Return range and the cross-section of expected index returns in international stock markets

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Return range and the cross-section of expected index returns in international stock markets

Abstract

This study examines the cross-sectional relation between return range and future returns for the first time in literature. We show that the return range can serve as a very practical measure of total volatility instead of standard deviation due to the range's high correlation with standard deviation and strong predictive ability. Range, standard deviation, and idiosyncratic volatility are cross-sectionally linked to future returns on indexes of small size, while earnings-to-price ratio and net share issuance predict returns of mid-cap and large-cap indexes, respectively. Maximum and minimum return effects along with the momentum effect are prevalent in returns of indexes of any size but stronger for small-cap indexes.

Key Words*: Portfolio management, International equity investment, Asset pricing.*

JEL Codes*: G11, G12, G17.*

1. Introduction

Understanding the cross-section of expected returns is at the heart of investment analysis. Asset-pricing models aim to identify systematic patterns in security returns. However, several anomalous return patterns that cannot be explained by asset-pricing models are widely reported. Although the traditional asset-pricing models postulate that only systematic risk factors, such as market beta, should be priced, empirical tests reveal that several volatility measures also matter for asset returns. For instance, i) total volatility (Bali, & Cakici, 2010; Baker et al., 2011), ii) idiosyncratic volatility (Merton, 1987; Malkiel & Xu, 2004; Ang et al., 2006, 2009), iii) tail risk associated with the skewness of return distribution (Harvey & Siddique, 2000; Conrad et al., 2013, Fu et al., 2016) are all found to be related to subsequent returns in the cross-section. Moreover, some studies even report that stocks with low betas outperform those with high betas, which is known as the low-beta anomaly (Frazzini & Pedersen, 2014). This finding is in direct opposition to the positive risk-return tradeoff commanded by asset-pricing models.

While a strand of the literature concentrates on detecting anomalous patterns in the cross-section of stock returns that cannot be explained by asset-pricing models, another strand aims to uncover whether the same return patterns can be found in the cross-section of international index returns.[1] Given the benefits of international diversification and the removal of barriers to foreign investors through the financial liberalization process, it is not surprising to see that investment in international equity indexes is becoming a popular phenomenon among portfolio managers and that the size of global portfolios is increasing over time (Moerman, 2008). The predictors of international index returns are crucial for international investors who aim to diversify their portfolio efficiently through international diversification without sacrificing expected returns. The increasing interest in international equity investment triggered the search for return predictors in alternative international asset universes. An example of such an alternative asset universe consists of international equity indexes. However, studies at the index level are far from being complete for at least two reasons. First, recently documented new return predictors at the stock level have not been investigated comprehensively yet at the index level. This calls further investigation to clarify whether the index-level counterparts of these new stock-level predictors are capable of forecasting index returns. Second, index-level studies mainly focus on country indexes whereas industry indexes are typically ignored, though recent studies provide evidence in favor of the increasing benefits of international diversification across industries (Boudoukh et al., 1994; Moskowitz & Grinblatt, 1999; Baca et al., 2000; Ferreira & Ferreira, 2006; Umutlu & Bengitöz, 2020; Umutlu & Gören Yargı, 2021). During the globalization process, country indexes become much more integrated (Phylaktis & Xia, 2006; Umutlu et al., 2010). As a result, return correlations among country indexes increase and the risk reduction obtained by diversifying across countries decreases, making the cross-industry diversification more attractive. Interestingly, few studies examine the predictability of industry index returns from the view point of a global investor aiming to diversify across industry indexes.

In this study, we address four issues. First, we aim to uncover whether the cross-sectional relation between several volatility measures (such as total volatility, idiosyncratic volatility, tail risk measured either as skewness or extreme returns such as maximum and minimum returns) and subsequent returns detected in the cross-section of stocks also exists in the cross-section of international indexes. Second, we propose a new return predictor called return range (*RANGE*), which is a proxy for total volatility. Third, besides the unsystematic volatility measures, we also examine whether the index-level counterparts of newly documented stock characteristics (such as operating profitability, investments, earnings surprise, and return on equity) that predict returns also forecast returns on international industry indexes. Fourth, we investigate whether the predictive power of volatility measures and index characteristics changes across indexes of different sizes.

We find that return range can serve as a very practical measure of total volatility instead of the traditional measure of standard deviation due to its high correlation with standard deviation and strong predictive ability of index returns. Our results show that the size of indexes plays a critical role in the relationship between a volatility measure (or an index characteristic) and subsequent returns. Univariate portfolio sorts based on volatility measures and index characteristics, bivariate sorts based on size and a volatility measure (or an index characteristic), cross-sectional Fama-MacBeth regressions for the whole sample and size subsamples collectively show that range, standard deviation, and idiosyncratic volatility are cross-sectionally linked to subsequent returns on indexes of small size, while earnings-to-price ratio and net share issuance predict returns of mid-cap and large-cap indexes, respectively. We also detect some anomalies that are independent of the size of indexes. Maximum and minimum return effects along with the momentum effect are prevalent in returns of indexes of any size but stronger for small-cap indexes.

Our paper contributes to the current literature in several ways. First, this is the first study that examines the cross-sectional relation between return range and future returns. This relation has been investigated for neither stock nor index returns. Thus, we extend the list of various volatility measures that predict future returns. Second, we use the most comprehensive set of volatility measures to examine their predictive ability in the cross-section of index returns. Each of the seven measures used in this study represents a different type of volatility. For instance, return range and standard deviation proxy for total volatility. The volatility of residuals from the ICAPM is used as the idiosyncratic volatility measure. Maximum and minimum returns over the last month aim to reflect upside and downside volatility, respectively. A version of total skewness measure, which is estimated based on daily data and not tested yet at the index-level, represents the tail risk. The last measure is the beta from the ICAPM and serves as the systematic risk measure. Third, in addition to the country indexes used in the previous literature, we use the local industry indexes as an alternative sample of international assets and thus provide new empirical evidence about the drivers of international index returns. Many of the previous studies focusing on international investments use only country indexes as international assets (Zaremba, 2019). The use of the local industry indexes offers the additional advantage of an increased sample size compared with the samples consisting of country indexes. Fourth, we examine the impact of portfolio size on the predictive power of index characteristics by conducting the most extensive bivariate sort analyses so far. We conducted bivariate sorts on size and 18 variables.

The rest of the article is organized as follows. Section 2 describes the data and the methodology. Section 3 presents and discusses the results. The final section concludes the paper.

2. Data and Methodology

Our sample consists of the industry indexes in multiple countries. We use the supersector definitions of the Industry Classification Benchmark (ICB) to determine industry groupings. ICB defines 19 supersectors that bring together sectors that share similar business operations.[2] The source for the data sets used in this study is the Thomson Reuters Datastream (DS). We collect monthly and daily return data for 19 industries (supersectors) from 37 countries of which 23 are developed (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States) and the remaining 14 are emerging/developing (Argentina, Brazil, Chile, China, India, Korea, Malaysia, Mexico, the Philippines, Poland, South Africa, Taiwan, Thailand, and Turkey). Daily and monthly Eurodollar deposit rates, again obtained from Datastream, are used as daily and monthly risk-free rates.

Besides return data, market capitalization, price-earnings ratio, and dividend yield of indexes are obtained on a monthly basis. Finally, some accounting data such as EBIT, interest paid, book equity, and total assets are collected annually to construct some of the anomaly variables. The monthly data are collected for the period between January 1973 and July 2015. The annual data for accounting items are available from June 1983.

The first group of variables is associated with risk measures. We examine a wide range of variables representing total, systematic, idiosyncratic, and tail risk. The definitions of risk measures are as follows: *RANGE* is the difference between the maximum and the minimum daily returns within the previous month. As will be explained in detail later, we use it as an alternative proxy for the total volatility. *MAX* is the maximum daily return over the past month and aims to represent extreme positive skewness associated with the upside risk (Bali et al., 2011). Similarly, *MIN* is the negative of the minimum daily return over the past month and can be considered as a measure for downside risk. *SD* is the monthly standard deviation of daily returns within the past month and is the traditional measure of total volatility. *IVOL* denotes idiosyncratic volatility, and it is the residual volatility where the residuals are from the ICAPM in which the daily excess industry returns within a month are regressed on the daily excess returns on the global market portfolio. The systematic risk, *BETA*, is the regression coefficient of the ICAPM (Scholes & Williams, 1977). To calculate the beta and idiosyncratic volatility of industry indexes in the ICAPM framework, returns on the DS World Market Index proxying the global market portfolio are also download both at the daily and monthly frequencies. *TSKEW* indicates total skewness and is a proxy for tail risk. *TSKEW* aims to capture the asymmetry of the return distribution. Following Bali et al. (2011), we calculate *TSKEW* by using daily return data in the trailing year as follows:

$$TSKEW_{it} = \frac{1}{D_t}\sum_{d=1}^{D_t}\left(\frac{R_{id}-\mu_i}{\sigma_i}\right)^3 \tag{1}$$

where R_{id} is the daily return on industry i, μ_i is the mean of daily returns over the trailing year, σ_i is the standard deviation of daily returns, and D_t is the number of trading days over the past year. We use idiosyncratic skewness (*ISKEW*) as an alternative measure of skewness, which is calculated as the skewness of daily residuals, ε_{id}, from the following model:

$$R_{id} - r_{fd} = \alpha_i + \beta_i(R_{Gd} - r_{fd}) + \gamma_i(R_{Gd} - r_{fd})^2 + \varepsilon_{id} \tag{2}$$

where R_{id} is the daily return on index i, R_{Gd} is the daily global market return, r_{fd} is the daily risk-free rate, and ε_{id} is the daily idiosyncratic return on day d. Daily data from month t-12 to month t-1 are used to calculate the monthly *ISKEW* variable in month t by estimating Equation (2) on a rolling basis with a window length of 12 months.

Several value characteristics form the second group of variables. *EP* is the reciprocal of the price-to-earnings ratio. *DY* represents the dividend yield and is the percent of dividend per share as a share of stock price and *EBITDA/EV* is the ratio of cash earnings to enterprise value. *EBITDA* is the earnings before interest, tax, depreciation, and amortization and *EV* is the enterprise value. The monthly data on price-to-earnings ratio, dividend yield, and *EV/EBITDA* ratio are directly obtained from Datastream.

MV represents the size of an index and is calculated as the natural logarithm of the market capitalization expressed in billion dollars. Next, we proceed with the momentum variables. We represent momentum by two variables calculated over different horizons. *MOM* indicates the intermediate-term momentum calculated as the cumulative monthly return from month t-12 to month t-2. *STMOM* shows the short-term momentum calculated as the cumulative monthly return from month t-6 to month t-1.

Variables such as operating profitability, earnings surprise, and return on equity form the variable group of profitability. We define operating profitability, *OP*, as earnings before interest and taxes (EBIT) minus interest divided by book equity, which is computed on an annual basis in each June based on available data in June of the previous year (Fama & French, 2015). Earnings surprise (*ES*) is defined as the changes in earnings forecasts of analysts in the spirit of Chan et al. (1996) and calculated as follows:

$$ES_t = \frac{\sum_{j=1}^{6}(DIEP_{t-j} - DIEP_{t-j-1})}{PI_{t-j-1}} \tag{3}$$

where *DIEP* is the 12-month forward earnings per share based on the Institutional Brokers' Estimate System (I/B/E/S) and *PI* is the price index. All data used to calculate *ES* are downloaded from Datastream. The last variable in this group is the return on equity (*ROE*), which is the net income divided by shareholders' equity.

In addition to all these variables that are classified into several groups, we also examine some stand-alone measures that were shown to affect asset returns. For instance, it is documented that net share issuance (*NSI*) and investments (*INV*) are negatively associated with future stock returns. Fama and French (2008) define *NSI* as the difference between the log of split-adjusted shares outstanding at the end and the beginning of the period. *INV* is defined as the growth rate of total assets from the June of year *t-2* to the June of year *t-1* (Fama & French, 2015). *INV* values are also calculated in each June.

