Journal of Financial Economics 149 (2023) 52–72

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

What matters in a characteristic?

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ARTICLE INFO

Article history:
Received 18 March 2022
Revised 17 April 2023
Accepted 18 April 2023
Available online 3 May 2023

JEL classification:
G12
G15

Keywords:
IPCA
Characteristics
Country
Industry
Alpha
Systematic risk

ABSTRACT

We investigate how different components in firm characteristics affect expected returns and comovements in international stock markets. We decompose characteristics into country, industry, and country- and industry-adjusted (i.e., orthogonal) components. Then, we use these components to capture time-series and cross-sectional variations in stock-level alphas and factor exposures. Decomposing characteristics is crucial to explain jointly expected returns and comovements: *(i)* adjusted (country) components are the most important determinant of alphas (comovements), *(ii)* component-based models outperform benchmark models, and *(iii)* alphas are statistically significant. However, alphas have been trending down over time, and alpha-chasing strategies are not profitable once we account for estimation risk and trading costs.

1. Introduction

Understanding the determinants of expected returns and comovements of individual stock returns is crucial to measure a firms cost of capital or allocate a stock portfolio. Unfortunately, exposures to economically-motivated factors, such as the aggregate market portfolio or consumption growth, do not satisfactorily describe both average returns and comovements when they are estimated from returns alone. Consequently, a large body of work uses firm characteristics, such as return momentum and profitability, to model differences in expected returns and comovements across stocks and their variation over time.

Previous studies have explored several questions about the role of characteristics. They include which and how many characteristics provide incremental information about the cross-section of expected returns (see, for example, Freyberger et al., 2020; Kozak et al., 2020), whether their effect remains after publication or is the result of data-mining (McLean and Pontiff, 2016; Jacobs and Müller, 2020), whether characteristics or exposures to characteristic-based risk factors provide a better description of average returns (see, among others, Kelly et al., 2019; Daniel and Titman, 1997; Berk, 2000), and how to construct efficient characteristic-based risk factors (Daniel et al., 2020).

In this paper, we instead focus on the role of *components* of firm characteristics to explain expected returns and comovements in a large sample of 55,541 stocks across 35 countries and 17 industries. Each month, we decompose each firm characteristic into *characteristic components*: a component that is common to all stocks in the same country (*CtyX*), a component that is common to all stocks in the same industry (*IndX*), and a country- and industry-adjusted component (*AdjX*). To do so, we cross-sectionally regress each characteristic on a set of country and industry indicator variables. After a convenient standardization, the country and industry indicator coefficients become *CtyX* and *IndX*, respectively, whereas regression residuals become *AdjX*.

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https://doi.org/10.1016/j.jfineco.2023.04.010

Then, we use these characteristic components in an asset pricing model to capture time-series and cross-sectional variations in expected returns and comovements across individual stocks. Our model estimates provide new economic insights about the importance of country, industry, and adjusted characteristics in international stock markets.

1.1. Methodology preview

A characteristic can be related to cross-sectional differences in expected returns, comovements (i.e., risk factor exposures), or both. The extent to which a characteristic is related to both expected return and risk has deep economic content: a positive relation with both indicates that differences in expected returns reflect compensation for different degrees of risk. In contrast, a characteristic related to expected returns but not to risk would indicate an alpha.

The typical approach to identifying whether a characteristic is related to both average return and risk consists of two steps. We form a characteristic portfolio (CP) by sorting stocks on their characteristic value and then adjust for risk by regressing the CPs returns on a set of preordained factors.[1] But this approach suffers from two drawbacks. First, the result crucially depends on the chosen set of factors used to adjust for risk, about which no consensus exists. Second, the number of characteristics investigated in the literature has exploded, and identifying their respective marginal importance is difficult given the proliferation of CPs. This problem is further compounded in our context as we consider components of characteristics, resulting in an even larger number of CPs.

To address these issues, we instead rely on the Instrumented Principal Component Analysis (IPCA) methodology of Kelly et al. (2019) (hereafter KPS) that simultaneously estimates systematic risk factors and how a possibly large number of characteristics are related to alphas and factor exposures (i.e., betas). The upside of this approach is that model estimates indicate which characteristic components are important and whether their effect is related to alphas or risk exposures. See Kelly et al. (2021b) for an econometric treatment of IPCA and Giglio et al. (2022) for a review of IPCA and factor model estimation methodologies.

1.2. Main findings

We estimate models separately for four regions: U.S. stocks, all developed markets excluding the U.S. (DM), emerging markets (EM), and finally, all countries together (World). We use DM and EM model estimates to compare results across more and less developed markets, and U.S. model estimates to see whether results differ in international markets compared to this widely studied market.

We obtain two main economic results. Our first main economic result is to show that the characteristics adjusted components are the dominant drivers of alphas across DM and EM individual stocks, especially when adjusted for industry effects. In contrast, the characteristics country components are by far the largest determinants of comovements. Therefore, decomposing firm characteristics into country, industry, and adjusted components–instead of using unadjusted characteristic values or adjusting only for either country or industry effects–is crucial to explain both expected returns and comovements.

We make our point using several empirical tests. First, we estimate IPCA models with different types and combinations of characteristic components to instrument alphas and betas. Our model with all characteristic components explains better average returns and risk than models with unadjusted characteristics, a subset of components, or components adjusted only for country or industry effects.

Second, Heston and Rouwenhorst (1994) and Griffin and Karolyi (1998) decompose stock returns into pure country and industry factors and find that the former is the primary determinant of return variance.[2] As further tests, we estimate their model (henceforth, *HR/GK*), in which there is a factor for each country and each industry, and individual stocks have a beta of one on their respective factors. We also estimate an IPCA model in which alphas and betas are functions of country and industry dummy variables. That model generalizes their model by allowing factors to be combinations of country and industry affiliations (e.g., a regional factor) instead of restricting factors to be associated with only one country or industry at a time. These benchmark models are competitive for capturing comovements but dramatically underperform when describing average returns. Only the model with all characteristic components explains both expected returns and comovements.

Next, characteristic-sorted portfolios are widely used as empirical risk factors to capture systematic risk. But their implementation varies across studies. For example, Hou et al. (2011) build global (country) risk factors by sorting stocks on characteristics across (within) countries, Fama and French (2017) sort DM stocks within regions to obtain regional factors, and Bekaert et al. (2009) and Chaieb et al. (2021) construct regional and global factors by value-weighting portfolios of stocks sorted by characteristics within countries.[3]

Our third empirical analysis compares our results to those of Bekaert et al. (2009) (*BHZ*), who build different factor models and capture time-varying factor betas using non-overlapping subperiod estimations. To implement their approach to individual stocks, we attribute the time-varying betas of test portfolios to their respective stock constituents. We find that these models fail to explain comovements of individual stock returns.[4]

After running this model specification horserace, we focus on our favored model specification to investigate

[1] See Barillas and Shanken (2016) for a discussion of this approach.

[2] See also Eiling et al. (2012b), Eiling et al. (2012a) and L'Her et al. (2002).

[3] Similarly, to measure the significance of alphas, Jacobs and Müller (2020) sort on characteristics and Bartram and Grinblatt (2021) sort on their mispricing measure within each country.

[4] An alternative is the estimation methodology of Chaieb et al. (2021) which allows for factor exposures to vary with stock-specific instruments. But as this approach requires running stock-level time-series regressions of returns on the factor returns interacted with each instrument, multicollinearity problems would lead us to discard many stocks.

the relative importance of the different component types within the same model specification. We first show that the *CtyX*s account for 75% of the sum of squared beta parameters across all factors, and the *AdjX*s account for more than 70% of the sum of squared alpha parameters. In line with their economic magnitude, we next find that the *AdjX* (*CtyX*) parameters are highly statistically significant for alphas (betas). But we also find that *IndX* and *AdjX* parameters are significant for alphas and betas, respectively, once again underlining the importance of using all characteristic components to explain jointly expected returns and comovements.

Our results have important implications for international portfolio diversification. As in *HR*/*GK*, we find that diversification benefits are driven by countries rather than industries. As in *BHZ*, we show, using our model estimated over rolling windows, that the countries' primacy for diversification has not changed over time.

However, our results sharpen these previous findings by showing that international comovements are more parsimoniously driven by country characteristic components than country dummies, but also how these characteristic components are related to expected returns. To further understand these modeling differences, we show how the *HR*/*GK* and *BHZ* models are nested in the IPCA framework and differ by their choice of instruments. Our model uses a rich set of characteristic components to instrument factor betas, instead of country and industry affiliations as in *HR*/*GK* or country, industry, and subperiod affiliations as in *BHZ*.

Our second main economic result is to show that alphas in models that include *AdjX*s remain significant even when we include up to eight risk factors. Therefore, at first sight, it appears that a significant part of expected stock returns is unrelated to systematic risk.

However, we provide extensive evidence that the magnitude of alphas has been trending down over time and that investors would have struggled to benefit from these alphas once we account for estimation risk and transaction costs. We show the latter point by computing the out-of-sample performances, net of transaction costs, of strategies that buy high and short-sell low-predicted alpha stocks. We find that risk-adjusted gross performances are almost always insignificant, indicating that estimation risk drastically lowers the economic magnitude of alphas. Accounting for transaction costs further worsens portfolio performances. Our results hold across regions, estimation window lengths, transaction cost measures, investment horizons, and for long-short and long-only portfolios.

Our results are important in light of the ongoing debate about the relative importance of mispricings and systematic risk factor exposures in individual stock returns. Using a new methodology to test factor models with individual U.S. stocks, Jegadeesh et al. (2019) show that characteristics better explain average returns than exposures to risk factors. In contrast, KPS show that the significance of characteristics as alphas vanishes once these characteristics also instrument factor exposures. The main modeling difference between these two papers is the nature of the risk factors. In the first paper, risk factors are long-short portfolios of stocks sorted on a predetermined set of characteristics. In the second paper, risk factors are latent (i.e., unobserved) factors, and factor exposures are parameterized as a function of characteristics.

In contrast to the U.S., the evidence of alphas is more substantial in international stock markets. Jacobs and Müller (2020) find no post-publication decline in anomaly returns, in contrast to McLean and Pontiff's (2016) results for the U.S. stock market. Bartram and Grinblatt (2021) find significant alphas in global markets, even when controlling for exposures to unobserved risk factors using IPCA. Our paper enters this debate by characterizing the role of characteristic components. Estimated alphas are larger and more statistically significant when we use *AdjX* rather than unadjusted (or partially adjusted) firm characteristics, but not large enough to overcome estimation risk and trading costs.

1.3. Other related literature

Several papers examine the relative importance of industry components in characteristics. Moskowitz and Grinblatt (1999) find that momentum in U.S. stock returns comes more from its industry component than its industry-adjusted component (see also, Asness et al., 2000). Arnott et al. (2019) construct long-short characteristic portfolios, with and without industry adjustments, to show that a momentum strategy of long-short *CP*s produces higher risk-adjusted returns than an industry momentum strategy. Asness et al. (2014) show that Frazzini and Pedersen's (2014) low-beta effect exists with and without industry adjustments. Our work is different in that we simultaneously consider country, industry, and adjusted components in momentum, market beta, and other characteristics such as size, value, profitability, investment, return reversal, and idiosyncratic volatility.

Our work is related to the literature on latent factor models for stock returns. KPS extend the PCA approach of Connor and Korajczyk (1986, 1988) to account for time-varying alphas and betas. Büchner and Kelly (2022), Kelly et al. (2020), and Kelly et al. (2021a) use this methodology to propose a factor model for option returns, for corporate bond returns, and to explain stock return momentum and long-term reversal, respectively. While Kim et al. (2021), Lettau and Pelger (2020a,b), and Giglio and Xiu (2021) provide related methodologies and showcase their benefits in the U.S. stock market, we use IPCA to empirically measure the relative importance of characteristic components in international stock markets.

The paper proceeds as follows. We describe the model and estimation methodology in Section 2, describe our data in Section 3, present our main empirical results in Section 4, construct investment strategies in Section 5, run some robustness checks in Section 6, and conclude in Section 7.

2. Model and estimation

In this section, we first describe our methodology to decompose each characteristic into country, industry, and adjusted components. Then, we show how we use these characteristic components to instrument time variations in alphas and factor exposures in a latent factor model. Finally, we use the latent factor model to explain how our methodology compares to existing benchmark models in international finance.

