating profitability, to compute the breakpoints of profitability. Finally, following FF (2015), we employ total assets to calculate the breakpoints of the investment factor. The change in total assets is equal to the difference between the total assets of the fiscal year ending in year t - 2 and the total assets of the fiscal year ending in year t - 1 divided by total assets in year t - 2. Finally, we collect the factors of developed and emerging markets from the library of Kenneth French (2012).

3.3. Methodology and asset pricing models

In this study, we follow FF's (1997) method to investigate the industry costs of equity in frontier markets. In particular, we investigate the uncertainty about the risk loading estimates of the five asset pricing models. The selection of the following five models was motivated by previous studies, to allow for comparison between different markets.

The CAPM, developed by Sharpe (1964) and Lintner (1965) (for the details of the variables, see Table 2) can be written as

$$R_{it} - R_{Ft} = \alpha_i + \beta_i(R_{Mt} - R_{Ft}) + e_{it} \quad (1)$$

FF's (1993) three-factor model, an extension of the CAPM with two additional factors, *SMB* and *HML*, can be written as

$$R_{it} - R_{Ft} = \alpha_i + \beta_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + e_{it} \quad (2)$$

Carhart's (1997) model, an extension of FF's (1993) three-factor model with one additional factor, winners minus losers (*WML*), can be written as

$$R_{it} - R_{Ft} = \alpha_i + \beta_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + m_i + WML_t + e_{it} \quad (3)$$

The FF (2015) five-factor model, an extension of FF's (1993) three-factor model with the additional factors robust minus weak (*RMW*) and conservative minus aggressive (*CMA*), can be written as

$$R_{it} - R_{Ft} = \alpha_i + \beta_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it} \quad (4)$$

The six-factor model, presented by FF (2018) adding the momentum factor to their five-factor model, can be written as

$$R_{it} - R_{Ft} = \alpha_i + \beta_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + m_i WML_t + r_i RMW_t + c_i CMA_t + e_{it} \quad (5)$$

First, we assume that the risk loadings are constant. We estimate the static versions of the five models using ordinary least squares regressions. We run the diagnostic tests for autocorrelation, heteroscedasticity, and multicollinearity, and we correct the statistical inferences for heteroskedasticity and autocorrelation by using Newey–West standard error correction with auto-Akaike information criterion lags.

Second, to examine the precision of the estimates, we allow for time-varying risk loadings in the models by implementing two approaches: i) rolling regression and ii) conditional regression. Regarding the conditional models, we limit ourselves to the conditional CAPM, the FF three-factor model, and the Carhart model to allow for comparison with previous studies. To control for market variation, all the conditioning variables we use are net of their cross-sectional means if they are industry related; otherwise they are net of their time-series means. The conditional CAPM, for which we follow Gregory and Michou (2009) and employ lagged Treasury bill rates as a conditioning variable for the excess market returns, can be written as follows:

$$R_{it} - R_{Ft} = \alpha_i + \beta_{1i}(R_{Mt} - R_{Ft}) + \beta_{2i}(z_{it-1}[R_{Mt} - R_{Ft}]) + e_{it} \quad (6)$$

For the conditional FF three-factor model, we follow FF (1997) and employ the lagged natural logarithm of the market value *(ME)* of the industry i as a conditioning variable for *SMB*, and the lagged natural logarithm of book to market ratio (*BE/ME)* of industries i for *HML*, measured once per year in December, as follows:

$$R_{it} - R_{Ft} = \alpha_i + \beta_i(R_{Mt} - R_{Ft}) + s_{1i}SMB_t + s_{2i}\ln(ME_{it-1})\,SMB_t + h_{1i}HML_t + h_{2i}\ln\left(\frac{BE}{ME}\right)_{it-1} HML_t + e_{it} \quad (7)$$

For the conditional Carhart model, we follow Lutzenberger (2017) and employ the lagged momentum of industry returns as a conditioning variable for *WML*, measured as the industry's returns from year *t* - 12 to *t* - 2, as follows:

$$R_{it} - R_{Ft} = \alpha_i + \beta_i(R_{Mt} - R_{Ft}) + s_{1i}SMB_t + s_{2i}\ln(ME_{it-1})\,SMB_t + h_{1i}HML_t + h_{2i}\ln\left(\frac{BE}{ME}\right)_{it-1} HML_t + m_{1i}WML_t + m_{2i}(IR_{t-1})WML_t + e_{it} \quad (8)$$

Third, to compare the performance of the five asset pricing models in explaining the portfolio returns, we employ the Gibbons–Ross–Shanken (1989, GRS) test, which examines if all the intercepts of a set of time-series regressions are jointly equal to zero.

Fourth, the predictive properties of the models are of great interest to fund managers and regulators. Therefore, we conduct a forecast of cost of equity estimates at time horizons of one, 12, 36, and 60 months, using the static, rolling, and conditional versions of the five models. Lastly, to examine the asset pricing integration of industry portfolios with developed and emerging markets, we regress the returns of industry portfolios on the explanatory factors of these markets, so that we can identify industries that exhibit integration with these markets.

<Insert Table 2 near here>

3.4. Portfolio construction

3.4.1. Industry portfolios across regions

We allocate the stocks into five regions and then divide the stocks of each region into 10 industry portfolios based on the GICS classification (see Table A.1 in Appendix). For a firm to be included in the analysis, it must have an accounting variable for the fiscal year ending in calendar year *t* - 1 and monthly returns from July in year *t* to June *t* + 1. The six-month gap between the availability of fiscal values and return values is to allow time for the market to receive the accounting data for that year. At the end of June of year *t*, we compute the value-weighted returns of each industry portfolio, where the stock weight is equal to its June capitalization value divided by the total capitalization value of this portfolio in that year.

3.4.2. Mimicking portfolios

To mimic the underlying risk factors in equity returns related to size, value, profitability, investment, and momentum, we follow FF's (2015) method. This study investigates the industry returns in international markets, where there are plenty of tiny stocks. Hence, to avoid the domination of tiny stocks in the sorting, we follow FF (2012) to compute the breakpoints of the risk factors. Therefore, the size breakpoints are at the 90th and 10th percentiles, with big stocks are in the top 90% of the market cap, and small stocks are in the bottom 10% of market cap. For the same reason, the breakpoints of the book-to-market ratio are at the 30th and 70th percentiles for big stocks. These breakpoints are then applied to the set of small and big stocks to create three value portfolios, low, neutral, and high.

To construct the mimicking portfolios for size factor *SMB* and for value factor *HML*, for each year at the end of June, we sort the stocks based on size and the book-to-market ratio, and we construct the six portfolios *SL, SN, SH, BL, BN*, and *BH* by intersecting the two size and three value portfolios. From July of year *t* to June of year *t* + 1, we compute these six portfolios' monthly value-weighted returns. The size factor *SMB* is the difference between the equal-weighted average of the three small and three big stock portfolios. The value factor *HML* is the difference between the equal-weighted average of the high portfolios, *SH* and *BH*, and the low portfolios, *SL* and *BL* (see Table 3).

Similarly, for each year at the end of June, we sort the stocks based on size and operating profitability, size, and investment. We construct six portfolios *SW, SN, SR, BW, BN*, and *BR* by intersecting the two size portfolios and three profitability portfolios. We also construct other six portfolios *SC, SN, SA, BC, BN*, and *BA* by intersecting the two size portfolios and three investment portfolios. From July of year t to June of year *t* + 1, we compute these six portfolios' monthly value-weighted returns. The profitability factor *RWM* is the difference between the equal-weighted average of the robust portfolios, *SR* and *BR*, and the weak portfolios, *SW* and *BW*. The investment factor *CMA* is the difference between the equal-weighted average of the conservative portfolios, *SC* and *BC*, and the aggressive portfolios, *SA* and *BA* (see Table 3).

Lastly, following FF (2018), the momentum variable equals the average monthly returns for the years *t* - 12 to *t* - 2. We sort the stocks based on size and momentum. The six portfolios *SW, SN, SL, BW, BN*, and *BL* are constructed by intersecting the two size portfolios and three momentum portfolios, and they are updated monthly. The momentum factor *WLM* is the difference between the equal-weighted average of the winner portfolios, *SW* and *BW*, and the loser portfolios, *SL* and *BL* (see Table 3).

<Insert Table 3 near here>

4. Results

4.1. Static regression

Table 4 reports the estimates of the full-period regression for equations (1) to (5) of the five regions[2]. In this table we report the two parameters that measure the model's explanatory power, α measures the cross-sectional variation, and the Adj.$R^{2.}$ measures the time-series variation. Panel A represents the estimates of Africa region. The five models' estimates show that all the beta coefficients are positively significant across the 10 industry portfolios at the 1% level. The real estate portfolio has negative alphas range between -1.37 and -1.62 with robust *t* statistic at the 1% level across five models. The communications portfolio exhibits the lowest adjusted *R*-squared values that vary between 5% and 9%. The consumer discretionary exhibits the highest adjusted *R*-squared values that vary between 31% and 32%. The average adjusted *R*-squared value is 16% for CAPM, FF three-factor, and Five-factor model, and it is 15% for Carhart and FF six-factor models, which is lower than the US market (63%), the UK market (32%) and the European markets (38%) (FF,1997; Gregory & Michou, 2009; Lutzenberger,2017). These findings imply that adding risk factors to the CAPM does not improve its explanatory power.

Panel B represents the estimates of Eastern Europe. Similarly, the estimates from five models show that all the beta coefficients are positively significant across the 10 industry portfolios at the 1% level. The consumer staples and healthcare portfolios show significant positive alpha with robust *t* statistic at the 10%. The consumer discretionary portfolio shows a significant negative loading on

[2] Due to the lack of space, we could not tabulate all the parameters in table 4, we report only α, $t(\alpha)$, Adj. $R^{2.}$. However, the full tables include all the parameters and their relevant *t* statistics are available upon request.

the size factor across the five models, which indicates a size premium within this industry. The average adjusted *R*-squared varies between 35% and 36%, which is lower than the US market (63%), European markets (38%), but higher than and what Gregory and Michou (2009) find for the UK market (32%)(FF,1997; Gregory & Michou, 2009; Lutzenberger,2017).

Panel C represents the estimates of the Middle East. Unlike the previous two regions, the five model estimates show that the beta coefficients of the communications, energy, industrials, and materials portfolios are negatively significant, whereas the beta coefficients of the consumer staples, health care, technology, real estate, and utility portfolios are insignificantly negative. Additionally, the adjusted *R*-squared value in this region is very low compared to the previous two regions, which varies between 1% and 2%, implying a weak explanatory power of the risk factors that have been used to estimate the models. Only the technology portfolio has significant loading on the size factor. The technology, materials and real estate portfolios have significant positive loadings on the momentum factor, which explains the higher mean of the adjusted *R*-squared of the Carhart and six-factor models compared to the mean of the remaining models.

Panel D represents the estimates of LAC region. Similar to Africa and Eastern Europe region, the five models' estimates show that all the beta coefficients are positively significant across the 10 industry portfolios at the 1% level. Six industry portfolios have significant negative loadings on the size factor. Four industry portfolios have significant negative loadings on the value factor. Two industry portfolios have significant positive loading on the momentum factor. The energy portfolio exhibits the highest adjusted *R*-squared (34%) across the five models. The technology portfolios exhibit the lowest adjusted *R*-squared (10%) across the five models. The average adjusted *R*-squared across the 10 industries varies between 20% and 21%.

Panel E represents the estimates of Asia. The five models' estimates show that all the beta coefficients are positively significant across the 10 industry portfolios at the 1% level except the healthcare, technology, materials, and utilities portfolios. The healthcare portfolio has significant positive alphas range between 0.73 and 0.82 at the 10% level. The communication and consumer discretionary portfolios have significant negative loading on the size factor at the 10% level. The consumer discretionary portfolio has significant negative loadings on the value factor across the five models. Three industry portfolios have negative loadings on the investment factor, and two have negative loadings on the profitability factor. The real estate portfolio has the highest adjusted *R*-squared across the models and the health care has the lowest one. The average adjusted *R*-squared of the 10 industry portfolios vary between 6% and 7% across the five models.