<Table 1 here>

Some descriptive statistics for index characteristics are provided in Table 1. Time-series averages of the monthly cross-sectional means of characteristics across industry indexes from all countries are reported in the first column of the table. The standard deviation, maximum, and minimum values of cross-sectional means are calculated using the monthly time-series data and are reported in the remaining columns of the table.

<Table 2 here>

Table 2 shows the time-series average of cross-correlations among variables across industry indexes. Cross-correlations are calculated for each month in the research period. Notably, the variables in the same groups are highly correlated. For instance, volatility measures of *RANGE*, *MAX*, *MIN*, *SD*, and *IVOL* are very strongly correlated with each other. Skewness measures of *TSKEW* and *ISKEW*, valuation ratios of *EP* and *DY,* and lastly momentum measures of *MOM* and *STMOM* have high pairwise correlations. When highly correlated variables are included in the same regression, the parameter estimates can suffer from the multi-collinearity problem. To eliminate econometric problems that can originate from the potential multi-collinearity, strongly correlated variables will not be included in the same regression specifications.

In univariate portfolio sorts, we rank indexes based on each of the 19 index characteristics into quintile portfolios for each month in the research period. Then equal- and value-weighted quintile returns are calculated over the next month. We also calculate returns on the zero-investment portfolio that goes long the quintile portfolio with the highest values of an index characteristic (portfolio 5) and shorts the quintile with the lowest values (portfolio 1). We test whether this long-short portfolio earns excess raw and risk-adjusted returns. Any significant nonzero return is indicative of a cross-sectional relationship between the characteristic of interest and subsequent index returns.

In estimating the returns that are adjusted for risk, we employ benchmark models such as the International CAPM (ICAPM), and the global versions of the Fama-French 3-factor model (FF3), and Fama-French-Carhart 4-factor model (FFC4). The ICAPM is represented by Eq. (4):

$$R_{5-1t} = \alpha_{ICAPM} + \beta_G R_{Gt} + \varepsilon_t \tag{4}$$

where $R_{5\text{-}1t}$ shows the return on the zero-investment long-short portfolio based on an index characteristic in month t; R_{Gt} denotes the excess return on the DS World Market Index proxying the global market portfolio; α_{ICAPM} is the intercept term representing the Jensen alpha from the ICAPM; ε_t is the error term. In the global FF3 model, in addition to the global market factor, we also include global small-minus-big and high-minus-low factors. The model is formulated as in Eq. (5):

$$R_{5-1t} = \alpha_{FF3} + \beta_G R_{Gt} + \beta_{GSMB} R_{GSMBt} + \beta_{GHML} R_{GHMLt} + \varepsilon_t \tag{5}$$

where R_{GSMBt} is the global small-minus-big factor, R_{GHMLt} is the global high-minus-low factor, and α_{FF3} is the Jensen alpha from the global version of the FF3 model. R_{GSMBt} is the value-weighted return on the zero-investment portfolio that goes long the quintile of country-industry indexes with the smallest market values and simultaneously shorts the one with the biggest values. Similarly, R_{GHMLt} is the value-weighted return on the zero-investment portfolio that goes long the quintile of country-industry indexes with the highest earnings-to-price ratio and shorts the one with the lowest values. Global factors are constructed using industry indexes from all countries in our sample. R_{Gt} is as defined in Eq. (4). Additionally, we also include Carhart's (1997) momentum factor along with the three factors of Fama-French in another benchmark model represented by Eq. (6).

$$R_{5-1t} = \alpha_{FFC4} + \beta_G R_{Gt} + \beta_{GSMB} R_{GSMBt} + \beta_{GHML} R_{GHMLt} + \beta_{GMOM} R_{GMOMt} + \varepsilon_t \tag{6}$$

where R_{GMOMt} is the value-weighted return on the long-short quintile portfolio based on *MOM*, which is the cumulative return on country-industry indexes from month *t*-12 to month *t*-2. All other variables are as defined previously. α_{FFC4} denotes the risk-adjusted return from the global FFC4 Model. In all these time-series regressions, we examine whether the risk-adjusted return, i.e., the intercept (alpha), significantly departs from zero. If alpha is significantly nonzero, this means that the zero-cost arbitrage portfolio earns abnormal returns. Then, there is a statistically significant return difference between the high and low quintiles' risk-adjusted returns. This suggests that the relevant variable has an impact on future index returns that cannot be explained by risk factors.

Next, we perform bivariate portfolio sorts on size and an index characteristic to disentangle the effect of an index characteristic from that of size, and to check whether the relation (if any) between an index characteristic and return is stronger or only existent in portfolios of certain sizes. We first rank country-industry indexes based on market capitalization into five portfolios. This practice produces quintiles of different size levels. However, indexes in each size quintile will have similar market values. Then, we further sort the indexes within each size quintile into five portfolios based on the index characteristic of interest. Thus, we obtain portfolios with varying levels of an index characteristic but without a considerable variation in size. Examining the return difference between the long-short portfolios based on the relevant index characteristic within a size quintile thus allows us to test whether the index characteristic and future portfolio returns are related after controlling for size.

It is also likely that variables are correlated with each other and explain returns jointly. Therefore, controlling for a set of variables other than size will help to examine the conditional effect of a variable given the others. In portfolio sorts, it is difficult to include a large array of control variables. Therefore, we examine whether volatility measures and index characteristics persistently predict international index returns when they are all included in a regression model to account for potential common effects. Eq. (7) represents the full regression model including all variables. We estimate some nested versions of the full model excluding the highly correlated variables.

$$R_{it+1} = \lambda_{0t} + \lambda_{1t}RANGE_{it} + \lambda_{2t}MAX_{it} + \lambda_{3t}MIN_{it} + \lambda_{4t}SD_{it} + \lambda_{5t}IVOL_{it} + \lambda_{6t}TSKEW_{it} + \lambda_{7t}ISKEW_{it} + \lambda_{8t}BETA_{it} + \lambda_{9t}MV_{it} + \lambda_{10t}EP_{it} + \lambda_{11t}DY_{it} + \lambda_{12t}MOM_{it} + \lambda_{13t}STMOM_{it} + \lambda_{14t}OP_{it} + \lambda_{15t}INV_{it} + \lambda_{16t}EBITDA/EV_{it} + \lambda_{17t}ES_{it} + \lambda_{18t}NSI_{it} + \lambda_{19t}ROE_{it} + \varepsilon_{it} \quad (7)$$

where R_{it+1} is the return on industry index i in month t+1. Independent variables are calculated in month t. The cross-sectional regression presented in Eq. (7) is estimated for each month in the research period and the coefficient estimates are restored. Time-series averages of coefficient estimates over the months and their Newey and West (1987) adjusted t-statistics are reported. Any coefficient estimate significantly departing from zero will indicate a relationship between the relevant variable and subsequent returns.

3. Results

3.1. Portfolio sorts

3.1.1 Univariate portfolios sorts

Table 3 shows the equal-weighted average monthly returns of the quintile portfolios, which are formed by sorting the country-industry indexes based on each anomaly variable. The table also reports the average raw return differences between portfolio 5 and 1 (5-1) and the regression intercepts from the ICAPM (α_{ICAPM}) and the global versions of the FF3 (α_{FF3}) and FFC4 (α_{FFC4}) models.

<Table 3 here>

For the variables of *RANGE*, *MAX*, *MIN*, *SD*, *IVOL*, *TSKEW*, *ISKEW*, *MV*, *EP*, *DY*, *MOM*, *STMOM*, *EBITDA/EV*, *NSI* and *ROE*, the null hypothesis that the equal-weighted mean returns of portfolios 1 and 5 are equal to each other is rejected. The return on the long-short (5-1) portfolios based on the above-mentioned variables are significantly different from zero at conventional significance levels. Furthermore, for these characteristics except *ROE*, the hypotheses that all intercept terms from the ICAPM, global FF3, and FFC4 models (α_{ICAPM}, α_{FF3}, and α_{FFC4}, respectively) are equal to zero are rejected. These findings suggest that *RANGE*, *MAX*, *MIN*, *SD*, *IVOL*, *TSKEW*, *ISKEW*, *MV*, *EP*, *DY*, *MOM*, *STMOM*, *EBITDA/EV*, and *NSI* have the potential to influence the equal-weighted index returns in the cross-section. We do not detect any raw or risk-adjusted return differences between the long-short portfolios based on *OP*, *INV*, and *ES*, suggesting no link between these variables and future returns.

<Insert Table 4 here>

Next, we examine the value-weighted portfolios and report the results in Table 4. One of the most important findings in Table 4 is that fewer number of long-short portfolios generate raw and risk-adjusted returns that are significantly different from zero. Trading strategies based on *MAX*, *MIN*, *BETA*, *MV*, and *MOM* continue to provide abnormal returns as evidenced by significant raw returns (0.0428, -0.0447, -0.0051, -0.0090, and 0.0055, respectively) and alphas from three different benchmark models. The highly significant t-statistics indicate that these variables are strong return predictors of indexes of any size. However, 5-1 portfolios based on *RANGE*, *SD*, *IVOL*, *TSKEW*, *ISKEW*, *EP*, *DY*, *STMOM*, *EBITDA/EV*, and *NSI* that were reported to yield abnormal returns for equal-weighted portfolios no longer provide significant returns for value-weighted portfolios. It is also found that *ES* and *ROE*, which have no impact on equal-weighted returns, significantly affect value-weighted returns.

In sum, the results for equal- and value-weighted portfolios do not fully overlap. This difference can be attributed to the size effect as equal-weighted portfolios ignore the size differences among indexes in calculating portfolio returns whereas value-weighted portfolios give much emphasis on large indexes. Thus, returns on small-cap indexes can be more influential for equal-weighted portfolio returns as small indexes may be numerous while returns on big indexes are more important for value-weighted portfolio returns as large-cap indexes have larger weights. To address this issue more formally, we conduct bivariate sorts on size and other variables in the next subsection.

3.1.2 Bivariate portfolio sorts on size and several variables

Motivated by the findings of Fama and French (2008) showing that the effects of characteristics on future returns are stronger for small-cap stocks, we test whether there is also a parallel size effect in the predictive ability of volatility measures and index characteristics in this subsection. The results of bivariate portfolio sorts based on size and several variables are presented in Table 5. In this table, we present the results for a selected group of variables that produces a nonzero raw or risk-adjusted return on long-short characteristic portfolios. For these portfolios, we further examine whether the power of the relationship changes across different size quintiles. If raw and risk-adjusted returns on 5-1 portfolios do not deviate significantly from zero in all five size quintiles, then we can conclude that the variable under investigation does offer useful information about returns after controlling for size. If significant results are obtained for only a subset of the size quintiles, this indicates the relation under investigation is specific to indexes of certain sizes. We present the insignificant results in Table A.1 of the Online Appendix and concentrate on the significant results in Table 5.

< Insert Table 5 here >

Each column in Panel A of Table 5 except the last one shows average monthly returns on indexes that have been sorted by *RANGE* after controlling for size. The last column, 5-1*MV*, indicates the return difference between big and small indexes. The 5-1*RANGE* portfolio in each size quintile is long in the portfolio with the highest values of *RANGE* and short in the one with the lowest values. The raw return on the 5-1*RANGE* portfolio significantly departs from zero for size portfolios of *MV*1, *MV*2, and *MV*3. The t-statistics for these portfolios are 7.22, 4.67, and 3.07, respectively. The risk-adjusted returns on these portfolios under the global version of ICAPM are still significantly different from zero, with t-statistics ranging from 2.55 to 8.79. The smallest two size quintiles, *MV*1 and *MV*2, continue to produce significant alphas under the global version of the FF3 and FFC4 models. The FF3 (FFC4) alphas on *MV*1 and *MV*2 are 0.02624 and 0.0062 (0.0260 and 0.0068), with t-statistics of 8.00 and 2.29 (7.94 and 2.44), respectively. For *MV*3, *MV*4, and *MV*5 size quintiles, none of the benchmark models delivers a nonzero alpha. It is noteworthy that the raw and risk-adjusted returns on the 5-1*RANGE* portfolios within various size quintiles decrease with increasing market capitalization of the size quintiles. These results suggest that the *RANGE* effect is more pronounced in returns of small-cap portfolios. To compare the relation between *RANGE* and index returns for large and small-cap portfolios more formally, we test whether the returns on 5-1*RANGE* portfolios within *MV*1 and *MV*5 portfolios are statistically different from each other. The intersection of the 5-1*RANGE* row and the 5-1*MV* column in Panel A of Table 5 shows that the risk-adjusted return differences between the 5-1*RANGE* portfolio in *MV*5 and that in *MV*1 are -0.0401, -0.0367, and -0.0367, all of which are significant at 1% significance level. Thus, the range effect is significantly more pronounced for small-cap indexes. This result confirms the result from the univariate portfolio sorts in Table 3, which shows that the range effect is only observed for equal-weighted portfolios dominated by small indexes.