2.1. A decomposition for characteristics

In this section, we decompose each of the J characteristics we use into different components to examine the relative importance of country, industry, and adjusted effects. Each month and for each characteristic, we run a cross-sectional regression of characteristic j for stock n at time t, $x_{n,t}^{(j)}$, using all available stocks,

$$x_{n,t}^{(j)} = \kappa_t^{(j)} + \sum_{c=1}^{N_C-1} C_{c,t}^{(j)} \mathbb{I}_{n\in c} + \sum_{i=1}^{N_I-1} I_{i,t}^{(j)} \mathbb{I}_{n\in i} + \upsilon_{n,t}^{(j)}, \quad n = 1, \ldots, N_t. \tag{1}$$

In this equation, $\kappa_t^{(j)}$ is a constant, $C_{c,t}^{(j)}$ is the coefficient for country c's effect for characteristic j at time t, $\mathbb{I}_{n\in c}$ is an indicator variable equal to one if stock n is in country c, $I_{i,t}^{(j)}$ is the coefficient for industry i's effect for characteristic j at time t, $\mathbb{I}_{n\in i}$ is an indicator variable equal to one if stock n is in industry i, $\upsilon_{n,t}^{(j)}$ is the regression residual that captures the adjusted component for characteristic j of stock n, and N_t is the number of stocks at time t.

In a second step, we standardize the estimated country effects, $C_{c,t}^{(j)}$, the industry effects, $I_{i,t}^{(j)}$, and the adjusted effect, $\upsilon_{n,t}^{(j)}$, by computing their respective cross-sectional ranks and normalizing these ranks to lie in the [-0.5, 0.5] interval. We refer to these normalized cross-sectional ranks as $\tilde{C}_{c,t}^{(j)}$, $\tilde{I}_{i,t}^{(j)}$, and $\tilde{\upsilon}_{n,t}^{(j)}$, respectively. Using normalized cross-sectional ranks ensures that we can compare the coefficient estimates of different characteristic components in the factor model that we present in the next section.

2.2. A general model for returns

We use a factor model for the excess return on stock n at time $t+1$ as,

$$r_{n,t+1} = \alpha_{n,t} + \beta_{n,t}' f_{t+1} + \epsilon_{n,t+1}, \tag{2}$$

where f_{t+1} is a K-by-one vector of latent systematic factors and $\epsilon_{n,t+1}$ is a firm-level idiosyncratic shock. We specify both the alpha, $\alpha_{n,t}$, and the factor betas, $\beta_{n,t}$, as linear functions of a L-by-one vector of stock-specific instruments $z_{n,t}$ as,

$$\alpha_{n,t} = A' z_{n,t} + \nu_{\alpha,n,t}, \tag{3}$$

and

$$\beta_{n,t} = B' z_{n,t} + \nu_{\beta,n,t}, \tag{4}$$

where A and B are a L-by-one vector and a L-by-K matrix of parameters, respectively. In the model specifications described in the following section, we use a constant as the first instrument and different sets of firm characteristics, characteristic components, and dummy variables as other instruments. The alpha and betas are also driven by the scalar $\nu_{\alpha,n,t}$ and the K-by-one vector $\nu_{\beta,n,t}$, respectively, to account for the fact that they may not be perfectly determined by the characteristics. To estimate model (2), we use the IPCA methodology of KPS, in which the parameters A and B are estimated using time-series regressions, the factor values f_{t+1} are estimated using cross-sectional regressions, and these estimations are iterated until a convergence criterion is satisfied for both parameter and factor values.

This approach has one major advantage. We do not have to specify what are the systematic factors f. We let the estimation decide to what extent returns are described by a set of alpha, exposures to systematic factors that affect all stocks, or both. This is important because we want to determine the extent to which alphas and systematic risk are captured by the different characteristic components. By choosing *a priori* a set of factors like the Fama-French model or the q-factor model, we could obtain results about the relative importance of the different components of characteristics that are dependent on the chosen factor model. Instead, we let the data speak about which systematic risk factors are important and whether there is evidence of characteristic-driven alphas.

This flexibility comes at a price. To estimate the parameters A, B, and f_t, KPS impose some identifying restrictions. First, they impose that $B'B = \mathbb{I}_K$, the unconditional second moment matrix of f_t is diagonal, the factors are ordered in descending order of variance and have non-negative means. These restrictions are the standard identifying assumptions in latent factor models and do not alter the economic content of Model (2).

Second, they impose the additional identifying assumption that $A'B = 0_{1\times K}$. This assumption has a strong economic content; as much explanatory power as possible is attributed to factor risk and, therefore, the magnitude of the estimated A, if any, indicates an alpha.

We detail in the next section the different sets of stock-specific instruments $z_{n,t}$.

2.3. Estimating the importance of characteristic components

To measure the importance of country, industry, and adjusted effects, we use different model specifications. First, we estimate the factor model (2) using the cross-sectional ranks of the unadjusted characteristics, $z_{n,t} = (1, \tilde{x}_{n,t}')'$. We remove the superscript (j) to denote the vector that contains all characteristics, $\tilde{x}_{n,t} = (\tilde{x}_{n,t}^{(1)}, \ldots, \tilde{x}_{n,t}^{(J)})'$. All models include a constant as the first instrument so the dimension of the instrument vector, $z_{n,t}$, is $L = 1 + J$. We refer to this model as Model "*Unadj X*".

In the second model, we use the cross-sectional regression (1) to decompose characteristics into industry and industry-adjusted components by restricting all country coefficients, $C_{c,t}^{(j)}$, to zero. Then, we estimate the factor model (2) with $z_{n,t} = (1, \tilde{I}_{in,t}', \tilde{\upsilon}_{n,t}')'$ where $\tilde{I}_{in,t}^{(j)} = \sum_{i=1}^{N_I-1} \tilde{I}_{i,t}^{(j)} \mathbb{I}_{n\in i}$ denotes the normalized cross-sectional rank of stock n's industry coefficient. In the instrument vector $z_{n,t}$, there are, in addition to the constant, J industry characteristic ranks and J adjusted characteristic ranks, and therefore $L = 1 + 2J$. Comparing this Model "*Ind and adj X*" to Model "*Unadj X*" above allows to determine the benefit of adjusting for industry effects in characteristics.

In the third model, we use the cross-sectional regression (1) to decompose characteristics into country and country-adjusted components by restricting all industry coefficients, $I_{i,t}^{(j)}$, to zero. Then, we estimate the factor model (2) with $z_{n,t} = (1, \tilde{C}'_{c_n,t}, \tilde{\upsilon}'_{n,t})'$ where $\tilde{C}_{c_n,t}^{(j)} = \sum_{c=1}^{N_C-1} \tilde{C}_{c,t}^{(j)} \mathbb{I}_{n \in c}$ denotes the normalized cross-sectional rank of stock n's country coefficient. The instrument vector $z_{n,t}$ has $L = 1 + 2J$ elements. Comparing this Model "*Cty and adj X*" to Model "*Unadj X*" above allows to determine the benefit of adjusting for country effects in characteristics.

In the fourth model, we use the cross-sectional regression (1) to decompose characteristics into country, industry, and country- and industry-adjusted components. Then, we estimate the factor model (2) with $z_{n,t} = (1, \tilde{C}'_{c_n,t}, \tilde{I}'_{i_n,t}, \tilde{\upsilon}'_{n,t})'$. With the constant, this model has $L = 1 + 3J$ instruments. Comparing this Model "*Cty, ind, and adj X*" to Model "*Unadj X*", we measure the benefit of adjusting for both country and industry effects in characteristics.

We consider two additional sets of benchmark models. First, we use models with country and industry characteristic components only to assess the benefit of using adjusted components. For example, we compare Model "*Ind and adj X*" to Model "*Ind X*". Similarly, we compare Models "*Cty and adj X*" and "*Cty, ind, and adj X*" to "*Cty X*" and "*Cty and ind X*", respectively.

Second, we also consider models with dummy variables for country and industry affiliations. Unfortunately, we cannot estimate models that contain both dummy variables for countries and industries and characteristic components. We need the instruments, $z_{n,t}$, to be linearly independent at each period to estimate the factor values f_{t+1}. Unfortunately, the country dummy variables and country characteristic components are linearly dependent at each period. Similarly, the industry dummy variables are linearly dependent with the industry characteristic components each period.

Instead, we estimate a model with industry dummy variables, $z_{n,t} = (1, \mathbb{I}'_{n \in i})'$, as a benchmark for Model "*Ind and adj X*". Similarly, we estimate a model with country dummy variables, $z_{n,t} = (1, \mathbb{I}'_{n \in c})'$, as a benchmark for Model "*Cty and adj X*" and a model with both country and industry dummy variables, $z_{n,t} = (1, \mathbb{I}'_{n \in c}, \mathbb{I}'_{n \in i})'$, as a benchmark for Model "*Cty, ind, and adj X*". We refer to these models as "*Ind D*", "*Cty D*", and "*Cty and ind D*", respectively. We remove the dummy variables for the country and the industry with the highest number of stocks to prevent linear dependence. Consequently, Model "*Ind D*" has $L = N_I$ instruments, Model "*Cty D*" has $L = N_C$ instruments, and Model "*Cty and ind D*" has $L = N_C + N_I - 1$ instruments.

2.4. How does our model relate to benchmark models?

In this section, we use the model specification in Eqs. (2)–(4) to compare our approach to two benchmark models in the international finance literature; the pure country and industry factor models of Heston and Rouwenhorst (1994) and Griffin and Karolyi (1998), and the PCA model with time-varying betas of Bekaert et al. (2009).

The main difference is that these models imply zero alphas ($A = 0$). They are designed to capture comovements in international stock markets, not expected returns. In contrast, we aim to explain *jointly* comovements and expected returns.

These models also differ in how they capture comovements. In the *HR/GK* model, there is one latent factor for each country and for each industry, and individual stocks have a beta of one on their respective country and industry factors. They use their model estimates to show that country factors are larger determinants of comovements than are industry factors, indicating that the former is a larger source of international diversification benefits than the latter.

We obtain the *HR/GK* model in Eqs. (2)–(4) by using $K = 1 + N_C + N_I$ factors, a K-by-one instrument vector that includes a constant and dummy variables for country and industry affiliations, and setting $B = \mathbb{I}_K$.

Compared to our methodology, this model does not need time-series regressions to obtain B parameters. Only cross-sectional regressions to estimate the factor values, f_{t+1}, are required. However, the cross-sectional regressions require some identification conditions that differ from those of the IPCA. Every period, they constrain the sum of country (industry) factors weighted by the number of stocks by country (industry) to be equal to zero. With these identification conditions, the value of the first factor is the equal-weighted portfolio of all stocks.[5]

Note that Model "*Cty and ind D*" is different from the *HR/GK* model. Model "*Cty and ind D*" is more general because it allows for composite factors. For example, a factor on which stocks in neighboring countries load would create a regional factor.

In their model, one of the largest determinants of comovements is whether two stocks belong to the same country or industry.[6] Our methodology differs in using characteristic components to drive cross-sectional and time-series variations in covariances. All else equal, two stocks are more highly correlated at time t if the country components of their value characteristic, for example, are both large and that component has a large B parameter on a factor.

Bekaert et al. (2009) extract principal components from weekly country-industry portfolio returns in non-overlapping six-month periods to capture time-variations in factor betas and risk. They use their model estimates to show that principal components constructed at the world and regional levels better capture comovements than other leading factor models, including the *HR/GK* model.[7]

We obtain the *BHZ* model in Eqs. (2)–(4) by using K factors, and a $(N_C \times N_I \times N_\tau)$-by-one vector of instruments

[5] We provide further details on the *HR/GK* and *BHZ* models implementation in Online Appendix C where we replicate these studies' main results.

[6] The equal-weighted portfolio factor is also a source of comovements. On the contrary, the covariances between a country and an industry factor are empirically negligible.

[7] They also use a second set of portfolios in which stocks are sorted by country, size, and book-to-market ratio instead of country and industry. The Fama-French three-factor model with global and regional factors also performs well. When we compare the empirical performance of these models in Section 3.2, we also report the performance for this alternative portfolio set and factor model.

$z_{n,t} = (\mathbb{I}'_{n\in C} \otimes \mathbb{I}'_{n\in I} \otimes \mathbb{I}'_{t\in\tau})'$, where $\otimes$ is the Hadamard product, $\mathbb{I}_{n\in C}$ is the N_C-by-one vector of country affiliation dummies $\mathbb{I}_{n\in c}$, $\mathbb{I}_{n\in I}$ is the N_I-by-one vector of industry affiliation dummies $\mathbb{I}_{n\in i}$, and $\mathbb{I}'_{t\in\tau}$ is a N_τ-by-one vector of subperiod affiliation dummies. This model specification ensures that there are different B parameters for each country, industry, and subperiod.

While the *BHZ* model is nested in our modeling framework, we do not use IPCA to estimate this model. Time variations in factor betas are captured using the subperiod affiliation dummies $\mathbb{I}_{t\in\tau_k}$. For subperiod k, all instruments involving subperiod dummies of subperiods other than k will be zero, and the instrument matrix will have many zero columns, rendering the IPCA estimation impossible. A possible solution is to estimate a different IPCA model for each subperiod using the instrument vector $z_{n,t} = (\mathbb{I}'_{n\in C} \otimes \mathbb{I}'_{n\in I})'$. Unfortunately, as the IPCA is based on large-T asymptotics, Kim et al. (2021) argue that it may have low power in small and fixed-T cases. In Section 3.2, we instead follow Bekaert et al. (2009) and estimate their models on portfolio returns. Then, we attribute the time-varying beta of a portfolio to its stock constituents.