The broad picture that emerges from Table 4 is that the adjusted *R*-squared values of the industry portfolios maintain the same pattern across the five models in the five regions. For instance, in Africa, the consumer discretionary portfolio records the highest adjusted *R*-squared value across the five models, and the communications portfolio records the lowest. In Eastern Europe, the industrials portfolio records the highest adjusted *R*-squared value across the five models whilst the real estate portfolio records the lowest. In the Middle East, the energy portfolio has the highest adjusted *R*-squared value across the five models. In LAC the energy (technology) portfolio records the highest (lowest) adjusted *R*-squared value across the five models. In Asia, the industrials (utility) portfolio has the highest (lowest) adjusted *R*-squared value across the five models. The best in-sample fit model varies across the five regions, overall the CAPM model is the best in-sample fit for the majority of the industries in Africa and Asia regions.

Lastly, the risk loading estimates of the five models in Table 4 seem precise, because their average standard errors range between 0.03 and 0.11 across the five regions, which are quite low. The corresponding figures for FF (1997) range between 0.04 and 0.07, and those for Lutzenberger (2017) range between 0.09 and 0.19. These low average standard errors imply that the industry costs of equity are precise, but this conclusion could be misleading, because the estimates of the full-period regression assume constant risk loadings, whereas industries experience growth and distress that can be evidenced by the temporal variation of risk loadings (FF, 1997). In the next section, we conduct rolling regression to examine if the risk loadings exhibit temporal variation.

<Insert Table 4 near here>

4.2 Rolling regression

We use rolling regression to document the temporal variation of regression slopes. We follow FF (1997), Gregory and Michou (2009), and Lutzenberger (2017) and conduct rolling regression to compute the implied standard deviation of each portfolio's true slope in the five regions. The aforementioned studies used a rolling regression window of 60 prior monthly returns. In this study, using 60 prior monthly returns is costly, due to the short period of the data set. We therefore use a rolling regression window of 20 prior monthly returns, which is proportionally equivalent to the 60 prior monthly returns relative to the period of the data set. Following FF (1997), the implied standard deviation of true factor slopes is the square root of the difference between the time-series variance of the portfolio's slope estimates generated by rolling regression and the average of the estimation error variances of the same slope estimates, as in the following equation:

$$\sigma(\text{true}) = [\sigma^2(\text{time series}) - \sigma^2(\text{estimation error})]^{1/2} \tag{9}$$

If the average estimation error variance exceeds the time-series variance, then the implied standard deviation of the true factor slope is set to zero.

Given that the slope coefficients have a stationary distribution, the implied standard deviation of the true slope reflects the distance between the observation of the slope estimated by a rolling regression and the true long-term average slope. Table 5 shows the dissimilarity between the regions in terms of the temporal variation of slopes. For instance, Africa, Eastern Europe, the Middle East, and LAC show limited variation in slopes, since the means of all the slopes are different from zero. The limited intertemporal variation in risk loadings is evidenced by the large proportion of industries for which the implied standard deviation is equal to zero. The implied standard deviation of the market, size, and value slopes of the FF three-factor are 0.03, 0.02, 0.03 in Eastern Europe and 0.01, 0,02, and 0.04 in the Middle East, respectively. These values are lower than the findings of FF (1997) in the US market (0.087, 0.135, and 0.170, respectively); Gregory and Michou (2009) in the UK market (0.167, 0.176, and 0.165, respectively); and Lutzenberger (2017) in the European markets (0.18, 0,18, and 0.36, respectively). These figures indicate that the true sensitivity to risk factors in Eastern Europe and the Middle East is less volatile than in the US, UK, and European markets. Subsequently, the industry costs of equity in these two regions are more precise than in the US, UK, and European markets, which is of importance to potential investors who want to diversify into frontier markets and to policymakers. However, Table 5 also shows a high intertemporal variation of the market factor in Asia, of the size factor in Africa, and of the value factor in LAC, relative to the aforementioned figures in the US, UK, and European markets.

<Insert Table 5 near here>

4.3. Conditional regression

Conditional regression is another method of documenting the temporal variation of the risk loadings. FF (1997) state the logic of the conditional regression as follows: i) when the sizes of an industry's firms decrease, the size loadings on the *SMB* factor increase, which can be evidenced by the negative conditional size slopes, and ii) when the industry's firms become distressed, the book-to-market ratio and its loading on the *HML* factor increase, which can be evidenced by the positive conditional book-to-market slope. Table 6 presents the estimates of the conditional regressions of the three models (6) to (8). In this table we report only the slopes of the conditional variables and the Adj. R^2. The estimates of the conditional CAPM show that the conditioning factor (Treasury bill rates) exhibits limited explanatory power, with only the healthcare portfolio in Africa and Eastern Europe show significant negative conditional beta. This result implies that the temporal variation of the market slope is not associated with Treasury bill rates, except for the healthcare industry in Africa and Eastern Europe. The estimates of the conditional FF three-factor model show that the technology and materials portfolios in LAC have significant negative conditional slopes of the size factor, implying that the limited temporal variation of the size slopes of these two portfolios is associated with the underlying change in industry size. For the book-to-market variable, the estimates of the five regions did not show any positive significant conditional slope, implying that the time-varying slopes of the book-to-market are not associated with the book-to-market ratio. The conditional Carhart model shows that only the energy portfolio in Asia exhibits a significant positive conditional momentum slope, suggesting that the temporal variation of momentum risk loadings is not associated with industry momentum for the remaining industries and regions.

These findings reveal that the explanatory power of the conditional regression is very limited, yet it improves for the static version in the Middle East and Asia, which is consistent with the findings of FF (1997) and Lutzenberger (2017), and it does not improve for the static model in Africa, Eastern Europe, LAC which is consistent with the results of Gregory and Michou (2009).

<Insert Table 6 near here>

4.4. Forecast

Forecasting methods are important to fund managers and allow them to make informed decisions. FF (1997) distinguish between long- and short-term forecasting. For short-term forecasting, they conclude for the US industries that the rolling regression's estimates are not better or worse than the estimates from the full-period constant slope regression. For long-term forecasting, they suggest using rolling or conditional regression to estimate the cost of equity if the true risk loadings are generated by random walk, and using the full-period constant slope regression if the true risk loadings are mean reverting. We follow FF (1997) and carry out the forecasts of the cost of equity estimates at time horizons of one, 12, and 36 months by using static, rolling, and conditional regressions. We add the intercept term when we estimate the risk loadings, and we then drop it when we estimate the forecasts.

Table 7 presents the forecast estimates of the five regions, and it exhibit significant variation between them. The magnitude of the average absolute forecast errors in Eastern Europe, the Middle East, and Asia are greater than those reported by FF (1997), but lower than those reported by Gregory and Michou (2009). The rolling regression of the three models dominates the static and conditional regression producing the lowest average absolute forecast errors and average standard deviations for all forecast horizons in the five regions. The dominance of rolling regression over the full-period static regression across different short- and long-term horizons signifies that the true risk loadings of the size and value factors in frontier markets are generated by random walk, in contrast to the true risk loadings of FF (1997) and Lutzenberger (2017), which are mean reverting. Additionally, the longer the forecasting horizon, the lower the absolute forecast errors and its relevant standard deviation in the five regions except in Asia. It is important to highlight that the forecast error terms of the conditional regression of the three models are significantly higher than the forecast error terms of these models using rolling regression. This difference signals that the conditioning variables we use in these two models are not good proxies for sensitivity to the relevant factors. These findings provide insights to fund managers considering diversifying into frontier markets. Fund managers should consider the rolling regression for short- and long-term forecasts, either for the CAPM or the multi-factor models.

<Insert Table 7 near here>

4.5. GRS test

We use the *GRS* test, developed by Gibbons et al. (1989), to examine if all the intercepts of a set of time-series regressions are jointly equal to zero. This test follows the *F*-distribution and assumes that the parameters' standard errors are independent and identically and normally distributed:

$$GRS = \left(\frac{T}{N}\right)\left(\frac{T-N-L}{T-L-1}\right)\left[\frac{\hat{a}'\hat{\Sigma}^{-1}\hat{a}}{1+\bar{\mu}'\hat{\Omega}^{-1}\bar{\mu}}\right] \quad (10)$$

where T is the size of the sample, N is the number of portfolios, L is the number of explanatory factors, $\hat{a}$ is the vector of intercepts, $\hat{\Sigma}$ is the sample covariance matrix of the residual, $\bar{\mu}$ is the vector of the sample mean, and $\hat{\Omega}$ is the sample covariance matrix of the explanatory factors. The test has an *F*-distribution with degrees of freedom equal to N and T - N - L, and the null hypothesis states that all the regression intercepts are jointly equal to zero.

Table 8, panel A presents the *GRS* estimates of Africa. It shows that the *GRS* test rejects the null hypothesis that all the intercepts are jointly equal to zero for the 10 industry portfolios at 5% level for the CAPM, FF five-factor models, and six-factor model and fails to reject the null hypothesis at the 5% level for the FF three-factor model, and the Carhart mode. This result suggests that the FF three-factor, and Carhart model can correctly explain the monthly returns of these industry returns in Africa, whereas the other models cannot, with the FF three-factor model exhibiting superior performance. The superiority of the FF three-factor model is evidenced by the higher average adjusted *R*-squared value of 0.16, compared to 0.15 by the Carhart model, accompanied with identical average absolute intercepts of 0.42. FF (1997) speculate that the *GRS* rejection is driven by the negative correlation between the intercepts and the value slopes, and this negative correlation is driven by the dynamics of growth and distress, which is evidenced by the time-varying risk loadings. The rolling regression estimates in Table 5 document the temporal variation of risk loadings, which confirms the result of the *GRS* test.

Panel B, C, D, E present the *GRS* test estimates of Eastern Europe, the Middle East, LAC, and Asia, respectively. The four panels show that the GRS test cannot reject the null hypothesis that all the intercepts are jointly equal to zero for the 10 industry portfolios in the four regions, as all the *P* values are higher than 0.05, with the CAPM model exhibiting superior performance evidenced by the lower average absolute intercepts compared to the other models' intercepts.

<Insert Table 8 near here>

4.6. The explanatory power of developed and emerging markets' risk factors

FF (2012) suggest that the power of global explanatory returns in explaining the average returns of global and local portfolios is evidence of market integration. The integration level in frontier markets is crucial for international investors considering diversification into frontier markets. However, country segmentation does not preclude industry integration (Carrieri et al., 2004). Therefore, examining the asset pricing integration of industry portfolios with developed and emerging markets aligns with the objective of this study and enhances the diversification strategy into frontier markets. To identify the industries that exhibit integrated asset pricing, we examine the extent to which the developed and emerging market factors can explain the cross-sectional returns of industry portfolios in frontier markets.

To estimate the five asset pricing models, we use the developed and emerging market risk factors as the right-hand side (RHS) explanatory factors, and the value-weighted returns of industries as the left-hand side (LHS) portfolios. Table 9 presents the regression estimates using developed market factors for the five regions. Panel A presents the estimates of the five models of Africa region, which show that the communications portfolios exhibit significant negative alphas at the 10% level, and the real estate portfolio exhibits highly significant negative alphas at the 1% level. These estimates signify that the developed market factors cannot explain the returns of these two industries in Africa, implying that the asset pricing of these industries is not integrated with the developed markets. On the other hand, the nonsignificant intercepts of the remaining industries show that the factors of developed markets can explain their returns and subsequently suggests that the asset pricing of these industries in Africa is integrated with the developed markets. Taken together and following Blackburn and Cakici (2017), the estimates suggest that only the asset pricing of the communication and real estate industry portfolios in Africa shows segmentation with developed markets. Panel B presents the estimates of Eastern Europe. The five models show that the communications portfolio exhibits significant negative alphas at the 10% level, and the energy portfolio exhibits highly significant negative alphas at the 1% level. These estimates signify that the developed market factors cannot explain the returns of these two industries in Eastern Europe, implying that the asset pricing of these industries is not integrated with the developed markets, whereas the nonsignificant intercepts of the remaining industries suggest that the asset pricing of these industries is integrated with the developed markets. Panel C, D, and E represent the Middle East, LAC, and Asia's estimates, respectively. The estimates of the five models did not show any significant alpha across the 10 industries and three regions, implying that the developed market factors can explain the returns of the industries in these regions, and that the asset pricing of these industries is integrated with the developed markets.