In Panel B where the returns on portfolios obtained from double sorts on *MV* and *MAX* are shown, raw returns on 5-1*MAX* portfolios are distinguished from zero in all size segments.

Moreover, the returns on long-short *MAX* portfolios remain significant after adjusting for risk under all three benchmark models. These findings suggest that the relationship between *MAX* and index returns is not sensitive to the size of portfolios and can be observed for portfolios of any size. This result conforms with the results for *MAX* in Table 3 indicating a *MAX* anomaly in both equal- and value-weighted portfolios. Thus, the *MAX* effect can manifest itself in all size segments. To test whether the power of the relationship between *MAX* and future returns varies for indexes of different sizes, we examine whether the return difference between the long-short *MAX* portfolios within the biggest and smallest size quintiles is equal to zero. The results show that the raw and risk-adjusted return differences between the 5-1*MAX* portfolios within quintiles *MV*5 and *MV*1 are distinguishable from zero. The raw return difference of -0.0759 is significantly different from zero. The return difference stays significant after controlling for risk factors as evidenced by significant alphas in the last column. These findings indicate a stronger link between *MAX* and returns for small portfolios.

Next, we move onto the results for *MIN* presented in Panel C. *MIN* is negatively related to returns on all size portfolios and this relation is more pronounced in small portfolios. More specifically, the returns on 5-1*MIN* portfolios within size quintiles monotonically decrease from small portfolios to big ones. The findings in Panel C of Table 5 demonstrate that the *MIN* effect is widespread among all size segments. Again, these findings support the results in Table 3 indicating that the effect is prevalent in both equal- and value-weighted portfolios, which are dominated by small and big indexes, respectively.

Panels D, E, and F presenting the results for bivariate sorts on *MV* and *SD*, *IVOL*, or *TSKEW* are very similar. The positive association between these variables and returns are limited to small portfolios. Panels G, H, J, I, K, L, and M show the results when the second sort variables are *BETA*, *EP*, *EBITDA/EV*, *MOM*, *ES*, *NSI,* and *ROE*, respectively

We can summarize the results from bivariate sorts in four categories. The first category reveals that *RANGE*, *SD*, *IVOL*, *TSKEW*, and *ROE* effects are concentrated only in small size quintiles, whereas the *ES* effect shows up exclusively in large-cap portfolios. The second category of results shows that *MAX*, *MIN*, *EP*, *MOM*, and *EBITDA/EV* effects are prevalent among a wide range of portfolio sizes, from small to large. However, the impact of these anomaly variables on returns is stronger for small size quintiles. The third category indicates that variables such as *BETA* and *NSI* are associated with returns of portfolios that are mixed in size. The last category of results provided in Table A1 of the Online Appendix shows the results for index characteristics such as *OP* and *INV*, which do not affect returns in any of the size quintiles. Table A1 also includes the results for *ISKEW*, *DY*, and *STMOM*, which are alternative variables to base case variables of *TSKEW*, *EP*, and *MOM*, respectively. The results for alternative variables are similar to those reported in the first and second categories in the sense that abnormal returns either exist or are more pronounced in the small-sized portfolios.

3.2. Index-level cross-sectional regressions

3.2.1 Cross-Sectional regressions for the full sample

Table 6 reports the results of cross-sectional regressions for country-industry portfolios. We do not include *RANGE, MAX, MIN, SD,* and *IVOL* in the same regression specification simultaneously due to high correlations among them as reported in Table 2. Similarly, we exclude the remaining partly overlapping variables from the analyses. For instance, we pick *EP* as the main value characteristic and exclude its alternative *DY* from the regression analyses. We employ *MOM* as the basic momentum variable and drop its alternative *STMOM*. A similar simplification is applied to the skewness-related variables of *TSKEW* and *ISKEW* and the former one is included as the only skewness variable in regressions. Lastly, out of two profitability characteristics of *OP* and *ROE*, we use *OP* in the base case regressions. Later on, in robustness tests, we also replace the main variables with their alternative counterparts to examine whether the results obtained are sensitive to the use of alternative variable definitions.

The first five rows show the results for the regression specifications that include only two of the volatility measures (*TSKEW* and one of the remaining volatility measures) but exclude the control variables of *EBITDA/EV*, *ES*, *NSI*, *OP*, and *INV*. The last five rows present the results for the specifications including these control variables as well. For the first five regressions specifications, the research period extends from March 1974 to July 2015. As the data needed to construct the excluded control variables in the first five specifications are jointly available from September 1985, the research period starts in that month for the last five regression specifications. The time-series averages of the slope coefficients over the research period along with their Newey and West (1987) adjusted t-statistics are reported in the table.

Five of the seven volatility measures (*RANGE*, *MAX*, *MIN*, *SD*, and *IVOL*) have highly significant coefficient estimates for all the specifications they are included. The last five rows further indicate that the inclusion of more control variables in regression analyses and the use of a more recent research period do not change the significant results of the five volatility measures. On the other hand, regressions produce some significant slope estimates for the remaining volatility measures of *TSKEW* and *BETA* but they are not consistently significant for all specifications, especially when more control variables are included. Moreover, the slope estimates on *TSKEW* and *BETA* change sign in some specifications.

Index characteristics such as *EP*, *MOM*, and *EBITDA/EV* produce slopes that differ significantly from zero in all specifications. The significance of the slopes on these characteristics is not affected by whether the full set or a subset of variables are included in regression specifications. Some other characteristics such as *BETA*, *MV*, *ES*, and *NSI* that were found to significantly predict returns in portfolio sorts accommodating no or only one control variable lose their significant impact when conditioned on several variables. Lastly, *OP* and *INV* fail to provide evidence for a significant impact on returns, as their slopes are not different from zero in some specifications.

In summary, the significant return predictors that survive after controlling for a large set of control variables in regression analyses are *RANGE*, *MAX*, *MIN*, *SD*, *IVOL*, *EP*, *MOM*, and *EBITDA/EV*. In the next section, we examine whether the documented relations between these variables and returns are specific to or more pronounced in certain size segments as we do in portfolio sorts.

3.2.2 Cross-sectional regressions across size quintiles

We conduct index-level cross-sectional regressions for size quintiles. Each panel of Table 7 shows the results for one of the quintiles. The most striking results in Table 7 are those obtained for the five volatility measures that were found to significantly affect returns previously. While the slope estimates for *RANGE*, *SD*, and *IVOL* decrease sharply from the smallest size quintile (whose results are shown in Panel A) to the biggest one (whose results are shown in Panel E) and turn into insignificant for size quintiles of *MV*4 and *MV*5, those for *MAX* and *MIN* persistently stay stable and significant across all size quintiles. These findings are a confirmation of the previous results from portfolio sorts, suggesting that *RANGE*, *SD*, and *IVOL* effects are confined to the subsamples of small and medium-cap indexes whereas *MAX* and *MIN* effects are spread over indexes of any size. Like the slopes on *MAX* and *MIN*, the slopes on *MOM* are positive significant for all size quintiles. Thus, the momentum effect is also a pervasive effect observed in the returns of industry indexes. Besides, we find significant slopes for *EP* in size quintiles of *MV*3 and *MV*4 and for *EBITDA/EV* in *MV*4, suggesting that anomalies based on these variables can arise in portfolios of different sizes. However, *TSKEW* and *ROE*, which were significantly associated with returns of small-cap portfolios in bivariate portfolio sorts, lose their significant impact after controlling for other index characteristics in cross-sectional regressions. Similarly, *ES* was significantly associated with returns on large-cap portfolios in bivariate sorts but its impact does not survive in the regressions for large-cap quintiles. For the remaining variables of *MV*, *OP*, *NSI*, and *INV*, we find neither significant nor consistent slopes in size-based cross-sectional regressions. Hence, there is no consistent evidence for the existence of *TSKEW*, *ROE*, *ES*, *MV*, *OP*, *NSI*, and *INV* anomalies across size portfolios after controlling for other variables in cross-sectional regressions.

<Insert Table 7 here>

3.3. Robustness tests

In the regression analysis performed so far, we used *EP*, *MOM*, *TSKEW*, and *OP* as the main variables to capture value, momentum, skewness, and profitability characteristics. In this subsection, we employ alternative counterparts to the main variables to check the robustness of the results. More specifically, we replace *EP*, *MOM*, *TSKEW*, and *OP* with *DY*, *STMOM*, *ISKEW*, and *ROE*, respectively, in regressions and report the results in Table 8.

<Table 8 here>

The results are mainly in conformity with the previous results from the regression specifications including the main variables, which are presented in Table 6. The use of alternative variables did not change the results regarding the five volatility measures (*RANGE*, *MAX*, *MIN*, *SD*, *IVOL*). All five volatility measures keep having significant coefficients. Moreover, alternative variables affect returns in the same way as the main variables do. Hence, the results from regression analyses are not sensitive to alternative definitions of variables.

3.4.Discussion of the results

The positive significant effect of *RANGE* on index returns is a new finding documented in this study. A potential explanation for the predictive ability of *RANGE* can be based on the findings of stock-level studies showing that *MAX* and *MIN* significantly predict returns. For instance, Bali et al. (2011) show that there is a negative (positive) correlation between *MAX* (*MIN*) and future stock returns. They explain the finding of a positive relation between *MAX* and stock returns as the manifestation of overinvestment in lottery-like stocks, which provide extreme positive returns with a small probability. High demand for such stocks causes them to be overvalued. Subsequently, these stocks revert to equilibrium prices with price depreciation, causing a decrease in future returns. This explanation at the stock level does not apply to our results for at least two reasons. First, we find a positive (negative) rather than a negative (positive) relation between *MAX* (*MIN*) and future index returns. Second, international indexes exhibit relatively stable return patterns rather than lottery-like payoffs compared to individual stocks. International indexes achieve a high degree of diversification, thus avoiding extreme price movements, and reduce the return volatility. Therefore, for international indexes, *MAX* might not represent the high demand for lottery-like assets. At the country level, Zaremba (2016) shows that a trading strategy that goes long (short) the country indexes with the lowest (highest) *MAX* earns negative returns. This trading strategy is the direct opposite of the strategy used in this study and that in Bali et al. (2011), which goes long (short) the assets with the highest (lowest) *MAX*. Therefore, the index-level results about *MAX* documented by Zaremba (2016) support our results, calling for further explanation of the *MAX* effect at the index level. The effect of *MIN* on asset returns has not been examined yet in the cross-section of index returns. In this study, we report a very strong negative correlation between *MIN* and future index returns, a finding that needs to be explained as well.

Another explanation for the maximum and minimum effects is that *MAX* and *MIN* proxy for the upside and downside volatility at the index level. The correlation analysis among variables shows that *MAX*, *MIN*, and the total volatility measure of *SD* are all very highly correlated with each other. The high correlation between *MAX* and *MIN* reported in Table 2 indicates that indexes with relatively high returns also experience relatively low returns. In addition to this finding, very high correlations between *MAX* and *SD* and between *MIN* and *SD* suggest that both *MAX* and *MIN* can proxy for *SD*. These two findings suggest that both *MAX* and *MIN* represent total volatility rather than upside and downside volatility. In light of these findings, we attempt to obtain a new single measure that tracks total volatility better by combining *MAX* and *MIN*. We use the dispersion measure of range in statistics, which is defined as the difference between the highest and lowest observations. The correlation analyses in Table 2 show that *RANGE* is the most highly correlated variable with *SD* with correlation coefficients of 0.9594. Thus, by combining *MAX* and *MIN* in *RANGE*, we construct a measure that captures total volatility better than *MAX* and *MIN*. This motivates us to examine whether *RANGE* as an alternative measure of total volatility explains future index returns, which is a question that has not been investigated before. Our finding that investors require a risk premium for holding indexes with high *RANGE* supports the results of Bali and Cakici (2010) and Hueng and Yau (2013), who show that there is a positive relationship between the total volatility and country index returns.