In the next sections, we rely on these different model specifications to shed light on country, industry, and adjusted effects in international stock returns. We also empirically compare our methodology to the *HR/GK* and *BHZ* models. We begin in the next section by describing our dataset.

3. Data

We present in this section our data set. We discuss in Section 3.1 the distribution of stocks across countries and industries. Then, we report in Section 3.2 summary statistics from the cross-sectional regressions for characteristics in Eq. (1).

3.1. The distribution of stocks across countries and industries

From Compustat *xpressfeed*, we use major local common stocks listed on the main stock exchange in each country. Data are monthly and denominated in U.S. dollars. We define a local stock as one listed on the main stock exchange,[8] whose company is headquartered in the same country and is designated by Compustat as the major security. To filter out misclassified non-common stocks, we apply the name filters of Griffin et al. (2010). We use the one-month U.S. T-bill rate as the risk-free rate.

A stock is used at time t if all its characteristics are available. We obtain an unbalanced panel of data because stock returns have different sample periods and because not all of their characteristics are available each month. We strike a balance between having as many characteristics as in other studies and sufficient coverage across countries and industries. We use market capitalization, book-to-price ratio, cash profitability, investment, past return based measures (lagged return and return from month $t-12$ to $t-2$), beta measured relative to the local market, and idiosyncratic volatility. Appendix A details our data construction.

We run all estimations using four different regions. First, we use stocks in the U.S. In this case, we consider only industry and industry-adjusted components, not country adjustments. We estimate these models using U.S. stocks to highlight the difference between U.S.-based results and those obtained with international stocks. Then, we consider all developed markets except the U.S., all emerging markets, and finally, all countries (World). We classify countries across DM and EM using the MSCI country classification.[9]

We set the starting date for each region as the first month when there are at least 100 stocks available and five stocks in each country and industry. Data start in January 1988 for the U.S., in July 1991 for DM ex U.S., and in October 1999 for EM. All data ends in August 2022.

We use Ken French's 17 industry classification based on SICs to classify stocks into industries.[10] We use 17 industries to have approximately the same number of countries as industries for the DM and EM estimations. There are 15 (19) countries in the DM ex U.S. (EM) region.

Adding a constant, the eight characteristics used imply that the vector of instruments $z_{n,t}$ has nine elements in Model "*Unadj X*", 17 in Models "*Cty and adj X*" and "*Ind and adj X*", 25 in Model "*Cty, ind, and adj X*", 17 in Model "*Ind D*", 15, 19, and 35 in Model "*Cty D*" for DM, EM, and World, respectively, and 31, 35, and 51 in Model "*Cty and ind D*" for DM, EM, and World, respectively.

We report the distribution of countries for DM ex U.S. in Figure B.1 and for EM in Figure B.2 of the Online Appendix. In each figure, the top graph reports on the distribution of countries weighted by market capitalization, and the bottom graph reports on the distribution by the number of stocks. Figures B.3-B.5 have the same structure as Figure B.1 and B.2, but report on the distribution of stocks across industries for the U.S., DM ex U.S., and EM, respectively.

The U.S. and Japan are the largest DM in terms of weight and number of stocks. China is by far the largest country in terms of market capitalization at the end of our sample period, but India, South Korea, and Taiwan are large countries during the entire period. The industry distributions for both DM and EM are more balanced than country distributions.

3.2. Country and industry factors in characteristics

Before investigating whether characteristic components help explain stock comovements and average returns, as we do in the next section, we analyze the extent of country and industry effects in stock characteristics. We report in Table 1 the time-series average of the adjusted R^2 from cross-sectional regression (1), in which we regress

[8] We use more than one stock exchange in some countries, see Appendix A for details.

[9] We group emerging and some frontier markets into the emerging category.

[10] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_17_ind_port.html for details.

Table 1
Cross-sectional regression for characteristics - Average R^2.

Characteristic	Industry dummies	Country dummies	Industry and country dummies	Industry dummies	Country dummies	Industry and country dummies
	Panel A: U.S.			*Panel B: DM ex U.S.*		
Size	9.08	-	-	6.80	7.17	12.72
Value	4.13	-	-	7.44	10.38	16.14
Profitability	12.48	-	-	10.96	21.75	29.29
Investment	2.38	-	-	4.41	5.65	7.94
Momentum	3.45	-	-	3.90	6.62	9.59
Lagged return	2.70	-	-	2.92	7.25	9.19
Beta	8.31	-	-	5.95	4.61	9.98
Idio-vol	7.31	-	-	7.06	8.38	12.51
Average	6.23	-	-	6.18	8.98	13.42
	Panel C: EM			*Panel D: World*		
Size	6.51	29.83	33.76	5.49	17.95	21.36
Value	3.79	27.40	30.18	5.18	16.13	20.55
Profitability	6.87	12.71	18.91	4.41	9.27	12.54
Investment	0.79	8.03	8.63	2.25	4.81	6.34
Momentum	1.68	15.23	16.52	2.29	8.55	10.28
Lagged return	1.50	17.64	18.41	1.84	9.45	10.71
Beta	3.08	10.65	13.28	4.83	5.40	10.57
Idio-vol	1.85	13.86	15.48	3.57	5.57	8.72
Average	3.26	16.92	19.40	3.73	9.64	12.63

We report the time-series average adjusted R^2 (in %) for the cross-sectional regressions in Eq. (1). Each month, we run a cross-sectional regression for each characteristic of their values on either industry dummy variables, country variables, or both industry and country dummy variables. We run regressions using all stocks in the U.S. in Panel A, for which specifications with country dummy variables are not estimated, in Developed Markets excluding the U.S. in Panel B, in Emerging Markets in Panel C, and in all countries in Panel D. We use a 17-industry classification. All data are monthly, in USD, and end in August 2022.

characteristic values across stocks on country and industry dummy variables. The time-series average R^2 measures how important are country and industry factors in explaining variations in characteristics.

We compute average R^2s from regressions using either only industry dummy variables, only country dummy variables, or both industry and country variables, except for U.S. stocks in Panel A for which we can only use industry dummies.

Using the regressions for the World region reported in Panel D, the R^2s is 12.63% on average across characteristics and ranges from 6.34% (investment) to 21.36% (size). The average R^2s are higher in EM (19.40%) than DM (13.42%). But the ranges are similar; the minimum values are for investment (8.63% for EM, 7.94% for DM) and the maximum is for size in EM (33.76%) and profitability in DM (29.29%). Finally, the average R^2s are higher in regressions using only country dummies (16.92% for EM and 8.98% for DM) than those using only industry dummies (3.26% for EM and 6.18% for DM).

Overall, results in Table 1 indicate that there is a factor structure in stock characteristics based on country and industry affiliations, which we exploit in the next section to build characteristic components.

4. Main empirical results

This section contains our main empirical results. We analyze the performance of different model specifications to explain comovements and expected returns across regions in Section 4.1 and test for the significance of alphas in Section 4.2. Then, we measure the statistical significance and relative economic importance of different characteristic components in the same model specification in Section 4.3. Finally, Section 4.4 tests whether there are any variations over time in our results.

4.1. Which model best captures comovements and average returns?

In this section, we empirically investigate whether using adjusted characteristics leads to a better description of expected returns and comovements. We estimate all models with up to eight factors, $K = 1, \ldots, 8$, to measure the importance of multiple sources of systematic risk.

In this and following sections, we follow KPS in comparing models using different measures and statistical tests. First, we report the Total R^2 defined as,

$$\text{Total } R^2 = 1 - \frac{\sum_{n,t} \left(r_{n,t+1} - \alpha_{n,t} - \beta'_{n,t} f_{t+1} \right)^2}{\sum_{n,t} r^2_{n,t+1}}, \tag{5}$$

which measures the variations in realized returns explained by time-varying alpha, time-varying betas, and factor shocks. Total R^2 indicates the ability of a model to describe the comovements of returns across stocks.[11]

[11] Note that there is no degree-of-freedom adjustment in the R^2 measures. While the number of instruments varies across models, the size of the panel (i.e., number of stocks times the number of months minus missing observations) is much larger. Therefore, adjusting for the number of parameters would make little difference.

Next, we report the Predictive R^2 defined as,

$$\text{Predictive } R^2 = 1 - \frac{\sum_{n,t}\left(r_{n,t+1} - \alpha_{n,t} - \beta'_{n,t}\lambda\right)^2}{\sum_{n,t} r^2_{n,t+1}}, \tag{6}$$

which captures the proportion of realized return variation explained by the model's conditional expected returns. To estimate the factor risk premia λ, we follow KPS in using the time-series average of the factors as $\hat{\lambda}_k = \frac{1}{T}\sum_{t=1}^{T} f_{t,k}$. The predictive R^2 indicates the ability of a model to explain cross-sectional differences in expected stock returns.[12]

Table 2 reports on Total R^2s and Table 3 on Predictive R^2s. In each table, we report results for U.S. stocks in Panel A, for DM ex U.S. stocks in Panel B, for EM stocks in Panel C, and for all stocks in Panel D. The first two columns report on the model name and number of instruments. The following columns report on different numbers of latent factors K. In each panel and for each column of Table 2 and 3, we report in bold font the maximum R^2 value.

For example, the Total and Predictive R^2s for U.S. stocks (see Panel A) are highest for Model "*Ind and adj X*". When $K = 8$, the respective values are 15.57% and 0.84%, higher than the values of 15.11% and 0.76% for Model "*Unadj X*". These values are different from the 19% and 0.70% reported by KPS for $K = 6$ because of the different sample period and set of characteristics.

Tables 2 – 3 show that models with either only industry characteristic components or industry dummies (row "*Ind X*" and "*Ind D*") are among the worst performing models across all regions. In contrast, models with either only country characteristic components or dummies (row "*Cty X*" and "*Cty D*") perform relatively well at capturing comovements. However, their Predictive R^2s are as bad or worse than models with only industry effects.

We find that models with adjusted characteristic components outperform other specifications, both in terms of Total and Predictive R^2s. When $K = 8$, the Total (Predictive) R^2s for Model "*Cty, ind, and adj X*" are almost always higher than other models at 15.57% (0.84%) for the U.S., 17.04% (0.42%) for DM ex U.S., 23.75% (0.80%) for EM, and 16.10% (0.60%) for World.

There are two exceptions. First, the model with country and industry dummies is competitive for describing comovements; its Total R^2s are slightly lower for DM and higher when EM are included to those of the model with all characteristic components (see rows "*Cty, ind, and adj X*" and "*Cty and ind D*" in Panels B-D of Table 2). However, it underperforms by a large magnitude when used to explain expected returns. Second, the Predictive R^2s are slightly higher for DM for Model "*Ind and adj X*", suggesting that country adjustments are not key to describe expected returns for developed markets. Despite these two exceptions, models with all characteristic components overall outperform other specifications.

Model "*Cty, ind, and adj X*" also compares favorably to other benchmark factor models in international finance. Table 5 compares the performance of the model with $K = 7$ factors to the *HR/GK* and *BHZ* models. The estimation of these models is described in the Online Appendix C where we replicate these papers' main findings using our dataset.

We report for each model the number of factors, Total and Predictive R^2s, and their percentage difference with Model "*Cty, ind, and adj X*". The pure country/industry dummy models in Panel A produce Total R^2s between 3% and 21% higher than our model. However, the Predictive R^2s are -32% to -55% lower than those of our model. Therefore, Model "*Cty, ind, and adj X*" achieves a Total R^2 almost as high and a Predictive R^2 much higher than the pure dummy model with drastically fewer factors (i.e., seven versus 33).[13]

We next report on the *BHZ* models estimated on either country-industry (*CI*) or country-style (*CS*) portfolios, and using either a combination of global and regional market, size, and value factors (*WLFF*) or three global principal components and three principal components for each region (*WLAPT*). We replicate their methodology with weekly returns in a robustness check, and use here instead two-year subperiods with monthly returns. To compute Total R^2s, we attribute portfolio-level time-varying betas to individual stocks based on their portfolio affiliation. Note that they work with demeaned returns as their focus is on modeling comovements. Consequently, we cannot evaluate their models' ability to explain average returns through Predictive R^2s.

For almost all factor models, we find lower Total R^2s than our model despite relying on more factors (12 for DM and EM, and 21 for World). The exception is for the *WLAPT* model with betas estimated on country-style portfolios. Regardless, these models do not better explain comovements despite having more factors and cannot be used to explain average returns.

While the results in this section shed light on the ability of different model specifications to capture comovements and expected returns in the data, they are largely descriptive. Therefore, we provide in the following sections different asset pricing tests about the significance of different components.

4.2. Are alphas significant?

We showed in the previous section that all characteristic components are important to model jointly comovements and expected returns. However, the analysis of average returns in Table 3 does not distinguish between the contributions from alphas and factor exposures. Therefore, we test in this section whether alphas are significant.