Similarly, we regress the value-weighted returns of the industry portfolios of the five regions of frontier market (LHS) onto the factors of emerging markets (RHS). Table 10 shows the regression estimates using emerging market factors. Panel A, presents the estimates of Africa. Similar to table 9, the estimates of the five models show that the communications portfolios exhibit significant negative alphas at the 10% and 5% levels, and the real estate portfolio exhibits highly significant negative alphas at the 1% level. These estimates signify that the emerging market factors cannot explain the returns of these two industries in Africa, implying that the asset pricing of these industries is not integrated with the emerging markets. Subsequently, the estimates suggest that only the asset pricing of the communication and real estate industry portfolios shows segmentation with emerging markets, and the remaining industries exhibit integration. Panel B, C, and D represent the estimates of Eastern Europe, the Middle East, LAC, respectively. The estimates of the five models did not show any significant alpha across the 10 industries and three regions, implying that the emerging market factors can explain the returns of the industries in these regions, and that the asset pricing of these industries is integrated with the emerging markets. Panel E, represents the estimates of Asia. The estimates of the five models show that the healthcare portfolio exhibits significant positive alphas at the 10% level. These estimates signify that the emerging market factors cannot explain the returns of the healthcare industry in Asia, implying that the asset pricing of this industry is not integrated with the emerging markets.

In sum, our findings show that the asset pricing of the communication and real estate industries in Africa, and the communications and energy industries in Eastern Europe are segmented from developed markets. This suggests that investors in developed markets considering international diversification into frontier markets should consider these industries in these regions. On the other hand, it is beneficial for investors in emerging markets considering international diversification into frontier markets to consider communications and real estate in Africa, and healthcare industry in Asia as they show segmentation with emerging markets.

<Insert Table 9 near here>

<Insert Table 10 near here>

5. Discussion

Unlike the previous studies, this study investigates the industry costs of equity in frontier markets by using five asset pricing models. Table 11 compares this study's results and the results of previous studies.

We include two major statistical measures in Table 11: the adjusted *R*-squared that explain the time-series variation, and the intercepts that explain the cross-sectional variation. The adj. *R*-squared values show that the explanatory power of the local risk factors in frontier markets varies across the five regions. In frontier markets, Africa records the highest adj. *R*-squared that range between 35% and 36%, which is lower than what FF (1997) find for the US market (63%) and what Lutzenberger (2017) finds for the European markets (38%), but higher than and what Gregory and Michou (2009) find for the UK market (32%). The adj. *R*-squared of Eastern Europe, the Middle East, Lac, and Asia are lower than the figures of the US, UK, and European markets.

In frontier markets, Asia records the higher intercepts across the three models (0.31, 0.42, 0.48, respectively). Middle East records the lowest intercepts across the three models (-0.004. 0.104. 0.017, respectively), which is lower than the figures that FF (1997) find for the US industries (0.05, -

0.03, -[3], respectively) and the figures that Lutzenberger (2017) finds for the European industries (0.15, 0.20, 0.24, respectively), but higher than the figures the Gregory and Michou (2009) finds for the UK industries (0.001, 0.001, 0.001 respectively). The true sensitivity to the risk factor in Eastern Europe and the Middle East, represented by the implied standard deviation of the risk factor's slopes, are less volatile than in the US, UK, and European markets, whereas they are more volatile in Africa, LAC, and Asia.

Taken together, the industry portfolios in different regions in frontier markets show dissimilarities, in terms of the explanatory power of the risk factors and the integration with developed and emerging markets. However, it is essential to highlight that adding risk factors to the CAPM model improves its explanatory power only in LAC region. Therefore, using the simple CAPM model in Africa, Eastern Europe, the Middle East, and Asia to estimate the cost of equity is empirically justified as the rational model that can capture the risk factor that drives the equity prices.

<Insert Table 11 near here>

6. Conclusion

Frontier markets have recently been considered an attractive destination for international diversification, due to their low integration with developed markets. However, the fact that country segmentation does not preclude industry integration (Carrieri et al., 2004) raises the question of maintaining an efficient diversification strategy into frontier markets. This question along with the limited research on frontier markets prompted us to undertake this study. First, our study investigates the preciseness of the industry costs of equity of 10 industry portfolios across five regions in frontier markets, using five asset pricing models, namely, the CAPM (Sharpe, 1964; Lintner, 1965), the FF (1993) three-factor model, the Carhart (1997) four-factor model, and the FF (2015) five- and the FF (2018) six-factor models. We uncover the uncertainty of risk factors that can explain the industry returns in frontier markets. Second, this study aims to identify the industries

[3] This is a missing value because FF (1997) did not examine the Carhart model in their paper.

that show asset pricing integration with developed and emerging markets to enhance diversification into frontier markets.

Our findings can be summarized as follows. First, the analysis indicates that the industry costs of equity in frontier markets are imprecise due to the temporal variation of risk loadings. However, the implied standard deviation signifies that the temporal variation varies across the regions. For instance, the temporal variation is very limited in Eastern Europe and the Middle East, which makes the true sensitivity to risk factors in these two regions less volatile than in the US, UK, and European markets, and subsequently, the industry costs of equity in these two regions are more precise than in the US, UK, and European markets. The variation between regions also applies to the *GRS* test; for instance, in Africa the *GRS* test fails to reject the null hypothesis that all the intercepts are jointly equal to zero for the FF three-factor model and for the Carhart model. Additionally, the *GRS* test cannot reject the null hypothesis that all the intercepts are jointly equal to zero for the 10 industry portfolios in Eastern Europe, the Middle East, LAC, and Asia. Third, the estimates show that the asset pricing of the communication and real estate industries in Africa, and the communications and energy industries in Eastern Europe are segmented from developed markets, which makes them good potential investment for investors in developed markets considering diversification into frontier markets. Similarly, it is beneficial for investors in emerging markets considering international diversification into frontier markets to consider communications and real estate in Africa, and healthcare industry in Asia as they show segmentation with emerging markets. Fourth, unlike previous studies, our findings show that the rolling regression of the five models produces the smallest error for short-term and long-term forecast horizons implying that the time-varying slopes in frontier markets are random walk, which offer practical insights to fund managers who aim to diversify into frontier markets.

We acknowledge that this study has limitations. First, we use a short period, because many of the stock exchanges in frontier markets are relatively new and do not have a long period of historical data. We are aware that the short sample period reduces the power of the test, however the highly diversified portfolios (stocks from 29 countries) boost the precision of the intercepts and subsequently increase the fits of the regression (FF, 2012). Future studies could thus improve our insights by extending the sample period. Second, although we investigate the temporal variation of risk loadings, we did not scrutinize the reason for it. Therefore, future studies could analyze the reasons for the limited temporal variation of risk loadings in frontier markets and investigate the relations between the factors found to be significant and the method used for factor construction.

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Table 1: Sample decomposition

Panel A: Sample decomposition by country

Country	No. of firms	Market value	Country	No. of firms	Market value
Argentina	101	70,572.16	Lithuania	28	2,932.66
Bahrain	43	18,767.91	Mauritius	95	5,680.91
Bangladesh	312	33,535.98	Morocco	76	5,680.91
Botswana	31	10,293.69	Namibia	39	122,859.7
Bulgaria	72	3,726.21	Nigeria	155	52,474.70
Ivory Coast	30	3,654.53	Oman	25	11,507.16
Croatia	104	17,269.67	Panama	30	13,266.22
Cyprus	55	1,685.34	Romania	383	814,767.5
Estonia	24	2,425.39	Slovenia	32	6,386.80
Ghana	37	24,165.22	Sri Lanka	308	16,513.96
Jamaica	63	6,506.663	Trinidad	34	16,948.1
Jordan	173	21,923.95	Tunisia	79	8,388.92
Kazakhstan	200	49,793.16	Vietnam	339	5,151.28
Kenya	64	9,128.91	Zambia	25	26,391.42
Latvia	15	691.927			

Panel B: Decomposition by industry

Industry	No. of firms	Market value	Industry	No. of firms	Market value
Communications	63	106,541.2	Industrials	378	160,114.7
Consumer discretionary	318	218,216.6	Materials	229	75,280.97
Consumer staples	258	53,169.6	Real estate	123	12,605.95
Energy	90	44,344.4	Utilities	66	47,136.09
Health care	70	100,304.7	Technology	52	122,051.2

Panel C: Decomposition by region

Industry	Africa	Eastern Europe	Middle East	LAC	Asia
Communications	13	7	6	7	26
Consumer discretionary	28	80	22	11	150
Consumer staples	63	50	14	21	94
Energy	21	19	4	6	33
Health care	8	13	6	7	34
Industrials	43	93	23	15	185
Technology	14	16	5	3	18
Materials	39	29	19	9	113
Real estate	19	27	36	4	33
Utilities	10	11	4	10	27

Note: The market value is the average market value, in millions of US dollars, of firms that have available market value data. The total number of observations is 183,232.

Table 2: Variables definitions

R_{it}	Monthly total return on portfolio i for period t.
R_{Ft}	The risk-free rate of return for period t (one-month Treasury bills).
R_{Mt}	Return on the value-weight market portfolio.
α_i	Intercept term for portfolio i (represents the abnormal return).
β_i	Regression slope of portfolio i (represents the portfolio's exposure to market returns).
e_{it}	Error term of portfolio i and period t.
SMB	Return on a portfolio of small stocks minus the return on a portfolio of big stocks.
HML	Return on a portfolio with a high book-to-market ratio minus the return on a portfolio with a low book-to-market ratio.
RMW	Return on a portfolio of stocks with robust profitability minus the return on a portfolio of stocks with weak profitability.
CMA	Return on a portfolio of stocks with conservative investment minus the return on a portfolio of stocks with aggressive investment.
WML	Return on a portfolio of winner stocks minus the return on a portfolio of loser stocks.
s_i, h_i, r_i, c_i, m_i	Slopes representing the portfolio exposure to size, value, profitability, investment, and momentum factors.
Z_{t-1}	Vector of lagged information, used as a conditioning variable.
ME	Market value of industry i
BE/ME	Book to market ratio of industry i

Table 3: Risk factor calculations

Asset pricing risk factors	**Acronym**	**Factor equation**
Size factor: small minus big	*SMB*	$SMB_{B/M} = (SH + SN + SL)/3 - (BH + BN + BL)/3$
		$SMB_{OP} = (SR + SN + SW)/3 - (BR + BN + BW)/3$
		$SMB_{INV} = (SC + SN + SA)/3 - (BC + BN + BA)/3$
		$SMB_{Five\text{-}factor} = (SMB_{B/M} + SMB_{OP} + SMB_{INV})/3$
Value factor: high minus low	*HML*	$HML = (SH + BH)/2 - (SL + BL)/2$
Momentum factor: winner minus loser	*WML*	$WML = (SW + BW)/2 - (SL + BL)/2$
Profitability factor: robust minus weak	*RMW*	$RMW = (SR + BR)/2 - (SW + BW)/2$
Investment factor: conservative minus aggressive	*CMA*	$CMA = (SC + BC)/2 - (SA + BA)/2$