4. Conclusion

We examine the predictive ability of several volatility measures including the return range and index characteristics in the cross-section of industry indexes from 37 countries. The return range is defined as the difference between the maximum and minimum daily returns over the past month and offered as an alternative total volatility measure. The results show that return range is a very convenient measure of total volatility as compared to the widely used total volatility measure of standard deviation because of the computational ease and fewer data requirements of range as well as the high correlation between range and standard deviation. We further show that the size of indexes matters for the predictive power of variables. For instance, while return range, standard deviation, and idiosyncratic volatility effects are only existent in returns of small-cap indexes, earnings-to-price ratio and net share issuance forecast returns of mid-cap and large-cap indexes, respectively. Besides, maximum and minimum return effects as well as momentum in returns are pervasive across all size quintiles. Nevertheless, these effects are stronger for small-cap indexes. Finally, the results are robust to the use of alternative definitions of the variables and after accounting for control variables.

Our results have implications for international portfolio management. First, this study shows that investigating the index-level counterparts of recently documented stock-return predictors is a worthwhile effort from a portfolio management point of view, as some of the variables that predict stock returns also forecast index returns. Second, the size of indexes is a crucial factor that can affect the predictive power of volatility measures and index characteristics. The predictive power of some variables only exists or remarkably improves in small-cap indexes. This result can shape the decision of global investors about index selection. Third, stock markets are not efficient even at the global level and this creates profit opportunities for global portfolio managers. An active portfolio management strategy based on total volatility, idiosyncratic volatility, momentum, and value characteristics can generate abnormal returns especially for industry indexes of small size.

Notes

[1] Bali and Cakici (2010) test whether the world market risk, country-specific total risk, and idiosyncratic risk are priced factors in the international capital asset-pricing model using the stock market indexes of 37 countries. Richards (1997) examines the "winner–loser reversals" for the national stock market indexes of 16 countries. Bhojraj and Swaminathan (2006) and Zaremba et al. (2019) study the impact of momentum in international stock market indexes. Liu et al. (2011) focus on the 52-week high-momentum strategy in international stock markets by examining 20 major stock markets. Kim (2012) search for the variables that can be used for forecasting the inter-country cross-sectional variations in the value premium.

[2] These 19 supersectors track the following industries: Automobile and parts, banks, basic resources, chemicals, construction and materials, financial services, food and beverages, health care, industrial goods and services, insurance, media, oil and gas, personal and household goods, real estate, retail, technology, telecom, travel and leisure, utilities.

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Table 1. Basic statistics

	Mean	Std. Dev.	Max	Min
RANGE	0.0011	0.0049	0.0959	0.0001
MAX	0.0006	0.0031	0.0637	0.0001
MIN	0.0005	0.0019	0.0322	0.0001
SD	0.0012	0.0049	0.0941	0.0002
IVOL	0.0011	0.0045	0.0850	0.0001
TSKEW	0.0017	0.0173	0.3522	-0.0324
ISKEW	0.0019	0.0137	0.2737	-0.0339
BETA	0.0084	0.0403	0.8811	-0.0120
MV	0.1066	0.3654	6.6430	0.0279
EP	0.0010	0.0027	0.0466	0.0002
DY	0.0004	0.0013	0.0222	0.0001
MOM	0.0004	0.0008	0.0030	-0.0049
STMOM	0.0002	0.0008	0.0072	-0.0041
OP	0.0040	0.0154	0.2489	-0.0014
INV	0.0051	0.0090	0.1123	0.0002
EBITDA/EV	0.0048	0.0110	0.1320	0.0002
ES	0.0189	0.1288	1.3011	-0.0008
NSI	0.0010	0.0033	0.0544	0.0000
ROE	0.2637	0.7662	10.3689	0.0077

This table provides the basic statistics for a total of nineteen volatility measures and index characteristics. *Mean* is the time-series average of the cross-sectional means of each variable calculated across nineteen indexes from thirty-seven countries. The standard deviation, maximum, and minimum values of *Mean* are computed using the monthly time-series data. *RANGE* is the difference between the previous month's maximum and minimum daily return. *MAX* is the maximum daily index return within the previous month. *MIN* is the negative of the minimum daily index return within the previous month. *SD* is the standard deviation of daily returns within the trailing month. *IVOL* is the residual volatility where residuals are from the ICAPM estimated with daily returns within the past month. *TSKEW* indicates total skewness of returns and is calculated using daily returns in the trailing year. *ISKEW* stands for idiosyncratic skewness and is the skewness of daily residuals from the model in which industry index return is regressed on the excess return and the square of excess return on the global market portfolio. *BETA* is the regression coefficient of the ICAPM. *MV* is the natural logarithm of the market value in billion dollars. *EP* is the reciprocal of the price-to-earnings ratio. *DY* represents the dividend yield and is the percent of dividend per share as a share of stock price. *MOM* denotes the intermediate-term momentum and is the cumulative monthly return over the period spanning from month *t*-12 to month *t*-2. *STMOM* is the short-term momentum calculated as the cumulative monthly return over the period from month *t*-6 to month *t*-1. *OP* is defined as operating profitability that is equal to the difference between EBIT and interest divided by book equity. *INV* refers to investments and is the growth rate of total assets. *EBITDA/EV* is the ratio of cash earnings to enterprise value. *ES* is the earnings surprise reflecting the changes in earnings forecasts of analysts. *NSI* is the net share issuance measured as the difference between the log of split-adjusted shares outstanding. *ROE* is the return on equity. The research period is January1973-July 2015.

Table 2. Correlation analyses

	RANGE	*MAX*	*MIN*	*SD*	*IVOL*	*TSKEW*	*ISKEW*	*BETA*	*MV*	*EP*	*DY*	*MOM*	*STMOM*	*OP*	*INV*	*EBITDA /EV*	*ES*	*NSI*	*ROE*
RANGE	1																		
MAX	0.8849	1																	
MIN	0.8521	0.5242	1																
SD	0.9594	0.8519	0.8159	1															
IVOL	0.9139	0.8158	0.7738	0.9466	1														
TSKEW	0.0852	0.0867	0.0613	0.0863	0.0857	1													
ISKEW	0.0678	0.0692	0.0478	0.0686	0.0633	0.9064	1												
BETA	0.3202	0.2741	0.2889	0.3564	0.1212	0.0089	0.0192	1											
MV	-0.2515	-0.2309	-0.2093	-0.2466	-0.3291	-0.0745	-0.0461	0.1923	1										
EP	0.0419	0.0382	0.0406	0.0399	0.0557	-0.0406	-0.0568	-0.0375	-0.1224	1									
DY	-0.0518	-0.0507	-0.0380	-0.0635	-0.0385	-0.1212	-0.1453	-0.0874	-0.0815	0.4119	1								
MOM	0.0200	0.0203	0.0110	0.0241	0.0286	0.1236	0.1621	0.0068	0.0023	-0.1040	-0.1451	1							
STMOM	0.0007	0.0047	-0.0061	0.0026	0.0089	0.1274	0.1535	-0.0054	0.0091	-0.1156	-0.1312	0.6171	1						
OP	-0.0055	-0.0072	-0.0027	-0.0074	-0.0012	0.0049	0.0040	-0.0185	0.0302	0.0811	0.0890	0.0105	0.0114	1					
INV	0.0208	0.0184	0.0203	0.0212	0.0271	0.0203	0.0125	-0.0038	-0.0298	-0.0006	-0.0254	-0.0064	-0.0110	0.0323	1				
EBITDA /EV	0.0517	0.0454	0.0461	0.0555	0.0645	-0.0115	-0.0177	-0.0073	-0.1014	0.2461	0.1179	-0.0144	0.0129	0.0663	-0.0327	1			
ES	0.0044	-0.0016	0.0083	0.0111	0.0054	0.0119	0.0211	0.0235	0.0248	-0.0259	-0.0312	0.0914	0.0773	-0.0153	-0.0113	-0.0010	1		
NSI	0.0210	0.0151	0.0208	0.0225	0.0301	-0.0068	-0.0071	-0.0099	-0.0538	0.0095	-0.0351	0.0296	0.0003	-0.0227	0.0425	-0.0406	-0.0076	1	
ROE	-0.0114	-0.0134	-0.0065	-0.0151	-0.0040	-0.0144	-0.0053	-0.0331	0.0015	0.1465	0.0921	0.0999	0.0531	0.3968	0.0094	0.0941	-0.0063	-0.0244	1

The time-series average of the monthly cross-correlations among variables across indexes are reported in the table.

Table 3. Returns on equal-weighted portfolios sorted by volatility measures or index characteristics

	1	2	3	4	5	5-1	α_{ICAPM}	α_{FF3}	α_{FFC4}
RANGE	0.0079	0.0097	0.0113	0.0135	0.0256	0.0177***	0.0143***	0.0062***	0.0064***
						(5.12)	(5.48)	(3.25)	(3.20)
MAX	-0.0133	0.0004	0.0092	0.0187	0.0533	0.0666***	0.0635***	0.0563***	0.0566***
						(19.17)	(25.28)	(29.12)	(23.76)
MIN	0.0334	0.0217	0.0150	0.0079	-0.0103	-0.0437***	-0.0464***	-0.0524***	-0.0521***
						(-15.43)	(-21.06)	(-28.93)	(-27.97)
SD	0.0075	0.0093	0.0107	0.0131	0.0275	0.0200***	0.0162***	0.0078***	0.0081***
						(5.43)	(5.96)	(3.84)	(3.81)
IVOL	0.0072	0.0091	0.0103	0.0132	0.0282	0.0209***	0.0178***	0.0087***	0.0091***
						(5.94)	(6.51)	(4.59)	(4.57)
TSKEW	0.0132	0.0124	0.0128	0.0144	0.0172	0.0040***	0.0036***	0.0029**	0.0028**
						(3.39)	(3.03)	(2.34)	(2.18)
ISKEW	0.0132	0.0124	0.0128	0.0138	0.0179	0.0047***	0.0045***	0.0041***	0.0038***
						(4.16)	(3.97)	(3.60)	(3.23)
BETA	0.0189	0.0118	0.0112	0.0112	0.0149	-0.0040**	-0.0071***	-0.0065***	-0.0066***
						(-1.72)	(-3.75)	(-3.48)	(-3.41)
MV	0.0206	0.0145	0.0120	0.0114	0.0096	-0.0110***	-0.0115***	-0.0102***	-0.0104***
						(-6.66)	(-7.41)	(-6.88)	(-7.04)
EP	0.0104	0.0116	0.0117	0.0138	0.0175	0.0070***	0.0071***	0.0049***	0.0052***
						(3.92)	(4.03)	(3.11)	(3.57)
DY	0.0113	0.0113	0.0119	0.0136	0.0173	0.0060***	0.0064***	0.0049***	0.0056***
						(3.44)	(3.71)	(3.53)	(4.37)
MOM	0.0118	0.0113	0.0127	0.0135	0.0195	0.0077***	0.0086***	0.0094***	0.0094***
						(2.87)	(3.36)	(3.61)	(3.61)
STMOM	0.0121	0.0101	0.0111	0.0132	0.0194	0.0073***	0.0083***	0.0085***	0.0049**
						(2.91)	(3.41)	(3.57)	(2.51)
OP	0.0150	0.0133	0.0129	0.0141	0.0143	-0.0007	-0.0007	0.0002	0.0000
						(-0.51)	(-0.53)	(0.17)	(0.02)
INV	0.0154	0.0130	0.0132	0.0133	0.0129	-0.0025	-0.0029*	-0.0024	-0.0022
						(-1.42)	(-1.81)	(-1.47)	(-1.28)
EBITDA/EV	0.0121	0.0118	0.0127	0.0145	0.0192	0.0071***	0.0072***	0.0055***	0.0052***
						(5.13)	(5.09)	(4.13)	(3.79)
ES	0.0109	0.0128	0.0114	0.0119	0.0113	0.0004	0.0007	0.0010	0.0001
						(0.31)	(0.56)	(0.69)	(0.11)
NSI	0.0155	0.0139	0.0135	0.0123	0.0137	-0.0018*	-0.0024**	-0.0025***	-0.0027***
						(-1.65)	(-2.41)	(-2.60)	(-2.85)
ROE	0.0130	0.0125	0.0141	0.0148	0.0162	0.0033**	0.0036**	0.0031**	0.0021
						(2.09)	(2.29)	(2.02)	(1.44)