Following KPS, we obtain the p-value for the null hypothesis, $H_0 : A'A = 0$ by bootstrapping.[14] The test statistic $A'A$ measures the extent to which the characteristics used in each model drive alphas. Failure to reject this null hy-

[12] The denominator uses a benchmark prediction of 0 instead of the sample average traditionally used in R^2 measures. Individual stock returns are noisy and a fitted value of 0 often provides a better fit than using a stock's sample average return, see Gu et al. (2020). Therefore, using 0 is a more stringent benchmark.

[13] We report on the equal-weighted version of the *HR/GK* model. Results for the value-weighted are available from the author.

[14] As in their approach, our results are obtained from a wild bootstrap using a Student t distribution with degree-of-freedom equal to 5. We generate for each model and region 5000 bootstrap samples. See their Section 3.1 for further details.

Table 2
Model performance - Total R^2.

Model	L	Number K of factors							
		1	2	3	4	5	6	7	8
Panel A: United States of America, 1988–2022									
Unadj X	9	11.89	13.14	13.99	14.41	14.64	14.84	15.01	15.11
Ind and adj X	17	**11.99**	**13.34**	**14.21**	**14.69**	**14.98**	**15.21**	**15.41**	**15.57**
Ind X	9	10.27	10.88	11.18	11.35	11.54	11.65	11.74	11.82
Ind D	17	10.10	10.95	11.46	11.67	11.85	11.96	12.06	12.13
Panel B: Developed Markets ex U.S., 1991–2022									
Unadj X	9	11.57	12.60	13.13	13.59	13.95	14.25	14.47	14.57
Ind and adj X	17	11.64	12.73	13.37	13.85	14.24	14.56	14.84	15.03
Ind X	9	10.62	11.10	11.51	11.75	11.90	12.02	12.10	12.17
Ind D	17	10.53	11.50	11.96	12.27	12.41	12.48	12.55	12.60
Cty and adj X	17	11.74	13.81	14.81	15.41	15.89	16.22	16.55	16.82
Cty X	9	10.72	12.76	13.51	14.01	14.29	14.52	14.68	14.82
Cty D	15	10.39	13.53	14.26	14.70	14.90	15.05	15.15	15.23
Cty, ind, and adj X	25	**11.82**	**13.92**	**14.89**	**15.52**	**16.07**	**16.44**	**16.76**	**17.04**
Cty and ind X	17	11.02	13.11	13.95	14.42	14.76	15.03	15.25	15.42
Cty and ind D	31	10.66	13.78	14.77	15.25	15.67	16.00	16.17	16.32
Panel C: Emerging Markets, 1999–2022									
Unadj X	9	13.25	15.54	16.43	17.02	17.37	17.67	17.85	18.00
Ind and adj X	17	13.28	15.60	16.50	17.09	17.43	17.78	17.99	18.15
Ind X	9	12.63	12.85	13.10	13.22	13.31	13.38	13.44	13.49
Ind D	17	12.62	13.09	13.26	13.39	13.50	13.56	13.61	13.65
Cty and adj X	17	13.47	18.24	19.91	21.11	21.95	22.61	23.13	23.58
Cty X	9	12.91	17.67	19.31	20.51	21.34	21.98	22.49	22.94
Cty D	19	13.16	18.89	21.54	22.62	23.45	24.04	24.53	24.96
Cty, ind, and adj X	25	**13.51**	18.22	19.98	21.23	22.05	22.74	23.27	23.75
Cty and ind X	17	12.99	17.70	19.42	20.67	21.48	22.15	22.68	23.15
Cty and ind D	35	13.22	**18.96**	**21.62**	**22.71**	**23.55**	**24.15**	**24.66**	**25.08**
Panel D: World, 1999–2022									
Unadj X	9	10.42	11.30	11.89	12.34	12.68	12.86	13.01	13.14
Ind and adj X	17	10.51	11.44	12.06	12.53	12.90	13.11	13.27	13.43
Ind X	9	9.58	9.89	10.09	10.24	10.34	10.42	10.49	10.53
Ind D	17	9.49	9.97	10.23	10.48	10.61	10.72	10.77	10.81
Cty and adj X	17	10.63	12.15	13.27	14.02	14.61	15.07	15.49	15.85
Cty X	9	9.67	11.15	12.18	12.88	13.39	13.79	14.11	14.37
Cty D	35	9.84	12.14	13.86	14.62	15.22	15.66	16.00	16.29
Cty, ind, and adj X	25	**10.74**	12.27	13.39	14.19	14.84	15.31	15.74	16.10
Cty and ind X	17	9.96	11.45	12.54	13.23	13.79	14.24	14.57	14.85
Cty and ind D	51	10.04	**12.37**	**14.13**	**14.94**	**15.57**	**16.08**	**16.45**	**16.79**

We report the Total R^2s from Eq. (5) in percent for different models and numbers of factors. Models are estimated on all stocks in the U.S. in Panel A, for which models with country effects are not estimated, in Developed Markets excluding the U.S. in Panel B, in Emerging Markets in Panel C, and in all countries in Panel D. Models differ by the instrument used in the specification of the αs (see Eq. (3)) and βs (see Eq. (4)). Model "*Unadj X*" uses unadjusted characteristics. Model "*Ind and adj X*" uses industry and industry-adjusted characteristic components, while Model "*Ind X*" uses only industry components. Model "*Ind D*" uses industry dummies. Model "*Cty and adj X*" uses country and country-adjusted characteristic components, while Model "*Cty X*" uses only country components. Model "*Cty D*" uses country dummies. Model "*Cty, ind, and adj X*" uses country, industry, and country- and industry-adjusted characteristic components, while Model "*Cty and ind X*" uses country and industry components. Finally, Model "*Cty and ind D*" uses country and industry dummies. For each model and region, we report the number L of instruments. For each number of factors and each region, we report the highest R^2 using a bold font. We use a 17-industry classification. All data are monthly, in USD, and end in August 2022. Start dates vary across regions.

pothesis does not imply that there are no alphas. Rather, it means that there is not enough evidence to conclude that there are alphas determined by the instruments $z_{n,t}$.

Table 4 reports p-values for $A'A = 0$ (in %) and has the same structure as Tables 2–3. First, we replicate KPS' findings for U.S. stocks: the alphas are no longer significant with $K = 6$ factors (see the first line in Panel A). This is interesting because we obtain the same result despite a different sample period and a smaller set of characteristics. The alphas in this model are also insignificant with $K = 6$ factors in other regions.

However, results for international stocks using adjusted characteristic components are drastically different. The alphas remain significant for the DM ex U.S., EM, and World regions, even when $K = 8$. For EM in particular, the characteristic components need to be adjusted for country components. In contrast, alphas are not significant in most cases when using only country and industry characteristic components or dummies. Our results show that KPS' results for the U.S. stock market, namely that characteristic-driven alphas are no longer significant once characteristics also determine factor exposures, do not hold in international stock markets when using adjusted characteristic components. In Section 5, we investigate the extent to which an investor could have benefited from these alphas out-of-sample and net of trading costs.

Overall, these results point to the importance of using characteristic components to model jointly comovements

Table 3
Model performance - Predictive R^2.

Model	L	Number K of factors							
		1	2	3	4	5	6	7	8
Panel A: United States of America									
Unadj X	9	0.77	0.76	0.76	0.76	0.76	0.76	0.76	0.76
Ind and adj X	17	**0.88**	**0.85**	**0.85**	**0.86**	**0.86**	**0.86**	**0.85**	**0.84**
Ind X	9	0.66	0.64	0.65	0.64	0.65	0.63	0.63	0.62
Ind D	17	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
Panel B: Developed Markets ex U.S.									
Unadj X	9	0.30	0.29	0.29	0.29	0.29	0.29	0.29	0.29
Ind and adj X	17	**0.47**	**0.47**	**0.45**	**0.45**	**0.44**	**0.43**	**0.44**	**0.44**
Ind X	9	0.34	0.34	0.33	0.33	0.32	0.32	0.32	0.32
Ind D	17	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
Cty and adj X	17	0.31	0.31	0.30	0.30	0.30	0.30	0.30	0.29
Cty X	9	0.20	0.20	0.19	0.19	0.19	0.19	0.18	0.19
Cty D	15	0.19	0.18	0.18	0.18	0.18	0.18	0.18	0.18
Cty, ind, and adj X	25	0.45	0.44	0.44	0.42	0.43	0.42	0.42	0.42
Cty and ind X	17	0.33	0.32	0.31	0.31	0.31	0.30	0.31	0.31
Cty and ind D	31	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19
Panel C: Emerging Markets									
Unadj X	9	0.65	0.65	0.64	0.64	0.64	0.64	0.64	0.65
Ind and adj X	17	0.73	0.72	0.72	0.72	0.72	0.72	0.72	0.72
Ind X	9	0.58	0.58	0.58	0.57	0.57	0.57	0.57	0.57
Ind D	17	0.51	0.51	0.51	0.51	0.51	0.51	0.51	0.51
Cty and adj X	17	0.76	0.77	0.77	0.79	0.75	0.74	0.70	0.71
Cty X	9	0.59	0.60	0.59	0.61	0.57	0.56	0.58	0.52
Cty D	19	0.53	0.52	0.51	0.52	0.52	0.52	0.52	0.52
Cty, ind, and adj X	25	**0.82**	**0.83**	**0.80**	**0.84**	**0.81**	**0.81**	**0.78**	**0.80**
Cty and ind X	17	0.64	0.65	0.62	0.67	0.64	0.63	0.61	0.63
Cty and ind D	35	0.54	0.53	0.51	0.52	0.52	0.52	0.52	0.52
Panel D: World									
Unadj X	9	0.50	0.50	0.50	0.49	0.49	0.49	0.49	0.49
Ind and adj X	17	0.60	0.59	0.59	0.58	0.57	0.57	0.57	0.57
Ind X	9	0.47	0.47	0.46	0.45	0.45	0.44	0.44	0.44
Ind D	17	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38
Cty and adj X	17	0.52	0.51	0.50	0.53	0.52	0.53	0.53	0.53
Cty X	9	0.40	0.38	0.38	0.39	0.39	0.40	0.40	0.39
Cty D	35	0.41	0.40	0.39	0.40	0.41	0.39	0.39	0.41
Cty, ind, and adj X	25	**0.63**	**0.61**	**0.62**	**0.62**	**0.62**	**0.60**	**0.60**	**0.60**
Cty and ind X	17	0.50	0.48	0.48	0.49	0.48	0.49	0.49	0.48
Cty and ind D	51	0.42	0.40	0.40	0.42	0.41	0.41	0.41	0.41

We report the Predictive R^2s from Eq. (6) in percent for different models and numbers of factors. Models are estimated on all stocks in the U.S. in Panel A, for which models with country effects are not estimated, in Developed Markets excluding the U.S. in Panel B, in Emerging Markets in Panel C, and in all countries in Panel D. Models differ by the instrument used in the specification of the αs (see Eq. (3)) and βs (see Eq. (4)). Model "*Unadj X*" uses unadjusted characteristics. Model "*Ind and adj X*" uses industry and industry-adjusted characteristic components, while Model "*Ind X*" uses only industry components. Model "*Ind D*" uses industry dummies. Model "*Cty and adj X*" uses country and country-adjusted characteristic components, while Model "*Cty X*" uses only country components. Model "*Cty D*" uses country dummies. Model "*Cty, ind, and adj X*" uses country, industry, and country- and industry-adjusted characteristic components, while Model "*Cty and ind X*" uses country and industry components. Finally, Model "*Cty and ind D*" uses country and industry dummies. For each model and region, we report the number L of instruments. For each number of factors and each region, we report the highest R^2 using a bold font. We use a 17-industry classification. All data are monthly, in USD, and end in August 2022. Start dates vary across regions.

and average returns. Using the test statistic $A'A$, we find that using characteristic components lead to higher statistical significance than using other model specifications. For simplicity, we use in the next sections the models with $K = 7$ factors to provide further economic insights. The null hypothesis of $A'A = 0$ for models using characteristic components and seven factors is rejected in the U.S., DM, EM, and World regions.

4.3. What is the relative economic importance of each component?

We compared in previous sections models across specifications with different instrument selections and numbers of factors. In this section, we instead provide statistical tests and measures of economic importance for the different characteristic components when they are all included in the *same* model specification, namely Model "*Cty, ind, and adj X*" with $K = 7$ factors.

We found in the previous section that $A'A$ was significant. To understand what is the source of these significant alphas, we test for the significance of groups of parameters.[15] We obtain by bootstrapping p-values for the null hypothesis $H_0 : A_c' A_c = 0$,

[15] While KPS test the significance of individual instruments, they suggest a test for a group of instruments in their footnote 22.

Table 4
Model performance - Asset pricing tests.