Table 4: Static regression

	Communication services	Consumer discretionary	Consumer staples	Energy	Health care	Industrials	Technology	Materials	Real estate	Utilities	Mean
Panel A: Africa											
CAPM											
α	-0.80	-0.18	-0.34	-0.12	0.55	-0.01	0.45	-0.08	-1.37	0.25	-0.17
t(α)	(-1.39)	(-0.41)	(-0.68)	(-0.21)	(0.97)	(-0.02)	(1.04)	(-0.13)	(-2.67)***	(0.64)	
Adj. R^2	0.05	0.32	0.17	0.08	0.10	0.23	0.15	0.17	0.11	0.22	0.16
FF Three-factor model											
α	-0.72	-0.07	-0.37	-0.41	0.36	-0.09	0.55	-0.13	-1.49	0.04	-0.23
t(α)	(-1.14)	(-0.16)	(-0.72)	(-0.60)	(0.56)	(-0.19)	(1.15)	(-0.18)	(-2.58)***	(0.10)	
Adj. R^2	0.09	0.32	0.16	0.07	0.09	0.23	0.15	0.16	0.10	0.22	0.16
FF five-factor model											
α	-0.82	-0.07	-0.42	-0.51	0.26	-0.07	0.57	-0.21	-1.58	0.02	-0.28
t(α)	(-1.31)	(-0.14)	(-0.82)	(-0.76)	(0.41)	(-0.15)	(1.16)	(-0.31)	(-2.76)***	(0.05)	
Adj. R^2	0.10	0.31	0.15	0.08	0.11	0.21	0.13	0.16	0.12	0.21	0.16
Carhart model											
α	-0.75	-0.02	-0.33	-0.29	0.37	-0.08	0.62	-0.09	-1.50	0.12	-0.19
t(α)	(-1.17)	(-0.04)	(-0.63)	(-0.42)	(0.58)	(-0.17)	(1.28)	(-0.13)	(-2.57)***	(0.28)	
Adj. R^2	0.08	0.32	0.15	0.07	0.08	0.22	0.14	0.15	0.09	0.22	0.15
Six-factor model											
α	-0.88	-0.01	-0.38	-0.41	0.25	-0.05	0.64	-0.19	-1.62	0.11	-0.26
t(α)	(-1.37)	(-0.02)	(-0.68)	(-0.59)	(0.39)	(-0.12)	(1.30)	(-0.28)	(-2.78)***	(0.24)	
Adj. R^2	0.09	0.31	0.15	0.07	0.10	0.21	0.13	0.15	0.11	0.21	0.15
Panel B: Eastern Europe											
CAPM											
α	-0.23	0.25	0.44	-0.22	0.60	0.30	0.45	0.53	0.28	0.41	0.28
t(α)	(-0.78)	(0.76)	(1.55)	(-0.60)	(1.56)	(1.07)	(1.03)	(1.13)	(0.84)	(1.59)	
Adj. R^2	0.42	0.47	0.37	0.38	0.42	0.50	0.27	0.28	0.19	0.31	0.36
FF Three-factor model											
α	-0.20	0.43	0.55	-0.16	0.84	0.45	0.41	0.49	0.28	0.43	0.35
t(α)	(-0.61)	(1.23)	(1.77)*	(-0.37)	(1.97)**	(1.46)	(0.84)	(0.93)	(0.77)	(1.44)	
Adj. R^2	0.43	0.47	0.38	0.37	0.43	0.50	0.26	0.27	0.19	0.30	0.36
FF five-factor model											
α	-0.24	0.41	0.53	-0.15	0.80	0.41	0.39	0.43	0.24	0.38	0.32
t(α)	(-0.74)	(1.13)	(1.69)*	(-0.37)	(1.85)*	(1.32)	(0.79)	(0.81)	(0.64)	(1.29)	
Adj. R^2	0.43	0.46	0.37	0.39	0.42	0.50	0.25	0.27	0.19	0.31	0.36

Carhart model											
α	-0.20	0.47	0.56	-0.09	0.75	0.47	0.40	0.45	0.30	0.45	0.36
t(α)	(-0.60)	(1.39)	(1.76)*	(-0.22)	(1.74)*	(1.49)	(0.80)	(0.85)	(0.81)	(1.43)	
Adj. R^2	0.43	0.46	0.37	0.37	0.43	0.50	0.25	0.27	0.18	0.30	0.35
Six-factor model											
α	-0.25	0.45	0.54	-0.10	0.69	0.42	0.38	0.38	0.25	0.39	0.31
t(α)	(-0.75)	(1.29)	(1.66)*	(-0.23)	(1.59)	(1.32)	(0.74)	(0.70)	(0.66)	(1.25)	
Adj. R^2	0.43	0.46	0.36	0.39	0.43	0.50	0.24	0.26	0.18	0.30	0.35
Panel C: Middle East											
CAPM											
α	0.17	-0.02	-0.48	0.20	-0.30	-0.08	0.28	0.13	-0.23	0.28	-0.004
t(α)	(0.47)	(-0.08)	(-1.40)	(0.47)	(-0.80)	(-0.20)	(0.33)	(0.29)	(-0.64)	(0.65)	
Adj. R^2	0.03	-0.01	0.00	0.12	0.00	0.08	-0.01	0.03	0.00	0.01	0.024
FF Three-factor model											
α	0.23	0.07	-0.40	0.11	-0.45	0.15	1.04	0.03	-0.13	0.39	0.104
t(α)	(0.59)	(0.32)	(-1.04)	(0.23)	(-1.08)	(0.34)	(1.08)	(0.06)	(-0.31)	(1.00)	
Adj. R^2	0.01	-0.02	-0.01	0.10	-0.01	0.08	0.00	0.01	-0.02	0.00	0.015
FF five-factor model											
α	0.24	0.10	-0.38	0.17	-0.45	0.19	1.02	0.04	-0.07	0.38	0.124
t(α)	(0.62)	(0.47)	(-0.98)	(0.36)	(-1.07)	(0.45)	(1.04)	(0.07)	(-0.18)	(0.91)	
Adj. R^2	0.00	0.00	-0.03	0.10	-0.03	0.07	-0.02	0.00	-0.02	0.00	0.008
Carhart model											
α	0.24	0.11	-0.54	0.08	-0.43	0.13	0.79	-0.22	-0.32	0.33	0.017
t(α)	(0.60)	(0.50)	(-1.41)	(0.17)	(-1.02)	(0.28)	(0.82)	(-0.43)	(-0.79)	(0.81)	
Adj. R^2	0.00	-0.02	0.02	0.09	-0.02	0.07	0.02	0.08	0.05	-0.01	0.029
Six-factor model											
α	0.26	0.15	-0.52	0.15	-0.44	0.18	0.75	-0.23	-0.27	0.31	0.034
t(α)	(0.64)	(0.68)	(-1.35)	(0.32)	(-1.24)	(0.40)	(0.76)	(-0.45)	(-0.66)	(0.69)	
Adj. R^2	-0.01	0.01	0.01	0.09	-0.04	0.06	0.00	0.07	0.04	0.00	0.021
Panel D: LAC											
CAPM											
α	-0.32	0.44	0.03	-0.07	-0.41	0.25	1.12	0.38	0.46	2.00	0.39
t(α)	(-0.28)	(0.58)	(0.07)	(-0.06)	(-0.32)	(0.51)	(0.75)	(0.37)	(0.54)	(1.55)	
Adj. R^2	0.14	0.23	0.23	0.34	0.11	0.24	0.08	0.20	0.24	0.16	0.20
FF Three-factor model											
α	0.83	0.79	0.55	0.87	0.85	0.32	2.11	1.54	1.06	3.42	1.23
t(α)	(0.66)	(0.97)	(1.01)	(0.67)	(0.62)	(0.58)	(1.28)	(1.36)	(1.12)	(2.42)**	
Adj. R^2	0.16	0.23	0.25	0.36	0.16	0.23	0.08	0.23	0.24	0.18	0.21

FF five-factor model											
α	0.78	0.77	0.56	0.85	0.77	0.33	1.94	1.46	0.98	3.38	1.18
t(α)	(0.62)	(1.10)	(1.01)	(0.65)	(0.56)	(0.59)	(1.18)	(1.28)	(1.02)	(2.39)**	
Adj. R^2	0.15	0.21	0.23	0.34	0.14	0.21	0.10	0.22	0.24	0.19	0.20
Carhart model											
α	0.85	0.58	0.41	0.87	0.92	0.28	1.78	1.18	0.91	3.30	1.11
t(α)	(0.67)	(0.76)	(0.75)	(0.66)	(0.66)	(0.50)	(1.07)	(1.05)	(0.94)	(2.29)**	
Adj. R^2	0.15	0.24	0.26	0.35	0.15	0.22	0.08	0.24	0.24	0.18	0.21
Six-factor model											
α	0.80	0.54	0.41	0.86	0.83	0.29	1.59	1.07	0.81	3.27	1.05
t(α)	(0.62)	(0.71)	(0.73)	(0.64)	(0.59)	(0.51)	(0.95)	(0.94)	(0.83)	(2.26)**	
Adj. R^2	0.15	0.23	0.24	0.34	0.14	0.21	0.10	0.23	0.24	0.18	0.21
Panel E: Asia											
CAPM											
α	-0.03	-0.20	0.39	0.33	0.80	0.29	0.13	0.64	0.12	0.60	0.31
t(α)	(-0.07)	(-0.51)	(1.11)	(0.63)	(1.79)*	(0.65)	(0.23)	(1.44)	(0.27)	(1.29)	
Adj. R^2	0.04	0.08	0.08	0.10	0.02	0.18	0.01	0.00	0.17	-0.01	0.07
FF Three-factor model											
α	0.31	0.19	0.53	0.34	0.78	0.39	0.08	0.74	0.17	0.64	0.42
t(α)	(0.55)	(0.44)	(1.37)	(0.59)	(1.76)*	(0.77)	(0.13)	(1.49)	(0.34)	(1.12)	
Adj. R^2	0.06	0.10	0.06	0.09	0.01	0.17	0.00	-0.02	0.17	-0.03	0.06
FF five-factor model											
α	0.32	0.12	0.51	0.20	0.73	0.34	0.05	0.65	0.06	0.55	0.35
t(α)	(0.56)	(0.26)	(1.31)	(0.36)	(1.69)*	(0.67)	(0.07)	(1.31)	(0.12)	(0.91)	
Adj. R^2	0.04	0.11	0.05	0.15	0.00	0.16	0.01	0.00	0.20	-0.03	0.07
Carhart model											
α	0.33	0.27	0.58	0.37	0.82	0.47	0.15	0.78	0.29	0.70	0.48
t(α)	(0.57)	(0.60)	(1.46)	(0.62)	(1.79)*	(0.92)	(0.23)	(1.54)	(0.56)	(1.11)	
Adj. R^2	0.05	0.10	0.06	0.08	0.00	0.17	0.00	-0.02	0.17	-0.03	0.06
Six-factor model											
α	0.35	0.18	0.56	0.20	0.77	0.41	0.12	0.68	0.16	0.61	0.40
t(α)	(0.60)	(0.41)	(1.39)	(0.34)	(1.70)*	(0.80)	(0.19)	(1.33)	(0.31)	(0.90)	
Adj. R^2	0.03	0.11	0.04	0.14	-0.01	0.16	0.00	-0.01	0.20	-0.04	0.06

Note: For brevity we report only α, t(α), Adj. R^2. However, the full tables include all the risk factors and their relevant *t* statistics are available on request. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Implied standard deviations of the true factor slopes in a 20-month rolling regression

		Africa	Eastern Europe	Middle East	LAC	Asia
CAPM model	β	0.09	0.02	0	0.03	0.25
FF 3-factor model	β	0.10	0.03	0.01	0.04	0.27
	s	0.21	0.02	0.02	0.04	0.01
	h	0.03	0.03	0.04	0.18	0.03
FF 5-factor model	β	0.14	0.04	0.02	0.02	0.20
	s	0.23	0.02	0.04	0.05	0.09
	h	0.02	0.01	0.04	0.18	0.03
	r	0.03	0.01	0.02	0.03	0.14
	c	0.04	0.03	0.06	0.11	0.07
Carhart model	β	0.06	0.02	0.03	0.02	0.21
	s	0.27	0.04	0.02	0.09	0.00
	h	0.06	0.02	0.03	0.22	0.02
	m	0.10	0.02	0.05	0.12	0.02
FF 6-factor model	β	0.12	0.03	0.06	0.01	0.15
	s	0.26	0.03	0.04	0.12	0.15
	h	0.01	0.00	0.02	0.21	0.02
	r	0.03	0.00	0.02	0.04	0.19
	c	0.04	0.03	0.09	0.10	0.10
	m	0.04	0.03	0.07	0.15	0.13

Note: Each column represents the mean of the implied standard deviations of the 10 industries in each region. The full tables show the implied standard deviations of each industry are available upon request.