Local industry indexes are sorted into quintile portfolios based on volatility measures or index characteristics for each month in the research period. Equal-weighted quintile returns as well as returns on the 5-1 long-short portfolios are calculated over the next month. Portfolio 1 (5) includes the indexes with the lowest (highest) values of a sort variable. The 5-1 portfolio is the zero-investment portfolio, which goes long the quintile with the highest values of a variable and shorts the one with the lowest values. Average raw returns and Jensen alphas from the ICAPM, the Fama-French three-factor model (FF3), and the Fama-French-Carhart four-factor model (FFC4) on the 5-1 portfolio are presented in the last four columns, respectively. The Newey-West (1987) t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 4. Returns on value-weighted portfolios sorted by volatility measures or index characteristics

	1	2	3	4	5	5-1	α_{ICAPM}	α_{FF3}	α_{FFC4}
RANGE	0.0091	0.0095	0.0097	0.0098	0.0136	0.0045	0.0004	-0.0029	-0.0024
						(1.10)	(0.12)	(-1.06)	(-0.81)
MAX	-0.0043	0.0072	0.0143	0.0206	0.0385	0.0428***	0.0392***	0.0370***	0.0374***
						(10.92)	(12.62)	(13.12)	(12.70)
MIN	0.0234	0.0126	0.0062	-0.0033	-0.0214	-0.0447***	-0.0476***	-0.0502***	-0.0499***
						(-15.28)	(-20.51)	(-21.78)	(-21.39)
SD	0.0089	0.0098	0.0096	0.0098	0.0154	0.0065	0.0021	-0.0015	-0.0012
						(1.50)	(0.64)	(-0.50)	(-0.39)
IVOL	0.0090	0.0088	0.0086	0.0132	0.0167	0.0077*	0.0048	-0.0017	-0.0019
						(1.91)	(1.40)	(-0.56)	(-0.61)
TSKEW	0.0103	0.0096	0.0099	0.0089	0.0096	-0.0007	-0.0017	0.0007	0.0014
						(-0.36)	(-0.87)	(0.36)	(0.75)
ISKEW	0.0094	0.0090	0.0088	0.0091	0.0122	0.0028	0.0020	0.0051***	0.0052***
						(1.52)	(1.06)	(2.85)	(2.90)
BETA	0.0134	0.0105	0.0092	0.0079	0.0083	-0.0051**	-0.0083***	-0.0054***	-0.0053**
						(-2.08)	(-3.74)	(-2.56)	(-2.42)
MV	0.0176	0.0141	0.0120	0.0117	0.0086	-0.0090***	-0.0093***	-0.0073***	-0.0074***
						(-4.96)	(-5.23)	(-4.82)	(-4.85)
EP	0.0069	0.0096	0.0101	0.0111	0.0122	0.0054**	0.0057**	0.0007	0.0015
						(2.23)	(2.33)	(0.29)	(0.64)
DY	0.0081	0.0092	0.0101	0.0112	0.0119	0.0039*	0.0050**	0.0005	0.0009
						(1.69)	(2.23)	(0.46)	(0.74)
MOM	0.0070	0.0079	0.0109	0.0115	0.0125	0.0055*	0.0063**	0.0075***	0.0075***
						(1.87)	(2.21)	(2.62)	(2.62)
STMOM	0.0084	0.0074	0.0080	0.0099	0.0132	0.0048*	0.0059**	0.0058*	0.0008
						(1.69)	(2.12)	(1.94)	(0.34)
OP	0.0078	0.0084	0.0100	0.0117	0.0110	0.0031*	0.0036*	0.0029*	0.0022
						(1.70)	(1.92)	(1.66)	(1.36)
INV	0.0108	0.0107	0.0098	0.0091	0.0101	-0.0007	-0.0019	0.0003	0.0001
						(-0.39)	(-0.99)	(0.15)	(0.07)
EBITDA/EV	0.0083	0.0104	0.0111	0.0124	0.0122	0.0039**	0.0046**	0.0011	0.0003
						(2.12)	(2.53)	(0.71)	(0.20)
ES	0.0085	0.0088	0.0102	0.0102	0.0043	-0.0042**	-0.0040**	-0.0043**	-0.0051***
						(-2.30)	(-2.12)	(-2.13)	(-2.71)
NSI	0.0100	0.0102	0.0095	0.0088	0.0087	-0.0014	-0.0024	-0.0032*	-0.0037**
						(-0.82)	(-1.56)	(-1.86)	(-2.09)
ROE	0.0069	0.0097	0.0105	0.0119	0.0115	0.0047**	0.0058**	0.0047**	0.0031*
						(1.99)	(2.54)	(2.42)	(1.74)

Local industry indexes are sorted into quintile portfolios based on volatility measures or index characteristics for each month in the research period. Value-weighted quintile returns as well as returns on the 5-1 long-short portfolios are calculated over the next month. Portfolio 1 (5) includes the indexes with the lowest (highest) values of a sort variable. The 5-1 portfolio is the zero-investment portfolio, which goes long the quintile with the highest values of a variable and shorts the one with the lowest values. Average raw returns and Jensen alphas from the ICAPM, the Fama-French three-factor model (FF3), and the Fama-French-Carhart four-factor model (FFC4) on the 5-1 portfolio are presented in the last four columns, respectively. The Newey-West (1987) t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 5. Returns on portfolios from bivariate sorts on size and a volatility measure or an index characteristic

Panel A: Bivariate sorts on *MV* and *RANGE*						
Quintiles	1 Small *MV*	2	3	4	5 Big *MV*	5-1 *MV*
1 Low *RANGE*	0.0069	0.0076	0.0077	0.0075	0.0093	0.0024
2	0.0087	0.0116	0.0113	0.0098	0.0095	0.0008
3	0.0153	0.0129	0.0112	0.0117	0.0086	-0.0067
4	0.0220	0.0146	0.0099	0.0144	0.0106	-0.0114
5 High *RANGE*	0.0495	0.0253	0.0190	0.0130	0.0112	-0.0383
5-1*RANGE*	0.0426***	0.0177***	0.0113***	0.0055	0.0018	-0.0407***
	(7.22)	(4.67)	(3.07)	(1.57)	(0.64)	(-7.88)
α_{CAPM} (5-1)	0.0384***	0.0141***	0.0080**	0.0017	-0.0016	-0.0401***
	(8.79)	(4.50)	(2.55)	(0.62)	(-0.74)	(-8.36)
α_{FF3} (5-1)	0.0264***	0.0062**	0.0016	-0.0034	-0.0021	-0.0367***
	(8.00)	(2.29)	(0.56)	(-1.29)	(-0.95)	(-8.07)
α_{FFC4} (5-1)	0.0260***	0.0068**	0.0025	-0.0036	-0.0024	-0.0367***
	(7.94)	(2.44)	(0.86)	(-1.33)	(-1.06)	(-8.16)
Panel B: Bivariate sorts on *MV* and *MAX*						
Quintiles	1 Small *MV*	2	3	4	5 Big *MV*	5-1 *MV*
1 Low *MAX*	-0.0214	-0.0152	-0.0138	-0.0106	-0.0068	0.0146
2	-0.0076	-0.0022	0.0009	0.0016	0.0021	0.0097
3	0.0098	0.0081	0.0090	0.0099	0.0087	-0.0011
4	0.0302	0.0221	0.0177	0.0187	0.0161	-0.0140
5 High *MAX*	0.0897	0.0583	0.0442	0.0361	0.0284	-0.0613
5-1 *MAX*	0.1111***	0.0735***	0.0579***	0.0467***	0.0352***	-0.0759***
	(19.76)	(19.01)	(15.92)	(13.46)	(11.16)	(-16.86)
α_{CAPM} (5-1)	0.1076***	0.0704***	0.0549***	0.0434***	0.0320***	-0.0756***
	(25.71)	(23.13)	(18.37)	(15.73)	(12.98)	(-17.56)
α_{FF3} (5-1)	0.0960***	0.0626***	0.0494***	0.0389***	0.0317***	-0.0726***
	(30.19)	(21.98)	(18.09)	(14.89)	(13.11)	(-17.81)
α_{FFC4} (5-1)	0.0960***	0.0630***	0.0506***	0.0391***	0.0315***	-0.0729***
	(30.14)	(20.07)	(17.65)	(14.04)	(12.33)	(-17.86)
Panel C: Bivariate sorts on *MV* and *MIN*						
Quintiles	1 Small *MV*	2	3	4	5 Big *MV*	5-1 *MV*
1 Low *MIN*	0.0463	0.0365	0.0326	0.0300	0.0269	-0.0195
2	0.0319	0.0264	0.0231	0.0191	0.0183	-0.0136
3	0.0242	0.0172	0.0153	0.0134	0.0103	-0.0139
4	0.0131	0.0072	0.0036	0.0070	0.0047	-0.0085
5 High *MIN*	-0.0111	-0.0134	-0.0142	-0.0127	-0.0104	0.0007
5-1 *MIN*	-0.0575***	-0.0498***	-0.0468***	-0.0427***	-0.0373***	0.0202***
	(-11.88)	(-15.86)	(-15.49)	(-13.49)	(-15.19)	(4.38)
α_{CAPM} (5-1)	-0.0605***	-0.0527***	-0.0494***	-0.0457***	-0.0400***	0.0205***
	(-15.31)	(-19.19)	(-18.14)	(-17.71)	(-20.45)	(4.82)
α_{FF3} (5-1)	-0.0678***	-0.0580***	-0.0536***	-0.0496***	-0.0404***	0.0225***
	(-20.60)	(-22.78)	(-20.97)	(-20.38)	(-20.30)	(5.33)
α_{FFC4} (5-1)	-0.0679***	-0.0578***	-0.0532***	-0.0494***	-0.0405***	0.0223***
	(-20.73)	(-22.10)	(-20.14)	(-19.68)	(-19.85)	(5.20)
Panel D: Bivariate sorts on *MV* and *SD*						
Quintiles	1 Small *MV*	2	3	4	5 Big *MV*	5-1 *MV*
1 Low *SD*	0.0063	0.0068	0.0073	0.0075	0.0093	0.0029
2	0.0077	0.0100	0.0105	0.0092	0.0090	0.0013
3	0.0120	0.0118	0.0110	0.0116	0.0088	-0.0032
4	0.0207	0.0159	0.0112	0.0144	0.0106	-0.0102
5 High *SD*	0.0554	0.0275	0.0191	0.0137	0.0115	-0.0439
5-1 *SD*	0.0491***	0.0207***	0.0117***	0.0062*	0.0022	-0.0469***