Model	L	Number K of factors							
		1	2	3	4	5	6	7	8
Panel A: United States of America									
Unadj X	9	0.00	0.00	0.00	0.16	0.00	54.74	25.14	1.64
Ind and adj X	17	0.06	0.00	0.00	0.00	0.00	0.00	0.00	3.30
Ind X	9	0.18	0.08	76.00	74.82	45.96	70.84	4.78	41.86
Ind D	17	64.52	33.56	12.56	50.36	25.12	10.70	23.60	7.92
Panel B: Developed Markets ex U.S.									
Unadj X	9	0.00	0.00	52.16	1.50	0.00	79.72	76.76	28.46
Ind and adj X	17	0.00	0.00	0.04	0.06	0.00	0.02	0.16	0.00
Ind X	9	0.12	39.22	52.28	23.68	99.12	59.60	14.94	36.72
Ind D	17	45.12	34.48	15.54	4.74	10.10	1.32	0.66	69.64
Cty and adj X	17	2.26	0.40	0.50	0.18	0.12	0.72	0.66	0.50
Cty X	9	32.46	21.32	43.78	82.64	38.86	56.94	89.32	78.78
Cty D	15	80.06	42.64	54.12	41.22	45.16	37.78	22.46	87.74
Cty, ind, and adj X	25	1.72	0.00	0.00	0.00	0.02	0.02	0.42	0.22
Cty and ind X	17	7.92	1.32	1.02	0.78	15.12	18.36	66.00	59.56
Cty and ind D	31	82.70	54.60	37.16	34.36	19.30	13.34	9.42	3.60
Panel C: Emerging Markets									
Unadj X	9	0.34	4.60	23.36	3.16	0.08	71.18	0.28	29.70
Ind and adj X	17	0.36	3.42	36.14	13.12	8.70	5.44	16.90	19.38
Ind X	9	6.90	23.22	0.42	95.56	89.66	65.28	68.40	36.64
Ind D	17	70.92	46.82	11.04	99.78	79.38	38.26	44.50	36.38
Cty and adj X	17	17.78	6.10	3.00	1.02	0.20	0.08	0.00	0.00
Cty X	9	74.36	75.78	71.60	63.12	53.90	57.20	98.24	27.22
Cty D	19	96.14	98.74	97.30	93.40	85.80	81.80	73.64	95.92
Cty, ind, and adj X	25	13.60	5.00	1.72	0.42	0.02	0.00	0.00	0.00
Cty and ind X	17	46.82	54.62	35.52	21.46	7.90	9.48	3.72	2.82
Cty and ind D	35	98.28	99.42	98.22	95.70	90.88	88.10	81.00	92.92
Panel D: World									
Unadj X	9	0.00	0.00	59.56	53.20	54.96	23.38	5.06	0.98
Ind and adj X	17	0.00	0.00	19.98	2.16	0.12	0.06	0.22	0.80
Ind X	9	0.48	0.98	7.52	0.54	35.74	5.62	4.20	10.88
Ind D	17	45.64	21.20	6.60	2.36	0.44	0.04	44.92	68.34
Cty and adj X	17	0.30	0.02	0.04	0.32	0.00	0.00	0.00	0.26
Cty X	9	30.84	12.52	64.86	11.60	2.26	19.58	43.96	88.96
Cty D	35	6.70	7.24	3.16	7.90	4.52	76.94	41.84	35.90
Cty, ind, and adj X	25	0.20	0.00	0.00	0.06	0.00	0.00	0.00	0.00
Cty and ind X	17	9.70	3.68	13.08	13.44	7.42	2.10	2.16	27.64
Cty and ind D	51	6.98	10.96	2.64	0.62	15.68	17.50	43.84	38.60

We report the p-value (in %) for the null hypothesis that the α are not driven by the instruments, $H_0 : A'A = 0$. Models are estimated on all stocks in the U.S. in Panel A, for which models with country effects are not estimated, in Developed Markets excluding the U.S. in Panel B, in Emerging Markets in Panel C, and in all countries in Panel D. Models differ by the instrument used in the specification of the αs (see Eq. (3)) and βs (see Eq. (4)). Model "*Unadj X*" uses unadjusted characteristics. Model "*Ind and adj X*" uses industry and industry-adjusted characteristic components, while Model "*Ind X*" uses only industry components. Model "*Ind D*" uses industry dummies. Model "*Cty and adj X*" uses country and country-adjusted characteristic components, while Model "*Cty X*" uses only country components. Model "*Cty D*" uses country dummies. Model "*Cty, ind, and adj X*" uses country, industry, and country- and industry-adjusted characteristic components, while Model "*Cty and ind X*" uses country and industry components. Finally, Model "*Cty and ind D*" uses country and industry dummies. For each model and region, we report the number L of instruments. The p-values are obtained by bootstrapping under the null hypothesis. We use a 17-industry classification. All data are monthly, in USD, and end in August 2022. Start dates vary across regions.

where A_c is the sub-vector of coefficients in A that correspond to country components. Similarly, we test for the significance of industry and adjusted component parameters using the test statistics $A_i'A_i$ and $A_a'A_a$, respectively. In a similar spirit, we highlight the role of different component groups in capturing factor exposures by testing the significance of $\sum_{k=1}^{K} B_{c,k}'B_{c,k}$, $\sum_{k=1}^{K} B_{i,k}'B_{i,k}$, and $\sum_{k=1}^{K} B_{a,k}'B_{a,k}$.

Panel A of Table 6 reports the p-values for the significance test of the parameter groups in A across regions. The significant alphas predominantly come from the *AdjX*s. While this result can also be obtained by comparing the p-values for the test $A'A$ in Table 4 between models with and without the *AdjX*s, the test results reported in Panel A further illustrate the significance of other components when they are all included in the same model specification. For example, we find that the *IndX* parameters are significant at the 5% level for all regions except DM where they are significant at the 10% level.

Panel B of Table 6 reports the p-values for the significance test for parameter groups in B across regions. We find that country and adjusted characteristic components are highly significant in all cases, whereas industry components are not. These results are in line with those in Table 2, which show that models with only industry effects have the lowest Total R^2 values.

While Table 6 conveys the statistical significance of parameter groups, we also want to compare their magni-

Table 5
Comparison to other factor models.

	DM ex U.S					EM					World				
Model	K	Total R^2	Δ%	Pred. R^2	Δ%	K	Total R^2	Δ%	Pred. R^2	Δ%	K	Total R^2	Δ%	Pred. R^2	Δ%
Cty, ind, and adj X	7	16.76		0.42		7	23.27		0.78		7	15.74		0.60	
Panel A: Heston and Rouwenhorst (1994) and Griffin and Karolyi (1998)															
Equal-weighted	33	17.31	3	0.19	-55	37	27.07	16	0.52	-33	53	19.03	21	0.41	-32
Panel B: Bekaert et al. (2009))															
WLFF - CI	12	10.66	-36	-		12	17.30	-26	-		21	9.05	-43	-	
WLAPT - CI	12	13.44	-20	-		12	21.65	-7	-		21	15.49	-2	-	
WLFF - CS	12	14.34	-14	-		12	19.82	-15	-		21	13.37	-15	-	
WLAPT - CS	12	15.73	-6	-		12	24.58	6	-		21	18.74	19	-	

We compare the number of factors, Total R^2s (see Eq. (5)) and Predictive R^2s (see Eq. (6)), in percent, between Model "*Cty, ind, and adj X*" and benchmark models. We report percentage differences between benchmark model R^2s and those of "*Cty, ind, and adj X*". Panel A reports on country-industry dummy model in which stock returns have a beta of one on a common factor and their respective country and industry factors. Panel B reports on the World-Local Fama-French (*WLFF*) and World-Local APT (*WLAPT*) models of Bekaert et al. (2009). We assign the portfolio-level betas to individual stocks based on either the country-industry portfolio set (*CI*) or the country-style portfolio set (*CS*). We use a 17-industry classification. All data are monthly, in USD, and end in August 2022.

Table 6
Significance tests for parameter groups.

	Characteristic components		
Region	Country	Industry	Adjusted
Panel A: p-values for the joint significance of A parameters			
U.S.	-	0.18	0.00
DM ex U.S.	73.62	9.72	0.00
EM	22.68	3.38	0.00
World	4.72	2.14	0.00
Panel B: p-values for the joint significance of B parameters			
U.S.	-	61.38	0.00
DM ex U.S.	6.20	15.42	0.00
EM	0.00	83.38	0.30
World	0.00	30.88	0.00

We report p-values (in %) for significance tests for parameter groups corresponding to characteristic components. In Panel A, we test the null hypothesis, $H_0 : A_c' A_c = 0$, where A_c is the sub-vector of coefficients in A that correspond to country components. Similarly, we test for the significance of industry and adjusted component parameters using the test statistics $A_i' A_i$ and $A_a' A_a$, respectively. In Panel B, we test the significance of parameter groups in B across factors using test statistics $\sum_{k=1}^{K} B_{c,k}' B_{c,k}$, $\sum_{k=1}^{K} B_{i,k}' B_{i,k}$, and $\sum_{k=1}^{K} B_{a,k}' B_{a,k}$. In all cases, we use Model "*Cty, ind, and adj X*" with $K = 7$ factors. The p-values are obtained by bootstrapping under the null hypothesis. We use a 17-industry classification. All data are monthly, in USD, and end in August 2022.

tude to shed light on their relative economic importance. To do so, we compare the sum of squared parameter values for different characteristic component groups (i.e., the test statistics discussed above) as a proportion of their total sum of squared parameters. Because all characteristic components are normalized to lie in the $[-0.5, 0.5]$ interval, we can directly compare the contributions from different groups of instruments to the sum of squared parameters. However, for betas, we weigh the sum of squared parameters across factors using the factors second moment matrix. This weighting is necessary to compare factor loadings of a given magnitude across factors with different second moments. This metric indicates the magnitude of the contribution of a component group to capturing systematic risk across all K factors. No such adjustment is required for alpha parameters.

Figure 1 contains our results. We report for each region the composition of the sum of squared alpha parameters, $A_c' A_c$, $A_i' A_i$, and $A_a' A_a$ as a proportion of the total sum, $A' A$, using blue bars, and the composition of the weighted sum of squared beta parameters, $\sum_{k=1}^{K} S_{f,k,k} B_{c,k}' B_{c,k}$, $\sum_{k=1}^{K} S_{f,k,k} B_{i,k}' B_{i,k}$, and $\sum_{k=1}^{K} S_{f,k,k} B_{a,k}' B_{a,k}$ as a proportion of the total sum, $\sum_{k=1}^{K} S_{f,k,k} B_k' B_k$, using red bars. Because $B' B = \mathbb{I}_K$ and S_f is diagonal by construction, we can write $\sum_{k=1}^{K} S_{f,k,k} B_{j,k}' B_{j,k} = tr(B_j S_f B_j')$ for $j \in \{c, i, a\}$ and $\sum_{k=1}^{K} S_{f,k,k} B_k' B_k = tr(S_f)$, where $tr(\cdot)$ is the trace operator. Note that the proportions do not add to 100% because of the contribution of the constant parameter.

These metrics indicate the relative importance of each component to model alphas and betas, not the relative importance of alpha and factor exposures to explain expected returns. Therefore, this analysis complements the one in the previous section.

For international markets, the *AdjX* components are more important determinants of alphas than other components. The contribution of $A_a' A_a$, at around 70% for DM and EM, is more than triple either $A_c' A_c$ or $A_i' A_i$. The *CtyX* and *IndX* components' combined contributions are around 30% for both DM and EM.

Results for betas are drastically different from those for alphas. For EM (DM), the weighted sum of squared beta parameters is dominated by the country contribution at 91% (63%). In both regions, the country contribution is larger than either industry or adjusted contributions, which range between 1% and 16%. Results for the World estimation using all stocks, reported in the bottom right graph, further confirm that country and adjusted components are crucial to capture beta and alpha parameters, respectively.[16]

These results contrast with those for the U.S. where the relative contributions of industry and adjusted components for alphas and betas all lie in a narrow range from 41% and 51%. Recall that we provide results for the U.S. stock mar-

[16] In Online Appendix D, we explore the contributions from each characteristic to the sum of squared alpha and beta parameters.

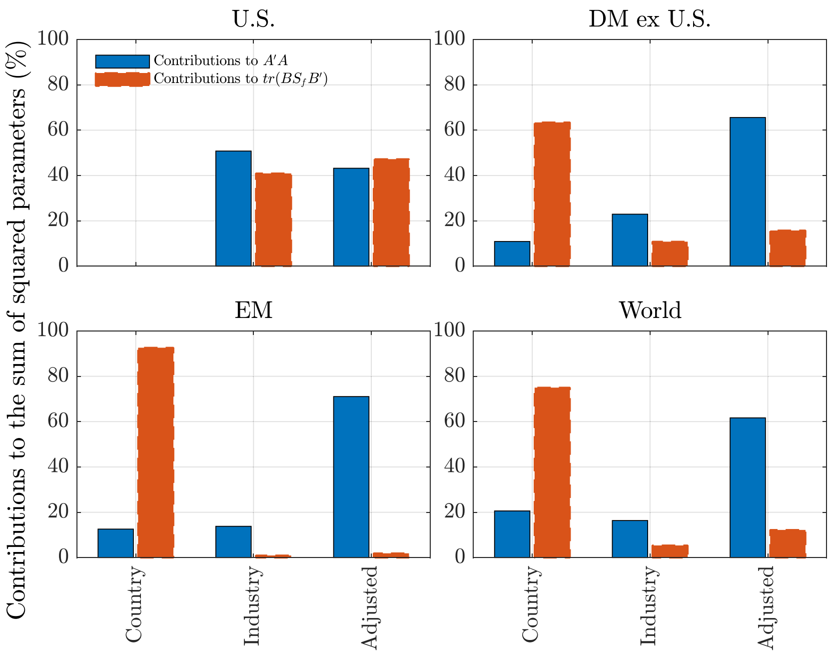

Fig. 1. What is the relative importance of each characteristic components for alphas and betas?
We report for each region the different contributions to the sum of squared alpha and weighted sum of squared beta parameters. We compute the contribution to the sum of squared alpha parameters from all country components, $A_c'A_c$. We repeat the analysis for the contributions to the sum of squared alpha parameters from all industry components, $A_i'A_i$, and adjusted components, $A_a'A_a$. Then, we compute the contributions to the weighted sum of squared beta parameters from all country components, $tr(B_cS_fB_c')$. The unconditional second moment matrix of factors, S_f, is diagonal by construction. Similarly, we compute the test statistics for industry components, $tr(B_iS_fB_i')$, and adjusted components, $tr(B_aS_fB_a')$. All models have $K = 7$ factors and are estimated on all stocks in a region. We estimate Model "*Ind and adj X*" for the U.S. (top left), and Model "*Cty, ind, and adj X*" for Developed Markets excluding the U.S. (top right), Emerging Markets (bottom left), and all countries (bottom right). We use a 17-industry classification. All data are monthly, in USD, and end in August 2022. Start dates vary across regions.

ket as a benchmark, but cannot use, in this case, country characteristic components.

The dominance of country components for betas has important economic implications for the determinants of comovements in international stock markets. Several studies find that stocks with similar within-country adjusted characteristics are correlated across countries (see, for example, Asness et al., 2013; Bekaert et al., 2009). In line with these correlations, we find that the *AdjX*s are statistically significant determinants of betas across individual international stock returns. But the *CtyX*s are drastically larger in magnitude and hence more important drivers of covariances.

In this and the previous section, we found that alphas in international markets are significant when using characteristic components and the relative importance of country and adjusted components differs between alphas and betas. In the next section, we investigate whether there are any variations over time in these results.

4.4. Are there variations over time in our results?

In this section, we first measure the significance of alphas over time to determine whether there are any trends. Every month, we estimate different model specifications using data over the last ten years and compute the test statistic $A'_{t-119:t}A_{t-119:t}$, where the subscript indicates that the estimation is done on the last 120 months. To save on computation time, we estimate the significance of $A'_{t-119:t}A_{t-119:t}$ every 12 months and use 1,000 bootstrap samples instead of 5,000.

Figure 2 presents our results. We report the test statistics for the U.S. in the top row, for DM ex U.S. in the second row, for EM in the third row, and for all stocks in the bottom row. The left columns reports on Model "*Unadj X*", the middle column on Model "*Ind and adj X*", and the right column on Model "*Cty, ind, and adj X*". In all cases, we use a model with $K = 7$ latent factors. In each graph, we report the test statistic and different gray areas for the median, the 75%, 90%, 95%, and 99% percentiles of the bootstrapped test statistics. A line above all gray areas indicates that the test statistic is significant at the 1% level.

The magnitude of alphas increases as we move from Model "*Unadj X*" to Model "*Ind and adj X*", but especially to Model "*Cty, ind, and adj X*", indicating that using country- and industry-adjusted characteristics extracts more alphas from international stock returns. Whereas the magnitude of alphas is insignificant in the U.S. for most ten-year periods ending in 2009 and later, those for other DM and EM are almost always significant at the 5% level for Model "*Cty, ind, and adj X*".

Overall, we observe a downward trend in the magnitude of the squared alpha parameters in all regions for models using characteristic components. Therefore, while

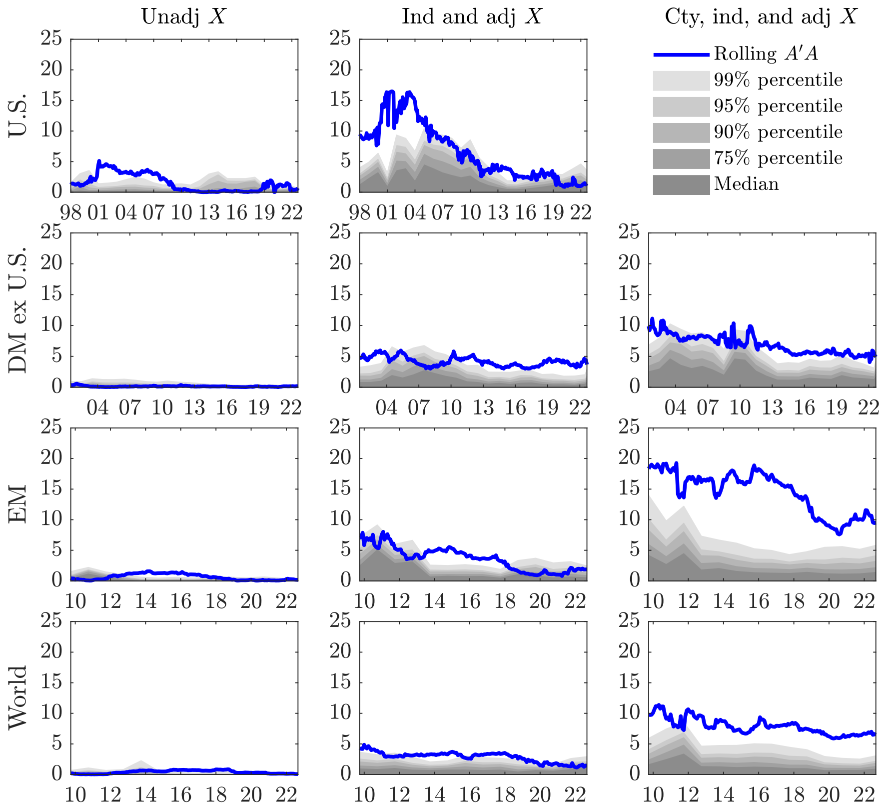

Fig. 2. Are alphas significant over time?
We report the test statistics for the significance of alphas, $A'_{t-119:t}A_{t-119:t}$, from models estimated on rolling ten-year windows. Models are estimated on U.S. stocks in the top row, on DM ex U.S. stocks in the second row, on EM stocks in the third row, and on all stocks in the bottom row. The left column reports on Model "*Unadj X*" using unadjusted characteristics, the middle column on "*Ind and adj X*" with industry and industry-adjusted characteristics, and the right column on "*Cty, ind, and adj X*" with country, industry, and country- and industry-adjusted characteristics. In each graph, we report the test statistic, and different gray areas for the median, the 75%, 90%, 95%, and 99% percentiles of the bootstrapped test statistics. A point above all gray areas indicates that the test statistic is significant at the 1% level. We use a 17-industry classification. All data are monthly, in USD, and end in August 2022. Start dates vary across regions.

we found in the last section that alphas were significant for these models when they were estimated on the whole sample period, we find using rolling window estimations that their magnitude has decreased over time.

Next, we use the same rolling estimates to compute the time-varying contributions to the sum of squared alpha and beta parameters. Each month t, we compute the proportion of the sum of squared alpha parameters from country components as,

$$\frac{A'_{c,t-119:t}A_{c,t-119:t}}{A'_{t-119:t}A_{t-119:t}}. \tag{7}$$

Similarly, we compute the proportions for industry components, $\frac{A'_{i,t-119:t}A_{i,t-119:t}}{A'_{t-119:t}A_{t-119:t}}$, and adjusted components, $\frac{A'_{a,t-119:t}A_{a,t-119:t}}{A'_{t-119:t}A_{t-119:t}}$.

We also compute over time the proportion of the weighted sum of squared beta parameters coming from country components, $\frac{tr(B_{c,t-119:t}S_{f,t-119:t}B'_{c,t-119:t})}{tr(S_{f,t-119:t})}$, industry components, $\frac{tr(B_{i,t-119:t}S_{f,t-119:t}B'_{i,t-119:t})}{tr(S_{f,t-119:t})}$, and adjusted components, $\frac{tr(B_{a,t-119:t}S_{f,t-119:t}B'_{a,t-119:t})}{tr(S_{f,t-119:t})}$. Recall that the sum of contributions for either alphas or betas is not equal to 100% because of the contribution of the constant.

Figure 3 reports the proportion in % over time from the rolling estimates. The left column contains alpha proportions across all regions. We find that the adjusted components dominate other components over the entire period. Industry components have become more important in the U.S. for the ten-year periods ending in 2009, but that uptrend has since reverted.

Beta proportions are reported in the right column. In the U.S., industry and industry-adjusted components are equally important. In international markets, the country components are predominant, especially for EM. We find that about 10% of the sum of squared beta parameters comes from the constant in all regions. Interestingly, there is no apparent trend over time for beta proportions suggesting that the relative importance of country, industry, and adjusted effects for

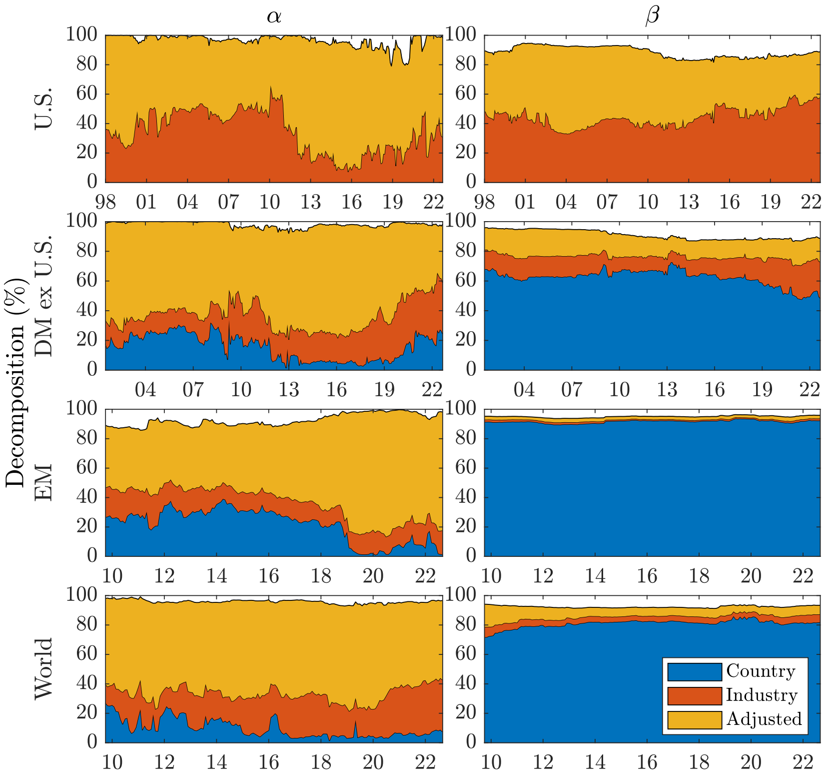

Fig. 3. Component contributions to alphas and beta over time.
We report for each region the different contributions to the sum of squared alpha and weighted sum of squared beta parameters estimated on rolling ten-year windows. Models are estimated on U.S. stocks in the top row, on DM ex U.S. stocks in the second row, on EM stocks in the third row, and on all stocks in the bottom row. Each month t, we compute the contribution to the sum of squared alpha parameters from all country components, $A'_{c,t-119:t}A_{c,t-119:t}$, industry components, $A'_{i,t-119:t}A_{i,t-119:t}$, and adjusted components, $A'_{a,t-119:t}A_{a,t-119:t}$. We also compute the contribution to the sum of squared beta parameters from all country components, $tr(B_{c,t-119:t}S_{f,t-119:t}B'_{c,t-119:t})$, industry component, $tr(B_{i,t-119:t}S_{f,t-119:t}B'_{i,t-119:t})$, and adjusted components, $tr(B_{a,t-119:t}S_{f,t-119:t}B'_{a,t-119:t})$. We report the contributions for alpha parameters in % normalized by the sum of all squared parameters, $A'_{t-119:t}A_{t-119:t}$, in the left column and the contributions for beta parameters in % normalized by the sum of all squared parameters, $tr(S_{f,t-119:t})$, in the right column. The white area indicates the contributions from parameters for the constant. We use a 17-industry classification. All data are monthly, in USD, and end in August 2022. Start dates vary across regions.

explaining exposures to systematic risk is stable over time.

In the next section, we examine whether investors would have been able to trade on these alphas once we account for estimation risk and transaction costs.

5. Are alphas tradable?

Section 4.4 shows that the magnitude of alphas has been trending down over time. This section further examines whether an investor could have used the alphas we document in the previous section to generate significant risk-adjusted returns in real time. We do so by computing the out-of-sample performance, net of transaction costs, of portfolios formed using predicted alphas and held for different holding periods.

We construct value-weighted quintile portfolios of stocks sorted by predicted alphas, form a long-short strategy that buys the top quintile and short-sells the bottom quintile, and measure these strategies' returns net of transaction costs.

A key issue for an investor is optimizing his trading to mitigate the detrimental effect of transaction costs on his net portfolio performance. Alpha opportunities that rapidly decay are costlier to trade, whereas persistent alphas involve smaller transaction costs. To address this issue, we form strategies that hold stocks for different buy-and-hold periods going from $h = 1$ to $h = 24$ months. For a strategy with a holding period of h months, we follow these steps:

1. At the beginning of month t, we estimate all models using the last ten years (i.e., using returns from period $t - 120$ to $t - 1$), and obtain parameter estimates $A_{t-120:t-1}$.
2. We compute predicted alphas for month t using the characteristics available at the end of month $t - 1$ as

$$\alpha_{t-1} = A'_{t-120:t-1}z_{t-1}. \tag{8}$$

3. We form a long-short portfolio that buys the top 20% predicted alpha stocks and short sells the bottom 20% predicted alpha stocks. We value-weight each portfolio. The N_t-by-one vector of weights is

$$w_t = w_t^{Long} - w_t^{Short} \tag{9}$$

where $\sum_{n=1}^{N_t} w_{n,t}^{Long} = \sum_{n=1}^{N_t} w_{n,t}^{Short} = 1$. We compute the gross of transaction cost performance from month t as,

$$r_t^{Gross} = \left(1 - w_t'\iota\right) r_{f,t} + w_t' r_t, \quad (10)$$

where ι is a vector of ones. Note that $w_t'\iota = 0$ initially, but $w_t'\iota$ may be different from zero in subsequent months as some stocks may be removed from the portfolio, see Step 5 below.

4. Following Ao et al. (2019), we compute the net of transaction cost performance as

$$r_t^{Net} = \left(1 - \sum_{n=1}^{N_t} c_{n,t-1} |w_{n,t} - w_{n,t-}|\right)\left(1 + r_t^{Gross}\right) - 1, \quad (11)$$

where $w_{n,t-}$ is the portfolio weight of asset n at the beginning of period t before rebalancing and $c_{n,t-1}$ is the per-dollar transaction cost for trading asset n.

5. While the portfolio is held until month $t+h-1$, some stocks delist or do not meet our filters anymore. Therefore, we incur transaction costs when we need to sell these stocks. We compute the net of transaction cost performance on month $k \in \{t+1, \dots, t+h-1\}$ using Eq. (11) in which $w_{n,t}$ is set to $w_{n,t-}$ if stock n is kept or 0 if it has been sold. To minimize transaction costs, the proceeds obtained by selling a stock are invested at the risk-free rate for the remainder of the buy-and-hold period instead of being invested in the remaining stocks.
6. We repeat steps 1–5 at the beginning of month $t+h$, $t+2h$, etc.

We report results on overlapping strategies. We compute the returns on the overlapping strategy with holding period h by investing an amount $1/h$ in h strategies initiated on months $1, \dots,$ and h, respectively. Novy-Marx and Velikov (2016) also consider a portfolio of overlapping strategies when evaluating the performance of different trading-cost mitigation methods.

To compute these strategies' net performance, we need a proxy for the transaction costs c_t. Fong et al. (2017) show that their FHT measure and the high-low price-based proxy of Corwin and Schultz (2012) (CS) are the best monthly bid-ask spread proxies when high-frequency data and closing bid-ask quotes are not available, which is the case for a large proportion of our international stock sample. In our main results, we use the more recently proposed high-low price-based proxy of Abdi and Ranaldo (2017), and repeat our analysis with the FHT and CS measures in Online Appendix G.

Finally, we use the regional five-factor model (see Fama and French, 2017) augmented with the regional momentum factor to compute the risk-adjusted performance (i.e., unconditional alpha) of each strategy. We obtain the six factors from Ken French's website, and use the set of U.S. factors, DM ex U.S. factors, and EM factors depending on the region. For the strategies that consider all stocks, we use all regional factors to risk-adjust performances.

Figure 4 presents the performance results. The regions and models are presented in the same order as in Fig. 2. For each holding period reported on the horizontal axis, we report the average risk-adjusted gross return using a continuous blue line and net return using a dashed red line. For both lines, we report 95% confidence intervals using shaded areas.

The alphas of U.S. stocks were not significant when estimated over the entire sample period in Section 4.2 and using rolling 10-year periods in Section 4.4. Accordingly, we find insignificant average returns in the top row of Fig. 4. In line with the significance of the rolling alphas for EM (see third row in Fig. 2), we find positive average gross returns for strategies that use characteristic components and rebalance often (see model "*Cty, ind, and adj X*" in the third row of Fig. 4).

However, the gross average returns are not significant in all cases as the confidence intervals include zero. Therefore, estimation risk (i.e., estimating and predicting stock alphas out-of-sample) severely hinders an investor's ability to extract alphas. Accounting for transaction costs further worsens performances as all risk-adjusted returns are negative and insignificant.[17]

Our experiment uses long-short portfolios and, although we adjust gross performances using a proxy for trading costs, we do not control for short-selling costs. Unfortunately, data on short-selling costs for international stocks are scarce. Therefore, we repeat our analysis by removing the short position in the low predicted alpha portfolio and buying only the top quintile value-weighted portfolio. We modify Step 3 above by setting $w_t = w_t^{Long}$.

We report the average risk-adjusted return of the top quintile portfolios in Fig. 5. The risk-adjusted performances of strategies using characteristic components in EM are still the highest and net returns are positive for longer investment horizons. However, all average returns are insignificant.

Overall, our results indicate that estimated alphas are large and statistically significant for models that include *AdjX*, but not large enough to overcome estimation risk and trading costs. In the next section, we examine the robustness of our results.

6. Robustness checks

We proceed in this section to several robustness checks. First, we exclude small capitalization stocks from our sample and repeat all our analyses. Second, we vary the estimation window and the measure of transaction costs to compute the net returns of arbitrage portfolios. Finally, we repeat our main empirical tests using weekly returns as in Heston and Rouwenhorst (1994), Griffin and Karolyi (1998), and Bekaert et al. (2009).

6.1. Expected returns and comovements in large-cap stocks

We repeat the analysis of Sections 4–5 by excluding small-cap stocks. Each month, we restrict our sample to the largest stocks that account for 85% of the total market capitalization in each country and refer to this subsam-

[17] We are testing separately for the significance of each strategy's risk-adjusted performance. Adjusting for multiple testing would not change our conclusion because it would make the confidence intervals even wider.

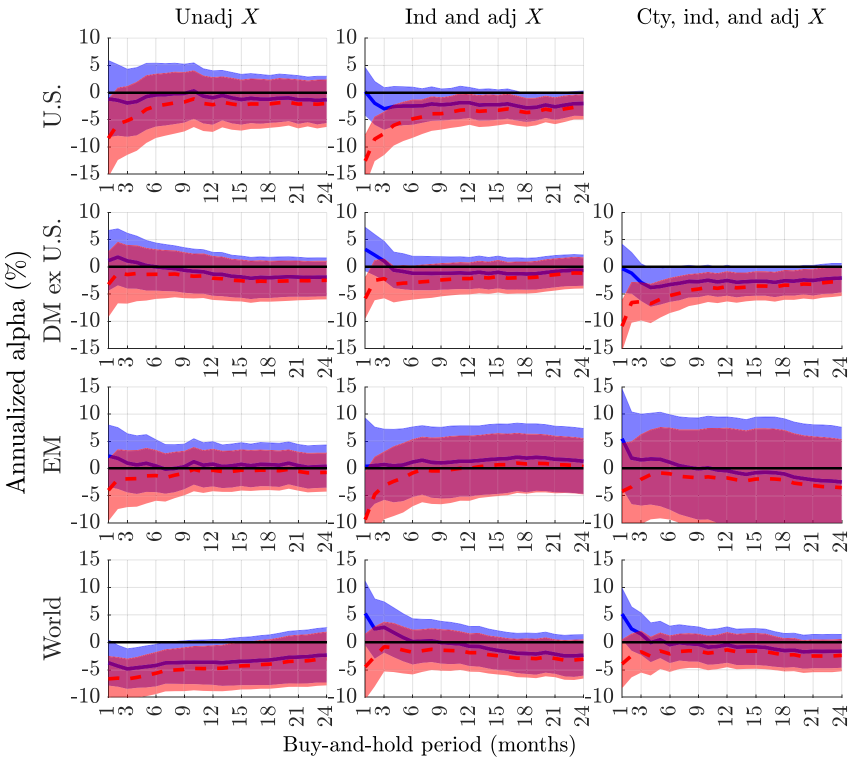

Fig. 4. Risk-adjusted returns of high-minus-low predicted alpha portfolios.
We report the average risk-adjusted return (annualized in %) gross of transaction costs (continuous blue line) and net of transaction costs (dashed red line) of long-short portfolios for different buy-and-hold periods. Each month, we use parameters $A_{t-120:t-1}$ estimated on a rolling ten-year window (from month $t-120$ to $t-1$), predict alphas as $\alpha_{n,t} = A'_{t-120:t-1} z_{n,t}$, buy a value-weighted portfolio with the top 20% predicted $\alpha_{n,t}$, and short-sell a value-weighted portfolio with the bottom 20% predicted $\alpha_{n,t}$. We hold this portfolio for different holding periods going from $h = 1$ to $h = 24$ months. The h-month strategy is the portfolio containing h overlapping strategies. We use the Fama-French five-factor model augmented with the momentum factor to adjust for risk. We use all factors for the World strategies. Shaded areas report 95% Newey-West corrected confidence intervals around average risk-adjusted gross and net returns. We use the high-low price based measure of Abdi and Ranaldo (2017) as a transaction cost proxy. Models are estimated on U.S. stocks in the top row, on DM ex U.S. stocks in the second row, on EM stocks in the third row, and on all stocks in the bottom row. The left column reports on Model "*Unadj X*", the middle column on "*Ind and adj X*", and the right column on "*Cty, ind, and adj X*". We use a 17-industry classification. All data are monthly, in USD, and end in August 2022. Start dates vary across regions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

ple as the large-cap sample. The objectives of the large-cap sample are two-fold. First, we want to ensure that small-caps do not drive results about characteristic components' role in explaining alphas and factor exposures. Second, we want to assess whether the alphas are also present in more liquid large-cap stocks.

Tables E.7-E.11 of the Online Appendix replicate Tables 1–4 and 6 for the large-cap sample. The average R^2s in Table E.7 for the characteristic regression (1) are higher for large-caps than for the entire sample, and country dummies similarly explain a larger fraction of characteristic variance than industry dummies.

As we found using the entire sample, the Total R^2s in Table E.8 are highest for Model "*Ind and adj X*" for U.S. and "*Cty, ind, and adj X*" for DM ex U.S. The Total R^2s for EM and World are highest for Model "*Cty and ind D*", although the values for Model "*Cty, ind, and adj X*" are marginally lower. For all regions, the R^2 levels are much higher than for the entire sample, because of the higher idiosyncratic volatilities of small cap stocks.

The Predictive R^2s in Table E.9 are overall similar to those obtained from the entire stock sample. The maximum Predictive R^2s are almost always for Model "*Cty, ind, and adj X*". The patterns of p-values for the null hypothesis $A'A = 0$ in Table E.10 are similar to those from the entire sample. The main difference is that the alphas for models with *AdjX*s are less significant than when estimated on the entire stock sample.

Table E.11 show that, as in the entire sample, A parameters for *AdjX* and B parameters for both *CtyX* and *AdjX* are highly significant. Contributions to the sum of squared alpha and weighted sum of squared beta parameters for all regions in Figure E.9 are close to those in Fig. 1.

Next, Figure E.10 reports the rolling ten-year estimated $A'A$ along with bootstrapped percentiles. The main difference between Fig. 2 and E.10 is that the magnitudes of the alphas are smaller for DM and EM for models using adjusted characteristic components. Importantly, the alphas in Model "*Cty, ind, and adj X*" for EM stocks are still significant at the 5% level. Rolling contributions to alphas and betas in Figure E.11 are close to those in Fig. 3.

Finally, Figures E.12-E.13 replicate Figs. 4–5 using the large-cap stock sample. We find that risk-adjusted returns of long-horizon strategies are significant for EM when us-

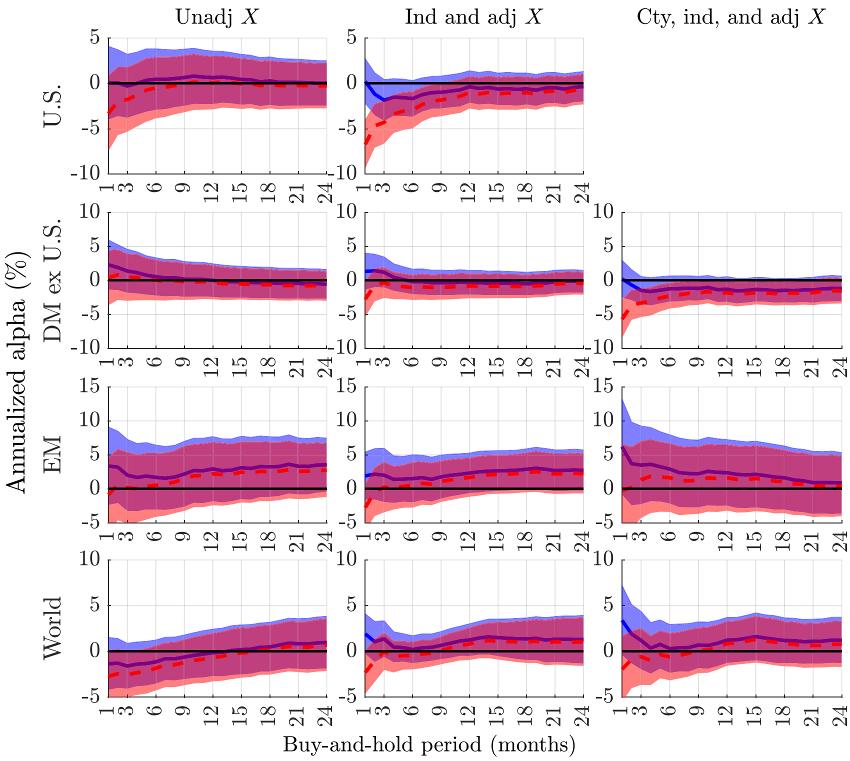

Fig. 5. Risk-adjusted returns of high predicted alpha portfolios.
We report the average risk-adjusted return (annualized in %) gross of transaction costs (continuous blue line) and net of transaction costs (dashed red line) of long-only portfolios for different buy-and-hold periods. Each month, we use parameters $A_{t-120:t-1}$ estimated on a rolling ten-year window (from month $t-120$ to $t-1$), predict alphas as $\alpha_{n,t} = A'_{t-120:t-1} z_{n,t}$, and buy a value-weighted portfolio with the top 20% predicted $\alpha_{n,t}$. We hold this portfolio for different holding periods going from $h = 1$ to $h = 24$ months. The h-month strategy is the portfolio containing h overlapping strategies. We use the Fama-French five-factor model augmented with the momentum factor to adjust for risk. We use all factors for the World strategies. Shaded areas report 95% Newey-West corrected confidence intervals around average risk-adjusted gross and net returns. We use the high-low price based measure of Abdi and Ranaldo (2017) as a transaction cost proxy. Models are estimated on U.S. stocks in the top row, on DM ex U.S. stocks in the second row, on EM stocks in the third row, and on all stocks in the bottom row. The left column reports on Model "*Unadj X*", the middle column on "*Ind and adj X*", and the right column on "*Cty, ind, and adj X*". We use a 17-industry classification. All data are monthly, in USD, and end in August 2022. Start dates vary across regions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

ing characteristic components. However, the performances of long-only portfolios are not significant, which indicates that the outperformance of long-short strategies mainly comes from the short portfolio. As previously discussed, given that we cannot account for short-selling costs when computing performances, the significantly positive performance of long-short strategies in EM may not be feasible.

Figure F.15 and F.19 report on rolling contributions to the sum of squared alpha and beta parameters. Our results about the relative importance of characteristic components are robust, namely the dominance of adjusted components for alphas and country components for betas. Finally, we find in Figures F.16, F.17, F.20, and F.21 similar insignificant average risk-adjusted returns of long-short and long-only portfolios.

6.2. Using a shorter rolling window

Section F.1 of the Online Appendix presents results obtained using five-year instead of ten-year rolling estimation windows.

Although the estimates are more volatile than those based on ten-year rolling windows, the results are overall robust to using a shorter estimation period. Rolling estimates of $A'A$ for the entire sample in Figure F.14 are significant at the 5% for Model "*Cty, ind, and adj X*" in DM ex U.S. and EM. Rolling estimates for $A'A$ for large-cap stocks reported in Figure F.18 are smaller in magnitude and less significant.

6.3. Using an expanding estimation window

Kim et al. (2021) point out that KPS' estimation methodology is more suitable for long estimation periods. Moreover, if the relation between instruments and alphas is stable over time, using a short estimation period will result in noisy alpha predictions and poor arbitrage portfolio performances.

We explore this issue by repeating our analyses using an expanding sample in which we use all past returns at each point in time instead of a rolling window. We provide all expanding window based results in Section F.2 of the Online Appendix. Overall, we find that all results based on expanding samples are very close to those based on rolling ten-year periods in Sections 4–5.

6.4. Using alternative liquidity measures

Next, we examine the robustness of arbitrage portfolios' performance results to using different proxies for transaction costs. We use the *FHT* proxy of Fong et al. (2017) in Section G.1 and the high-low price-based measure of Corwin and Schultz (2012) in Section G.2.

We replicate Figs. 4, 5, E.12, and E.13 in Figures G.30–37. The main difference is that there is a smaller difference between gross and net performances when we use the *FHT* measure because it is, on average, smaller than either *AR* or *CS*. The main conclusion from this robustness check is that the out-of-sample performances of arbitrage portfolios remain insignificant.

6.5. Using weekly returns

In Section 4, we compared our model's performances to those of Heston and Rouwenhorst (1994), Griffin and Karolyi (1998), and Bekaert et al. (2009). As these studies use weekly returns, we replicate in this section our main results using weekly instead of monthly returns.[18] Tables H.12–15 and Figures H.38–40 of the Online Appendix replicate Tables 2–5 and Figs. 1–3.

There are two differences with results based on monthly returns. First, asset pricing tests for the null hypothesis $A'A = 0$ for Model "*Cty, ind, and adj X*" in DM are not rejected (see Panel B of Table H.14). Similarly, rolling $A'A$ in Figure H.39 are not significant for DM. This reflects the lower signal-to-noise ratio in weekly returns that lowers the significance of estimated alphas.

Second, Predictive R^2s are the highest for model "*Ind and adj X*" and Model "*Cty, ind, and adj X*" is a close second. Therefore, Total and Predictive R^2s in Tables H.12–13 convey the importance of controlling for industry and country to properly control for expected returns and comovements, respectively. Once again, this underlines the importance of having all characteristic components in a model to explain jointly expected returns and comovements. All other results are similar to those based on monthly returns.

7. Conclusion

We use cross-sectional regressions for firm characteristics to estimate their country, industry, and country- and industry-adjusted components. We use these components in a factor model for individual stock returns to instrument the time-series and cross-sectional variations in their alphas and betas on multiple systematic risk factors.

We find that comovements are determined mainly by the country components in characteristics, whereas adjusted components are the primary drivers of alphas. We do not find a trend over time in the relative importance of characteristic components for alphas and betas. We find that alphas are more significant in international stock markets than in the U.S. However, their magnitude has decreased over time and risk-adjusted returns of alpha-chasing strategies are not significant once we account for estimation risk and transaction costs.

We use countries and SIC-based industries to decompose characteristics. While these categories have intuitive interpretations, it would also be interesting to investigate the optimal level of clustering for characteristics. We leave this endeavor for future research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

Nikolai Roussanov was the editor for this article. I am thankful to the Editor, an anonymous Associate Editor, an anonymous referee, Bruno Biais, Ines Chaieb, Mathieu Fournier, Denis Gromb, Kris Jacobs, Mohammad Jahan-Parvar, Augustin Landier, Daniele Massacci, Piotr Orlowski (discussant), Roberto Renó, Guillaume Roussellet, Colin Ward, Irina Zviadadze, and seminar participants at the Barclays Quantitative Portfolio Strategy Group, Collegio Carlo Alberto, 9th HEC-McGill Winter Finance Workshop, King's College London, and NASMES 2021 for helpful comments.

Appendix A. Data

In this appendix, we describe the steps followed to build our equity sample. We impose a six-month lag on all accounting data to ensure that data was available at each point in time.

1. **Stock Universe:** We retrieve all securities which are classified as common or ordinary shares (*tpci* = *'0'*).
2. **Major Stock Exchanges:** We keep only stocks listed on a country major stock exchange. We define a major stock exchange as the one with the highest number of equities listed. However, we include more than one stock exchange in some countries: Brazil (Rio de Janeiro and Bovespa), Canada (Toronto and TSX Venture), China (Shanghai and Shenzhen), Paris (Paris and NYSE Euronext), Germany (Deutsche Boerse and Xetra), India (BSE and National Stock Exchange), Japan (Tokyo and Osaka), Russia (Moscow and MICEX), South Korea (Korea and KOSDAQ), Switzerland (Swiss Exchange and Zurich), United Arab Emirates (Abu Dhabi and Dubai), and the U.S. (NYSE, NYSE Arca, Amex, and NASDAQ).
3. **Refining the common stock universe:** Securities are sometimes misclassified. We apply the name filters as in Griffin et al. (2010) based on the presence of the same keywords in their issue description (*dsci*). We add

[18] Given the computational time required, we use 1000 bootstraps instead of 5,000.

"BDR" to the list of keywords to remove Brazilean Depositary Receipts. We also use additional keyword filters used by Lee (2011): "AFV" in Belgium due to their preferential tax treatment, "INC.FD." in Canada because they are income trusts, and "RSP" in Italy due to their nonvoting provisions.

4. **Preliminary cleaning of time series:** We use only days for which a price (*prccd*) is available with a price code status (*prcstd*) either equal to 3 (high, low and close prices) or 10 (prices as reported). We also include price code status 4 (bid, ask, average/last volume close) for North American issues because Compustat historically delivered prices as the average of the bid/ask pricing for U.S. and Canadian issues.
5. **Computing monthly returns:** We build monthly returns by using the last available total return index value during the previous month and the last available value in the current month. We build total return indexes using prices (*prccd*), adjustment factors (*ajexdi*), quotation units (*qunit*), exchange rates (*exratd*), and total return factors (*trfd*). We follow Shumway (1997) and apply a −30% delisting return when delisting is performance related (using the delisting reason *dlrsni*).
6. **Computing market capitalizations:** We build monthly lagged market capitalizations by using the last available market capitalization during the previous month. We build market capitalization by multiplying the number of shares by prices (*prccd*). For non-North American stocks, we use the current number of shares outstanding (*cshoc*). For North American stocks, we use the last reported number of shares outstanding (*cshoi*).
7. **Value**: We use the log of the book-to-price ratio measured as in Asness and Frazzini (2013). For book value of equity, we use in order of availability stockholder's equity, the sum of common equity and preferred stocks, or total assets minus the sum of total liabilities, minority interest, and preferred stocks. We divide by common shares outstanding or, if it is not available, the sum of shares outstanding for all company issues with an earnings participation flag. We divide the book value per share by the most recent stock price. We set to missing if either the book equity is negative or the stock price is missing.
8. **Profitability**: We divide cash profitability by total asset.
9. **Investment**: We measure total asset growth on an annual basis.
10. **Lagged monthly return**: Total return for month $t-1$.
11. **Momentum**: Total return from month $t-12$ to month $t-2$.
12. β_M: Following Lewellen and Nagel (2006), we estimate each month t and for each stock i the following regression of daily excess returns on a constant and the contemporaneous and lagged excess returns on the local stock market portfolio using daily data over the previous 12 months,

$$r_{i,t_d} - r_{f,t_d} = \alpha_{i,t} + \beta_{0,i,t}\left(r_{M,t_d} - r_{f,t_d}\right) + \beta_{1,i,t}\left(r_{M,t_d-1} - r_{f,t_d-1}\right) + \beta_{2,i,t}\left(\frac{\sum_{k=2}^{4}\left(r_{M,t_d-k} - r_{f,t_d-k}\right)}{3}\right) + \epsilon_{i,t_d}, \quad \text{(A.1)}$$

where t_d are indexes for days in months $t-12$ to $t-1$. Finally, we compute the local beta as $\beta_{M,i,t} = \beta_{0,i,t} + \beta_{1,i,t} + \beta_{2,i,t}$. The local stock markets are the Thomson Reuters Datastream country market indexes denominated in USD.

13. **Idiosyncratic volatility**: Volatility of the CAPM regression residuals ϵ_{i,t_d} in Eq. (A.1).

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfineco.2023.04.010.

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