Table 6: Conditional regression

	Communication services	Consumer discretionary	Consumer staples	Energy	Health care	Industrials	Technology	Materials	Real state	Utilities	Mean
Panel A: Africa											
CAPM											
β_2	0.37	2.52	1.71	0.64	-3.36	1.34	0.87	-0.02	-1.08	0.90	0.39
$t(\beta_2)$	(0.21)	(1.11)	(1.12)	(0.33)	(-1.92)*	(0.77)	(0.64)	(-0.01)	(-0.67)	(0.75)	
Adj. R^2	0.05	0.35	0.18	0.07	0.13	0.21	0.13	0.16	0.10	0.22	0.16
FF 3-factor model											
S_2	-0.02	-0.05	-0.15	0.05	0.43	0.03	0.07	-0.01	0.35	-0.06	0.07
$t(s_2)$	(-0.20)	(-0.98)	(-0.41)	(0.50)	(1.23)	(0.21)	(1.07)	(-0.07)	(1.25)	(-0.50)	
h_2	0.60	0.01	-0.25	-0.02	0.82	-0.22	-0.23	0.49	-0.70	0.01	0.05
$t(h_2)$	(1.18)	(0.05)	(-0.32)	(-0.03)	(1.02)	(-0.37)	(-0.97)	(0.61)	(-0.99)	(0.02)	
Adj. R^2	0.07	0.32	0.15	0.05	0.09	0.19	0.13	0.15	0.11	0.21	0.15
Carhart model											
S_2	-0.08	-0.07	-0.18	0.03	0.35	0.02	0.05	-0.03	0.40	-0.12	0.04
$t(s_2)$	(-0.01)	(-1.14)	(-0.49)	(0.24)	(0.83)	(0.18)	(0.76)	(-0.26)	(1.38)	(-1.06)	
h_2	-0.44	0.33	0.40	0.35	-0.07	0.14	0.00	-0.47	-1.38	0.33	-0.08
$t(h_2)$	(-0.24)	(0.67)	(0.61)	(0.53)	(-0.19)	(0.30)	(-0.01)	(-0.58)	(-1.76)*	(1.38)	
m_2	-0.20	0.02	-0.01	0.01	-0.09	-0.15	0.17	-0.03	-0.12	0.09	-0.03
$t(m_2)$	(-0.03)	(0.46)	(-0.09)	(0.11)	(-0.70)	(-1.50)	(1.61)	(-0.26)	(-0.76)	(1.29)	
Adj. R^2	0.06	0.31	0.14	0.04	0.08	0.20	0.14	0.13	0.10	0.23	0.14
Panel B: Eastern Europe											
CAPM											
β_2	-0.78	1.08	0.38	-1.11	-3.88	0.88	-0.17	-0.05	0.43	-0.91	-0.41
$t(\beta_2)$	(-0.83)	(0.73)	(0.43)	(-0.93)	(-3.33)***	(1.01)	(-0.12)	(-0.04)	(0.42)	(-0.87)	
Adj. R^2	0.40	0.46	0.35	0.35	0.46	0.50	0.26	0.29	0.18	0.31	0.36
FF 3-factor model											
S_2	0.00	-0.05	0.02	-0.02	-0.15	-0.01	0.02	-0.02	-0.15	0.03	-0.03
$t(s_2)$	(0.01)	(-0.97)	(0.10)	(-0.35)	(-0.61)	(-0.10)	(0.31)	(-0.35)	(-0.83)	(0.34)	
h_2	-0.09	-0.11	0.15	-0.21	-0.23	-0.24	-0.04	-0.68	0.50	0.06	-0.09
$t(h_2)$	(-0.34)	(-0.43)	(0.33)	(-0.44)	(-0.42)	(-0.63)	(-0.19)	(-1.13)	(1.10)	(0.17)	
Adj. R^2	0.40	0.46	0.37	0.34	0.41	0.51	0.25	0.28	0.18	0.30	0.35
Carhart model											
S_2	0.02	-0.05	0.05	-0.05	-0.11	-0.01	0.02	-0.01	-0.16	0.02	-0.03

$t(s_2)$	(0.00)	(-0.87)	(0.24)	(-0.72)	(-0.38)	(-0.13)	(0.30)	(-0.12)	(-0.87)	(0.19)	
h_2	0.75	0.24	0.08	-0.37	0.16	0.19	-0.40	0.00	-0.34	0.14	0.05
$t(h_2)$	(0.21)	(0.56)	(0.20)	(-0.90)	(0.64)	(0.60)	(-0.91)	(0.01)	(-0.67)	(0.63)	
m_2	1.68	0.04	0.07	0.13	-0.03	0.00	0.08	0.09	0.03	0.04	0.21
$t(m_2)$	(0.12)	(0.91)	(0.96)	(1.81)*	(-0.40)	(0.05)	(0.74)	(0.96)	(0.35)	(0.62)	
Adj. R^2	0.41	0.46	0.36	0.35	0.41	0.50	0.24	0.27	0.17	0.29	0.35
Panel C: Middle East											
CAPM											
β_2	0.46	-0.31	0.00	-1.40	0.51	0.30	-0.17	-0.88	-1.07	0.91	-0.16
$t(\beta_2)$	(0.39)	(-0.51)	(0.00)	(-1.04)	(0.44)	(0.25)	(-0.12)	(-0.60)	(-0.94)	(0.67)	
Adj. R^2	0.02	-0.02	-0.01	0.10	-0.01	0.07	0.26	0.02	0.00	0.01	0.05
FF 3-factor model											
S_2	0.01	0.00	-0.16	0.04	-0.32	0.17	0.02	0.00	0.19	-0.04	-0.01
$t(s_2)$	(0.17)	(-0.05)	(-0.63)	(0.57)	(-1.40)	(1.43)	(0.31)	(0.00)	(0.95)	(-0.34)	
h_2	0.04	-0.02	-0.39	0.02	-0.74	-0.57	-0.04	-0.25	-0.47	-0.10	-0.25
$t(h_2)$	(0.17)	(-0.12)	(-0.72)	(0.04)	(-1.40)	(-1.05)	(-0.19)	(-0.41)	(-0.93)	(-0.21)	
Adj. R^2	-0.01	-0.04	-0.02	0.07	-0.01	0.09	0.25	-0.01	-0.02	-0.02	0.03
Carhart model											
S_2	0.08	-0.01	-0.06	0.05	-0.47	0.18	0.02	0.06	0.18	-0.01	0.00
$t(s_2)$	(0.01)	(-0.32)	(-0.21)	(0.69)	(-1.74)*	(1.45)	(0.30)	(0.79)	(0.90)	(-0.09)	
h_2	-0.07	-0.09	0.17	-0.05	0.11	0.36	-0.40	0.01	-0.48	0.14	-0.03
$t(h_2)$	(-0.02)	(-0.31)	(0.38)	(-0.11)	(0.43)	(0.80)	(-0.91)	(0.01)	(-0.89)	(0.48)	
m_2	-1.97	0.01	0.02	-0.03	-0.06	-0.03	0.08	-0.10	-0.07	-0.02	-0.22
$t(m_2)$	(-0.17)	(0.36)	(0.28)	(-0.32)	(-0.74)	(-0.33)	(0.74)	(-1.03)	(-0.64)	(-0.30)	
Adj. R^2	0.01	-0.05	0.01	0.06	-0.02	0.08	0.24	0.06	0.04	-0.03	0.04
Panel D: LAC											
CAPM											
β_2	4.56	2.36	-0.45	0.99	1.66	3.47	7.31	4.93	2.39	2.76	3.00
$t(\beta_2)$	(1.29)	(0.84)	(-0.29)	(0.26)	(0.42)	(2.30)**	(1.58)	(1.54)	(0.90)	(1.38)	
Adj. R^2	0.15	0.24	0.22	0.33	0.12	0.28	0.09	0.21	0.25	0.00	0.19
FF 3-factor model											
S_2	-0.20	-0.14	-0.26	-0.19	-0.54	-0.15	-0.68	-0.40	0.58	-0.10	-0.21
$t(s_2)$	(-1.00)	(-1.44)	(-0.74)	(-0.90)	(-0.75)	(-1.02)	(-3.00)***	(-2.74)***	(1.30)	(-0.46)	
h_2	1.43	-0.36	-0.28	-0.15	0.10	0.02	0.91	-0.28	-2.18	-0.34	-0.11
$t(h_2)$	(1.46)	(-0.72)	(-0.37)	(-0.10)	(0.06)	(0.02)	(1.17)	(-0.22)	(-1.90)*	(-0.55)	
Adj. R^2	0.20	0.23	0.25	0.35	0.22	0.27	0.12	0.24	0.29	-0.04	0.21

Carhart model											
S_2	-1.06	-0.10	-0.28	-0.20	-0.41	-0.16	-0.63	-0.29	0.47	-0.13	-0.28
$t(s_2)$	(-0.23)	(-1.21)	(-0.76)	(-0.92)	(-0.48)	(-1.03)	(-2.62)***	(-1.80)*	(1.01)	(-0.51)	
h_2	0.30	-0.86	-0.08	0.81	-0.86	-0.36	0.14	0.14	0.74	-0.16	-0.02
$t(h_2)$	(0.32)	(-2.05)**	(-0.13)	(0.63)	(-1.12)	(-0.65)	(0.10)	(0.11)	(0.58)	(-0.45)	
m_2	0.04	-0.05	-0.12	0.00	0.22	-0.08	0.07	0.12	0.20	-0.06	0.03
$t(m_2)$	(0.01)	(-0.93)	(-0.99)	(0.02)	(0.88)	(-0.68)	(0.20)	(0.60)	(0.81)	(-0.82)	
Adj. R^2	0.18	0.24	0.25	0.34	0.21	0.26	0.11	0.25	0.28	-0.05	0.21
Panel E: Asia											
CAPM											
β_2	1.36	0.99	1.25	-0.41	2.31	-0.42	1.04	2.23	1.03	5.63	1.50
$t(\beta_2)$	(0.85)	(0.79)	(1.16)	(-0.25)	(1.52)	(-0.30)	(0.58)	(1.62)	(0.72)	(1.41)	
Adj. R^2	0.04	0.08	0.09	0.11	0.05	0.18	0.00	0.03	0.18	0.18	0.09
FF 3-factor model											
S_2	-0.01	-0.09	0.06	-0.03	0.42	-0.07	-0.04	0.01	0.09	-0.40	-0.01
$t(s_2)$	(-0.12)	(-1.42)	(0.23)	(-0.35)	(1.40)	(-0.51)	(-0.50)	(0.19)	(0.35)	(-1.10)	
h_2	0.01	0.02	0.11	0.09	0.94	0.17	0.68	0.21	-0.15	0.77	0.28
$t(h_2)$	(0.02)	(0.08)	(0.19)	(0.15)	(1.36)	(0.26)	(2.24)	(0.37)	(-0.23)	(0.60)	
Adj. R^2	0.05	0.08	0.06	0.11	0.03	0.16	0.03	-0.02	0.16	0.23	0.09
Carhart model											
S_2	-0.12	-0.14	0.06	-0.05	0.56	-0.08	-0.06	0.01	0.15	-0.40	-0.01
$t(s_2)$	(-0.01)	(-1.89)**	(0.24)	(-0.51)	(1.60)	(-0.54)	(-0.64)	(0.15)	(0.58)	(-1.08)	
h_2	-0.02	-0.46	0.31	-1.06	-0.32	0.09	-0.71	0.49	0.41	1.06	-0.02
$t(h_2)$	(-0.01)	(-0.83)	(0.66)	(-1.90)*	(-0.99)	(0.18)	(-1.28)	(0.82)	(0.58)	(1.35)	
m_2	1.58	-0.06	0.03	0.20	0.11	0.15	-0.08	0.02	-0.09	0.35	0.22
$t(m_2)$	(0.19)	(-1.00)	(0.30)	(1.94)*	(1.07)	(1.37)	(-0.57)	(0.26)	(-0.67)	(1.61)	
Adj. R^2	0.05	0.08	0.04	0.12	0.02	0.17	0.02	-0.04	0.15	0.24	0.09