	(7.91)	(5.30)	(3.04)	(1.69)	(0.71)	(-8.67)
α_{CAPM} (5-1)	0.0445***	0.0168***	0.0081**	0.0023	-0.0016	-0.0461***
	(10.02)	(5.31)	(2.50)	(0.76)	(-0.70)	(-9.45)
α_{FF3} (5-1)	0.0312***	0.0084***	0.0012	-0.0037	-0.0023	-0.0426***
	(9.31)	(3.11)	(0.43)	(-1.35)	(-1.03)	(-9.13)
α_{FFC4} (5-1)	0.0311***	0.0091***	0.0022	-0.0039	-0.0029	-0.0432***
	(9.28)	(3.23)	(0.75)	(-1.41)	(-1.25)	(-9.33)
Panel E: Bivariate sorts on *MV* and *IVOL*						
Quintiles	1 Small *MV*	2	3	4	5 Big *MV*	5-1 *MV*
1 Low *IVOL*	0.0059	0.0066	0.0071	0.0071	0.0085	0.0026
2	0.0080	0.0105	0.0098	0.0092	0.0091	0.0011
3	0.0109	0.0113	0.0106	0.0118	0.0089	-0.0021
4	0.0211	0.0153	0.0121	0.0139	0.0100	-0.0111
5 High *IVOL*	0.0556	0.0282	0.0197	0.0145	0.0126	-0.0431
5-1 *IVOL*	0.0498***	0.0215***	0.0126***	0.0074**	0.0041	-0.0457***
	(7.98)	(5.65)	(3.36	(2.10	(1.48)	(-8.37)
α_{CAPM} (5-1)	0.0452***	0.0179***	0.0094***	0.0040	0.0016	-0.0436***
	(10.22)	(5.73)	(2.94	(1.38	(0.72)	(-9.17)
α_{FF3} (5-1)	0.0319***	0.0098***	0.0027	-0.0016	-0.0007	-0.0407***
	(9.50)	(3.70)	(0.93	(-0.58	(-0.33)	(-8.57)
α_{FFC4} (5-1)	0.0317***	0.0104***	0.0036	-0.0016	-0.0014	-0.0413***
	(9.48)	(3.81)	(1.21	(-0.57	(-0.61)	(-8.70)
Panel F: Bivariate sorts on *MV* and *TSKEW*						
Quintiles	1 Small *MV*	2	3	4	5 Big *MV*	5-1 *MV*
1 Low *TSKEW*	0.0177	0.0131	0.0130	0.0117	0.0097	-0.0080
2	0.0193	0.0133	0.0100	0.0126	0.0104	-0.0089
3	0.0224	0.0137	0.0117	0.0121	0.0108	-0.0117
4	0.0207	0.0153	0.0125	0.0099	0.0096	-0.0111
5 High *TSKEW*	0.0239	0.0184	0.0145	0.0124	0.0106	-0.0133
5-1 *TSKEW*	0.0062**	0.0053***	0.0015	0.0008	0.0009	-0.0053
	(2.28)	(2.93)	(0.77)	(0.44)	(0.54)	(-1.62)
α_{CAPM} (5-1)	0.0065**	0.0050***	0.0012	0.0001	0.0001	-0.0064**
	(2.42)	(2.72)	(0.60)	(0.08)	(0.03)	(-1.96)
α_{FF3} (5-1)	0.0048*	0.0049***	0.0008	0.0005	0.0027	-0.0045
	(1.85)	(2.65)	(0.34)	(0.24)	(1.53)	(-1.40)
α_{FFC4} (5-1)	0.0044*	0.0049**	0.0008	0.0006	0.0029	-0.0039
	(1.67)	(2.53)	(0.37)	(0.27)	(1.62)	(-1.15)
Panel G: Bivariate sorts on *MV* and *BETA*						
Quintiles	1 Small *MV*	2	3	4	5 Big *MV*	5-1 *MV*
1 Low *BETA*	0.0320	0.0206	0.0173	0.0117	0.0117	-0.0203
2	0.0144	0.0116	0.0117	0.0104	0.0095	-0.0049
3	0.0125	0.0114	0.0103	0.0106	0.0095	-0.0030
4	0.0155	0.0116	0.0096	0.0116	0.0093	-0.0062
5 High *BETA*	0.0286	0.0172	0.0109	0.0122	0.0091	-0.0194
5-1 *BETA*	-0.0034	-0.0034	-0.0064	0.0005	-0.0025	0.0009
	(-0.76)	(-1.13)	(-2.29)	(0.19)	(-0.93)	(0.18)
α_{CAPM} (5-1)	-0.0057	-0.0061	-0.0090	-0.0026	-0.0062	-0.0004
	(-1.41)	(-2.15)	(-3.50)	(-1.13)	(-2.77)	(-0.09)
α_{FF3} (5-1)	-0.0061	-0.0075	-0.0104	-0.0047	-0.0037	0.0034
	(-1.73)	(-2.71)	(-4.06)	(-1.99)	(-1.70)	(0.77)
α_{FFC4} (5-1)	-0.0068	-0.0079	-0.0097	-0.0052	-0.0033	0.0044
	(-1.96)	(-2.73)	(-3.57)	(-2.20)	(-1.48)	(1.03)
Panel H: Bivariate sorts on *MV* and *EP*						
Quintiles	1 Small *MV*	2	3	4	5 Big *MV*	5-1 *MV*
1 Low *EP*	0.0180	0.0108	0.0065	0.0091	0.0065	-0.0115

2	0.0154	0.0128	0.0104	0.0106	0.0099	-0.0055
3	0.0156	0.0138	0.0107	0.0117	0.0099	-0.0057
4	0.0179	0.0146	0.0135	0.0116	0.0108	-0.0071
5 High *EP*	0.0260	0.0173	0.0161	0.0128	0.0113	-0.0147
5-1 *EP*	0.0080**	0.0065***	0.0096***	0.0037*	0.0048**	-0.0033
	(2.00)	(2.95)	(4.68)	(1.81)	(1.96)	(-0.74)
α_{CAPM} (5-1)	0.0084**	0.0062***	0.0095***	0.0033*	0.0052**	-0.0032
	(2.27)	(2.92)	(4.67)	(1.68)	(2.12)	(-0.75)
α_{FF3} (5-1)	0.0079**	0.0058***	0.0091***	0.0023	0.0006	-0.0078**
	(2.55)	(2.83)	(4.38)	(1.15)	(0.24)	(-1.97)
α_{FFC4} (5-1)	0.0075**	0.0055***	0.0094***	0.0032*	0.0010	-0.0081**
	(2.50)	(2.80)	(4.84)	(1.68)	(0.40)	(-2.10)

Panel I: Bivariate sorts on *MV* and *MOM*

Quintiles	1 Small *MV*	2	3	4	5 Big *MV*	5-1 *MV*
1 Low *MOM*	0.0190	0.0117	0.0104	0.0079	0.0081	-0.0109
2	0.0143	0.0111	0.0108	0.0111	0.0093	-0.0050
3	0.0203	0.0137	0.0110	0.0112	0.0101	-0.0102
4	0.0183	0.0149	0.0125	0.0123	0.0121	-0.0062
5 High *MOM*	0.0301	0.0209	0.0157	0.0154	0.0114	-0.0187
5-1 *MOM*	0.0111***	0.0092**	0.0053*	0.0075***	0.0033	-0.0078**
	(2.67)	(2.50)	(1.71)	(2.77)	(1.23)	(-2.16)
α_{CAPM} (5-1)	0.0122***	0.0106***	0.0062**	0.0085***	0.0040	-0.0082**
	(3.16)	(3.05)	(1.99)	(3.23)	(1.48)	(-2.08)
α_{FF3} (5-1)	0.0136***	0.0108***	0.0066**	0.0094***	0.0034	-0.0077**
	(3.53)	(3.14)	(2.00)	(3.30)	(1.27)	(-2.08)
α_{FFC4} (5-1)	0.0136***	0.0108***	0.0066**	0.0094***	0.0034	-0.0098**
	(3.53)	(3.14)	(2.00)	(3.30)	(1.27)	(-2.55)

Panel J: Bivariate sorts on *MV* and *EBITDA/EV*

Quintiles	1 Small *MV*	2	3	4	5 Big *MV*	5-1 *MV*
1 Low *EBITDA/EV*	0.0158	0.0110	0.0104	0.0102	0.0071	-0.0091
2	0.0139	0.0124	0.0095	0.0098	0.0094	-0.0047
3	0.0177	0.0136	0.0120	0.0103	0.0101	-0.0079
4	0.0186	0.0148	0.0122	0.0124	0.0107	-0.0083
5 High *EBITDA/EV*	0.0292	0.0189	0.0153	0.0135	0.0121	-0.0171
5-1 *EBITDA/EV*	0.0131***	0.0079***	0.0049***	0.0033*	0.0051***	-0.0080*
	(3.11)	(3.73)	(2.86)	(1.76)	(2.81)	(-1.73)
α_{CAPM} (5-1)	0.0127***	0.0073***	0.0049***	0.0035*	0.0062***	-0.0065
	(3.26)	(3.50)	(2.58)	(1.79)	(3.53)	(-1.49)
α_{FF3} (5-1)	0.0110***	0.0065***	0.0053**	0.0024	0.0043**	-0.0083*
	(3.46)	(3.23)	(2.52)	(1.14)	(2.52)	(-1.88)
α_{FFC4} (5-1)	0.0102***	0.0061***	0.0053**	0.0024	0.0037**	-0.0081*
	(3.23)	(3.01)	(2.51)	(1.11)	(2.09)	(-1.87)

Panel K: Bivariate sorts on *MV* and *ES*

Quintiles	1 Small *MV*	2	3	4	5 Big *MV*	5-1 *MV*
1 Low *ES*	0.0123	0.0112	0.0110	0.0094	0.0092	-0.0032
2	0.0164	0.0122	0.0113	0.0132	0.0084	-0.0080
3	0.0174	0.0118	0.0118	0.0110	0.0092	-0.0082
4	0.0144	0.0112	0.0125	0.0110	0.0106	-0.0038
5 High *ES*	0.0156	0.0143	0.0099	0.0108	0.0040	-0.0115
5-1 *ES*	0.0032	0.0031	-0.0011	0.0014	-0.0052***	-0.0084**
	(1.08)	(1.28)	(-0.52)	(0.86)	(-2.73)	(-2.49)
α_{CAPM} (5-1)	0.0039	0.0033	-0.0008	0.0021	-0.0050**	-0.0089***
	(1.34)	(1.40)	(-0.36)	(1.27)	(-2.48)	(-2.63)
α_{FF3} (5-1)	0.0034	0.0028	0.0007	0.0022	-0.0058***	-0.0087**
	(1.12)	(0.97)	(0.31)	(1.30)	(-2.68)	(-2.45)
α_{FFC4} (5-1)	0.0027	0.0016	-0.0001	0.0014	-0.0065***	-0.0089**

	(0.91)	(0.60)	(-0.05)	(0.85)	(-3.09)	(-2.41)
Panel L: Bivariate sorts on *MV* and *NSI*						
Quintiles	1 Small *MV*	2	3	4	5 Big *MV*	5-1 *MV*
1 Low *NSI*	0.0245	0.0133	0.0131	0.0125	0.0110	-0.0135
2	0.0187	0.0138	0.0122	0.0122	0.0104	-0.0083
3	0.0165	0.0171	0.0118	0.0115	0.0110	-0.0054
4	0.0212	0.0142	0.0126	0.0113	0.0095	-0.0117
5 High *NSI*	0.0216	0.0146	0.0105	0.0106	0.0090	-0.0126
5-1 *NSI*	-0.0029	0.0014	-0.0026*	-0.0019	-0.0020	0.0009
	(-0.75)	(0.84)	(-1.71)	(-1.47)	(-1.47)	(0.23)
α_{CAPM} (5-1)	-0.0040	0.0013	-0.0033**	-0.0025*	-0.0026**	0.0014
	(-1.15)	(0.80)	(-2.21)	(-1.86)	(-2.06)	(0.38)
α_{FF3} (5-1)	-0.0054*	0.0010	-0.0035**	-0.0022	-0.0036**	0.0010
	(-1.91)	(0.55)	(-2.38)	(-1.62)	(-2.51)	(0.28)
α_{FFC4} (5-1)	-0.0053***	0.0009	-0.0032**	-0.0026*	-0.0038***	0.0007
	(-1.91)	(0.53)	(-2.20)	(-1.86)	(-2.61)	(0.20)
Panel M: Bivariate sorts on *MV* and *ROE*						
Quintiles	1 Small *MV*	2	3	4	5 Big *MV*	5-1 *MV*
1 Low *ROE*	0.0166	0.0117	0.0112	0.0104	0.0081	-0.0085
2	0.0168	0.0141	0.0108	0.0107	0.0090	-0.0078
3	0.0189	0.0129	0.0141	0.0121	0.0105	-0.0084
4	0.0232	0.0144	0.0119	0.0120	0.0115	-0.0117
5 High *ROE*	0.0269	0.0158	0.0124	0.0118	0.0109	-0.0160
5-1 *ROE*	0.0103***	0.0041*	0.0012	0.0013	0.0028	-0.0075**
	(3.18)	(1.71)	(0.60)	(0.66)	(1.23)	(-2.16)
α_{CAPM} (5-1)	0.0105***	0.0049**	0.0018	0.0016	0.0033	-0.0073**
	(3.63)	(2.14)	(0.90)	(0.77)	(1.54)	(-2.16)
α_{FF3} (5-1)	0.0103***	0.0042*	0.0015	0.0011	0.0013	-0.0096***
	(3.48)	(1.70)	(0.75)	(0.55)	(0.73)	(-2.92)
α_{FFC4} (5-1)	0.0094***	0.0032	0.0007	0.0002	0.0002	-0.0099***
	(3.27)	(1.36)	(0.35)	(0.09)	(0.10)	(-3.03)

The size quintiles are formed for every month in the research period by sorting the country-industry indexes based on *MV*. Then, the indexes in each size quintile are further sorted based on a volatility measure or an index characteristic, so that twenty-five portfolios are obtained. Each column in the table except the last one reports the equal-weighted average monthly returns on the indexes that are sorted by a volatility measure or an index characteristic after controlling for size. The last column, 5-1*MV*, indicates the return difference between high-cap and low-cap indexes. The 5-1 portfolio in each size quintile goes long the portfolio with the highest values of the second sort variable and shorts the one with the lowest values. Second sort variable changes in each panel. Average raw returns and Jensen alphas from the ICAPM, the Fama-French three-factor model (FF3), and the Fama-French-Carhart four-factor model (FFC4) on the 5-1 portfolio in each size quintile are presented in the last four rows, respectively. The Newey-West (1987) t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels respectively.