Note: For brevity we report only the slopes of conditional variables and their relevant *t* statistics, and the Adj. R^2. However, the full tables include all the risk factors and their relevant *t* statistics are available on request.
The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Average absolute forecast errors and average standard deviations

Panel A: Africa	**CAPM**			**FF three-factor model**			**Carhart model**		
	1 month	1 year	3 years	1 month	1 year	3 years	1 month	1 year	3 years
Static	5.21	5.52	5.64	5.28	5.49	5.87	5.35	5.57	5.94
SD	(5.69)	(5.75)	(5.65)	(5.69)	(5.73)	(5.65)	(5.69)	(5.73)	(5.65)
Rolling	4.06	4.09	3.94	4.15	4.19	4.08	4.26	4.31	4.23
SD	(3.44)	(3.41)	(3.30)	(3.51)	(3.47)	(3.37)	(3.59)	(3.57)	(3.41)
Conditional	7.29	7.64	7.55	14.78	14.05	14.57	14.69	13.96	14.47
SD	(5.65)	(5.71)	(5.63)	(12.79)	(10.51)	(10.19)	(12.69)	(10.48)	(10.18)
Panel B: Eastern Europe	**CAPM**			**FF three-factor model**			**Carhart model**		
	1 month	1 year	3 years	1 month	1 year	3 years	1 month	1 year	3 years
Static	4.10	4.27	4.24	4.17	4.28	4.39	4.22	4.33	4.39
SD	(4.50)	(4.56)	(4.58)	(4.50)	(4.55)	(4.58)	(4.50)	(4.55)	(4.58)
Rolling	2.95	2.98	2.88	3.05	3.11	3.04	3.14	3.20	3.11
SD	(2.41)	(2.41)	(2.37)	(2.50)	(2.52)	(2.48)	(2.53)	(2.55)	(2.51)
Conditional	4.62	4.78	4.77	4.75	4.59	4.51	14.55	13.81	14.65
SD	(3.64)	(3.70)	(3.77)	(3.81)	(3.47)	(3.31)	(12.61)	(10.08)	(9.78)
Panel C: Middle East	**CAPM**			**FF three-factor model**			**Carhart model**		
	1 month	1 year	3 years	1 month	1 year	3 years	1 month	1 year	3 years
Static	3.88	3.92	3.59	3.85	3.92	3.47	3.74	3.79	3.44
SD	(3.94)	(3.96)	(3.84)	(3.94)	(3.98)	(3.84)	(3.94)	(3.98)	(3.84)
Rolling	2.99	3.02	2.94	3.00	3.05	2.93	3.09	3.15	3.02
SD	(2.65)	(2.67)	(2.62)	(2.66)	(2.69)	(2.63)	(2.73)	(2.75)	(2.67)
Conditional	3.70	3.77	3.78	6.13	5.91	6.06	15.07	14.36	15.18
SD	(3.16)	(3.20)	(3.11)	(5.09)	(4.52)	(4.48)	(13.08)	(10.63)	(10.50)
Panel D: LAC	**CAPM**			**FF three-factor model**			**Carhart model**		
	1 month	1 year	3 years	1 month	1 year	3 years	1 month	1 year	3 years
Static	11.57	10.80	10.37	12.81	12.07	11.89	12.68	12.02	11.94
SD	(11.52)	(11.38)	(11.66)	(11.520	(11.38)	(11.66)	(11.52)	(11.38)	(11.66)
Rolling	8.21	8.10	8.18	8.09	7.92	7.99	8.48	8.34	8.43
SD	(6.99)	(6.65)	(6.78)	(6.94)	(6.54)	(6.66)	(7.13)	(6.73)	(6.80)
Conditional	16.70	17.37	17.77	13.86	13.22	13.58	16.51	15.56	16.21
SD	(13.27)	(13.61)	(14.40)	(11.44)	(10.26)	(10.09)	(14.35)	(11.61)	(11.73)
Panel E: Asia	**CAPM**			**FF three-factor model**			**Carhart model**		
	1 month	1 year	3 years	1 month	1 year	3 years	1 month	1 year	3 years
Static	5.02	4.91	5.07	5.15	4.92	5.12	5.28	5.06	5.18
SD	(4.92)	(4.93)	(5.09)	(4.92)	(4.93)	(5.09)	(4.92)	(4.93)	(5.09)
Rolling	4.14	4.16	4.35	4.47	4.55	4.78	5.03	5.20	5.54
SD	(3.61)	(3.65)	(3.86)	(3.89)	(3.95)	(4.21)	(4.32)	(4.42)	(4.58)
Conditional	5.91	6.00	6.07	13.40	12.77	13.35	14.94	14.11	14.77
SD	(4.58)	(4.65)	(4.55)	(11.16)	(9.60)	(9.44)	(12.62)	(10.14)	(9.91)

Note: This table reports the average absolute forecast errors (across the 10 industries for each region) and its relevant standard deviations (*SD*) from full-period static regressions, 20-month rolling regressions, and conditional regressions. In each region panel, the first row reports the average absolute forecast errors, and the second row reports the average standard deviations of the forecast errors (in parentheses). The forecast errors are computed monthly from $t = 20 + N$ to $t = T$, where t = March 2014, T = June 2021, and N = 1, 12, 36, and 60 months according to the forecast horizon.

The average absolute forecast errors of the static regression at time t equals the regressions' errors at time t plus the intercepts. For the rolling forecast, we first estimate the model using rolling regression windows of 20 months of past returns from the period $t - 20 - N$ to $t - N$. Second, we use the coefficients estimated in the first step and the explanatory factors and returns at time t to estimate the model parameters for the relevant horizon. Third, we compute the absolute average of forecast errors as the mean of the realized returns minus the return predicted by the model. For the conditional regression forecast, the average absolute forecast error at time t equals the difference between the realized returns at time t and the returns estimated using the realized explanatory factor at t, the coefficients estimated from $t = 20 + N$ to T, and the conditioning variables at $t - N$.

Table 8: *GRS* statistics and correlations

Panel A: Africa						
	GRS	***p*-Value**	***|α|***	***R^2***	***S(α)***	***SR(α)***
CAPM	2.08**	0.03	0.42	0.16	0.50	0.47
FF 3-factor model	1.78	0.08	0.42	0.16	0.55	0.48
Carhart model	1.93	0.05	0.42	0.15	0.56	0.51
FF 5-factor model	2.20**	0.02	0.44	0.16	0.57	0.56
6-factor model	2.55**	0.01	0.48	0.16	0.58	0.62
Panel B: Eastern Europe						
	GRS	***p*-Value**	***|α|***	***R^2***	***S(α)***	***SR(α)***
CAPM	1.25	0.27	0.37	0.36	0.35	0.36
FF three-factor model	1.28	0.25	0.42	0.36	0.39	0.41
Carhart model	1.14	0.34	0.42	0.35	0.40	0.39
FF five-factor model	1.80	0.07	0.50	0.37	0.40	0.50
Six-factor model	1.71	0.09	0.52	0.37	0.41	0.50
Panel C: Middle East						
	GRS	***p*-Value**	***|α|***	***R^2***	***S(α)***	***SR(α)***
CAPM	0.45	0.92	0.22	0.02	0.42	0.22
FF three-factor model	0.46	0.91	0.30	0.02	0.47	0.25
Carhart model	0.52	0.87	0.32	0.03	0.47	0.26
FF five-factor model	0.40	0.94	0.27	0.00	0.49	0.24
Six-factor model	0.51	0.88	0.32	0.02	0.49	0.27
Panel D: LAC						
	GRS	***p*-Value**	***|α|***	***R^2***	***S(α)***	***SR(α)***
CAPM	0.66	0.76	0.55	0.20	0.99	0.26
FF three-factor model	0.85	0.58	1.23	0.21	1.08	0.33
Carhart model	0.72	0.70	1.11	0.21	1.10	0.31
FF five-factor model	0.99	0.46	1.43	0.21	1.12	0.37
Six-factor model	0.87	0.57	1.30	0.21	1.14	0.36
Panel E: Asia						
	GRS	***p*-Value**	***|α|***	***R^2***	***S(α)***	***SR(α)***
CAPM	1.32	0.23	0.35	0.07	0.48	0.37
FF three-factor model	0.64	0.77	0.42	0.06	0.54	0.29
Carhart model	0.59	0.82	0.48	0.06	0.55	0.28
FF five-factor model	0.77	0.66	0.52	0.07	0.55	0.33
Six-factor model	0.72	0.70	0.59	0.07	0.56	0.33

Note: The term *GRS* is the *GRS* test statistic, the *p*-value is the respective *p*-value of the *GRS* test statistic, *|α|* is the average absolute intercept, R^2 is the average adjusted R^2 value, *S(α)* is the average standard error of the intercepts, and *SR(α)* is the Sharpe ratio for the intercepts. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Regression using developed markets factors

	Communication services	Consumer discretionary	Consumer staples	Energy	Health care	Industrials	Technology	Materials	Real Estate	Utilities	Mean
Panel A: Africa											
CAPM											
α	-1.08	-0.61	-0.71	-0.40	0.25	-0.44	0.09	-0.49	-1.63	-0.11	-0.51
t(α)	(-1.82)*	(-1.19)	(-1.24)	(-0.64)	(0.42)	(-1.04)	(0.20)	(-0.81)	(-2.99)***	(-0.28)	
Adj. R^2	0.05	0.29	0.14	0.06	0.08	0.23	0.16	0.12	0.07	0.21	0.14
FF Three-factor model											
α	-1.12	-0.37	-0.43	-0.14	0.47	-0.28	0.16	-0.24	-1.41	0.05	-0.33
t(α)	(-1.91)*	(-1.03)	(-0.87)	(-0.23)	(0.79)	(-0.65)	(0.36)	(-0.38)	(-2.59)**	(0.12)	
Adj. R^2	0.11	0.38	0.24	0.09	0.11	0.26	0.18	0.18	0.10	0.23	0.19
FF five-factor model											
α	-1.11	-0.43	-0.38	-0.09	0.45	-0.25	0.22	-0.09	-1.48	0.06	-0.31
t(α)	(-1.88)*	(-1.30)	(-0.76)	(-0.14)	(0.74)	(-0.57)	(0.48)	(-0.14)	(-2.68)***	(0.14)	
Adj. R^2	0.12	0.37	0.24	0.08	0.10	0.26	0.17	0.20	0.09	0.22	0.18
Carhart model											
α	-1.04	-0.53	-0.53	-0.25	0.52	-0.46	0.18	-0.44	-1.45	-0.10	-0.41
t(α)	(-1.73)*	(-1.50)	(-1.06)	(-0.39)	(0.85)	(-1.09)	(0.39)	(-0.68)	(-2.60)***	(-0.25)	
Adj. R^2	0.11	0.40	0.24	0.09	0.10	0.29	0.17	0.19	0.09	0.25	0.19
Six-factor model											
α	-1.08	-0.61	-0.53	-0.20	0.46	-0.47	0.21	-0.34	-1.51	-0.09	-0.42
t(α)	(-1.79)*	(-1.66)*	(-1.05)	(-0.30)	(0.74)	(-1.09)	(0.46)	(-0.53)	(-2.68)***	(-0.21)	
Adj. R^2	0.11	0.41	0.25	0.08	0.10	0.30	0.16	0.22	0.08	0.24	0.19
Panel B: Eastern Europe											
CAPM											
α	-0.66	-0.22	0.03	-0.82	0.09	-0.20	0.03	0.02	0.05	-0.01	-0.17
t(α)	(-2.09)**	(-0.53)	(0.12)	(-2.24)**	(0.20)	(-0.59)	(0.06)	(0.04)	(0.13)	(-0.02)	
Adj. R^2	0.38	0.38	0.37	0.43	0.34	0.47	0.22	0.25	0.13	0.31	0.33
FF Three-factor model											
α	-0.62	-0.03	0.18	-0.77	0.12	-0.03	0.17	0.20	0.14	0.00	-0.06
t(α)	(-1.92)*	(-0.11)	(0.62)	(-2.05)**	(0.26)	(-0.11)	(0.37)	(0.40)	(0.39)	(0.00)	
Adj. R^2	0.37	0.44	0.41	0.43	0.33	0.52	0.25	0.27	0.13	0.31	0.35
FF five-factor model											
α	-0.61	-0.07	0.16	-0.79	0.18	-0.03	0.13	0.17	0.10	-0.02	-0.08
t(α)	(-1.92)*	(-0.20)	(0.55)	(-2.08)**	(0.40)	(-0.12)	(0.26)	(0.34)	(0.27)	(-0.08)	
Adj. R^2	0.37	0.43	0.40	0.42	0.32	0.51	0.25	0.27	0.12	0.31	0.34

Carhart model											
α	-0.62	-0.11	0.10	-0.81	0.05	-0.17	0.14	0.21	0.07	-0.03	-0.11
t(α)	(-1.85)*	(-0.33)	(0.35)	(-2.12)**	(0.12)	(-0.59)	(0.30)	(0.42)	(0.22)	(-0.10)	
Adj. R^2	0.36	0.44	0.42	0.43	0.32	0.54	0.24	0.26	0.13	0.31	0.35
Six-factor model											
α	-0.57	-0.16	0.09	-0.83	0.12	-0.17	0.07	0.15	0.03	-0.03	-0.13
t(α)	(-1.94)*	(-0.45)	(0.29)	(-2.13)**	(0.27)	(-0.59)	(0.14)	(0.29)	(0.08)	(-0.11)	
Adj. R^2	0.37	0.43	0.41	0.42	0.32	0.54	0.24	0.26	0.12	0.30	0.34
Panel C: Middle East											
CAPM											
α	0.37	-0.03	-0.41	0.50	-0.22	0.18	0.33	0.38	-0.13	0.44	0.14
t(α)	(1.03)	(-0.14)	(-1.16)	(1.13)	(-0.57)	(0.45)	(0.36)	(0.80)	(-0.36)	(1.19)	
Adj. R^2	0.06	-0.01	0.00	0.12	0.00	0.10	-0.01	0.06	0.01	0.02	0.03
FF Three-factor model											
α	0.29	-0.07	-0.45	0.35	-0.29	0.10	0.13	0.22	-0.22	0.41	0.05
t(α)	(0.81)	(-0.36)	(-1.27)	(0.78)	(-0.72)	(0.26)	(0.14)	(0.46)	(-0.57)	(1.03)	
Adj. R^2	0.08	0.03	0.03	0.14	-0.01	0.09	0.03	0.10	0.01	0.03	0.05
FF five-factor model											
α	0.27	-0.11	-0.42	0.25	-0.32	-0.01	0.21	0.23	-0.19	0.41	0.03
t(α)	(0.75)	(-0.53)	(-1.16)	(0.57)	(-0.81)	(-0.01)	(0.23)	(0.47)	(-0.51)	(1.03)	
Adj. R^2	0.06	0.05	0.03	0.14	-0.01	0.11	0.01	0.08	0.06	0.02	0.05
Carhart model											
α	0.32	0.03	-0.47	0.29	-0.14	0.21	0.22	0.23	-0.06	0.53	0.12
t(α)	(0.86)	(0.14)	(-1.29)	(0.64)	(-0.34)	(0.52)	(0.24)	(0.48)	(-0.16)	(1.35)	
Adj. R^2	0.07	0.08	0.02	0.13	0.02	0.10	0.02	0.09	0.04	0.04	0.06
Six-factor model											
α	0.30	-0.02	-0.46	0.21	-0.19	0.13	0.31	0.25	-0.08	0.54	0.10
t(α)	(0.80)	(-0.09)	(-1.26)	(0.47)	(-0.46)	(0.30)	(0.33)	(0.51)	(-0.22)	(1.34)	
Adj. R^2	0.05	0.09	0.02	0.14	0.01	0.12	0.00	0.07	0.07	0.03	0.06
Panel D: LAC											
CAPM											
α	-0.91	0.00	-0.26	-1.33	-0.84	-0.09	-0.13	-0.41	-0.32	0.78	-0.35
t(α)	(-0.75)	(0.01)	(-0.47)	(-1.02)	(-0.62)	(-0.17)	(-0.08)	(-0.37)	(-0.36)	(0.53)	
Adj. R^2	0.08	0.14	0.11	0.25	0.04	0.14	0.04	0.15	0.20	0.11	0.13
FF Three-factor model											
α	-0.59	0.18	-0.13	-0.82	-0.87	0.09	0.10	-0.42	-0.19	1.03	-0.16
t(α)	(-0.49)	(0.23)	(-0.24)	(-0.64)	(-0.64)	(0.16)	(0.06)	(-0.37)	(-0.20)	(0.70)	
Adj. R^2	0.11	0.14	0.12	0.29	0.05	0.15	0.03	0.13	0.21	0.12	0.14

FF five-factor model											
α	-0.57	0.01	-0.16	-0.81	-0.91	0.03	-0.07	-0.46	-0.33	0.73	-0.25
t(α)	(-0.46)	(0.02)	(-0.28)	(-0.62)	(-0.66)	(0.06)	(-0.04)	(-0.40)	(-0.35)	(0.49)	
Adj. R^2	0.11	0.16	0.10	0.27	0.04	0.14	0.01	0.12	0.20	0.12	0.13
Carhart model											
α	-0.73	0.03	-0.22	-0.96	-1.05	-0.02	-0.23	-0.49	-0.27	0.70	-0.33
t(α)	(-0.59)	(0.04)	(-0.39)	(-0.73)	(-0.76)	(-0.04)	(-0.15)	(-0.42)	(-0.29)	(0.47)	
Adj. R^2	0.11	0.14	0.11	0.28	0.05	0.15	0.03	0.13	0.20	0.12	0.13
Six-factor model											
α	-0.61	-0.18	-0.26	-0.94	-1.19	-0.08	-0.40	-0.55	-0.42	0.42	-0.42
t(α)	(-0.49)	(-0.26)	(-0.45)	(-0.70)	(-0.85)	(-0.14)	(-0.22)	(-0.47)	(-0.44)	(0.28)	
Adj. R^2	0.11	0.17	0.10	0.27	0.04	0.14	0.01	0.11	0.20	0.12	0.13
Panel E: Asia											
CAPM											
α	-0.18	7.83	0.22	-0.04	0.63	2.15	-0.11	4.49	-0.21	0.50	1.53
t(α)	(-0.34)	(0.96)	(0.61)	(-0.07)	(1.23)	(0.95)	(-0.18)	(1.14)	(-0.42)	(1.04)	
Adj. R^2	0.02	-0.01	0.06	0.11	0.03	0.00	0.03	-0.01	0.13	-0.01	0.04
FF Three-factor model											
α	-0.07	7.80	0.24	0.21	0.57	2.23	0.01	4.50	-0.12	0.48	1.58
t(α)	(-0.14)	(0.94)	(0.65)	(0.39)	(1.14)	(0.96)	(0.02)	(1.12)	(-0.25)	(1.01)	
Adj. R^2	0.02	-0.02	0.08	0.16	0.09	-0.02	0.02	-0.02	0.14	-0.01	0.04
FF five-factor model											
α	-0.02	8.16	0.32	0.30	0.60	2.44	0.11	4.66	-0.08	0.66	1.72
t(α)	(-0.04)	(0.97)	(0.89)	(0.57)	(1.19)	(1.03)	(0.17)	(1.14)	(-0.15)	(1.00)	
Adj. R^2	0.01	-0.04	0.09	0.17	0.08	-0.03	0.02	-0.04	0.13	0.00	0.04
Carhart model											
α	-0.14	7.34	0.15	0.24	0.54	2.11	0.00	4.31	-0.10	0.40	1.48
t(α)	(-0.26)	(0.86)	(0.39)	(0.44)	(1.07)	(0.89)	(0.00)	(1.05)	(-0.19)	(0.76)	
Adj. R^2	0.02	-0.03	0.09	0.15	0.08	-0.03	0.01	-0.03	0.13	-0.02	0.04
Six-factor model											
α	-0.12	7.87	0.23	0.30	0.60	2.39	0.11	4.54	-0.08	0.58	1.64
t(α)	(-0.21)	(0.91)	(0.63)	(0.54)	(1.15)	(0.99)	(0.18)	(1.09)	(-0.16)	(0.99)	
Adj. R^2	0.01	-0.05	0.10	0.16	0.07	-0.04	0.01	-0.05	0.13	0.00	0.03

Note: For brevity we report only α, t(α), Adj. R^2. However, the full tables include all the risk factors and their relevant *t* statistics are available on request. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Regression using emerging market factors

	Communication services	Consumer discretionary	Consumer staples	Energy	Health care	Industrials	Technology	Materials	Real Estate	Utilities	Mean
Panel A: Africa											
CAPM											
α	-0.91	-0.31	-0.47	-0.17	0.45	-0.12	0.36	-0.20	-1.52	0.16	-0.27
t(α)	(-1.58)	(-0.68)	(-0.95)	(-0.27)	(0.78)	(-0.28)	(0.81)	(-0.32)	(-2.96)***	(0.36)	
Adj. R^2	0.06	0.29	0.16	0.04	0.08	0.18	0.13	0.13	0.14	0.18	0.14
FF Three-factor model											
α	-0.98	-0.37	-0.55	-0.22	0.35	-0.16	0.32	-0.31	-1.53	0.14	-0.33
t(α)	(-1.72)*	(-0.86)	(-1.13)	(-0.36)	(0.63)	(-0.39)	(0.74)	(-0.50)	(-2.98)***	(0.36)	
Adj. R^2	0.09	0.35	0.20	0.05	0.14	0.20	0.15	0.18	0.14	0.17	0.17
FF five-factor model											
α	-0.87	-0.37	-0.46	-0.27	0.44	0.04	0.59	-0.16	-1.32	0.26	-0.21
t(α)	(-1.48)	(-0.82)	(-0.93)	(-0.42)	(0.77)	(0.09)	(1.34)	(-0.26)	(-2.52)**	(0.63)	
Adj. R^2	0.08	0.36	0.20	0.04	0.14	0.24	0.19	0.18	0.15	0.17	0.17
Carhart model											
α	-1.48	-0.46	-0.95	-0.38	-0.01	-0.09	0.44	-0.70	-1.52	0.09	-0.51
t(α)	(-2.24)**	(-1.11)	(-1.70)**	(-0.52)	(-0.02)	(-0.19)	(0.87)	(-0.98)	(-2.54)**	(0.19)	
Adj. R^2	0.10	0.34	0.21	0.05	0.14	0.20	0.14	0.18	0.13	0.16	0.16
Six-factor model											
α	-1.38	-0.55	-0.82	-0.41	0.00	0.04	0.73	-0.61	-1.26	0.17	-0.41
t(α)	(-2.03)**	(-1.29)	(-1.43)	(-0.54)	(0.01)	(0.08)	(1.42)	(-0.83)	(-2.06)**	(0.35)	
Adj. R^2	0.09	0.36	0.20	0.03	0.14	0.23	0.18	0.18	0.14	0.16	0.17
Panel B: Eastern Europe											
CAPM											
α	-0.38	0.09	0.31	-0.38	0.44	0.16	0.31	0.37	0.19	0.32	0.14
t(α)	(-1.23)	(0.26)	(1.07)	(-0.99)	(1.07)	(0.47)	(0.69)	(0.76)	(0.57)	(1.07)	
Adj. R^2	0.40	0.41	0.36	0.34	0.35	0.41	0.24	0.26	0.17	0.24	0.32
FF Three-factor model											
α	-0.37	0.05	0.27	-0.40	0.40	0.11	0.29	0.29	0.19	0.30	0.11
t(α)	(-1.34)	(0.14)	(0.96)	(-1.04)	(0.97)	(0.37)	(0.63)	(0.62)	(0.57)	(1.06)	
Adj. R^2	0.39	0.45	0.39	0.34	0.36	0.46	0.24	0.30	0.16	0.23	0.33
FF five-factor model											
α	-0.37	0.05	0.33	-0.27	0.57	0.12	0.37	0.33	0.21	0.48	0.18
t(α)	(-1.16)	(0.15)	(1.15)	(-0.68)	(1.37)	(0.40)	(0.79)	(0.67)	(0.59)	(1.64)*	
Adj. R^2	0.38	0.45	0.39	0.34	0.37	0.45	0.23	0.29	0.15	0.25	0.33
Carhart model											

α	-0.35	0.09	0.26	-0.46	0.54	0.05	0.21	0.34	0.14	0.19	0.10
t(α)	(-0.99)	(0.23)	(0.78)	(-1.01)	(1.13)	(0.15)	(0.41)	(0.62)	(0.36)	(0.54)	
Adj. R^2	0.38	0.44	0.39	0.33	0.36	0.45	0.23	0.29	0.15	0.23	0.33
Six-factor model											
α	-0.36	0.05	0.29	-0.36	0.69	0.04	0.27	0.43	0.14	0.34	0.15
t(α)	(-0.97)	(0.13)	(0.86)	(-0.78)	(1.43)	(0.11)	(0.50)	(0.77)	(0.34)	(1.03)	
Adj. R^2	0.37	0.44	0.39	0.34	0.37	0.44	0.22	0.29	0.14	0.25	0.32
Panel C: Middle East											
CAPM											
α	0.23	-0.01	-0.50	0.21	-0.29	-0.01	0.50	0.17	-0.21	0.34	0.04
t(α)	(0.68)	(-0.05)	(-1.44)	(0.46)	(-0.75)	(-0.03)	(0.58)	(0.37)	(-0.57)	(0.93)	
Adj. R^2	-0.19	0.00	-0.01	-0.24	-0.07	-0.26	-0.30	-0.19	-0.08	-0.17	-0.15
FF Three-factor model											
α	0.29	-0.01	-0.46	0.30	-0.28	0.07	0.55	0.25	-0.17	0.36	0.09
t(α)	(0.84)	(-0.03)	(-1.33)	(0.73)	(-0.73)	(0.20)	(0.63)	(0.55)	(-0.47)	(1.01)	
Adj. R^2	0.10	-0.03	0.02	0.16	-0.01	0.18	0.00	0.08	0.01	0.01	0.05
FF five-factor model											
α	0.33	0.12	-0.41	0.22	-0.29	0.00	0.50	0.41	0.00	0.45	0.13
t(α)	(0.96)	(0.61)	(-1.16)	(0.51)	(-0.74)	(0.00)	(0.55)	(0.87)	(-0.01)	(1.27)	
Adj. R^2	0.13	0.05	0.03	0.15	-0.03	0.17	-0.01	0.09	0.04	0.00	0.06
Carhart model											
α	0.10	0.15	-0.09	0.00	-0.22	0.36	1.04	0.34	0.19	0.48	0.23
t(α)	(0.25)	(0.65)	(-0.22)	(0.00)	(-0.50)	(0.85)	(1.01)	(0.64)	(0.57)	(1.01)	
Adj. R^2	0.10	-0.02	0.04	0.17	-0.02	0.19	0.00	0.08	0.03	0.00	0.06
Six-factor model											
α	0.22	0.31	0.03	-0.10	-0.21	0.29	0.95	0.51	0.43	0.56	0.30
t(α)	(0.54)	(1.40)	(0.07)	(-0.20)	(-0.46)	(0.66)	(0.90)	(0.94)	(1.40)	(1.18)	
Adj. R^2	0.12	0.07	0.06	0.16	-0.04	0.18	-0.02	0.08	0.07	-0.01	0.07
Panel D: LAC											
CAPM											
α	-0.49	0.24	-0.03	-0.41	-0.51	0.16	0.17	0.23	0.15	1.25	0.08
t(α)	(-0.42)	(0.31)	(-0.05)	(-0.32)	(-0.39)	(0.31)	(0.10)	(0.21)	(0.17)	(0.90)	
Adj. R^2	0.10	0.22	0.13	0.25	0.06	0.15	0.07	0.12	0.25	0.16	0.15
FF Three-factor model											
α	-0.48	0.17	-0.07	-0.49	-0.67	0.07	0.14	0.13	0.14	1.23	0.02
t(α)	(-0.40)	(0.22)	(-0.13)	(-0.39)	(-0.52)	(0.15)	(0.08)	(0.12)	(0.16)	(0.88)	
Adj. R^2	0.09	0.23	0.13	0.26	0.08	0.22	0.05	0.14	0.25	0.15	0.16
FF five-factor model											
α	-0.88	0.15	-0.23	-0.58	-0.23	0.05	-0.80	0.05	0.01	0.58	-0.19

t(α)	(-0.72)	(0.18)	(-0.42)	(-0.44)	(-0.18)	(0.10)	(-0.49)	(0.04)	(0.01)	(0.41)	
Adj. R^2	0.09	0.24	0.12	0.26	0.10	0.23	0.09	0.12	0.24	0.16	0.17
Carhart model											
α	-0.03	0.27	0.24	0.21	-1.41	0.16	-0.68	0.71	0.36	1.17	0.10
t(α)	(-0.02)	(0.27)	(0.39)	(0.14)	(-0.94)	(0.28)	(-0.36)	(0.56)	(0.36)	(0.72)	
Adj. R^2	0.09	0.23	0.13	0.26	0.08	0.21	0.05	0.13	0.24	0.14	0.16
Six-factor model											
α	-0.43	0.14	0.11	-0.07	-1.17	0.04	-1.60	0.68	0.23	0.45	-0.16
t(α)	(-0.31)	(0.13)	(0.17)	(-0.05)	(-0.77)	(0.07)	(-0.84)	(0.52)	(0.22)	(0.27)	
Adj. R^2	0.09	0.23	0.12	0.26	0.10	0.23	0.08	0.12	0.23	0.16	0.16
Panel E: Asia											
CAPM											
α	-0.03	8.13	0.36	0.26	0.86	2.46	0.04	4.72	0.04	0.65	1.75
t(α)	(-0.05)	(1.02)	(1.02)	(0.49)	(1.71)*	(1.10)	(0.07)	(1.24)	(0.09)	(1.33)	
Adj. R^2	0.01	-0.01	0.04	0.07	-0.01	-0.01	0.02	-0.01	0.12	-0.01	0.02
FF Three-factor model											
α	-0.07	8.54	0.35	0.14	0.80	2.53	0.00	4.85	-0.05	0.56	1.76
t(α)	(-0.13)	(1.08)	(0.96)	(0.28)	(1.66)*	(1.14)	(0.00)	(1.27)	(-0.11)	(0.91)	
Adj. R^2	0.01	0.01	0.03	0.18	0.09	0.00	0.02	0.00	0.20	0.05	0.06
FF five-factor model											
A	-0.11	10.75	0.38	0.27	0.95	3.19	-0.14	5.89	-0.02	0.67	2.18
t(α)	(-0.20)	(1.17)	(1.02)	(0.51)	(1.94)*	(1.23)	(-0.23)	(1.35)	(-0.04)	(1.06)	
Adj. R^2	0.00	0.06	0.02	0.18	0.10	0.05	0.02	0.05	0.20	0.04	0.07
Carhart model											
A	-0.50	5.21	0.11	0.24	0.87	1.67	0.15	3.46	0.05	0.38	1.16
t(α)	(-0.81)	(0.57)	(0.26)	(0.40)	(1.55)	(0.64)	(0.22)	(0.78)	(0.10)	(0.54)	
Adj. R^2	0.01	0.00	0.03	0.17	0.08	-0.01	0.02	-0.01	0.20	0.04	0.05
Six-factor model											
A	-0.49	5.32	0.16	0.33	0.96	1.74	0.06	3.47	0.03	0.50	1.21
t(α)	(-0.77)	(0.58)	(0.36)	(0.55)	(1.67)*	(1.08)	(0.08)	(1.40)	(0.06)	(0.67)	
Adj. R^2	0.01	0.06	0.02	0.17	0.09	0.05	0.01	0.05	0.19	0.03	0.07

Note: For brevity we report only α, t(α), Adj. R^2. However, the full tables include all the risk factors and their relevant *t* statistics are available on request. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Comparison between this study and previous studies.

Authors	This study					FF (1997)	Gregory and Michou (2009)	Lutzenberger (2017)
	Frontier Markets							
Markets	Africa	Eastern Europe	Middle East	LAC	Asia	US Markets	UK Markets	EU Markets
CAPM								
Avg. intercept	-0.17	0.28	-0.004	0.39	0.31	0.05	0.001	0.15
Avg. *adj.* R^2	0.16	0.36	0.024	0.20	0.07	0.63	0.32	0.38
Implied SD (β)	0.09	0.02	0	0.03	0.25	0.123	0.164	0.21
FF three-factor model								
Avg. intercept	-0.23	0.35	0.104	1.23	0.42	-0.03	0.001	0.20
Avg. *adj.* R^2	0.16	0.36	0.015	0.21	0.06	0.68	0.35	0.48
Implied SD (β)	0.10	0.03	0.01	0.04	0.27	0.087	0.167	0.18
Implied SD (S)	0.21	0.02	0.02	0.04	0.01	0.135	0.176	0.18
Implied SD (h)	0.03	0.03	0.04	0.18	0.03	0.170	0.165	0.36
Carhart model								
Avg. intercept	-0.19	0.36	0.017	1.11	0.48		0.001	0.24
Avg. *adj.* R^2	0.15	0.35	0.029	0.21	0.06		0.36	0.42
Implied SD (β)	0.06	0.02	0.03	0.02	0.21		0.149	0.16
Implied SD (S)	0.27	0.04	0.02	0.09	0.00		0.144	0.18
Implied SD (h)	0.06	0.02	0.03	0.22	0.02		0.152	0.32
Implied SD (m)	0.10	0.02	0.05	0.12	0.02		0.124	0.17

Note: blank cells mean that these figures were not reported in the relevant study.

Appendix

Table A.1: Sector definitions

Sector names	Sector definitions
Communication Services	Contains companies that provide content, such as information, advertising, entertainment, news, and social media, delivered on networks, primarily through the Internet, broadband, cellular, cable, and land lines.
Consumer discretionary	Contains businesses that are more sensitive to economic cycles, including makers of automobiles, household durable goods, leisure equipment, and textiles and apparel. Also covers services such as hotels, restaurants, and other leisure facilities, as well as retailing.
Consumer staples	Covers businesses that are less sensitive to economic cycles, including manufacturers and distributors of food, beverages, and tobacco, as well as producers of nondurable household goods and personal products. Also includes food and drug retailers.
Energy	Covers companies engaged in the exploration and production, refining and marketing, and storage and transportation of oil and gas and coal and consumable fuels. Also includes companies that offer oil and gas equipment and services.
Financials	Includes banks and thrifts, as well as providers of diversified financial services, specialized finance, consumer finance, asset management and the custody of securities, investment banking and brokerage services, capital markets services, financial exchanges, data and analytics, insurance underwriters and brokers, and mortgage real estate investment trusts (REITs).
Health care	Includes health care providers and services, companies that manufacture and distribute health care equipment and supplies, and health care technology companies. Also includes pharmaceutical and biotechnology companies.
Industrials	Includes manufacturers and distributors of capital goods, such as building products, electrical equipment and machinery, and aerospace and defense products. Includes providers of commercial services, such as construction and engineering, printing, environmental services, human resource services, research and consulting services, and transportation services.
Information technology	Covers companies that offer software and information technology consulting and data processing, excluding Internet services and home entertainment. Includes manufacturers and distributors of technology hardware and equipment, such as communications equipment, cell phones, computers, electronic equipment, and semiconductors.
Materials	Includes companies that manufacture chemicals, construction materials, glass, paper, forest products, and related packaging products, as well as metals, minerals, and mining companies, including steel producers.
Real estate	Includes companies operating in real estate management and development activities, and equity REITs, including diversified, industrial, hotel and resort, office, health care, residential, rental, and specialized REITs, but excluding mortgage REITs.
Utilities	Includes utility companies, such as electric, gas, and water utilities. Also includes independent power producers, energy traders, and companies that generate and distribute electricity using renewable sources.

Source: S&P Global Industry Classification Standards (https://www.spglobal.com/spdji/en/landing/investment-themes/sectors/).