Table 6. Fama-MacBeth cross-sectional regressions

RANGE	*MAX*	*MIN*	*SD*	*IVOL*	*TSKEW*	*BETA*	*MV*	*EP*	*MOM*	*EBITDA/ EV*	*ES*	*NSI*	*OP*	*INV*	R^2
0.1854***					-0.0007*	-0.0026**	-0.0002	0.0401***	0.0089***						0.1557
(6.75)					(-1.67)	(-2.39)	(-0.86)	(4.42)	(4.24)						
	1.1466***				-0.0018***	-0.0104***	0.0026***	0.0296***	0.0085***						0.2281
	(25.16)				(-4.69)	(-8.01)	(8.91)	(3.31)	(3.70)						
		-0.9459***			0.0004	0.0065***	-0.0040***	0.0551***	0.0090***						0.1921
		(-21.57)			(0.92)	(5.81)	(-14.87)	(6.09)	(3.43)						
			0.2506***		-0.0007**	-0.0034***	0.0001	0.0378***	0.0090***						0.1656
			(7.87)		(-1.96)	(-3.16)	(0.43)	(4.26)	(4.45)						
				0.2454***	-0.0007*	-0.0023**	0.0002	0.0378***	0.0089***						0.1653
				(7.88)	(-1.84)	(-1.96)	(0.60)	(4.29)	(4.42)						
0.1137***					0.0004	-0.0022	-0.0001	0.0468***	0.0104***	0.0134***	0.3310	-0.0017	-0.0011	-0.0016*	0.2213
(3.22)					(0.63)	(-1.52)	(-0.33)	(3.02)	(3.34)	(3.32)	(0.18)	(-0.79)	(-0.50)	(-1.71)	
	1.1881***				-0.0011*	-0.0133***	0.0026***	0.0525***	0.0106***	0.0098**	1.0916	-0.0015	-0.0022	-0.0018*	0.2797
	(20.69)				(-1.71)	(-7.58)	(7.81)	(3.72)	(3.15)	(2.41)	(0.47)	(-0.63)	(-1.13)	(-1.83)	
		-1.1566***			0.0014**	0.0092***	-0.0034***	0.0422**	0.0089***	0.0176***	0.9447	-0.0012	0.0005	-0.0006	0.2687
		(-17.85)			(2.43)	(6.20)	(-9.53)	(2.50)	(3.07)	(4.17)	(0.60)	(-0.52)	(0.21)	(-0.68)	
			0.1495***		0.0002	-0.0024	0.0001	0.0458***	0.0107***	0.0127***	0.3360	-0.0018	-0.0009	-0.0016*	0.2279
			(3.70)		(0.33)	(-1.55)	(0.37)	(3.30)	(3.52)	(3.20)	(0.18)	(-0.84)	(-0.46)	(-1.93)	
				0.1517***	0.0002	-0.0023	0.0002	0.0453***	0.0107***	0.0127***	0.5454	-0.0016	-0.0009	-0.0017*	0.2274
				(3.91)	(0.34)	(-1.36)	(0.51)	(3.23)	(3.52)	(3.19)	(0.29)	(-0.73)	(-0.48)	(-1.90)	

Returns on local industry indexes are regressed on volatility measures along with index characteristics calculated in the previous month for each month in the research period. Each row represents a different cross-sectional regression specification. The slope estimates and R-square values from the monthly index-level cross-sectional regressions are averaged over the months and reported in the table. All variables are as explained in Table 1. The Newey-West (1987) adjusted t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 7. Index-level cross-sectional regressions for size quintiles

Panel A: Small *MV* 1

RANGE	*MAX*	*MIN*	*SD*	*IVOL*	*TSKEW*	*BETA*	*MV*	*EP*	*MOM*	*EBITDA/ EV*	*ES*	*NSI*	*OP*	*INV*	R^2
0.2378***					-0.0022**	0.0008	-0.0031	0.0122	0.0150***						0.2767
(7.66)					(-2.16)	(0.41)	(-1.23)	(0.60)	(4.01)						
	1.1570***				-0.0025***	-0.0057***	0.0006	-0.0037	0.0136***						0.3509
	(19.60)				(-2.84)	(-3.23)	(0.21)	(-0.19)	(3.46)						
		-0.8103***			-0.0016	0.0070***	-0.0095***	0.0378**	0.0122***						0.2996
		(-13.93)			(-1.45)	(3.87)	(-4.17)	(1.93)	(3.19)						
			0.3214***		-0.0022**	-0.0002	-0.0026	0.0080	0.0151***						0.2896
			(8.97)		(-2.24)	(-0.09)	(-1.03)	(0.40)	(4.20)						
				0.3235***	-0.0022**	0.0006	-0.0025	0.0081	0.0151***						0.2897
				(9.05)	(-2.21)	(0.30)	(-1.01)	(0.39)	(4.20)						
0.2440***					-0.0020	0.0001	-0.0025	0.0211	0.0116**	0.0202	-0.0551	0.0064	0.0093	0.0027	0.4657
(3.96)					(-0.99)	(0.02)	(-0.84)	(0.60)	(2.36)	(1.03)	(-0.07)	(0.85)	(1.08)	(0.47)	
	1.4470***				-0.0046***	-0.0133***	0.0062**	0.0139	0.0128***	0.0154	0.1858	0.0032	-0.0041	0.0011	0.5212
	(15.72)				(-2.73)	(-5.90)	(2.35)	(0.36)	(2.61)	(0.87)	(0.29)	(0.48)	(-0.41)	(0.21)	
		-1.0747***			-0.0007	0.0120***	-0.0145***	0.0289	0.0082	0.0167	-1.0473	0.0062	0.0177**	0.0034	0.4908
		(-11.07)			(-0.30)	(4.02)	(-4.45)	(0.97)	(1.50)	(0.87)	(-1.37)	(0.97)	(1.98)	(0.63)	
			0.3346***		-0.0017	-0.0028	-0.0008	0.0150	0.0135***	0.0239	-0.4052	0.0062	0.0089	0.0035	0.4726
			(5.15)		(-0.87)	(-1.02)	(-0.28)	(0.43)	(2.77)	(1.33)	(-0.55)	(0.83)	(1.04)	(0.62)	
				0.3325***	-0.0018	-0.0018	-0.0009	0.0136	0.0128***	0.0228	-0.3884	0.0065	0.0088	0.0039	0.4733
				(5.16)	(-0.91)	(-0.71)	(-0.32)	(0.39)	(2.62)	(1.26)	(-0.53)	(0.87)	(1.01)	(0.68)	

Panel B: *MV* 2

RANGE	*MAX*	*MIN*	*SD*	*IVOL*	*TSKEW*	*BETA*	*MV*	*EP*	*MOM*	*EBITDA/ EV*	*ES*	*NSI*	*OP*	*INV*	R^2
0.1822***					0.0011	-0.0021	-0.0007	0.0524***	0.0105***						0.2465
(5.62)					(1.18)	(-1.42)	(-0.51)	(4.43)	(3.65)						
	1.2729***				-0.0008	-0.0106***	0.0035***	0.0413***	0.0117***						0.3099
	(25.73)				(-0.91)	(-6.28)	(2.58)	(3.44)	(4.12)						
		-1.0583***			0.0022**	0.0074***	-0.0060***	0.0586***	0.0103***						0.2852
		(-21.22)			(2.31)	(5.07)	(-4.26)	(4.62)	(3.06)						
			0.2382***		0.0010	-0.0030**	-0.0003	0.0480***	0.0104***						0.2539
			(6.83)		(1.13)	(-1.99)	(-0.22)	(4.01)	(3.69)						
				0.2317***	0.0010	-0.0020	-0.0003	0.0485***	0.0104***						0.2537
				(6.70)	(1.11)	(-1.33)	(-0.25)	(4.05)	(3.71)						
0.1326**					-0.0011	-0.0044*	-0.0013	0.0146	0.0181***	0.0206*	-1.5800	-0.0096	-0.0032	0.0052**	0.3821
(1.97)					(-0.94)	(-1.77)	(-0.35)	(0.60)	(2.95)	(1.95)	(-0.27)	(-1.64)	(-0.58)	(1.96)	
	1.2784***				-0.0026**	-0.0148***	0.0036	0.0188	0.0178***	0.0054	-10.5804	-0.0067	-0.0121***	0.0019	0.4304
	(16.78)				(-2.38)	(-6.16)	(0.99)	(0.73)	(3.52)	(0.44)	(-1.30)	(-1.20)	(-2.93)	(0.71)	
		-1.1725***			-0.0010	0.0096***	-0.0081**	-0.0185	0.0200*	0.0406***	-10.4557	-0.0093	0.0012	0.0076**	0.4166

		(-13.35)			(-0.71)	(2.97)	(-2.52)	(-0.70)	(1.85)	(3.56)	(-1.00)	(-1.23)	(0.20)	(2.37)	
			0.1683**		-0.0012	-0.0048**	-0.0014	0.0146	0.0187***	0.0162*	-3.5173	-0.0107*	-0.0045	0.0047*	0.3867
			(2.49)		(-1.06)	(-1.96)	(-0.35)	(0.60)	(2.93)	(1.66)	(-0.54)	(-1.88)	(-0.90)	(1.88)	
				0.1631***	-0.0010	-0.0042*	-0.0017	0.0198	0.0173***	0.0148	-1.7572	-0.0100*	-0.0049	0.0040*	0.3866
				(2.46)	(-0.91)	(-1.73)	(-0.43)	(0.80)	(3.33)	(1.48)	(-0.36)	(-1.81)	(-1.02)	(1.73)	

Panel C: *MV* 3

RANGE	*MAX*	*MIN*	*SD*	*IVOL*	*TSKEW*	*BETA*	*MV*	*EP*	*MOM*	*EBITDA/ EV*	*ES*	*NSI*	*OP*	*INV*	R^2
0.1561***					-0.0006	-0.0037***	0.0008	0.0617***	0.0129***						0.2623
(3.95)					(-0.69)	(-2.76)	(0.69)	(4.39)	(4.72)						
	1.2559***				-0.0018***	-0.0133***	0.0032***	0.0489***	0.0132***						0.3163
	(18.98)				(-2.59)	(-7.27)	(3.07)	(3.46)	(4.15)						
		-1.1167***			0.0006	0.0062***	-0.0027**	0.0735***	0.0117***						0.2929
		(-17.31)			(0.76)	(4.61)	(-2.24)	(5.34)	(3.92)						
			0.2055***		-0.0007	-0.0044***	0.0008	0.0598***	0.0138***						0.2708
			(4.74)		(-0.95)	(-3.24)	(0.72)	(4.29)	(5.01)						
				0.1982***	-0.0008	-0.0041***	0.0007	0.0591***	0.0136***						0.2703
				(4.65)	(-0.96)	(-2.97)	(0.68)	(4.25)	(5.04)						
0.1238**					0.0014	-0.0038**	-0.0018	0.0520**	0.0068*	0.0069	0.5427	0.0046	0.0014	-0.0016	0.3501
(2.33)					(1.29)	(-2.10)	(-1.12)	(2.28)	(1.77)	(0.69)	(0.49)	(0.98)	(0.41)	(-1.25)	
	1.2034***				-0.0005	-0.0146***	0.0010	0.0358	0.0085**	0.0062	-1.2940	-0.0044	-0.0066*	-0.0029	0.3916
	(14.70)				(-0.46)	(-5.82)	(0.63)	(1.36)	(2.19)	(0.59)	(-0.55)	(-0.76)	(-1.79)	(-1.42)	
		-1.1338***			0.0028**	0.0070***	-0.0046***	0.0606***	0.0079*	0.0195**	2.8064*	0.0112***	0.0073*	-0.0008	0.3858
		(-12.59)			(2.54)	(3.56)	(-3.34)	(3.25)	(1.89)	(1.94)	(1.71)	(2.65)	(1.94)	(-0.70)	
			0.1580***		0.0013	-0.0045***	-0.0013	0.0513**	0.0071*	0.0053	-0.1254	0.0057	0.0005	-0.0018	0.3535
			(2.82)		(1.25)	(-2.58)	(-0.82)	(2.14)	(1.94)	(0.53)	(-0.11)	(1.09)	(0.14)	(-1.40)	
				0.1588***	0.0013	-0.0051***	-0.0012	0.0524**	0.0071**	0.0055	-0.0771	0.0059	0.0003	-0.0017	0.3530
				(2.91)	(1.27)	(-2.82)	(-0.78)	(2.18)	(1.96)	(0.55)	(-0.07)	(1.13)	(0.08)	(-1.33)	

Panel D: *MV* 4

RANGE	*MAX*	*MIN*	*SD*	*IVOL*	*TSKEW*	*BETA*	*MV*	*EP*	*MOM*	*EBITDA/ EV*	*ES*	*NSI*	*OP*	*INV*	R^2
0.1186**					-0.0024**	-0.0001	-0.0001	0.0369***	0.0112***						0.2794
(2.53)					(-2.43)	(-0.04)	(-0.06)	(3.12)	(3.94)						
	1.2176***				-0.0044***	-0.0108***	0.0014	0.0401***	0.0113***						0.3169
	(15.81)				(-4.01)	(-6.39)	(1.28)	(3.31)	(3.44)						
		-1.0756***			-0.0005	0.0104***	-0.0013	0.0373***	0.0119***						0.3105
		(-15.42)			(-0.48)	(6.12)	(-1.44)	(2.98)	(3.89)						
			0.1438***		-0.0023**	-0.0004	-0.0001	0.0375***	0.0111***						0.2848
			(2.92)		(-2.35)	(-0.23)	(-0.08)	(3.21)	(3.89)						
				0.1427***	-0.0023**	-0.0004	0.0000	0.0375***	0.0110***						0.2843
				(3.08)	(-2.36)	(-0.28)	(-0.01)	(3.21)	(3.89)						
0.0353					0.0000	-0.0032*	-0.0002	0.0412*	0.0101***	0.0157**	0.0757	0.0007	0.0013	0.0002	0.3268
(0.84)					(0.01)	(-1.79)	(-0.20)	(1.83)	(2.60)	(2.29)	(0.05)	(0.20)	(0.30)	(0.14)	
	1.1992***				-0.0020**	-0.0168***	0.0015	0.0217	0.0100*	0.0150**	0.4190	0.0019	-0.0044	-0.0004	0.3660

	(17.93)				(-2.43)	(-7.34)	(1.25)	(1.01)	(2.44)	(2.18)	(0.24)	(0.57)	(-1.08)	(-0.25)	
		-1.3342***			0.0016	0.0108***	-0.0021*	0.0470**	0.0096*	0.0176**	-1.0312	-0.0013	0.0092**	0.0013	0.3725
		(-19.59)			(1.55)	(5.60)	(-1.87)	(2.15)	(2.31)	(2.53)	(-0.75)	(-0.31)	(2.19)	(0.80)	
			0.0313		-0.0001	-0.0022	-0.0002	0.0398*	0.0102***	0.0159**	0.0316	0.0003	0.0014	-0.0001	0.3321
			(0.66)		(-0.06)	(-1.16)	(-0.22)	(1.77)	(2.70)	(2.28)	(0.02)	(0.09)	(0.33)	(-0.06)	
				0.0323	-0.0001	-0.0034*	-0.0004	0.0404*	0.0102***	0.0159**	0.0066	0.0004	0.0012	0.0000	0.3314
				(0.72)	(-0.10)	(-1.94)	(-0.33)	(1.76)	(2.68)	(2.26)	(0.00)	(0.10)	(0.28)	(0.01)	

Panel E: Big *MV* 5

RANGE	*MAX*	*MIN*	*SD*	*IVOL*	*TSKEW*	*BETA*	*MV*	*EP*	*MOM*	*EBITDA/ EV*	*ES*	*NSI*	*OP*	*INV*	R^2
0.0392					0.0000	0.0010	-0.0006	0.0443**	0.0097***						0.3468
(0.96)					(0.04)	(0.58)	(-1.20)	(2.06)	(2.80)						
	1.2428***				-0.0027**	-0.0115***	0.0022***	0.0741***	0.0092***						0.3813
	(17.73)				(-2.45)	(-6.83)	(4.09)	(3.55)	(2.57)						
		-1.4574***			0.0022**	0.0127***	-0.0044***	0.0030	0.0123***						0.3855
		(-24.20)			(2.03)	(6.98)	(-8.18)	(0.13)	(3.53)						
			0.0799*		0.0001	0.0005	-0.0003	0.0489**	0.0094***						0.3522
			(1.70)		(0.06)	(0.26)	(-0.49)	(2.38)	(2.71)						
				0.0817*	0.0001	-0.0004	-0.0002	0.0488**	0.0095***						0.3521
				(1.91)	(0.12)	(-0.23)	(-0.36)	(2.39)	(2.75)						
-0.0055					0.0017	-0.0008	-0.0005	0.0997**	0.0106**	0.0016	1.6619	-0.0185**	0.0056	-0.0005	0.4187
(-0.09)					(1.44)	(-0.32)	(-0.79)	(2.36)	(2.45)	(0.23)	(0.46)	(-2.17)	(1.38)	(-0.20)	
	1.3761***				-0.0010	-0.0159***	0.0019***	0.1218***	0.0113**	0.0026	1.1715	-0.0145*	0.0029	-0.0007	0.4531
	(15.27)				(-0.84)	(-7.19)	(3.54)	(3.58)	(2.41)	(0.38)	(0.30)	(-1.91)	(0.80)	(-0.32)	
		-1.6139***			0.0039***	0.0151***	-0.0033***	0.0509	0.0140***	0.0056	-0.0268	-0.0151*	0.0071*	-0.0005	0.4617
		(-23.79)			(3.00)	(6.57)	(-5.53)	(1.28)	(3.37)	(0.83)	(-0.01)	(-1.69)	(1.79)	(-0.21)	
			0.0040		0.0013	-0.0007	-0.0005	0.0976***	0.0098**	0.0015	1.9010	-0.0188**	0.0073	-0.0001	0.4227
			(0.05)		(1.32)	(-0.26)	(-0.82)	(2.65)	(2.34)	(0.22)	(0.53)	(-2.49)	(1.57)	(-0.06)	
				0.0169	0.0012	-0.0018	-0.0004	0.0945***	0.0096**	0.0010	1.4426	-0.0191**	0.0073	-0.0002	0.4223
				(0.26)	(1.25)	(-0.76)	(-0.75)	(2.58)	(2.30)	(0.14)	(0.38)	(-2.53)	(1.58)	(-0.07)	

Returns on local industry indexes in a size quintile are regressed on volatility measures and index characteristics calculated in the previous month for each month in the research period. Each row represents a different cross-sectional regression specification. Panels A, B, C, D, and E report the time-series averages of the coefficient estimates and R-square values from the monthly index-level cross-sectional regressions for each size quintile. All variables are as explained in Table 1. The Newey-West (1987) adjusted t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 8. Index-level cross-sectional regressions with alternative variables

Returns on local industry indexes are regressed on alternative volatility measures and index characteristics calculated in the previous month for each month in the research period. Each row represents a different cross-sectional regression specification. The table reports the time-series averages of the coefficient estimates and R-square values from the monthly index-level cross-sectional regressions. All variables are as explained in Table 1. The Newey-West (1987) adjusted t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

RANGE	*MAX*	*MIN*	*SD*	*IVOL*	*ISKEW*	*BETA*	*MV*	*DY*	*STMOM*	*EBITDA/ EV*	*ES*	*NSI*	*ROE*	*INV*	R^2
0.1782***					0.0001	-0.0023**	-0.0001	0.1097***	0.0147***						0.1548
(6.61)					(0.23)	(-2.15)	(-0.48)	(4.71)	(4.86)						
	1.1718***				-0.0007**	-0.0103***	0.0028***	0.1311***	0.0141***						0.2279
	(27.05)				(-2.34)	(-7.84)	(13.18)	(5.86)	(4.64)						
		-0.9992***			0.0008**	0.0068***	-0.0039***	0.0954***	0.0153***						0.1945
		(-28.96)			(2.55)	(6.29)	(-14.33)	(4.05)	(4.06)						
			0.2429***		0.0000	-0.0031***	0.0002	0.1159***	0.0148***						0.1644
			(7.86)		(0.06)	(-3.01)	(1.10)	(5.02)	(5.09)						
				0.2386***	0.0000	-0.0020*	0.0003	0.1159***	0.0148***						0.1640
				(7.86)	(0.16)	(-1.76)	(1.31)	(5.04)	(5.05)						
0.0979***					0.0004	-0.0018	-0.0003	0.0852***	0.0157***	0.0120***	-1.5246	-0.0001	0.0000	-0.0011*	0.2172
(2.75)					(0.87)	(-1.15)	(-0.98)	(3.50)	(3.73)	(3.48)	(-0.90)	(-0.07)	(1.35)	(-1.81)	
	1.2081***				-0.0004	-0.0136***	0.0025***	0.1376***	0.0176***	0.0072*	0.0744	0.0000	0.0001**	-0.0010*	0.2776
	(20.86)				(-0.70)	(-8.38)	(7.81)	(5.28)	(3.69)	(1.93)	(0.04)	(-0.01)	(2.11)	(-1.68)	
		-1.2221***			0.0010*	0.0096***	-0.0035***	0.0292	0.0122***	0.0170***	-0.8076	0.0005	0.0000	-0.0012	0.2675
		(-20.15)			(1.93)	(6.18)	(-10.19)	(1.16)	(3.11)	(4.67)	(-0.56)	(0.26)	(1.21)	(-1.52)	
			0.1273***		0.0003	-0.0020	-0.0001	0.0894***	0.0165***	0.0115***	-1.4442	0.0000	0.0000	-0.0014**	0.2236
			(2.93)		(0.55)	(-1.14)	(-0.34)	(3.65)	(3.96)	(3.38)	(-0.81)	(0.00)	(1.24)	(-2.01)	
				0.1325***	0.0003	-0.0021	-0.0001	0.0887***	0.0163***	0.0113***	-1.0632	0.0002	0.0000	-0.0014	0.2234
				(3.27)	(0.53)	(-1.23)	(-0.25)	(3.57)	(3.93)	(3.35)	(-0.58)	(0.09)	(1.33)	(-1.97)	

Returns on local industry indexes are regressed on alternative volatility measures and index characteristics calculated in the previous month for each month in the research period. Each row represents a different cross-sectional regression specification. The table reports the time-series averages of the coefficient estimates and R-square values from the monthly index-level cross-sectional regressions. All variables are as explained in Table 1. The Newey-West (1987) adjusted t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively