Familiarity in International Fund Allocation and Performance: Information or Bias *

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Abstract

This paper finds that familiarity can generate both informational advantages and biases in international equity investments. Using a dataset we construct on managers' countries of education as a proxy for familiarity, together with detailed holdings of U.S.-based international funds from 2000–2024, we find that funds over-allocate to equities from their managers' education countries despite no abnormal country-level returns. At the equity level, we find that only the most confident equity positions in familiar markets generate significant excess returns, earning an annual alpha of 5.31%, while the remaining holdings track the benchmark returns. The outperformance persists over time but these positions account for only one-quarter of education-country holdings. This pattern indicates that familiarity provides a persistent informational edge, but only in a narrow set of most confident positions, while broader overweights reflect familiarity bias. Overall, our results highlight familiarity as both a source of private information and a driver of bias in global equity portfolio allocation.

Keywords: International Equity Investment, Mutual Funds, Information Advantage, Investor Behaviors

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1 Introduction

Familiarity is a well-established determinant of investment allocations. Driven largely by information asymmetries, investors favor assets in markets with which they are familiar (Coval and Moskowitz (1999), Coval and Moskowitz (2001), Baik et al. (2010), Bernile et al. (2015), Kuchler et al. (2022)). In the international setting, where information frictions are more pronounced, familiarity plays an even more significant role. For example, Lane and Milesi-Ferretti (2004) and Portes and Rey (2005) show that geographic proximity—often a proxy for cultural similarity and economic integration—strongly influences international portfolio allocations. The persistent explanatory power of physical distance in shaping cross-border investment flows remains one of the central puzzles in international finance (e.g., Koijen and Yogo (2020)).

We use U.S. mutual fund managers' post-secondary educational backgrounds in non-US countries as a source of familiarity exposure and examine the extent to which bias and informational advantage exist in their international investments. Familiarity rooted in educational background can generate both informational advantages and bias. It provides informational advantages abroad through training in language and regulation, exposure to local institutions, and networks that improve access to firm-level news and market sentiment. These informational advantages are private and continuously evolving, making them less susceptible to the decay observed in many return-predictive factors. At the same time, education ties may also foster bias: managers can become overconfident in familiar markets, a tendency amplified by international frictions.

The international equity setting provides a compelling context for analyzing how familiarity shaped by managers' educational experiences influences investment behavior. First, international markets feature greater information frictions and segmentation than U.S. domestic markets, making familiarity effects especially salient. Second, the U.S. international equity fund industry is large—managing over $4 trillion in assets—yet little is known about manager-level behavior in this space, in part due to historical data limitations. Third, fund managers' decisions directly affect portfolio allocations, and the combination of detailed equity-level holdings with education background as a quasi-exogenous source of familiarity enables us to identify how familiarity impacts both allocation and performance. Finally, education is a universal, observable, and systematically recorded characteristic, providing a scalable and non-exclusive dimension for studying investment behavior in global markets.

We begin by documenting that U.S.-based international equity mutual funds allocate significantly more capital to countries where their current managers received their post-secondary education.[1] Specifically, funds overweight these countries by an average of 1.27 percentage points in raw portfolio weights—a 33.74% increase scaled by benchmark allocations. This substantial overweighting suggests that funds place elevated confidence in countries where their managers have educational ties. However, higher confidence in investing does not necessarily imply superior performance.

We next examine whether U.S. international funds generate excess returns in country-level portfolios linked to managers' education ties. Evidence of outperformance in these holdings would indicate informational advantages. A substantial body of research shows that most actively managed mutual funds fail to outperform market benchmarks after fees, and any outperformance that does occur is rarely persistent (Jensen (1968), and Berk and Green (2004) Barras et al. (2010) and Conrad et al. (2015)). Consistent with these findings, our results show that mutual funds, on average, do not outperform in their international portfolios—even in countries where managers have education ties. Specifically, the average monthly alpha from country-level sub-portfolios linked to manager education countries is only 6.2 basis points, statistically indistinguishable from zero. This finding suggests that overweighting in education countries reflects bias toward familiar markets rather than genuine informational advantages.

To investigate whether informational advantages are concealed within the broader pattern of country-level familiarity bias, we analyze managers' most confident stock selec-

[1]We follow Datastream's classification of countries, which may include both countries and broader geographic regions. The country classification does not reflect our opinion.

tions—particularly those in their education countries—focusing on both their ability to generate α and their portfolio composition. Prior work, such as Cohen et al. (2008) and Antón et al. (2021), shows that in U.S. domestic markets a small subset of actively selected equities can deliver significant α, reflecting managers' informational advantages. Building on this insight, we extend the analysis internationally by studying equity-level returns within each fund's country-specific sub-portfolio. To identify top picks, we develop the I-measure, an activeness metric tailored to international portfolios that captures managers' ex-ante conviction in individual holdings.[2] Using the I-measure, we rank stocks within each country-level sub-portfolio, define the top quantile as "Top Picks," and aggregate holdings into four portfolios: (1) Top Picks in education countries, (2) Other Picks in education countries, (3) Top Picks outside education countries, and (4) Other Picks outside education countries.

We find that the portfolio consisting of managers' ex-ante top picks in their countries of education generates an annual alpha of 5.31%. This performance is significantly higher (p-value = 0.001) than that of the education country non-top pick portfolio, which exhibits an annual alpha statistically indistinguishable from zero. Moreover, the education country top picks outperform both portfolios outside the education countries, which show annual alphas of 0.34% and 0.98% for top and non-top picks, respectively. The alphas of these three portfolios—education country non-top picks and both non-education country groups—do not differ significantly from each other. These findings remain robust across alternative definitions of the sorting measure and various subsamples. Examining each fund's top picks within managers' education countries, we find little overlap across funds in the same education country, indicating that these selections are highly idiosyncratic. Moreover, the α from these top picks is persistent over the 2000–2024 sample, including the post-2015 period when most return-predictive factors weakened. These findings show that funds generate alpha through distinct stock choices, reflecting unique private information, and that this informational advantage is persistent over time.

[2] Section 4.1.2 discusses the limitations of applying the active share measure from Antón et al. (2021) internationally; Appendix C reports results using their measure.

Furthermore, our analysis shows that even after excluding the top-performing equities, funds continue to over-allocate to their education-country investments, indicating a strong familiarity bias. Quantitatively, non-outperforming bottom-quantile portfolios still show substantial overweighting toward the education country, confirming that managers' preferences for familiar markets extend beyond information-driven allocations.

In summary, our main contribution is to provide evidence on the extent to which informational advantages and familiarity bias coexist in familiar markets within the context of international investment. We show that in international equity allocation, familiarity provides a private and durable source of informational advantage concentrated only in the most confident one-quarter of positions, while familiarity bias drives persistent over-allocation to education-country equities for the remainder of the portfolio. Although the stock-level informational gains persist over time, the broader tendency to overweight familiar markets offsets these benefits, reducing overall portfolio performance and underscoring the dual role of familiarity as both a source of information and a driver of bias.

Section 2 discusses the related literature, section 3 describes data used for this paper, section 4 describes empirical methods, section 5 presents the empirical results, section 6 conducts robustness checks, and section 7 concludes.

2 Related Literature

This paper mainly contributes to three strands of the literature.

First, the paper contributes to the literature on familiarity and investment outcomes. Huberman (2001) shows that investors favor familiar assets, deviating from standard portfolio theory. Subsequent studies explore different sources of familiarity and their implications for performance, with mixed results. On the one hand, Cohen et al. (2008), Ben-David et al. (2019), and Sialm et al. (2020) find that investors earn excess returns in familiar equities, industries, and locations. On the other hand, Pool et al. (2012) report that managers do not earn superior returns from stocks in their home states, and Jagannathan et al. (2022) find some evidence of outperformance in managers' home countries by global mutual funds, although not universal across funds. We extend this literature by examining managers' educational ties as a source of familiarity to disentangle the extent to which such familiarity embed both informational advantages and biases.

Second, it relates to research on international portfolio allocation. A longstanding observation is that actual cross-border holdings deviate substantially from the predictions of classical models (French and Poterba, 1991). Prior work has identified several forces behind this gap. Coval and Moskowitz (1999), Portes and Rey (2005), and Koijen and Yogo (2020) highlight informational frictions as a key driver of international investment patterns. Benartzi (2001) and Chan et al. (2005) document the influence of familiarity bias in both domestic and international contexts. More recently, Maggiori et al. (2020) shows that currency bias shapes global portfolio allocations. Our findings contribute to this literature by demonstrating the coexistence of information and familiarity bias in international asset allocation, and by identifying the specific contexts in which each occurs.

Third, we contribute to the literature on whether mutual fund managers possess skill. A well-established view is that equity mutual funds underperform their benchmarks after fees (Malkiel (1995), Fama and French (2010)). Subsequent studies show that while actively managed funds on average fail to beat passive benchmarks, managers may nevertheless exhibit skill through subsets of stock selections that generate outperformance (Cremers and Petajisto (2009), Pomorski (2009), Jiang et al. (2014), Antón et al. (2021)). Our paper extends this debate to the international context by examining managers' ability to generate alpha within global portfolios, clarifying the scope of these skill advantages, and assessing their persistence over time.

3 Data

3.1 Sources

The analysis draws on several data sources: U.S. mutual funds' international equity holdings, fund benchmark holdings, fund managers' educational backgrounds, and international equity price data. The sample covers the period from 2000 to 2024 across all data sources.

Funds and benchmarks' holdings: We use the Morningstar universe[3] of U.S. actively managed international equity funds as our primary sample. The final dataset includes 642 distinct parent share-class funds. We collect equity holdings data at a quarterly frequency for all funds, with monthly holdings available for a subset. Table 4 summarizes key characteristics of the sample. Morningstar holdings data are cross-validated and have been employed in numerous prior studies. For each international fund, we also collect the monthly holdings of its corresponding benchmark, as assigned by Morningstar. The sample funds are mapped to 13 different Morningstar benchmarks. Table 7 presents the benchmark distribution across the sample.

Fund and Benchmark Characteristics: We collect both total returns and gross returns for each benchmark, as well as for each fund at the share class level. In addition, we obtain fund-level characteristics such as net expense ratios and net asset values from Morningstar.

Fund manager education: Morningstar provides a paragraph of each manager's biography including the information on their post-secondary educations. We collect managers' biographies from Morningstar's website, use text search to find the education institutions of each manager, and map those education institutions to the country of location by feeding into ChatGPT4.0 and cross-validating with Bing search. Manager education data is merged

[3]According to Morningstar's definition, stock funds that have invested 40% or more of their equity holdings in foreign stocks (on average over the past three years) are classified as international equity funds. The holding data are free of survivorship bias and span from 2000 to 2024. Morningstar data selection criteria: U.S. Category Group = International Equity; Oldest Share Class = Yes; Management Approach – Active = Yes; the "Only surviving investments" filter is unchecked.

with fund-holding data using manager names and their tenure at the fund (dates they manage the fund). Our initial sample of fund holdings consists of 642 funds. We restrict our final sample to the funds with managers' education information, which leaves a final sample of 599 funds.

International equity price and return: We obtain daily international equity price, return, and market capitalization data from Datastream for the period 2000–2024. These data are merged with mutual fund holdings using equity ISIN identifiers. We assign each equity's country of origin based on the location of the company's primary business activity, as recorded by Datastream. This classification reflects our view that fund managers' information advantages or confidence in a company are more likely to stem from where the firm operates rather than where it is listed.

Fama-French Factors: We also obtain the Fama and French (2015) five factors from the Dartmounth Data Library. We obtain the time series of Fama-French five factors for emerging markets, developed markets, and the U.S. market separately for the years 2000-2024. The data sample contains 10 factors at the monthly level. We use a 3-month U.S. treasury rate as the risk-free rate.

3.2 Summary Statistics

Table 4 summarizes the characteristics of the fund sample over the 2000–2024 period. All observations are reported at the fund-quarter level, except for manager tenure, which is reported at the fund level in summary statistics, and the net expense ratio, which is available at the fund-year level. On average, funds hold equities from 18 different countries. The average fund has managers with educational experience in 1.57 countries, including 0.69 non-U.S. countries. Table 6 reports the distribution of manager education countries across funds. Over the sample period, 94.0% of funds had at least one manager educated in the United States, while 42.5% had at least one manager educated in the United Kingdom. Other leading countries of manager education include India (13.5%), Canada (12.8%), and

China (7.8%).

The average total net assets of funds in our sample are approximately \$2 billion, which is larger than the average size of U.S. domestic mutual funds documented in Pool et al. (2012), who also utilize Morningstar data to study U.S. equity mutual funds. The sample funds have an average net expense ratio of 1.12%, comparable to the equal-weighted average expense ratio across all U.S. actively managed mutual funds.[4] The average manager tenure in our sample is between 7 and 8 years, notably longer than the 4.75-year average reported for U.S. domestic funds in Pool et al. (2012). Across all funds, we identify 1,892 distinct fund managers with educational backgrounds spanning 46 countries. Of these, 694 managers (36.7%) received at least part of their education outside the United States. Table 5 presents the distribution of top managers' countries of education.

Table 7 shows a benchmark breakdown of the sample funds and their corresponding mean TNAs. Funds that are assigned global benchmarks have a higher average TNAs and they consist of the majority of the funds in the sample. A small share of the sample funds are categorized by Morningstar under the single country benchmarks.

Table 8 compares the portfolio allocation patterns of the average fund in our sample with those of the global benchmark and the average assigned benchmark. On average, funds hold equities from 19 countries, with a mean portfolio weight of 7% per country. The typical fund holds 108 individual stocks, with an average allocation of 1.4% per stock. In contrast, the global benchmark spans a significantly broader investment universe, covering approximately 50 countries with an average weight of 2% per country, and includes more than 5,000 stocks with a mean weight of just 0.02% per stock. The average assigned benchmark—which includes both regional and single-country indices—also exhibits substantially broader coverage than the typical fund portfolio.

The average performance of the sample funds, net of expense ratios, is broadly comparable to that of their benchmarks, though slightly lower on average. In Figure 9, we plot the

[4] `https://www.morningstar.com/business/insights/blog/funds/us-fund-fee-study`

weighted average cumulative return of the sample funds alongside the weighted average cumulative return of their corresponding benchmarks. Fund total returns are constructed by aggregating reported share-class-level total returns using the net asset value of each share class. Benchmark returns are constructed by weighting each benchmark according to the frequency of its appearance across the fund sample. Reported fund returns are net of expense ratios, and, on average, fund performance slightly underperforms that of the benchmark.

4 Empirical Methods

4.1 Variable Construction

This section introduces the two key measures used in the analysis: the manager education measure and the equity-level activeness measure. The education measure is constructed at the fund level and captures familiarity with certain countries through managers' educational ties. The activeness measure is constructed at the equity level and reflects a fund's ex-ante beliefs about the relative performance of its international equity holdings. Further details are provided below.

4.1.1 Education Measure

The fund-level education measure captures whether a fund has any current managers with educational backgrounds in specific countries. For each manager in the dataset, we observe both the hiring and termination dates associated with their tenure at each fund. However, when multiple managers are employed concurrently, we only observe the fund's aggregate portfolio holdings—not manager-specific allocations.

We construct an education dummy variable at the fund-time-country level, based on the educational backgrounds of managers hired during the current period. Specifically, the indicator variable $\mathbb{1}(EC)_{jc}(t) = \mathbb{1}(c \in \text{Education}_j(t))$ equals 1 for fund j at time t if any manager hired by the fund at that time has an educational background in country c, and

0 otherwise. Here, $\text{Education}_j(t)$ denotes the set of education countries associated with all managers actively employed by fund j at time t.

We also construct an additional continuous measure, $Frac\_EC_{jc}(t)$, which represents the proportion of current managers in fund j at time t who were educated in country c. It is defined as the number of managers in fund j at time t with education in country c, divided by the total number of managers employed by the fund at that time.

4.1.2 Activeness Measure

Antón et al. (2021) introduce a measure of equity-level activeness that identifies fund managers' top stock picks within U.S. domestic mutual fund portfolios and demonstrates its predictive power for cross-sectional returns. However, their approach is tailored to single-country investment settings and does not translate effectively to the more complex environment of international portfolios.[5] This limitation is particularly salient given that mutual fund managers differ in their ability to generate alpha across countries. That is, stock selection skill may be country-specific and shaped by informational advantages or familiarity with local market conditions, which in turn may be influenced by managers' prior experiences.

Motivated by these considerations, we build on their approach and develop a novel measure—the I-measure—that captures managers' equity-level deviations from their benchmarks in international portfolios. The I-measure is designed to proxy for managers' ex-ante conviction and stock-picking activity within the global investment universe, accounting for the inherent heterogeneity across countries and benchmarks in international fund allocations.

We start with a simple definition of excess weights:

$$I_j^i(t) = \omega_j^i(t) - B_j^i(t) \tag{1}$$

Here, equity i belongs to country c. $\omega_j^i(t)$ is the portfolio weight of equity i in fund j's

[5] We replicate the Antón et al. (2021) measure and apply the portfolio analysis described in Section 4.3. Details on measure construction and results are presented in Appendix C.

portfolio at time t, $B_j^i(t)$ is the portfolio weight of equity i in benchmark B's portfolio at time t. Comparing equity excess weights across countries is challenging due to substantial cross-country heterogeneity in equity markets—for example, differences in average market capitalization. To isolate within-country stock selection activity from broader country-level allocation effects, we focus on equity-level "activeness" within each country. Specifically, we scale a fund's portfolio weight in a given equity by its total portfolio weight in the equity's country of domicile. We then subtract the corresponding benchmark's scaled weight in the same equity—calculated using the benchmark's total investment in that country. After the above adjustments we arrive at:

$$I_{jc}^i(t) = \frac{\omega_{jc}^i(t)}{\sum_{i' \in \Omega_{jc}(t)} \omega_{jc}^{i'}(t)} - \frac{B_{jc}^i(t)}{\sum_{i' \in \Omega_{jc}^B(t)} B_{jc}^{i'}(t)} \equiv \frac{\omega_{jc}^i(t)}{\omega_{jc}(t)} - \frac{B_{jc}^i(t)}{B_{jc}(t)} \tag{2}$$

The notation is the same as above, and $\Omega_{jc}(t)$ is the universe of equities fund j is holding in country c at time t. Similarly, $\Omega_{jc}^B(t)$ is the universe of equities the corresponding benchmark is holding in the country c at time t. Again, equity i belongs to the country c, and $\omega_{jc}^i(t)$ is the portfolio weight of equity i in fund j's portfolio at time t. Similarly, $B_{jc}^i(t)$ is the portfolio weight of equity i in benchmark B's portfolio at time t. Define $\omega_{jc}(t) \equiv \sum_{i' \in \Omega_{jc}(t)} \omega_{jc}^{i'}(t)$ as the fund j's total portfolio weight in the country c at time t. $B_{jc}(t) \equiv \sum_{i' \in \Omega_{jc}^B(t)} B_{jc}^{i'}(t)$ is the benchmark's total portfolio weight in the country c at time t. For each fund, j, Morningstar assigns a corresponding benchmark B, and we follow that correspondence when constructing our measures.

Another motivation for scaling individual equity weights by their corresponding country weights is that most funds in our sample operate under explicit country-level investment mandates. In the absence of manager turnover, these country allocations remain relatively stable over time. By normalizing equity weights in this way, we effectively control for differences in country-level exposures between funds and benchmarks, allowing us to isolate within-country stock selection and better measure equity-level activeness.

Despite this adjustment, the activeness measure defined in Equations (1) and (2) still suffers from a significant limitation: it is inherently biased toward large-cap stocks. As documented in Table 8, benchmarks typically span far larger investment universes than the funds themselves. On average, sample funds hold approximately 108 equities globally, while their assigned benchmarks include around 1,941 securities. The most commonly used benchmark, the Morningstar Global ex-US NR USD, holds over 5,200 equities across nearly 50 countries. By contrast, the average fund holds only slightly more than 100 equities from on average 19 countries. This implies that, within a given country, the average fund holds about 5 stocks, while the benchmark holds over 100. This discrepancy causes the existing activeness measure to disproportionately highlight positions in which the fund has large absolute weights. Since the benchmark often assigns weights to individual equities at a much smaller scale relative to funds, these fund positions mechanically appear as highly "active". As a result, the measure becomes skewed toward large-cap stocks.

Given the stark difference in investment universe breadth between funds and their benchmarks, we correct for this asymmetry. Specifically, we aim to abstract from the benchmark's long tail of low-weight holdings—many of which fall outside the fund's feasible investment scope—and focus instead on deviations within the fund's relevant opportunity set. To address this issue and more accurately capture managers' active convictions, we introduce a refined measure, which we term the I-measure. The I-measure is based on the assumption that, absent active security selection, a fund would proportionally track the benchmark's allocations across the equities within its investment universe. Deviations from this proportional allocation reveal the manager's relative emphasis or confidence in specific securities. By following the benchmark proportionally, we mean that if the benchmark holds, for example, 5 times the market value of equity A relative to equity B, then the fund will also hold equity A and B in the same 5:1 market value ratio.

Conceptually, the I-measure quantifies how salient a particular equity is in the fund's portfolio relative to its importance in the benchmark's portfolio—measured within the fund's investment universe at the country level. In essence, it captures the extent to which a fund over- or underweights a stock relative to the benchmark. The I-measure is formally defined as follows:

$$I^i_{jc}(t) = \begin{cases} \frac{\omega^i_{jc}(t)}{\sum_{i' \in \Omega_{jc}(t)} \omega^{i'}_{jc}(t)} - \frac{B^i_{jc}(t)}{\sum_{i' \in \Omega_{jc}(t)} B^{i'}_{jc}(t)} \equiv \frac{\omega^i_{jc}(t)}{\omega_{jc}(t)} - \frac{B^i_{jc}(t)}{\sum_{i' \in \Omega_{jc}(t)} B^{i'}_{jc}(t)} & if \ \sum_{i' \in \Omega_{jc}(t)} B^{i'}_{jc}(t) \neq 0 \\ \frac{\omega^i_{jc}(t)}{\sum_{i' \in \Omega_{jc}(t)} \omega^{i'}_{jc}(t)} \equiv \frac{\omega^i_{jc}(t)}{\omega_{jc}(t)} & if \ \sum_{i' \in \Omega_{jc}(t)} B^{i'}_{jc}(t) = 0 \end{cases} \tag{3}$$

The notation follows from the previous section, with one key modification: how we scale the benchmark's weight on each equity. In Equation (2), the fund's and benchmark's weights on equity i are normalized by their respective total portfolio weight allocated to the entire country. In contrast, the I-measure refines this approach by scaling the fund's and benchmark's weight on equity i using only the total weight in the fund's investment universe within the country. This adjustment ensures a more meaningful comparison by restricting attention to securities that are potentially investable by the fund. When the benchmark holds none of the equities that the fund owns in a given country, the I-measure simplifies to the fund's weight on equity i, scaled by its total allocation to that country. In the portfolio analysis that follows, we use the I-measure to rank equities within each fund-country-time cell. In cases with no benchmark overlap, this ranking is equivalent to sorting equities by their raw portfolio weights within the fund.

To illustrate the importance of this adjustment, consider a simple example involving two equities, A and B, within a single country. Suppose a fund allocates 60% of its country exposure to A and 40% to B, while the benchmark allocates 1.9% to A and just 0.1% to B. Based on the raw excess weights in Equation (2), the activeness measure would be 58.1% for A and 39.9% for B, implying greater activeness in A. However, this overlooks an important point: equity B, likely a small-cap stock, is minimally held by the benchmark, suggesting that the fund's position in B reflects a more deliberate and active choice. Our I-measure captures this distinction. When we scale by the fund's total country allocation and the benchmark's weight over the fund's investment universe, the I-measure assigns -35% to A and +35% to B, correctly identifying B as the more active position. In a scenario where the fund mimics the benchmark proportionally—investing 95% in A and 5% in B to mirror the benchmark's 1.9% and 0.1% weights—both equities would receive an I-measure of zero. Thus, the I-measure isolates deviations from proportional benchmark tracking within the fund's investment universe, providing a more precise signal of stock-level activeness.

4.1.3 Additional Two Measures for Robustness Check

V-measure

A potential concern with the I-measure is its reliance on the specific benchmark assigned to each fund by Morningstar. We address this issue by (i) clarifying how these benchmarks are constructed and (ii) introducing an alternative, benchmark-independent measure—the V-measure—as a robustness check.

First, the Morningstar benchmarks used in our analysis are predominantly market-capitalization-weighted indices that cover, on average, 97% of the market capitalization within their respective categories. The only exceptions are four benchmarks labeled with "TME" (Target Market Exposure), which apply caps on the weights of individual stocks to limit exposure to extremely large-cap firms. Nonetheless, these TME benchmarks remain close approximations of market-cap-weighted indices. Importantly, all benchmarks are passive and represent broad, investable universes, minimizing concerns about active stock selection within the benchmarks themselves.

Second, to test the robustness of our findings, we construct an alternative measure—the V-measure—that does not depend on Morningstar's benchmark assignments. Specifically, it is similar to replacing Morningstar assigned benchmark with a single, unified market-cap-weighted benchmark of all investable equities across our sample. The V-measure is then calculated using this comprehensive benchmark and is formally defined as follows:

$$V_{jc}^{i}(t) = \frac{\omega_{jc}^{i}(t)}{\sum_{i' \in \Omega_{jc}(t)} \omega_{jc}^{i'}(t)} - \frac{V_{c}^{i}(t)}{\sum_{i' \in \Omega_{jc}(t)} V_{c}^{i'}(t)} \equiv \frac{\omega_{jc}^{i}(t)}{\omega_{jc}(t)} - \frac{V_{c}^{i}(t)}{\sum_{i' \in \Omega_{jc}(t)} V_{c}^{i'}(t)}$$

The notation follows that of the I-measure, with the key distinction being the substitution of the benchmark portfolio weight $B_{jc}^{i}(t)$ with the market capitalization of the equity, denoted $V_{c}^{i}(t)$. Unlike the I-measure, which depends on the assigned benchmark, the V-measure is constructed using a market-capitalization-weighted benchmark that includes all investable equities. As such, it provides a benchmark-independent measure of equity-level activeness.

U-measure

In the construction of the I-measure, the fund's investment universe is defined as the set of equities currently held by the benchmark. To address the concern that this definition may influence our results, we consider an alternative specification that expands the investment universe to include all equities held by the fund at any point over the past eight quarters (two years). We refer to the resulting measure as the U-measure, which is defined as follows:

$$U_{jc}^{i}(t) = \begin{cases} \frac{\omega_{jc}^{i}(t)}{\sum_{i' \in \Omega_{jc}(t-8,t)} \omega_{jc}^{i'}(t)} - \frac{B_{jc}^{i}(t)}{\sum_{i' \in \Omega_{jc}(t-8,t)} B_{jc}^{i'}(t)} & if \ \sum_{i' \in \Omega_{jc}(t-8,t)} B_{jc}^{i'}(t) \neq 0 \\ \frac{\omega_{jc}^{i}(t)}{\sum_{i' \in \Omega_{jc}(t-8,t)} \omega_{jc}^{i'}(t)} & if \ \sum_{i' \in \Omega_{jc}(t-8,t)} B_{jc}^{i'}(t) = 0 \end{cases}$$

The only difference from the I-measure definition is that we replace the investment universe $\Omega_{jc}(t)$, the universe of equities held by the fund at time t, by $\Omega_{jc}(t-8,t)$, the universe of equities ever held by the fund from time $t-8$ (8 quarters before) to t.

4.2 Regression Analysis

In this section, we first examine whether managers' foreign educational ties are associated with systematic deviations in country-level portfolio allocations. We then assess the performance implications of these education-driven deviations from benchmark weights. Together, these analyses clarify how market familiarity shapes international mutual funds' country-level investment decisions and provide initial evidence on whether such familiarity reflects bias or information. While the current analysis focuses on aggregated country-level holdings, we extend the investigation to equity-level portfolio choices in Section 4.3.

We exclude funds' U.S. stock holdings from all the analyses in this section because we are looking at a sample of international funds that are based in the U.S.. We exclude those investments to eliminate any potential impacts from U.S. equity allocation decisions.

4.2.1 Manager Excess Holding in Education Country

The literature has documented several instances where mutual funds systematically deviate from their benchmark holdings. For example, Pool et al. (2012) find that U.S. domestic mutual funds, on average, over-allocate to their managers' home states by approximately 18.8% relative to benchmark weights. Extending this line of inquiry to the international context, we examine whether fund managers' educational backgrounds influence country-level portfolio allocations—beyond standard diversification motives in international investing.

It is important to note that our analysis does not aim to establish a causal relationship between manager education and country-level portfolio allocations. We do not disentangle whether the observed correlation arises because funds increase their exposure to a country by hiring managers educated there, whether it is driven by managers' own investment preferences, or a combination of both.

To assess the correlation between manager education and a fund's excess holdings in a given country, we estimate the following regression specification:

$$Y_{jc}(t) = \alpha + \beta \mathbb{1}(EC)_{jc}(t) + FE + \epsilon_{jc}(t) \tag{4}$$

Here we use two different outcome variable for $Y_{jc}(t)$: the direct excess weight relative to benchmark $\omega_{jc}(t) - B_{jc}(t)$, and the scaled excess weight relative to benchmark $\frac{\omega_{jc}(t)-B_{jc}(t)}{B_{jc}(t)}$. $\omega_{jc}(t)$ is fund j's portfolio weight in country c at time t, $B_{jc}(t)$ is the weight of country c in fund j's corresponding benchmark, as specified by Morningstar. The difference between the two is the fund j's excess holding in country c at time t. We scale it by the benchmark holding $B_{jc}(t)$ to get the fractional excess weight as the second outcome variable. We regress the excess holdings on the education measure $\mathbb{1}(EC)_{jc}(t)$, which takes value 1 if any of the managers in the fund at time t have an educational background in the country c. We include fixed effects at different levels, like country-by-time levels, fund-by-country, or both, for multiple robustness checks. The country-time fixed effect removes the country-level time trend. We also test different fixed effects for robustness. The fund-country level fixed effect is to exclude the time-variant fund preference in investing in certain countries, so that the variance comes from the change of manager within the sample period.

Here the main coefficient of interest is β, with raw excess weight as the outcome variable, we can interpret the β estimate as the increase in raw excess portfolio weight invested in a country if the fund has a manager with that country's educational background. If we use the scaled excess weight as the outcome, β would represent the fractional increase in weight invested in a country if the fund has a manager with that country's educational background.

To get a point estimate that is comparable with the estimate in Pool et al. (2012), we also run an alternative specification where we replace the independent variable $\mathbb{1}(EC)_{jc}(t)$ by $Frac\_EC_{jc}(t)$, which is the fraction of managers in the fund j at time t that have education background at country t.

$$Y_{jc}(t) = \alpha + \beta Frac\_EC_{jc}(t) + FE + \epsilon_{jc}(t) \tag{5}$$

We still use the same two outcome variables as in the previous specification. When using raw excess weight as the outcome variable, the estimated β represents the increase in excess weight invested in a country when the composition of the manager with the given country's education increases by 100%. When using scaled excess weight as the outcome variable, the estimated β represents the fractional increase in weight invested in a country when the composition of the manager with the given country's education increases by 100%. The β estimated with scaled excess weight as the outcome is comparable in interpretation to the 18.8% estimated in Pool et al. (2012).

The estimated β from this specification captures a combination of two effects: (1) an idiosyncratic, fund-level shift in investment preference toward a given country, followed by the hiring of a manager educated in that country; and (2) an increase in investment in the manager's education country after the manager joins the fund. For the purposes of this paper, we document the empirical fact that funds with managers educated in a given country tend to overweight that country. We do not attempt to disentangle the relative contributions of these two channels. Importantly, both mechanisms reflect confidence in the manager's ability to invest more effectively in their education country—whether that confidence originates from the fund or the manager themselves.

4.2.2 Education country's equity return predictability

Deviations from benchmark holdings may arise from either informational advantages or behavioral biases. If a fund's overweighting of a manager's education country reflects superior information, we should observe stronger portfolio performance in that market. Conversely, if the overweighting is mainly driven by familiarity biases, performance should be indistinguishable from—or even worse than—that of other countries. In this section, we test this by examining country-level sub-portfolios to assess whether funds earn higher realized returns in managers' education countries.

As in the previous sections, we use the same two measures for fund's manager education country exposure: one is $\mathbb{1}(EC)_{jc}(t)$, which takes value 1 if any of the manager hire by fund j at time t have education background in country c, and takes value 0 otherwise. The other is $Frac\_EC_{jc}(t)$, which is the fraction of managers hired by fund j at time t that have an educational background in country c. We regress the funds' sub-portfolio return at country c at time t over the education measure of the same fund at the same country from the previous period, following the specification:

$$
\begin{aligned}
R_{jc}(t+1) &= \alpha + \beta \mathbb{1}(EC)_{jc}(t) + FE + \epsilon_{jc}(t) \\
R_{jc}(t+1) &= \alpha + \beta Frac\_EC_{jc}(t) + FE + \epsilon_{jc}(t)
\end{aligned}
\tag{6}
$$

The outcome variable $R_{jc}(t+1)$ denotes fund j's value-weighted return on country c from holdings as of time t. It is constructed as

$$
R_{jc}(t+1) \equiv \frac{\sum_{i \in \Omega_c(t)} \omega_c^i(t) R_c^i(t+1)}{\sum_{i \in \Omega_c(t)} \omega_c^i(t)}
$$

where $\Omega_c(t)$ represents the set of stocks in country c held by fund j at time t, $\omega_c^i(t)$ is the weight of stock i in the portfolio, and $R_c^i(t+1)$ is the return of stock i from t to $t+1$.

We include various sets of fixed effects to ensure robustness, and the results are consistent across specifications. Since our focus is on within-country stock-picking ability, the main specification includes country-by-time fixed effects, which absorbs all time-series variation in aggregate country-level returns. We also include fund fixed effects to control for time-invariant fund characteristics.

When we use $\mathbb{1}(EC)_{jc}(t)$ as the independent variable, the coefficient β captures the differential return of fund j in country c when it is managed by someone educated in that country. Alternatively, when using $\text{Frac\_EC}_{jc}(t)$, β estimates the increase in country-level return associated with a full (100 percentage point) increase in the fraction of managers with education in that country. This specification tests whether funds exhibit superior stock-picking ability in countries where their managers were educated. A positive β implies that such funds earn higher average returns in that country than other funds.

4.3 Portfolio Analysis

To further assess the informational scope of market familiarity through educational ties, we examine whether fund managers exhibit superior stock-picking ability at the equity level, especially in their education countries. Antón et al. (2021) show that while mutual funds may not consistently outperform the market at the aggregate level, their implied ex-ante "best ideas" can still generate positive and significant alpha. Their findings suggest that skilled stock selection may be obscured when performance is evaluated at the portfolio level. Building on this insight, we conduct a portfolio analysis to test whether fund managers exhibit comparable stock-picking skill in international markets—and whether their "best ideas" are even stronger in the countries where they received their education.

Within each fund-country-time triplet, we use the I-measure to sort fund holdings into four quantiles based on equity-level activeness. Specifically, for each fund j's holdings in country c at time t, let $\Omega_{jc}(t)$ denote the set of equities held. Each equity $i \in \Omega_{jc}(t)$ is ranked according to its I-measure within that set and assigned to one of four mutually exclusive quantile portfolios, denoted $\Omega_{jc}(t)^k$, where $k \in \{1, 2, 3, 4\}$. We then pool equities across all funds j, countries c, and times t by quantile. Quantiles 1 through 3 are grouped into the non-top quantile portfolio, while quantile 4 constitutes the top quantile portfolio.

This procedure is conducted separately for education and non-education countries, resulting in four distinct portfolios: (1) top quantile–education country, (2) top quantile–non-education country, (3) non-top quantile–education country, and (4) non-top quantile–non-education country.

We evaluate the performance of each portfolio relative to the most commonly used benchmark among funds in our sample: the Morningstar Global Markets ex-US NR USD Index (also referred to as Morningstar Gbl xUS NR USD). According to Morningstar, this index tracks the performance of large-, mid-, and small-cap equities across both developed and emerging markets outside the United States. It covers approximately 97% of the investable universe by market capitalization. We choose this benchmark to compare to since our constructed portfolios are also composed of non-U.S. equities.

We rebalance the constructed portfolios at a quarterly frequency and track performance using monthly returns. To ensure consistency, we calculate returns for both the benchmark and each portfolio using the same methodology: combining quarterly holdings data with monthly returns for each equity position. Specifically, we fix each portfolio's composition based on quarter-end holdings—assuming rebalancing occurs at the end of each quarter—and compute monthly value-weighted returns accordingly.

The constructed portfolios are market value weighted. To further isolate the effect of equity selection from differences in country-level allocation, we further adjust each portfolio's weights so that its country-level allocation matches that of the benchmark. This reweighting allows us to abstract from country composition effects and focus on performance differences driven by within-country stock selection. Specifically, denote the original weight of equity $i \in \Omega_c(t)$ in the constructed portfolio by $\omega_c^i(t)$, then the reweighted $\hat{\omega}_i$ is:

$$\hat{\omega}_c^i(t) = \frac{\omega_c^i(t) \frac{B_c(t)}{\sum_{c' \in \Gamma(t)} B_{c'}(t)}}{\frac{\omega_c(t)}{\sum_{c' \in \Gamma(t)} \omega_{c'}(t)}} \tag{7}$$

In the above expression $B_c(t) \equiv \sum_{i' \in \Omega_c^B(t)} B_c^{i'}(t)$ is the benchmark's total weight in country c at time t, and $\omega_c(t) \equiv \sum_{i' \in \Omega_c(t)} \omega_c^{i'}(t)$ is the portfolio's total weight in country c at time t. $\Gamma(t)$ is the portfolio's universe of countries where it has non-zero weight. For consistency across all analyses, we use the Morningstar Global Markets xUS NR USD index as the benchmark in this rebalancing exercise.

For each portfolio P_n, we compute its monthly return $R_{P_n}(t)$ at time t as the weighted average of individual equity returns, using the rebalanced portfolio weights described above. Specifically, $R_c^i(t)$ denotes the monthly return of stock i in country c at time t, $\Gamma_{P_n}$is the set of countries in which portfolio P_n holds positions, and $\Omega_c(t)$ represents the set of equities held by portfolio P_n in country c at time t.

$$R_{P_n}(t) = \frac{\sum_{c \in \Gamma_{P_n}} \sum_{i \in \Omega_c(t-1)} \hat{\omega}_c^i(t) R_c^i(t)}{\sum_{c \in \Gamma_{P_n}} \sum_{i \in \Omega_c(t-1)} \hat{\omega}_c^i(t)} \tag{8}$$

To evaluate each portfolio's performance relative to the benchmark, we compute its monthly CAPM α. Specifically, we estimate a regression using the Fama-French five-factor model. To account for global exposure, we include both the five factors for developed markets and the five for emerging markets, resulting in a total of ten factors. The five factors—market excess return, SMB, HML, CMA, and RMW—are denoted by $F_i^{developed}(t)$ and $F_i^{emeerging}(t)$ respectively, where $i \in \{1,\ 2,\ 3,\ 4,\ 5\}$.

$$R_{P_n}(t) - R_f(t) = \alpha_n + \beta_n[R_B(t) - R_f(t)] + \sum_{i=1}^{5} \gamma_i F_i^{developed}(t) + \sum_{i=1}^{5} \gamma_i F_i^{emerging}(t) + \epsilon_n(t) \quad (9)$$

Here $R_{P_n}(t)$ is the monthly portfolio return of each constructed portfolio, $R_f(t)$ is the monthly 3-month risk free rate, and $R_B(t)$ is the monthly gross return of the benchmark.

For robustness check, we also run the CAPM regression with no factors:

$$R_{P_n}(t) - R_f(t) = \alpha_n + \beta_n[R_B(t) - R_f(t)] + \epsilon_n(t) \quad (10)$$

We conduct the main portfolio analysis using the I-measure for sorting and rely on the V-measure and U-measure as robustness checks, as detailed in Section 6. Additionally, we report results based on two alternative specifications of the I-measure: one without adjusting for country allocations and investment universe (Equation 1), and another without adjusting for the investment universe alone (Equation 2). These comparisons highlight the importance of incorporating a fund's actual investment universe when evaluating equity-level activeness.

To better visualize the relative performance of the four portfolios over time, we also plot their cumulative returns against the cumulative return of the benchmark.

5 Results

5.1 Manager Education and Excess Holdings

We document robust evidence that mutual funds systematically overweight countries in which their current managers received their education. This over-allocation is reflected in

VARIABLES	(1) Excess ω	(2) Excess ω	(3) Scaled Excess ω	(4) Scaled Excess ω
$\mathbb{1}(EC)$	1.270***		33.74***	
	(0.209)		(7.775)	
Frac_EC		2.635***		67.66***
		(0.415)		(14.85)
Constant	0.0220***	0.0216***	-21.42***	-21.40***
	(0.00316)	(0.00308)	(0.109)	(0.1000)
Observations	2,526,739	2,526,739	2,335,628	2,335,628
Fund FE	Y	Y	Y	Y
CountryXTime FE	Y	Y	Y	Y
Sub-Sample	N	N	N	N
Funds Number	599	599	599	599

Table 1: Education Effect on Excess Weight

significantly larger excess portfolio weights assigned to equities from the managers' education countries. The main regression results supporting this finding are reported in Table 1.

In column (1) of Table 1, the dependent variable is the raw deviation of a fund's portfolio weight from the benchmark allocation. The primary explanatory variable, $\mathbb{1}$(EC), is an indicator equal to one if any of the fund's current managers received education in the country in question. The coefficient estimate indicates that, on average, the presence of a manager with educational ties to a country increases the fund's excess portfolio weight in that country by 1.270 percentage points. This magnitude is economically meaningful: the median fund holds positions in 18 countries, implying an average allocation of approximately 5% per country. This effect is robust across alternative specifications, including models with different sets of fixed effects and across different fund subsamples. As shown in Table 10, the point estimates of over-allocation consistently range from 1.210% to 1.270%.

In column (3) of Table 1, the dependent variable is the fund's portfolio weight deviation scaled by the benchmark's weight in the corresponding country. The estimated coefficient on $\mathbb{1}$(EC) indicates that funds overweight countries where their managers have educational ties by 33.74%. For example, if the benchmark assigns a 10% weight to a given country, a fund with at least one manager educated in that country would, on average, allocate an additional raw weight of 3.374 percentage points to that country compared to a similar fund without such managerial ties. This benchmark-scaled over-allocation effect is statistically and economically significant, and remains robust across alternative specifications and fund subsamples, as reported in Table 11.

In the specification given by Equation 5, we replace the indicator variable for manager education used in Equation 4 with the fraction of managers within the fund who have received education in the focal country.

Column (2) of Table 1 presents the main results for this specification, where the dependent variable is the raw deviation in portfolio weight from the benchmark. The coefficient on $\mathbb{1}(\text{EC})$ is 2.635, implying that a 100% increase in the fraction of managers educated in a country is associated with a 2.635 percentage point increase in the fund's excess portfolio weight in that country. For example, if a fund currently has one manager without ties to a given country and subsequently hires a second manager who was educated in that country, the share of educated managers increases from 0 to 50%, implying an expected increase of $0.5 \times 2.635 = 1.3175\%$ in excess portfolio weight. This effect is economically meaningful and statistically robust, with point estimates ranging from 2.614% to 2.697% across alternative specifications, as reported in Table 12.

However, direct comparison of raw weight deviations across domestic and international settings may be misleading due to differences in portfolio granularity. U.S. domestic funds typically allocate across 50 states, whereas international funds invest across a much smaller set of countries. As a result, we place greater emphasis on benchmark-weight-scaled deviations, which provide a more consistent measure of over-allocation across contexts.

We report benchmark-scaled results in column (4) of Table 1. A 100% increase in the fraction of fund managers with educational backgrounds in a given country is associated with a 67.66% increase in benchmark-scaled portfolio weight allocated to that country. Robustness checks across alternative specifications are presented in Table 13.

Pool et al. (2012) document that in the U.S. domestic equity market, a 100% increase in the fraction of fund managers originating from a given state leads to an over-allocation of roughly 18.8%. In our international setting, we estimate a much larger effect: a 67.66% increase in portfolio weight, substantially greater than the domestic benchmark. This suggests that education-based familiarity exerts an even stronger influence in international contexts, where information frictions are more pronounced. Our result is also consistent with Jagannathan et al. (2022), which documents home bias in global mutual funds over 1991-2014. Our results reinforce the existence of familiarity bias using alternative measures that are comparable across countries.

These comparisons highlight that education-driven over-investment is considerably more pronounced in international equity markets than the home-state bias observed within the U.S. One plausible explanation is that information frictions and market segmentation are more severe in cross-border settings. Consequently, fund managers may assign greater value to their perceived informational advantage in countries where they received their education, resulting in more substantial deviations from benchmark allocations.

There are two potential sources of variation in the observed over-allocation. First, funds that specialize in particular countries may be more likely to hire managers who were educated in those countries. Second, within the same fund, country-level allocations may shift following changes in fund management. As a robustness check, we isolate the second source of variation by focusing on within-fund manager changes, and we include Country-Fund fixed effects to absorb any time-invariant fund-level preferences. The results from this specification, which includes both Country-Time and Country-Fund fixed effects, are reported in Table 9. The estimated coefficients are slightly smaller than those in Table 1. Specifically, for a given fund, a manager change associated with a 100% increase in the fraction of managers with educational backgrounds in a given country leads to a 47.17% increase in the benchmark-scaled portfolio weight allocated to that country. While smaller than the 67.66% effect in our main specification, the estimate remains statistically significant. This result highlights the impact of manager changes on country-level allocation within funds.

5.2 Education Country Sub-portfolio Return

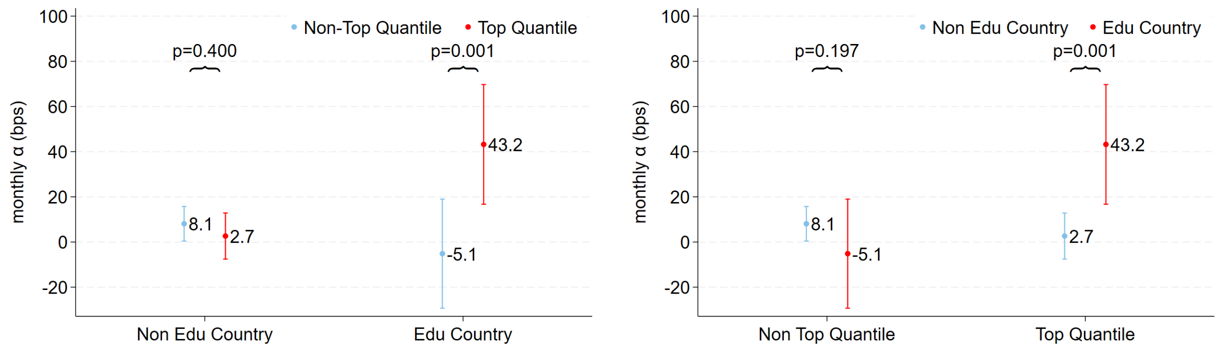
The results from the country-level equity return regressions are presented in Table 14. In this analysis, we compare the performance of a fund's country-level sub-portfolios between countries where any of its current managers received education and countries without such manager ties. On average, sub-portfolios in education countries outperform those in non-education countries by 6.163 basis points in the month following portfolio rebalancing. However, this performance differential is not statistically significant.

Note that the number of observations here is less than half of the observations in Table 1. This is because in excess weight regression, we need to fill in the country-fund-time level observations as 0 weight if the fund does not hold any equity in that country. This is not a concern in return regression.

The lack of statistical significance is consistent across specifications with alternative fixed effects. These findings suggest that, despite funds significantly over-weighting countries where their managers were educated, they do not achieve superior overall returns in those markets. And the results are suggestive of a bias-driven investment in familiar markets.

5.3 Portfolio Analysis

The previous section shows that, at the country level, holdings in countries with managers educational ties do not significantly improve the returns of the fund's sub-portfolio in that market. This result is consistent with Jagannathan et al. (2022), who find that home-country sub-portfolios of global funds do not deliver statistically significant outperformance. We next take a step further and study equity-level selection within these country-level sub-portfolios. In this section, we shift the focus to individual stocks and examine the extent to which fund investments in education countries are driven by informational advantages rather than purely familiarity bias.



I-measure Sorting Quantile Comparison   I-measure Sorting Education Comparison

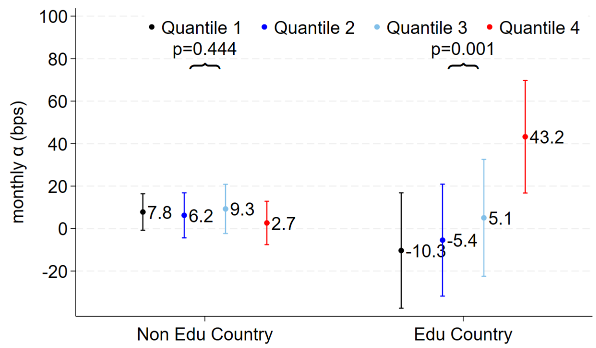
Figure 1: Portfolio α with I-measure sorting with 5 Factors

Notes: This figure provides portfolio α I-measure sorting with 5 Factors. The graph on the left compares the top VS non-top portfolio within either an education country or a non-education country. The graph on the right compares the education VS non-education portfolio within either top or non-top portfolio. The bars provide 95% confidence intervals.

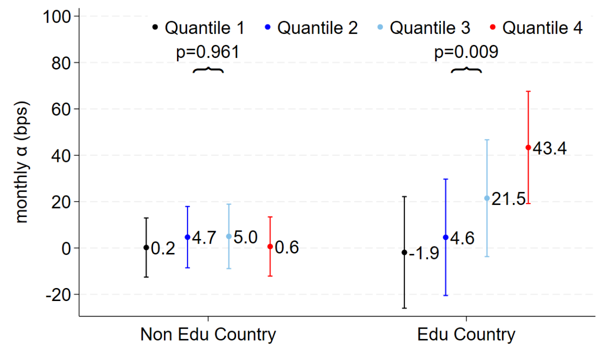
Figure 1 displays the monthly α (in basis points) for the constructed portfolios, estimated using the Fama-French five-factor model. Figure 8 presents the corresponding α estimates excluding the Fama-French factors. The portfolios are sorted by the I-measure and classified into four categories: (1) non-education country, non-top quantile activeness portfolio; (2) non-education country, top quantile activeness portfolio; (3) education country, non-top quantile activeness portfolio; and (4) education country, top quantile activeness portfolio. For brevity, we refer to the "top quantile activeness portfolio" and "non-top quantile activeness portfolio" as the "top portfolio" and "non-top portfolio," respectively.

The monthly α values for these four portfolios are plotted from left to right in the left subplot. Two subplots show the results for the same 4 portfolios, but the left subplot compares performance across activeness quantiles within education and non-education countries, and the right subplot compares performance across education and non-education countries within the same activeness quantile.

The top portfolio in education countries—comprising the equities most actively held by funds in countries where their current managers received their education—generates a substantial monthly α of 43.2 basis points relative to the market portfolio. This translates



I-measure Sorting 4 quantiles 5 Factors



I-measure Sorting 4 quantiles no Factors

Figure 2: Portfolio α for 4 Quantiles with I-measure sorting with 5 Factors VS no Factors
Notes: This figure provides portfolio α for all 4 quantiles.The graph on the left reports the portfolio α with 5 factors for each of the 4 quantiles in education and non-education countries separately. The graph on the left reports the portfolio α with no factors for each of the 4 quantiles in education and non-education countries separately. The bars provide 95% confidence intervals. The p-values are for the joint test of the difference between the top quantile (quantile 4) and bottom quantile (quantile 1).

to an annualized α of 5.31%, which exceeds the 2.8% to 4.5% annual α reported in Antón et al. (2021) for "best ideas" portfolios in the U.S. domestic equity market. This elevated performance suggests that funds possess superior information or stock-picking ability in a concentrated (and most confident) subset of firms located in their managers' education countries.

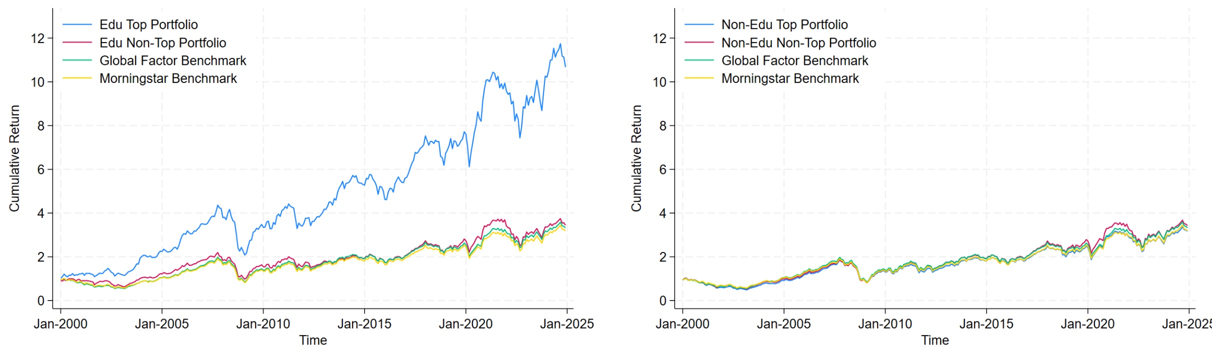
In contrast, the non-top portfolio within education countries—which consists of less actively held equities—delivers a negative monthly α of -5.1 basis points. This estimate is not statistically different from zero, indicating that these positions, on average, fail to outperform the global benchmark even before accounting for management fees. Notably, the performance gap between the top and non-top portfolios within education countries is both economically sizable and statistically significant at the 5% level (p-value $= 0.001$), underscoring the importance of active conviction (confidence) in generating excess returns in managers' education countries.

In non-education countries, we find no statistically significant differences in performance between the top and non-top activeness portfolios. The top portfolio yields a modest monthly

α of 2.7 basis points, while the non-top portfolio achieves 8.1 basis points, corresponding to annualized alphas of 0.34% and 0.98%, respectively. These results suggest that heightened activeness in non-education countries does not translate into superior performance, consistent with limited information advantages in those markets. In the right panel of the figure, we reorganize the results to compare education and non-education countries within each activeness group. The top portfolio in education countries significantly outperforms its counterpart in non-education countries (p-value = 0.001), while no meaningful difference is observed between non-top portfolios across the two country types.

Figure 2 further decomposes the non-top portfolios into quantiles based on I-measure and reports the portfolio α for each of the four quantiles separately, for both education and non-education countries. In non-education countries, we continue to find no statistically significant differences in α across the four quantiles, indicating that variation in activeness does not translate into meaningful performance differences. In contrast, within education countries, the fourth quantile (representing the highest I-measure holdings) exhibits a significantly higher α than the first quantile (lowest I-measure). Meanwhile, in the education countries, the estimated α increases monotonically from Quantile 1 to Quantile 4, indicating stronger performance among the more confidently held positions. In contrast, no such pattern is observed in the non-education countries. These patterns holds across both the Fama-French five-factor model and the CAPM specification without factor controls.

Figure 3 plots the cumulative returns of the constructed portfolios alongside their respective benchmarks. The left panel shows the cumulative returns of the education-country top and non-top portfolios, normalized to 1 at the start of the sample period in January 2000. Over the 25-year horizon (January 2000 to December 2024), the top portfolio in education countries grows nearly 11-fold (approximately 1000%), while the non-top portfolio grows 3.5-fold (about 250%), closely tracking the benchmark performance. The right panel displays the cumulative returns for portfolios in non-education countries. Here, both top and non-top portfolios show return paths that are largely indistinguishable from the bench-



Cumulative Return Edu Country

Cumulative Return Non-Edu Country

Figure 3: Portfolio Cumulative Return

Notes: This figure provides portfolio cumulative return by quantile using I-measure. The four lines on the left graph are cumulative returns for the Morningstar benchmark portfolio, global factor benchmark portfolio, the education country's top quantile portfolio, and the education country's non-top portfolio. The right plots are the non-education country counterparts. The starting period (Jan 2000) is normalized to 1. The education country's top quantile portfolio performs the best, while all other portfolios closely track the benchmark.

mark. The stark divergence in cumulative performance—especially the sharp rise of the education-country top portfolio—underscores the ability of funds to identify and concentrate in a select set of high-performing stocks in countries where their managers received their education, suggesting superior information or insight on those equities.

Portfolio	RF-Adj. Mean Ret.	Mean Ret.	RF-Adj. Std. Err.	Sharpe Ratio
Glb. ex-US Benchmark	4.983	6.828	20.25	0.246
Edu Top	10.13	12.10	21.24	0.477
Edu Non-Top	5.360	7.220	20.90	0.256
Non-Edu Top	5.127	6.974	21.05	0.244
Non-Edu Non-Top	5.526	7.369	21.55	0.256
US Benchmark	7.752	9.615	18.94	0.409

Table 2: Portfolio performance for years 2000-2024 (Yearly)

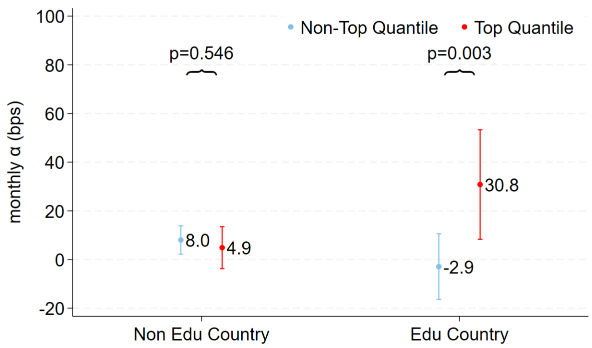
Notes: From left to right are: Portfolio Name, Risk-Free Rate Adjusted Mean Returns (Yearly in %), Unadjusted Mean Returns (Yearly in %), Adjusted Returns Standard Deviation (Yearly in %), and Sharpe Ratios.

Table 2 reports detailed portfolio performance metrics. The education-country top portfolio delivers the strongest performance across all sorted portfolios, outperforming both the global ex-U.S. benchmark and the U.S. benchmark. Specifically, it achieves a risk-free adjusted annual return of 10.13% and a Sharpe ratio of 0.477. In contrast, the global ex-U.S. benchmark posts a 4.98% annual return with a Sharpe ratio of 0.246. The remaining three sorted portfolios exhibit performance and Sharpe ratios that closely mirror the benchmark. Notably, the education-country top portfolio even slightly outperforms the well-performing U.S. benchmark, which delivers a 7.75% risk-adjusted return and a Sharpe ratio of 0.409.

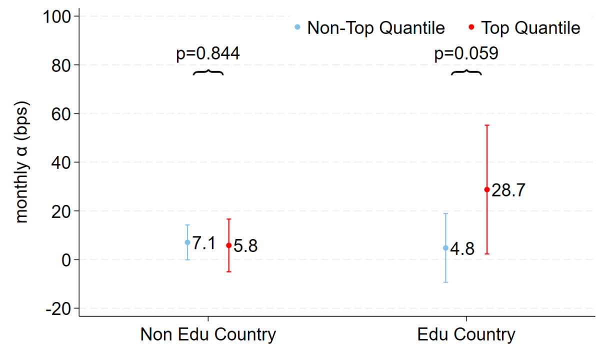
Importantly, the average annual expense ratio for mutual funds in our sample is 1.12%. Accounting for this, the three portfolios other than the education-country top portfolio would underperform the benchmark by approximately 0.6 to 1.0 percentage points annually. These findings suggest that funds rely heavily on their top education-country picks to close the gap with benchmark returns after fees, highlighting the economic value of concentrated information advantages in select foreign equities.

Next, we investigate the persistence of the informational advantage over time. Prior research, such as McLean and Pontiff (2016), shows that the return predictability of factors and estimated alphas declines over time, particularly after an anomaly is published. More broadly, return predictability has weakened in recent years as markets have become more integrated and efficient. This raises a natural question: does the return predictability associated with manager education—presumably reflecting private information—also exhibit decay in recent years? To address this, we replicate our portfolio-sorting analysis based on the I-measure, but restrict the sample to various subsample periods. Figure 4 presents the results for three intervals: the post-recession period (July 2009–December 2024), the last 10 years (January 2015–December 2024), and the most recent 5 years (January 2020–December 2024).

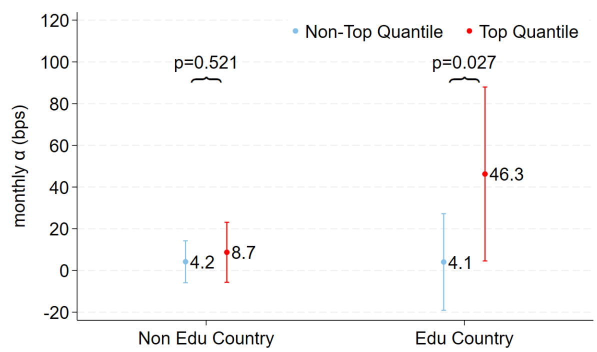
The results indicate that the education-country top portfolio continues to generate economically and statistically significant alphas across all subsamples. During the post-recession period, the top portfolio earns a monthly alpha of 30.8 basis points. In the past 10 years, the alpha remains strong at 28.7 basis points, and even in the most recent 5-year window, the top portfolio delivers a monthly alpha of 46.3 basis points—statistically different from



I-measure Sorting After Recession



I-measure Sorting 2015-2024



I-measure Sorting 2020-2024

Figure 4: Portfolio α with I-measure for Different Time Periods

Notes: This figure provides portfolio α I-measure sorting with 5 Factors. The graph on the top left use the sample after recession (July 2009 to December 2024). The graph on the top right uses recent 10 years sample (January 2015 to December 2024). The graph on the bottom uses recent 5 years sample (January 2020 to December 2024). The bars provide 95% confidence intervals.

the returns of any other portfolio. While statistical noise increases in shorter samples due to reduced observations, the out-performance of the education-country top portfolio remains robust. These findings suggest that the return predictability associated with manager education does not exhibit meaningful decay, even in the most recent years. This contrasts with many documented anomalies and supports the interpretation that the education channel conveys private information that continues to inform investment decisions and yield superior stock selection outcomes.

Appendix Figure 10 presents the portfolio sorting results based on alternative versions of the I-measure: one without adjusting for country allocations and investment universe

(Equation 1), and another without adjusting for the investment universe alone (Equation 2). While the overall pattern of results remains directionally consistent, the performance sorting is noticeably less sharp compared to the full I-measure specification. This contrast reflects the substantial differences between the investment universe of the mutual funds and that of the benchmark. These findings underscore the importance of incorporating both country-level adjustment and universe weighting into the I-measure to accurately capture investors' ex-ante beliefs in portfolio construction.

5.4 Characteristics of Top Picks

5.4.1 Do Top Picks Overlap Across Managers?

A natural question is whether fund managers tend to converge on the same top equity picks within a country, indicating shared insights into common opportunities, or whether their selections are largely idiosyncratic, reflecting distinct informational advantages. We focus on the education-country top quantile portfolio, sorted by the I-measure, and plot the fraction of non-overlapping top picks across managers within each country-time pair.

The education-country top portfolio is constructed from each manager's top quantile of holdings, meaning the number of unique equities included varies by country, depending on how many fund managers received their education there. For instance, the median number of unique equities per country is just three over the sample period. In contrast, the United Kingdom, with the largest number of educated managers in our sample, has a median of 65 unique equities in its education-country top portfolio. This variation in equity count directly affects the degree of overlap across managers: countries with more education-affiliated managers tend to have more overlaps, which may mechanically lower the observed percentage of non-overlap in top holdings.

To account for this, we group country-time observations by the number of unique equities in the education-country top portfolio and examine the fraction of equities that are non-overlapping—i.e., held by only one manager. Figure 5 shows six groups based on the equity count in each country-time cell: 1; 2–5; 6–10; 11–25; 26–50; and more than 50 equities. Green bars represent the number of country-time cell observations in each group, while the red line plots the average fraction of equities in each group that are manager-specific non-overlapping top picks.

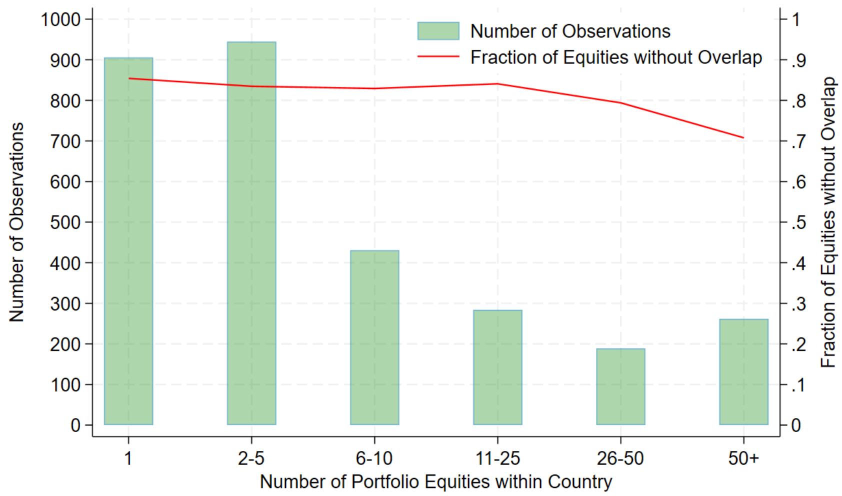


Figure 5: Top Pick Overlap Pattern

The results show that the fraction of non-overlapping holdings remains consistently high across all groups, mostly over 80%. Even in country-time observations with more than 50 equities in the education-country top portfolio, 70.8% of these equities are held by only one manager. This suggests that top picks in education countries are largely idiosyncratic, reflecting individual managers' unique insights and informational advantages rather than coordinated selection of common investment targets. This is consistent with our proposed interpretation that education-based information is primarily idiosyncratic/private across managers.

5.4.2 Market Cap Comparison of Equities in Each Quantile

Next, we examine whether there is heterogeneity in the average market capitalization of equities across different quantiles sorted by the I-measure, and whether managers deviate more actively from the benchmark in larger or smaller stocks within each country. Figure 6 presents the average log market capitalization of stocks held by funds across four I-measure quantiles, separately for education and non-education countries, using the same definitions as in the portfolio analysis in Section 5.3. Across all quantiles, the differences in market capitalization between the two groups are modest. For quantiles 2 through 4, average log market caps fall between 22 and 23 (approximately 3.6 to 9.7 billion), with differences of less than one log point between education and non-education countries. These patterns suggest that differences in stock-picking behavior between education and non-education country portfolios are not primarily driven by systematic differences in the size of firms targeted by fund managers.

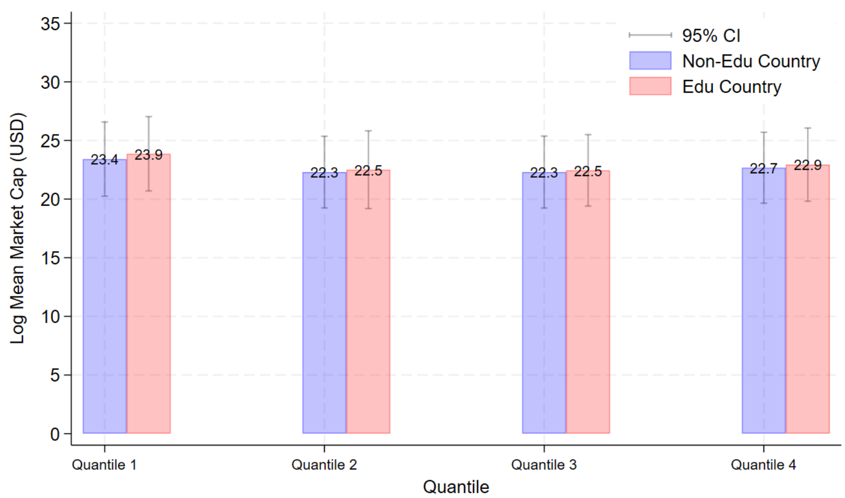


Figure 6: Market Cap Comparison

Furthermore, within each education group, average market capitalization remains relatively stable across I-measure quantiles. In both education and non-education countries, Quantile 1 tends to include slightly larger-cap stocks. This pattern is consistent with the notion that funds are less active in larger-cap equities, where it is generally more difficult to obtain an informational edge. Across the remaining quantiles, average market capitalizations are similar, indicating that the I-measure does not mechanically sort equities by firm size. Figure 6 also includes 95% confidence intervals for the mean, which further confirms the lack of systematic differences. Overall, the similarity in market capitalization across quantiles and groups suggests that firm size is unlikely to be a primary driver of the observed performance differences.

5.4.3 Do Top Picks Have More Extreme Positions in Education Countries?

We further examine whether fund managers take larger excess weights from the benchmark in the ex-ante top-pick equities, as captured by the I-measure. Figure 7 shows the average excess portfolio weight across investment quantiles, separately for education and non-education countries. Excess weight is defined as the raw difference between a fund's portfolio weight and the benchmark weight for stock i, $\omega_j^i(t) - B_j^i(t)$. We focus on raw weights because they directly contribute to a fund's excess returns. If top picks in education countries reflect education-based informational advantages, we expect managers to assign larger weights to these positions—demonstrating stronger confidence. Accordingly, excess weights should be higher for top-ranked stocks in education countries relative to their counterparts in non-education countries. In contrast, for lower-ranked (non-top pick) equities, which are less likely to be informed positions, we expect excess weights to be small and similar across education and non-education countries.

Across the first three quantiles, the average excess weights are nearly identical between education and non-education country groups, with raw weight differences of less than 0.1 percentage points. This pattern suggests that, for the majority of portfolio holdings, a manager's educational background does not systematically influence deviations from the benchmark. In turn, this implies that education-based informational advantages, if present, are concentrated in a small subset of positions and are unlikely to play a meaningful role in shaping most non-top equity allocations.

By contrast, in the top quantile (Quantile 4), funds with managers educated in the corresponding country allocate an average excess weight of 1.3%, compared to just 0.9% for top picks in non-education countries. This difference is economically meaningful, particularly given that the average raw weight a fund assigns to a single equity across the sample is only

0.81%. The larger deviation in Quantile 4 suggests higher confidence in education-country top picks, consistent with the idea that managers leverage informational advantages stemming from their educational backgrounds. In contrast, this confidence appears significantly attenuated for top picks in non-education countries and for non-top picks in education countries. Figure 7 also presents the 5th–95th percentile range of excess weights for each group, highlighting the dispersion in position sizing across managers.

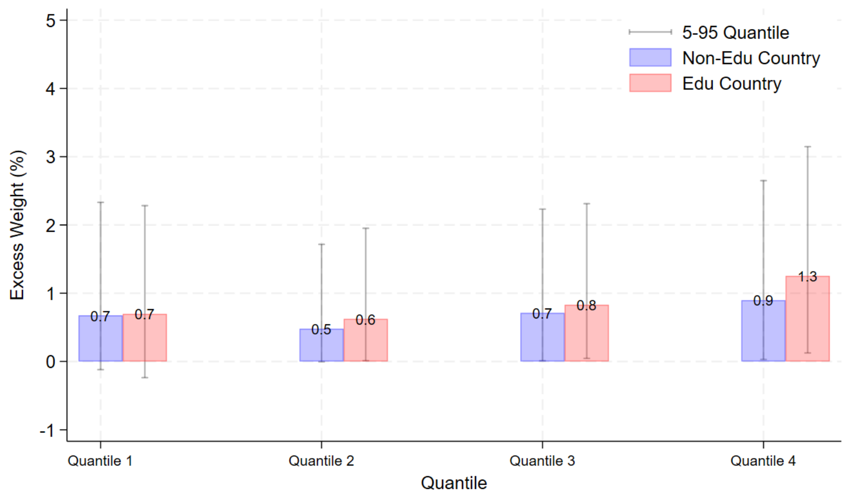


Figure 7: Excess Weight Comparison

However, raw comparisons may be influenced by country-specific and time-varying factors that confound interpretation. To formally evaluate the observed differences, we estimate the following regression specification:

$$\begin{aligned} \omega_j^i(t) - B_j^i(t) = \alpha &+ \beta \mathbb{1}(\text{Top\_Quant})_j^i(t) + \chi \mathbb{1}(\text{EC})_{jc}(t) \\ &+ \gamma\ \mathbb{1}(\text{Top\_Quant})_j^i(t) \times \mathbb{1}(\text{EC})_{jc}(t) + \theta X_{i,j,t} + \text{FE} + \epsilon_j^i(t) \end{aligned} \tag{11}$$

We define $\mathbb{1}(\text{Top\_Quant})_j^i(t)$ as an indicator equal to one if equity i is among the top-quartile picks for fund j based on the I-measure, and $\mathbb{1}(\text{EC})_{jc}(t)$ as an indicator equal to one if a manager of fund j received education in country c, where equity i is domiciled. The coefficient of interest, γ, captures the interaction between education-based affiliation and top-pick status. We estimate alternative specifications incorporating various combinations of country and time fixed effects, and control for observable characteristics such as equity-level market capitalization and the number of securities the fund holds within the country.

The regression results are consistent with the pattern shown in Figure 7, and are robust across specifications. Table 15 presents the results. The estimated coefficient on the interaction term ranges from 0.236 to 0.269, providing consistent evidence that information advantages and associated investment confidence are concentrated in top-quantile positions within a manager's education country.

5.5 Familiarity Bias in Non-Outperforming Education-Country Investments

VARIABLES	(1) Excess NT ω	(2) Excess NT ω	(3) Scaled Excess NT ω	(4) Scaled Excess NT ω
$\mathbb{1}(EC)$	0.601***		26.07***	
	(0.152)		(7.204)	
Frac_EC		1.345***		54.53***
		(0.274)		(13.86)
Constant	-0.508***	-0.509***	-29.66***	-29.66***
	(0.00230)	(0.00204)	(0.101)	(0.0933)
Observations	2,526,779	2,526,779	2,335,644	2,335,644
Fund FE	Y	Y	Y	Y
CountryXTime FE	Y	Y	Y	Y
Sub-Sample	N	N	N	N
Funds Number	599	599	599	599

Table 3: Education Effect on Excess Weight of Non-Top(NT) Holdings

The previous portfolio results indicate that while most education-country portfolios do not generate excess returns, part of the observed over-allocation may be justified by the most confident holdings, which outperform. A natural question is whether, after excluding those equity picks that can be justified by potential informational advantages, managers still over-invest in their education country due to familiarity bias, even within subportfolios that do not outperform. To examine this, we reconstruct the country-level allocation excluding the top quantile portfolios for both education and non-education countries, and estimate equations 4 through 5 using the adjusted country weights.

Specifically, for each fund j's holdings in country c at time t, let $\Omega_{jc}(t)$ denote the set of equities held. Each equity $i \in \Omega_{jc}(t)$ is ranked by its I-measure and assigned to one of four mutually exclusive quantile portfolios, denoted $\Omega_{jc}(t)^k$, where $k \in 1, 2, 3, 4$. In equations 4 and 5, the country-level weight is defined as the sum of the weights of all equities invested in that country, $\omega_{jc}(t) = \sum_{i \in \left(\cup_{k=1}^{4} \Omega_{jc}(t)^k\right)} \omega_{jc}^i(t)$. Under our adjustment, the country-level weight is instead the sum of the weights of equities in the bottom three quantiles, $\omega_{jc}(t) = \sum_{i \in \left(\cup_{k=1}^{3} \Omega_{jc}(t)^k\right)} \omega_{jc}^i(t)$.

As shown in the previous section, the bottom-three-quantile portfolios in education countries perform similarly to the non-education-country portfolios and the benchmark. If the education-country over-investment were driven solely by information advantages from the familiar market, we would expect no over-investment in the bottom three quantiles. However, the results show otherwise. Despite the absence of outperformance, funds still allocate disproportionately to the education-country non-top portfolios. These findings are presented in Table 3.

In the non-outperforming bottom-three-quantile portfolios, funds overweight the manager's education country by 1.345% in raw weight when the fraction of managers educated in that country increases by 100%, as shown in column (2). This coefficient is about half the 2.635% reported in our main regression in Table 1. However, since the weight in the bottom three quantiles is mechanically about $\frac{3}{4}$ of the total (with an average fraction of 73.6%), we scale the coefficient by $\frac{1}{0.736}$ to make it comparable to the main regression coefficient. The scaled coefficient is 1.827, suggesting that over-investment in non-outperforming equities is smaller than in outperforming equities, but familiarity bias in non-outperforming investments remains substantial. The results using Scaled Excess ω further confirm this bias.

Although the α estimates are not statistically significant, Figure 2 shows that the third quantile portfolio in education countries achieves moderate mean returns. As an additional robustness check, we reconstruct the country weight using only the bottom two quantiles instead of the bottom three. Table 17 presents the results. Column (2) reports a coefficient of 0.803, which, when scaled by the average weight share of the bottom two quantiles (55.3%), yields a value of 1.452. This estimate is slightly smaller than the scaled coefficient of 1.827 for the bottom three quantiles and the 2.635 from the original specification, but it confirms that familiarity bias persists even in non-outperforming education-country investments.

Overall, these results demonstrate that familiarity bias exists beyond managers' most informed or confident investments. Even after excluding the top-performing holdings, funds continue to overweight their education country in portfolios that do not exhibit superior performance. While the magnitude of over-investment is smaller than in the outperforming subset, it remains economically and statistically significant. This pattern suggests that portfolio allocations are not solely driven by information advantages but are also shaped by a systematic preference for familiar markets associated with managers' country of education.

6 Robustness Checks

We conduct a series of robustness checks to support the main findings in Section 5.3: fund managers generate significant portfolio α in their top equity picks within countries where they received education, but not in countries where they did not. This pattern is consistent with the view that managers possess superior information or deeper familiarity with a select subset of firms in their education countries, while lacking such informational advantages both in other firms within those same countries and in firms located in non-education countries.

This section provides an overview of each robustness check. Across all tests, the results remain qualitatively consistent with those in Section 5.3. Figures are provided in Appendix B.

6.1 Sorting with V-Measure

As discussed in Section 4.1.3, the I-measure used to sort equities relies on benchmark assignments provided by Morningstar. While this is generally not a concern—given that Morningstar benchmarks are primarily market-cap-weighted and cover approximately 97% of the global investable equity universe—we nevertheless construct an alternative measure that is independent of benchmark assignment to test the robustness of our results. The construction details are provided in Section 4.1.3.

Specifically, in developing the value-weighted measure (V-measure), we replace the Morningstar-assigned benchmark used in the I-measure with a market-cap-weighted portfolio that includes all investable equities in the global equity universe. Formally, the V-measure is defined as:

$$V_{jc}^{i}(t) = \frac{\omega_{jc}^{i}(t)}{\sum_{i' \in \Omega_{jc}(t)} \omega_{jc}^{i'}(t)} - \frac{V_{c}^{i}(t)}{\sum_{i' \in \Omega_{jc}(t)} V_{c}^{i'}(t)} \equiv \frac{\omega_{jc}^{i}(t)}{\omega_{jc}(t)} - \frac{V_{c}^{i}(t)}{\sum_{i' \in \Omega_{jc}(t)} V_{c}^{i'}(t)}$$

The notation follows that used in the definition of the I-measure, with one key modification: we replace the benchmark portfolio weight $B_{jc}^{i}(t)$ with the market capitalization of the equity, $V_{c}^{i}(t)$. The V-measure captures a fund's deviation from a market-cap-weighted portfolio within its investment universe in a given country. Unlike the I-measure, the V-measure is fully independent of Morningstar's benchmark assignments.

Figure 12 presents the sorting results based on the V-measure. The findings are both qualitatively and quantitatively consistent with those using the I-measure. In non-education countries, the monthly Fama-French five-factor α is 5.6 basis points for the non-top portfolio and 5.5 basis points for the top portfolio. These differences are not statistically significant (p-value = 0.995). In contrast, for education countries, the monthly α is -1.9 bps for the non-top portfolio and a sizable 33.9 basis points for the top portfolio, with the difference being statistically significant at the 5% level (p-value = 0.011). Furthermore, the α of the education country's top portfolio is significantly higher than that of the top portfolio in non-education countries (p-value = 0.025).

These results remain robust when we re-estimate α using the CAPM model (i.e., excluding factor controls). Under this specification, the education country's top portfolio earns a monthly α of 45.3 basis points, which is statistically significant at the 5% level relative to all other portfolios.

6.2 Sorting with U-measure

In defining the I-measure, we restrict the comparison universe to equities that the fund is currently investing in. This choice helps reduce noise from equities that are irrelevant to the fund's active portfolio. As a robustness check, we examine whether our results are sensitive to this specific definition of the investment universe. To do so, we expand the relevant universe to include all equities in a given country that the fund has held at any point over the past eight quarters (i.e., the previous two years). This approach is motivated by Koijen and Yogo (2019), who show that approximately 92% of equities held in a given quarter were also held by the same fund in the prior eight quarters. Further extending the horizon beyond eight quarters has minimal effect on results.

For convenience, we refer to this modified measure as the U-measure. It is defined as:

$$U^i_{jc}(t) = \begin{cases} \frac{\omega^i_{jc}(t)}{\sum_{i' \in \Omega_{jc}(t-8,t)} \omega^{i'}_{jc}(t)} - \frac{B^i_{jc}(t)}{\sum_{i' \in \Omega_{jc}(t-8,t)} B^{i'}_{jc}(t)} & if \ \sum_{i' \in \Omega_{jc}(t-8,t)} B^{i'}_{jc}(t) \neq 0 \\ \frac{\omega^i_{jc}(t)}{\sum_{i' \in \Omega_{jc}(t-8,t)} \omega^{i'}_{jc}(t)} & if \ \sum_{i' \in \Omega_{jc}(t-8,t)} B^{i'}_{jc}(t) = 0 \end{cases}$$

The only difference from the I-measure definition is that we replace the relevant investment universe $\Omega_{jc}(t)$, the universe of equities held by the fund at time t, by $\Omega_{jc}(t-8,t)$, the universe of equities ever held by the fund from time $t-8$ (8 quarters before) to t.

The results using the U-measure are both quantitatively and qualitatively consistent with those based on the I-measure. Figure 13 reports the sorting results using the U-measure. In non-education countries, the monthly 5-factor α is 10.4 basis points for the non-top portfolio and 1.2 basis points for the top portfolio. The difference between the two is not statistically significant (p-value = 0.170). In contrast, for education countries, the monthly 5-factor α is –3.2 basis points in the non-top portfolio and 38.1 basis points in the top portfolio. The difference is statistically significant at the 1% level (p-value = 0.005). Moreover, the top portfolio in education countries significantly outperforms the top portfolio in non-education countries, with a p-value of 0.003.

The results remain consistent when using the CAPM (i.e., no-factor model) instead of the 5-factor model. Under this specification, the monthly α of the education country top portfolio is 37.1 basis points, and it remains statistically significant at the 10% level compared to the α of any other portfolio.

6.3 Excluding the United Kingdom from the Analysis

As shown in Table 6, the United Kingdom (GBR) accounts for a disproportionately large share of non-U.S. education backgrounds among fund managers. Specifically, 238 funds have had at least one manager with a U.K. education, whereas the second most common education country—India (IND)—is associated with only 79 such funds. Other countries have fund counts on a comparable scale to India, and none individually are likely to drive the results. To ensure that our findings are not disproportionately influenced by the U.K., we conduct a robustness check by excluding U.K.-related investments from the analysis.

We remove all U.K. equities from the portfolio construction and repeat the sorting exercise. The results, presented in Figure 14, show that in non-education countries, the monthly 5-factor α is 12.9 basis points for the non-top portfolio and 6.3 basis points for the top portfolio. The difference is not statistically significant (p-value = 0.334). In contrast, in education countries, the non-top portfolio yields a monthly α of 20.8 basis points, while the top portfolio generates a significantly higher α of 74.7 basis points. The difference is statistically significant at the 5% level (p-value = 0.025). Furthermore, the monthly α of the education country top portfolio is significantly greater than that of the non-education country top portfolio, with a p-value of 0.000.

7 Conclusion

In this paper, we combine detailed international mutual fund holdings with a dataset on fund managers' educational backgrounds to examine how education-based familiarity shapes portfolio allocation and performance. Our analysis shows that, despite the absence of excess country-level returns, funds systematically overweight countries where their managers received post-secondary education, highlighting a behavioral channel through which international capital flows toward familiar markets.

We then turn to the stock level to investigate whether familiarity-based information coexists with bias. To capture managers' ex-ante conviction in individual equity positions, we develop the I-measure to capture managers' ex-ante confidence in the equity. Using this metric, we show that one-quarter of the most confident top picks in education-country portfolios generate a substantial annual alpha of 5.31% and a Sharpe ratio of 0.477, while all other positions earn returns indistinguishable from the benchmark.

Further evidence indicates that these top picks vary substantially across managers, suggesting that the informational advantage associated with familiarity is highly idiosyncratic. Funds also allocate larger raw weights to these positions relative to the most confident counterparts in non-education countries, consistent with the concentration of higher investment confidence in education-country top picks. Collectively, these findings indicate that country familiarity conveys a private, persistent informational edge concentrated in only the most confident one-quarter of equity positions, whereas broader country-level allocations primarily reflect familiarity bias rather than information.

Overall, our results contribute to the literature on familiarity bias and international portfolio allocation by clarifying the dual role of familiarity: it provides both a source of private, persistent, and concentrated informational advantage and a driver of systematic over-allocation. We identify the scope of familiarity-based information in global equity markets, highlighting how and where familiarity simultaneously enhances stock selection while biasing capital allocation.

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Tables

Table 4: Time Series Average of Fund Characteristics

Time series average	**Mean**	**Median**	**Std**	**N**
Number of countries held	18.36	18	6.96	32,826
Number of manager education countries	1.57	1	0.89	31,377
Number of manager education countries (non-US)	0.69	0	0.91	31,377
Fund Total Net Asset (billions $)	2.00	0.28	8.41	34,925
Average Manager Tenure (yrs)	8.45	7.95	4.84	462
Annual Net Expense Ratio (%)	1.12	1.11	0.46	10,439

This table calculates the sample average of fund characteristics using data from Morningstar. Manager tenure is provided as fund average to date and is observed once per fund. Net expense ratio is observed at annual frequency, while all other variables are observed at the fund*quarter level.

Table 5: Country Distribution of Manager Educations

Note: The last column is the share of managers with that country's education, which is the # of managers with the country's education divided by the total number of managers (1892). The sum of shares adds to over 1, since a manager can have multiple country's education backgrounds.

Country	**# of Managers**	**Share of Managers w/ Edu**
USA	1427	0.7540
GBR	373	0.1970
CAN	56	0.0296
IND	54	0.0286
CHN	42	0.0222
AUS	36	0.0190
IRL	24	0.0127
JPN	17	0.0090
DEU	16	0.0085
FRA	11	0.0058
ZAF	9	0.0048
NLD	8	0.0042
SGP	8	0.0042
DNK	7	0.0037
HKG	7	0.0037
KOR	7	0.0037
ITA	6	0.0032
NZL	6	0.0032
CHE	5	0.0026
ISR	5	0.0026
SWE	5	0.0026
CHL	4	0.0021
TWN	4	0.0021
ARG	3	0.0016
BEL	3	0.0016
BRA	3	0.0016
POL	3	0.0016
RUS	3	0.0016
ESP	2	0.0011
MEX	2	0.0011
NGA	2	0.0011
TUR	2	0.0011
VEN	2	0.0011
AUT	1	0.0005
BGR	1	0.0005
COL	1	0.0005
CUB	1	0.0005
EGY	1	0.0005
EST	1	0.0005
GTM	1	0.0005
HUN	1	0.0005
PRT	1	0.0005
ROU	1	0.0005
SAU	1	0.0005
THA	1	0.0005
UKR	1	0.0005
Total # of Managers	1892	1.000

Table 6: Country Distribution of Manager Education at Fund Level

Note: The last column is the share of funds with that country's education, which is the # of funds with the country's education divided by the total number of funds (599). The sum of shares adds to over 1, since a fund can have multiple country's education backgrounds due to multiple managers, and each manager can also have multiple countries' education background.

Country	**# of Funds**	**Share of Fund w/ Edu**
USA	564	0.942
GBR	255	0.426
IND	81	0.135
CAN	77	0.129
CHN	47	0.078
IRL	47	0.078
AUS	33	0.055
DEU	28	0.047
JPN	26	0.043
NZL	19	0.032
FRA	17	0.028
SGP	15	0.025
ITA	14	0.023
DNK	13	0.022
HKG	12	0.020
NLD	12	0.020
ZAF	11	0.018
ISR	10	0.017
KOR	10	0.017
SWE	9	0.015
BEL	8	0.013
CHE	7	0.012
NGA	6	0.010
RUS	6	0.010
AUT	5	0.008
ESP	5	0.008
TWN	5	0.008
BRA	4	0.007
MEX	4	0.007
POL	4	0.007
ROU	4	0.007
TUR	4	0.007
ARG	3	0.005
CHL	3	0.005
CUB	3	0.005
VEN	3	0.005
THA	2	0.003
BGR	1	0.002
COL	1	0.002
EGY	1	0.002
EST	1	0.002
GTM	1	0.002
HUN	1	0.002
PRT	1	0.002
SAU	1	0.002
UKR	1	0.002
Total # of Funds	599	1.000

Table 7: Sample Fund TNA Breakdown by Benchmarks

Morningstar Index	**Mean Market Cap (B)**	**Std. Dev (B)**	**Ave. Num Funds**
Morningstar Gbl NR USD	3.990	1.183	45.73
Morningstar Gbl Growth TME NR USD	3.702	1.262	28.07
Morningstar Gbl xUS Growth TME NR USD	3.530	1.138	49.32
Morningstar Gbl xUS NR USD	2.719	1.079	121.87
Morningstar Gbl xUS Val TME NR USD	2.320	0.966	34.60
Morningstar DM APAC xJpn NR USD	1.279	0.922	2.79
Morningstar EM NR USD	1.124	0.496	69.86
Morningstar EM Americas NR USD	0.944	0.991	1.13
Morningstar Gbl xUS SMID NR USD	0.726	0.232	33.74
Morningstar Gbl Val TME NR USD	0.639	0.193	18.01
Morningstar DM Eur NR USD	0.598	0.263	2.28
Morningstar Gbl SMID NR USD	0.561	0.222	9.60
Morningstar Jpn NR USD	0.314	0.246	1.44
Morningstar India NR USD	0.255	0.234	1.00
Morningstar Gbl Lrg NR USD	0.230	0.074	9.43
Morningstar DM APAC NR USD	0.184	0.125	1.00
Morningstar China NR USD	0.141	0.191	2.29

Note: This table calculate the mean market cap of funds and the mean number of funds that belong to each of the Morningstar benchmarks at quarterly frequency.

Table 8: Portfolio Holdings Patterns

	Time-series Average			
	Mean	Median	Std	N
Sample Funds				
# of countries held	18.86	19	7.18	34,925
Country-level portfolio share(%)	6.97	5.02	10.92	34,925
# of stocks held	107.69	76	135.90	31,451
Stock-level portfolio share(%)	1.41	1.24	1.40	31,451
Morningstar Gbl xUS NR USD				
# of countries held	49.92	51	2.83	84
Country-level portfolio share(%)	1.96	1.92	0.10	84
# of stocks held	5,244.81	5,116	865.79	84
Stock-level portfolio share(%)	0.02	0.02	0.00	84
All Benchmarks (equal weights)				
# of countries held	27.64	26	20.34	1,905
Country-level portfolio share(%)	16.48	3.54	28.25	1,905
# of stocks held	1,899.32	1,348	1,851.12	1,905
Stock-level portfolio share(%)	0.16	0.07	0.24	1,905

Note: This table shows country and stock level # of holdings and the share of holdings in the fund sample, the xUS global benchmark and all benchmarks

VARIABLES	(1) Excess ω	(2) Excess ω	(3) Scaled Excess ω	(4) Scaled Excess ω
$\mathbb{1}(EC)$	0.640***		19.70**	
	(0.192)		(8.636)	
Frac_EC		1.594***		39.05**
		(0.477)		(16.84)
Constant	1.866***	1.864***	78.78***	78.79***
	(0.00290)	(0.00355)	(0.121)	(0.113)
Observations	2,526,438	2,526,438	2,335,364	2,335,364
CountryXFund FE	Y	Y	Y	Y
CountryXTime FE	Y	Y	Y	Y
Sub-Sample	N	N	N	N
Funds Number	599	599	599	599

Table 9: Education Effect on Excess Weight

Table 10: Excess Weight over Benchmark (%)

VARIABLES	(1) Excess ω	(2) Excess ω	(3) Excess ω	(4) Excess ω
$\mathbb{1}(EC)$	1.270***	1.260***	1.210***	1.235***
	(0.209)	(0.209)	(0.218)	(0.220)
Constant	0.0220***	0.0221	0.0615***	0.0612***
	(0.00316)	(0.0173)	(0.00309)	(0.0201)
Observations	2,526,739	2,526,740	2,111,060	2,111,061
Fund FE	Y	N	Y	N
CountryXTime FE	Y	Y	Y	Y
Sub-Sample	N	N	Y	Y
Funds Number	599	599	443	443

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Scaled Excess Weight over Benchmark (%)

VARIABLES	(1) Scaled Excess ω	(2) Scaled Excess ω	(3) Scaled Excess ω	(4) Scaled Excess ω
$\mathbb{1}(EC)$	33.74***	39.73***	26.28***	28.87***
	(7.775)	(7.854)	(6.575)	(6.309)
Constant	-21.42***	-21.50***	-26.41***	-26.45***
	(0.109)	(1.536)	(0.0900)	(1.365)
Observations	2,335,628	2,335,628	1,986,426	1,986,426
Fund FE	Y	N	Y	N
CountryXTime FE	Y	Y	Y	Y
Sub-Sample	N	N	Y	Y
Funds Number	599	599	443	443

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Excess Weight over Benchmark (%)

VARIABLES	(1) Excess ω	(2) Excess ω	(3) Excess ω	(4) Excess ω
Frac_EC	2.635***	2.614***	2.660***	2.697***
	(0.415)	(0.418)	(0.423)	(0.430)
Constant	0.0216***	0.0218	0.0607***	0.0604***
	(0.00308)	(0.0172)	(0.00286)	(0.0199)
Observations	2,526,739	2,526,740	2,111,060	2,111,061
Fund FE	Y	N	Y	N
CountryXTime FE	Y	Y	Y	Y
Sub-Sample	N	N	Y	Y
Funds Number	599	599	443	443

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Scaled Excess Weight over Benchmark (%)

VARIABLES	(1) Scaled Excess ω	(2) Scaled Excess ω	(3) Scaled Excess ω	(4) Scaled Excess ω
Frac_EC	67.66***	74.38***	52.76***	53.08***
	(14.85)	(15.06)	(10.90)	(10.81)
Constant	-21.40***	-21.44***	-26.39***	-26.39***
	(0.1000)	(1.533)	(0.0704)	(1.361)
Observations	2,335,628	2,335,628	1,986,426	1,986,426
Fund FE	Y	N	Y	N
CountryXTime FE	Y	Y	Y	Y
Sub-Sample	N	N	Y	Y
Funds Number	599	599	443	443

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Return at 1 Month Horizon (bps)

VARIABLES	(1) Monthly Return	(2) Monthly Return	(3) Monthly Return	(4) Monthly Return
$\mathbb{1}(EC)$	6.163	5.606		
	(7.596)	(8.380)		
Frac_EC			7.784	8.021
			(14.24)	(15.30)
Constant	100.0***	100.0***	100.1***	100.1***
	(0.213)	(0.235)	(0.199)	(0.214)
Observations	963,849	963,534	963,849	963,534
R-squared	0.022	0.042	0.022	0.042
Time FE	Y		Y	
Country FE	Y		Y	
Fund FE	Y	Y	Y	Y
Fund Cluster	Y	Y	Y	Y
TimeXCountry FE		Y		Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Excess Weight	(2) Excess Weight	(3) Excess Weight	(4) Excess Weight
$\mathbb{1}(EC)$	-0.00746	-0.00526	-0.0366	-0.0346
	(0.0364)	(0.0373)	(0.0223)	(0.0226)
$\mathbb{1}(Top\, Quantile)$	0.270***	0.273***	0.325***	0.327***
	(0.0331)	(0.0328)	(0.0335)	(0.0334)
$\mathbb{1}(EC)\#\mathbb{1}(Top\, Quantile)$	0.269***	0.267***	0.237***	0.236***
	(0.0539)	(0.0540)	(0.0495)	(0.0495)
Number of Equities Held			-0.00741***	-0.00763***
			(0.00175)	(0.00186)
Mkt Cap (In Billion USD)			0.00200***	0.00195***
			(0.000397)	(0.000403)
Constant	0.640***	0.639***	0.777***	0.784***
	(0.00638)	(0.00639)	(0.0493)	(0.0521)
Observations	5,286,873	5,286,649	5,257,535	5,257,312
Time FE	Y		Y	
Country FE	Y		Y	
Country Cluster	Y	Y	Y	Y
CountryXTime FE		Y		Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Excess Weight Comparison

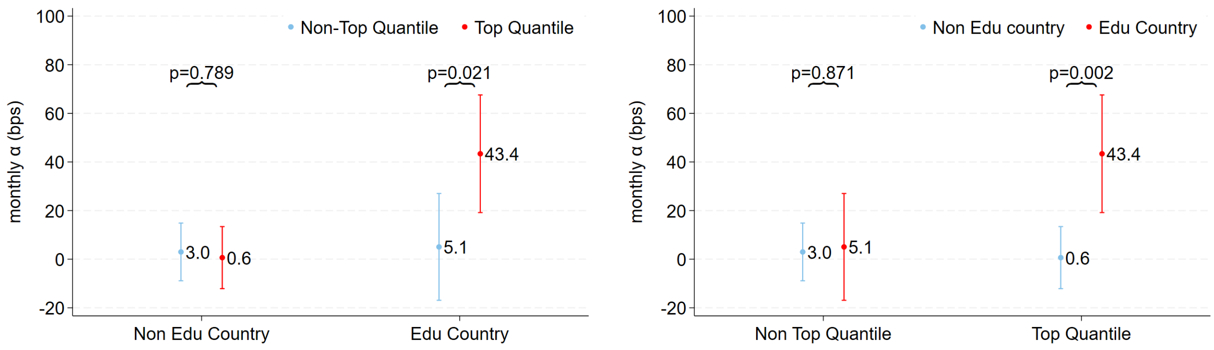
Table 16: Portfolio Return for Year 2000-2024 (Yearly, in %)

Portfolio	# Years	Mean Return	Std. Dev.	Min Return	Max Return
Glb. ex-US Benchmark	25	6.828	20.32	-45.37	42.82
Edu Top	25	12.10	21.48	-42.13	59.39
Edu Non-Top	25	7.220	20.98	-42.15	45.46
Non-Edu Top	25	6.974	21.18	-43.61	39.20
Non-Edu Non-Top	25	7.369	21.60	-45.15	44.54
US Benchmark	25	9.615	18.81	-36.99	35.25
Glb. ex-US Benchmark (RF Adj.)	25	4.983	20.25	-46.06	42.62
Edu Top (RF Adj.)	25	10.13	21.24	-42.85	57.83
Edu Non-Top (RF Adj.)	25	5.360	20.90	-42.88	44.03
Non-Edu Top (RF Adj.)	25	5.127	21.05	-44.32	38.14
Non-Edu Non-Top (RF Adj.)	25	5.526	21.55	-45.84	44.33
US Benchmark (RF Adj.)	25	7.752	18.94	-37.78	35.18

VARIABLES	(1) Excess BH ω	(2) Excess BH ω	(3) Scaled Excess BH ω	(4) Scaled Excess BH ω
$\mathbb{1}(EC)$	0.324**		18.31***	
	(0.145)		(5.492)	
Frac_EC		0.803***		39.36***
		(0.261)		(10.84)
Constant	-0.918***	-0.919***	-47.49***	-47.49***
	(0.00219)	(0.00194)	(0.0772)	(0.0729)
Observations	2,526,779	2,526,779	2,335,644	2,335,644
Fund FE	Y	Y	Y	Y
CountryXTime FE	Y	Y	Y	Y
Sub-Sample	N	N	N	N
Funds Number	599	599	599	599

Table 17: Education Effect on Excess Weight of Bottom Half(BH) Holdings

Figures



I-measure Sorting Quantile Comparison I-measure Sorting Education Comparison

Figure 8: Portfolio α with I-measure sorting with no Factors

Notes: This figure provides portfolio α I-measure sorting with no Factors. The graph on the left compares top VS non-top portfolio within either education country or non-education county. The graph on the right compares education VS non-education portfolio within either top or non-top portfolio. The bars provide 95% confidence intervals.

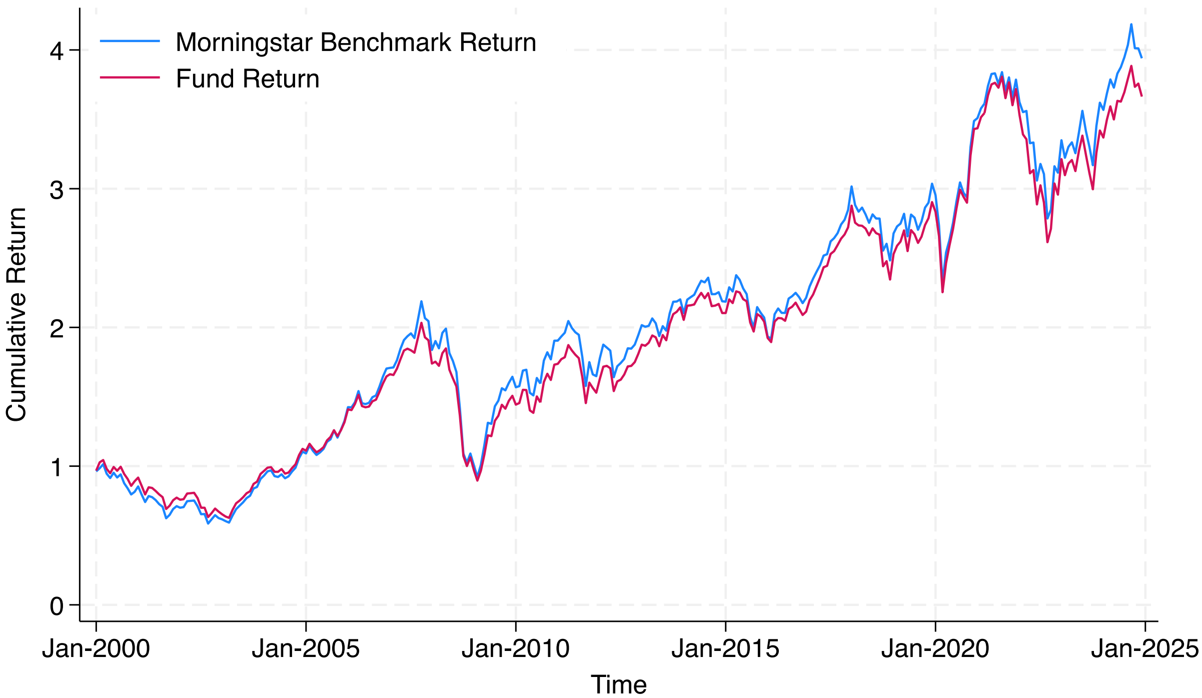
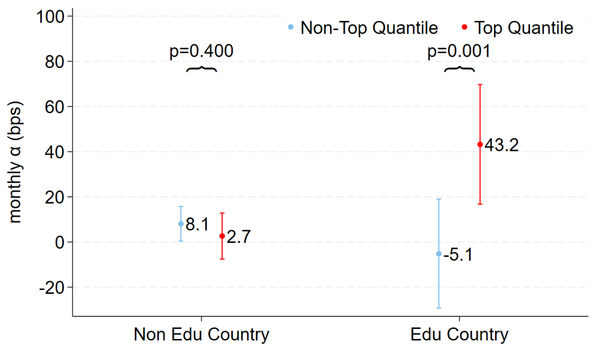
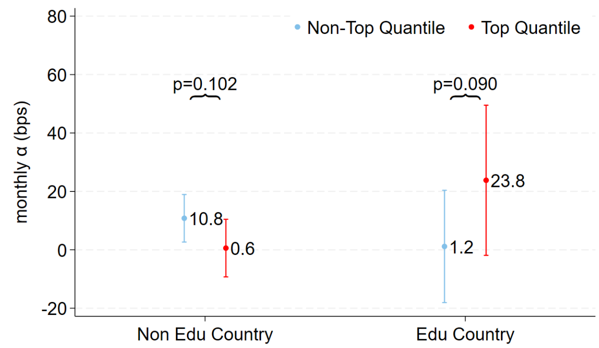


Figure 9: Weighted Benchmark Return VS Fund Sample Return

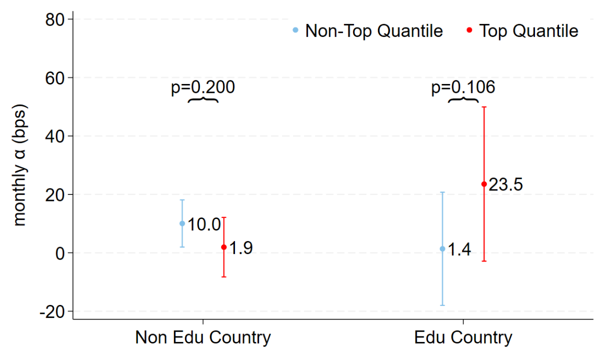
Notes: This figure plots the monthly cumulative total return of sample funds and the weighted total return of their corresponding benchmarks. The two lines align well with each other, with correlation of cumulative index 99.81%, and correlation of monthly return 98.84%.



I-measure Sorting



I-measure (without universe weighting) Sorting



I-measure (without country and universe weighting) Sorting

Figure 10: Portfolio α with I-measure and adjusted I-measure sorting with 5 Factors

Notes: This figure provides portfolio α for three sorting methods using (a) I-measure and (b) I-measure (without universe weighting) Sorting with 5 Factors (c) I-measure (without country and universe weighting) Sorting with 5 Factors. The two dots on the left of each graph are portfolio α for the sub-portfolio of equities with activeness (as measured in the 3 ways above) in the bottom 3 quantile and top 1 quantile separately in countries where the fund manager did not have education in. The two dots on the right of each graph are the portfolio α for sub-portfolios in managers' education countries sorted by activeness. The bars provide 95% confidence intervals.

Appendix A. Equity Return Construction

Appendix A.1. Return Index Construction

As mentioned in the description of the data, we use the Datastream return index to calculate the monthly gross return on each equity. The return index includes both the price return and the dividend return. However, due to the data limitation on international equity, around 20% of the equities in the sample have a missing return index, but almost no equities have the price data missing. Thus, we back out the gross return as the sum of the price return and the country's average dividend of the month. We use the change in the market cap of the stock to discipline the price return. This is because price changes might be caused by stock splits and reverse splits. We use only the price returns that are within the range of 0.1% of the percentage change of market cap in the same month. For those equity-month observations with missing return index, we define the monthly gross return as $price\_return_{i,t} + divident_{c,t}$ if $|price\_return_{i,t} - \%\Delta market\_cap| < 0.1\%$, here $divident_{c,t}$ is the country average return in country c which equity i belongs to in month t.

	(1)	(2)
VARIABLES	Constructed Return	Constructed Return
Reported Return	1.024***	0.982***
	(0.00513)	(0.0102)
Constant	0.000299	-0.000122
	(0.000239)	(0.000497)
Observations	63,106	300
R-squared	0.969	0.969
Correlation	0.9843	0.9844
Sample	All Sample Funds	Global xUS Benchmark

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: Comparison of Reported Return and Constructed Return

Appendix A.2. Test Reliability of Return Index Construction and Reported Holding

For a joint test of how reliable the detailed holding and constructed returns are, we constructed the return using the equity level detailed holding and the constructed return and compared the constructed return with the reported return. We do this exercise for both all

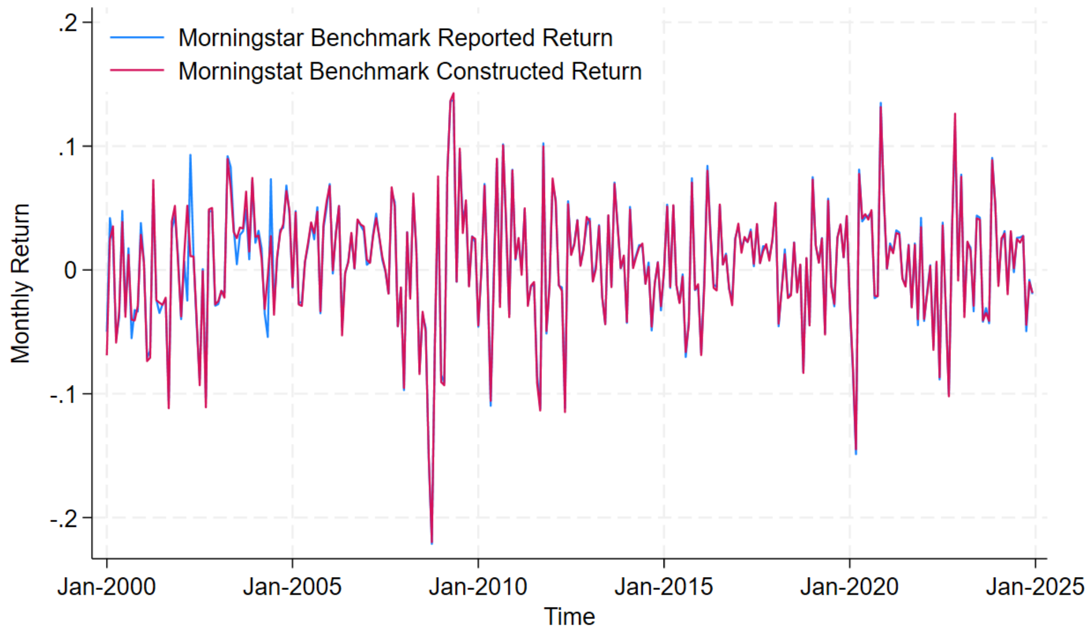


Figure 11: Reported Benchmark Return VS Constructed Benchmark Return

Notes: This figure plots the monthly gross return reported by Morningstar for benchmark Morningstar Gbl xUS USD against the constructed cumulative gross return for the same index from holding and price data. The two lines align well with each other, with the correlation of monthly return 98.44%

the funds in our data sample, and also for the global xUS benchmark (Morningstar Gbl xUS USD).

We constructed the fund return as the weighted return of individual equities $R_{f,t} = \frac{\sum_{i\in\Omega_{f,t-1}} \omega_{i,t-1} r_{i,t}}{\sum_{i\in\Omega_{f,t-1}} \omega_{i,t-1}}$, where $\Omega_{f,t-1}$ is the universe of equities held by the fund f. Note that this is only the return on equity investments for funds. For benchmark, there is no holding other than equities. However, for funds, there might be a small fraction of holding on liquid fixed incomes or even cash, so the reported return will take that part into account, and our constructed return will not.

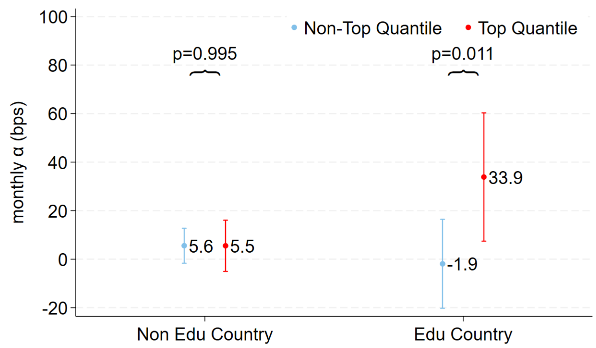
We run a simple OLS regression of the constructed return on the reported return with observations at the month-fund level, and the results are reported in Table 18. The R-squared is 0.969 for the sample of all funds, and the correlation of the two series is 0.9843. The regression coefficient is 1.024, which is 2.4% larger than 1. This might come from the fact that the funds in our sample hold on average $2\% - 3\%$ cash or very liquid assets as buffers for redemption. We also do the same for the Morningstar Gbl xUS USD benchmark, with the R-square and correlation at 0.969 and 0.9844, which are very close to the values for all sample funds.

For better visualization of the alignment of constructed return and reported return, we plot the monthly series of constructed return against the reported return in Figure 11, and the two lines almost overlap with each other, especially starting from 2005.

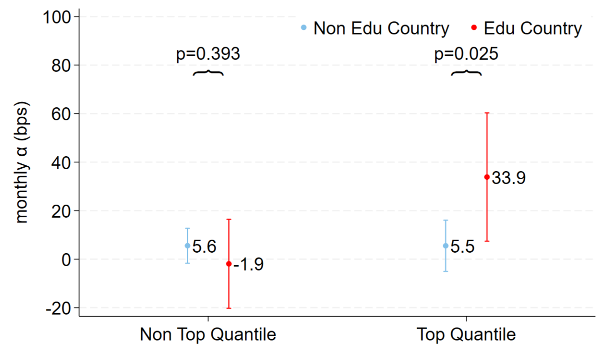
The comparison of the constructed and reported return verifies the reliability of both the reported holding and the constructed equity level returns. The results in the main text are unlikely to be driven by the error in either equity return construction or holding misreporting by Morningstar.

Appendix B. Robustness Check Results

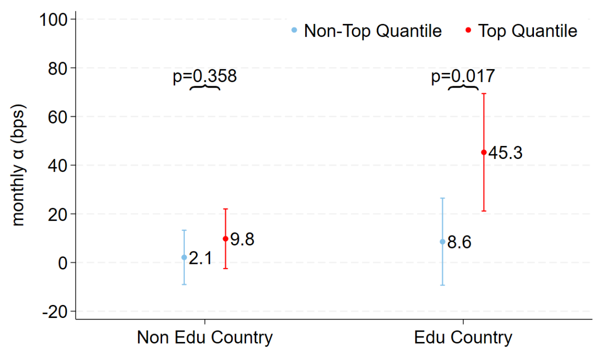
Appendix B.1 Construct I-measure using Market Value Weighted Market Portfolio



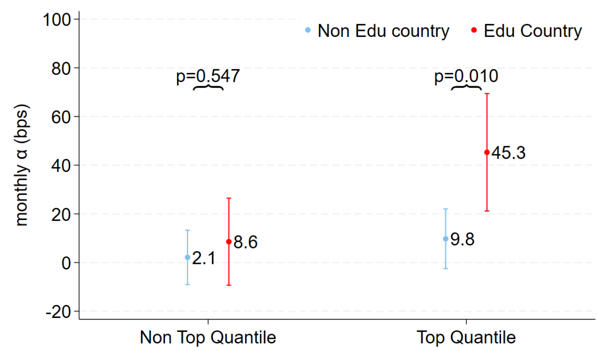
V-measure Quantile Comparison 5 Factors



V-measure Education Comparison 5 Factors



V-measure Quantile Comparison No Factors

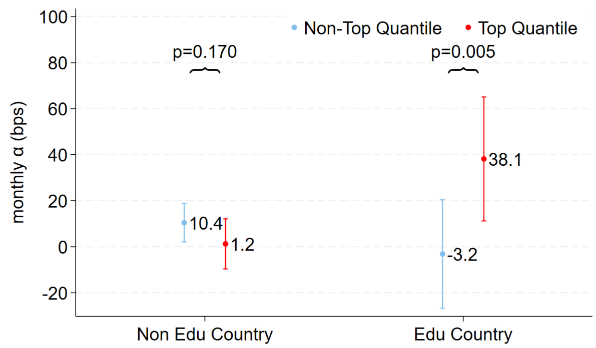


V-measure Education Comparison No Factors

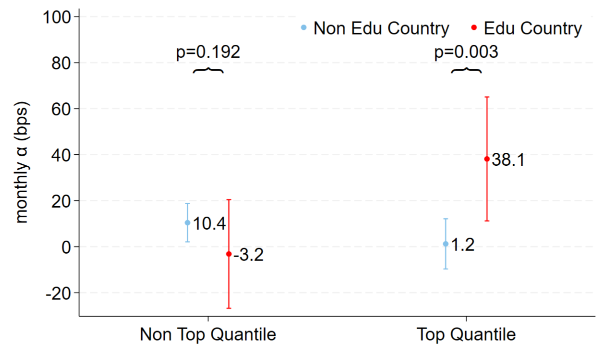
Figure 12: Portfolio α with Value-measure sorting

Notes: This figure provides portfolio α with value-measure sorting. The graph on the left top compares top VS non-top portfolio within either education country or non-education county with 5 factors. The graph on the right top compares education VS non-education portfolio within either top or non-top portfolio with 5 factors. The graph on the left bottom compares top VS non-top portfolio within either education country or non-education county with no factors. The graph on the right bottom compares education VS non-education portfolio within either top or non-top portfolio with no factors. The bars provide 95% confidence intervals.

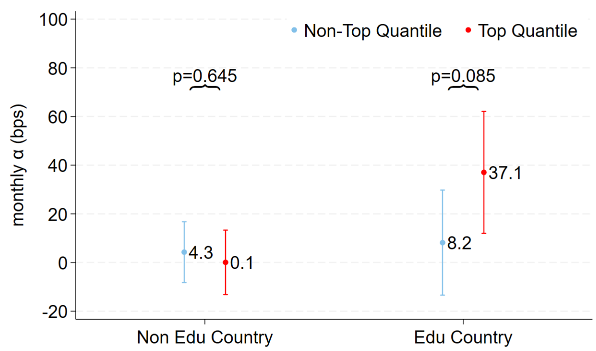
Appendix B.2 Expanding Investment Universe of Funds to Equities the Fund Ever Hold in Past 2 Years



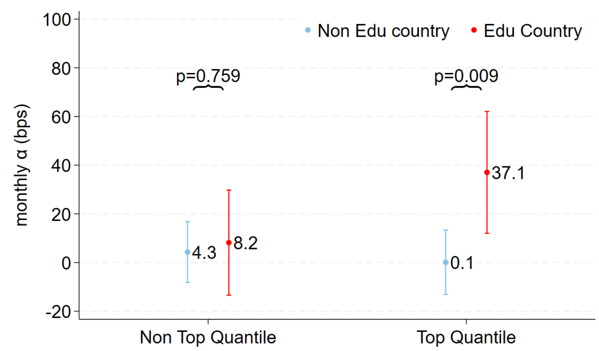
I-measure Quantile Comparison 5 Factors



I-measure Education Comparison 5 Factors



I-measure Quantile Comparison No Factors

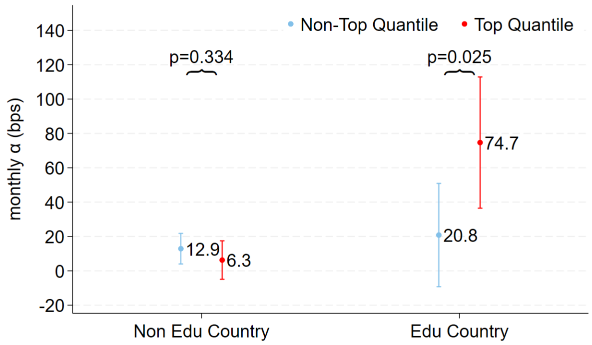


I-measure Education Comparison No Factors

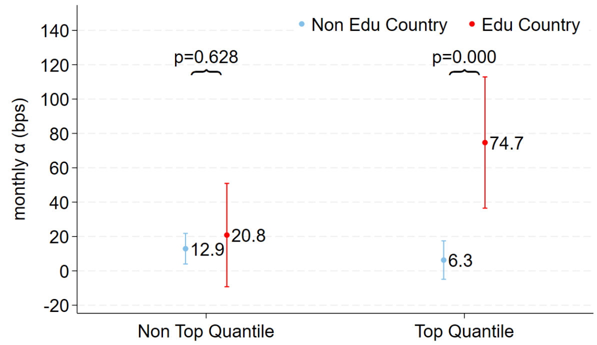
Figure 13: Portfolio α with I-measure sorting with Expanded Universe

Notes: This figure provides portfolio α with I-measure sorting with expanded funds' investment universe. The graph on the left top compares top VS non-top portfolio within either education country or non-education county with 5 factors. The graph on the right top compares education VS non-education portfolio within either top or non-top portfolio with 5 factors. The graph on the left bottom compares top VS non-top portfolio within either education country or non-education county with no factors. The graph on the right bottom compares education VS non-education portfolio within either top or non-top portfolio with no factors. The bars provide 95% confidence intervals.

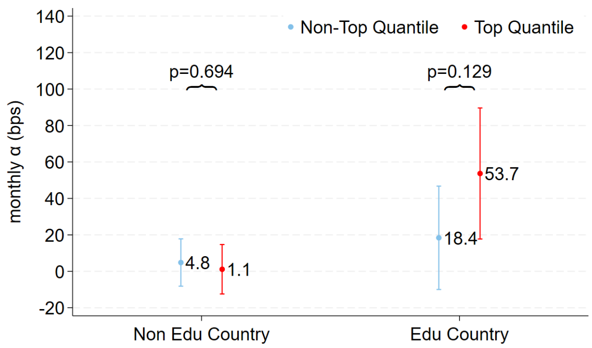
Appendix B.3 Excluding U.K. from Analysis



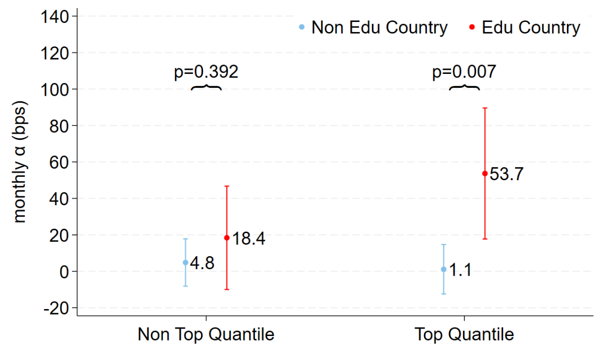
I-measure Quantile Comparison Ex-U.K.



I-measure Education Comparison Ex-U.K.



I-measure Quantile Comparison Ex-U.K.



I-measure Education Comparison Ex-U.K.

Figure 14: Portfolio α with I-measure sorting with 5 Factors Exclude U.K.

Notes: This figure provides portfolio α I-measure sorting with 5 Factors, excluding U.K. investments. The graph on the left compares top VS non-top portfolio within either education country or non-education county. The graph on the right compares education VS non-education portfolio within either top or non-top portfolio. The bars provide 95% confidence intervals.

Appendix C. Comparison to Antón et al. (2021) measure

Appendix C.1 Measure Construction

In Antón et al. (2021), the authors set up a simple portfolio choice problem as follows:

$$max_{\lambda}\lambda_t'(E_t\mathbf{R}_{t+1} - R_{f,t+1}\mathbb{1}) - \frac{k}{2}\lambda_t'\Omega_t\lambda_t \tag{12}$$

Here the managers choose vector of portfolio weight λ_t at time t to maximize risk-adjusted portfolio return. $E_t\mathbf{R}_{t+1}$ is the expect return of next time period at time t, $R_{f,t+1}$ is the risk free rate, k is risk aversion parameter, and Ω_t is the return correlation matrix.

The solution to this maximization problem is:

$$\lambda_t = \frac{1}{k}\Omega_t^{-1}(E_t\mathbf{R}_{t+1} - R_{f,t+1}\mathbb{1}) \tag{13}$$

Defining $\mu_t \equiv (E_t\mathbf{R}_{t+1} - R_{f,t+1}\mathbb{1})$, the excess return, then $\mu_t = k\Omega_t\lambda_t$. Then for the portfolio manager, the subjective CAPM α is $\mu_t - \mu_{Vt}$, where μ_{Vt} is the market portfolio (or value-weighted portfolio) of the equities in the fund's investment universe. Assuming that the variance-covariance matrix Ω is diagonal, then the subjective Sharpe Ratio will be $\frac{k\sigma_{i,t}^2(\omega_{i,t}-\omega_{V,i,t})}{\sigma_{i,t}}$ if we denote the i-th element of μ_t as $\omega_{i,t}$, $i-th$ element of μ_{Vt} as $\omega_{V,i,t}$, and $i-th$ diagonal element of Ω_t as σ_t. The the equity with largest Sharpe Ratio would be the one with the largest $\sigma_{i,t}(\omega_{i,t}-\omega_{V,i,t})$. Antón et al. (2021) refers to this measure as information ratio (IR).

σ_{it} is the predicted volatility using the following predictive regression:

$$\sigma_{i,t} = \beta\sigma_{i,t-1} + \gamma\log(Market\_Cap_{i,t-1}) + FE_{c,t} + \epsilon_{i,t} \tag{14}$$

In our specification, we use last year's volatility and the log of market cap to predict next year's volatility, and absorb for the variation in country-time level using country-time fixed effect. The regression results are reported in Table 19.

Appendix C.2 Portfolio Sorting Result

Following Antón et al. (2021), we sort each fund's portfolio at each point in time using the activeness measure $\sigma_{i,t}(\omega_{i,t} - \omega_{V,i,t})$, consistent with their methodology. We make one minor modification: instead of selecting the top X picks as in their original approach, we select the top 2% of holdings, which is approximately equivalent to the top two picks in Antón et al. (2021), given that our sample funds hold, on average, around 100 equities. This adjustment

VARIABLES	(1) Next Year Volatility
log(Market Cap)	-0.0128***
	(0.00174)
Previous Year Volatility	0.348***
	(0.0284)
Constant	0.343***
	(0.0346)
Observations	5,373,835
R-squared	0.393
TimeXCountry FE	Y
Country Cluster	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Volatility Regression

helps mitigate the high variance associated with constructing top portfolios from a very small number of equities.

It is important to note two key differences between this sorting method and the I-measure-based sorting used in our main analysis. First, this sorting is applied at the overall fund level and does not condition on country, whereas we use the I-measure to sort within country sub-portfolios. Second, the activeness measure used here does not account for differences in the investment universe between the fund and its benchmark. In Appendix C.3, we adjust for these two differences and present the corresponding sorting results.

Figure15 presents the results of replicating the methodology from Antón et al. (2021) in the international context. The left panel reports the monthly CAPM alphas for portfolios sorted by their activeness measure. The portfolio composed of the top 2% of top pick—based on the IR measure—earns a monthly alpha of 23.7 basis points, while the remaining 98% generates a monthly alpha of 8.7 basis points. Although the activeness measure from Antón et al. (2021) shows some ability to identify high-performing equities in U.S. domestic market, its effectiveness appears limited internationally. In particular, the α of the "best ideas" portfolio is not statistically significantly higher than that of the rest of the portfolio.

The right panel of Figure 15 plots the cumulative returns of the same top 2% and bottom 98% portfolios, alongside the global benchmark. Consistent with the alpha results, the "best ideas" portfolio grows approximately fivefold over the sample period—substantially less than the elevenfold growth observed for the top portfolio identified using our I-measure. These results further suggest that while activeness-based sorting directly following Antón et al.

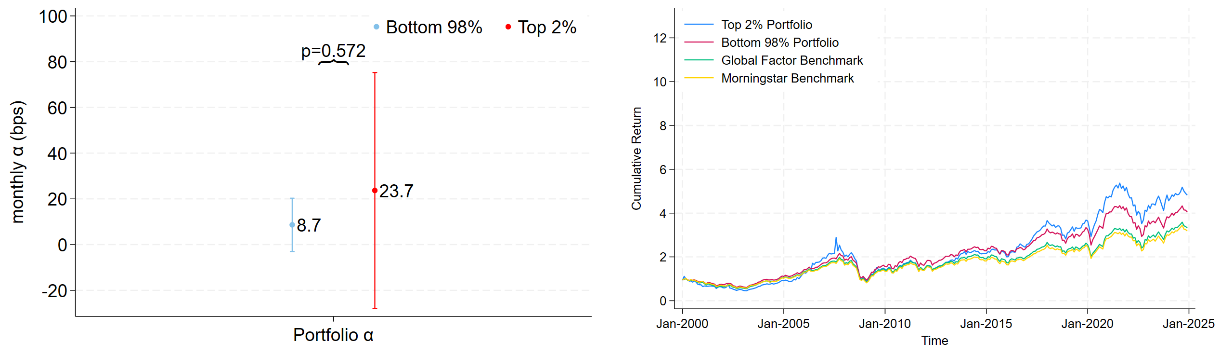


Figure 15: Antón et al. (2021) Sorted Return

Notes: This figure provides results using Antón et al. (2021) measures. Graph on the left side shows the monthly CAPM α of the "best ideas" portfolio (top 2%), the other portfolio (bottom 98%), and the p -value of their differences. Graph on the rights plots the cumulative returns of the same two portfolios and two global benchmarks.

(2021) can offer modest excess return, it is less effective than the I-measure at isolating fund managers' most informed positions in an international setting.

Appendix C.3 Sorting using Modified IR from Antón et al. (2021)

In this section, we adjust the sorting above using IR by sorting within each country sub-portfolio, and take into account the differential investment universe when constructing the measure.

In our international equity context, we suppose that the portfolio choice problem happens within the country due to friction in international equity investment across countries. Then we define the relevant market portfolio as the benchmark sub-portfolio of equities in the fund's universe in the respective country. Then the within-country portfolio choice problem follows the same derivation as above would imply that the equity with the largest $\sigma_{it}\left(\frac{\omega^i_{jc}(t)}{\sum_{i'\in\Omega_{jc}(t)}\omega^{i'}_{jc}(t)} - \frac{B^i_{jc}(t)}{\sum_{i'\in\Omega_{jc}(t)}B^{i'}_{jc}(t)}\right)$ as the one with the largest subjective α relative to the defined benchmark. This is equal to $\sigma_{it}I^i_{jc}(t)$.

Using the modified IR measure, we find that in non-education countries, the monthly 5-factor α is 10.3 basis points for the non-top portfolio and 4.8 basis points for the top portfolio. The difference between the two is not statistically significant, with a p-value of 0.659. It is worth noting that, since this measure tends to over-select high-volatility stocks into the top portfolio, the estimated α for the non-education country top portfolio exhibits substantially larger variance relative to results based on other sorting measures.

In contrast, for education countries, the monthly 5-factor α is -2.5 basis points for the non-top portfolio and 37.2 basis points for the top portfolio. The difference is statistically significant at the 5% level, with a p-value of 0.017. Furthermore, the α of the education country top portfolio is also significantly larger than that of the non-education country top portfolio, with a p-value of 0.094, significant at the 10% level.

While the modified IR sorting is not as sharp as the I-measure sorting—largely due to the tendency to select volatile small-cap equities, as discussed in Antón et al. (2021)—it nonetheless reveals a consistent pattern. The contrast between the results in Appendix C.2 and Appendix C.3 highlights two key points in the international context: the importance of conducting portfolio sorting within countries, and the importance of the interaction between education and activeness, rather than activeness alone.

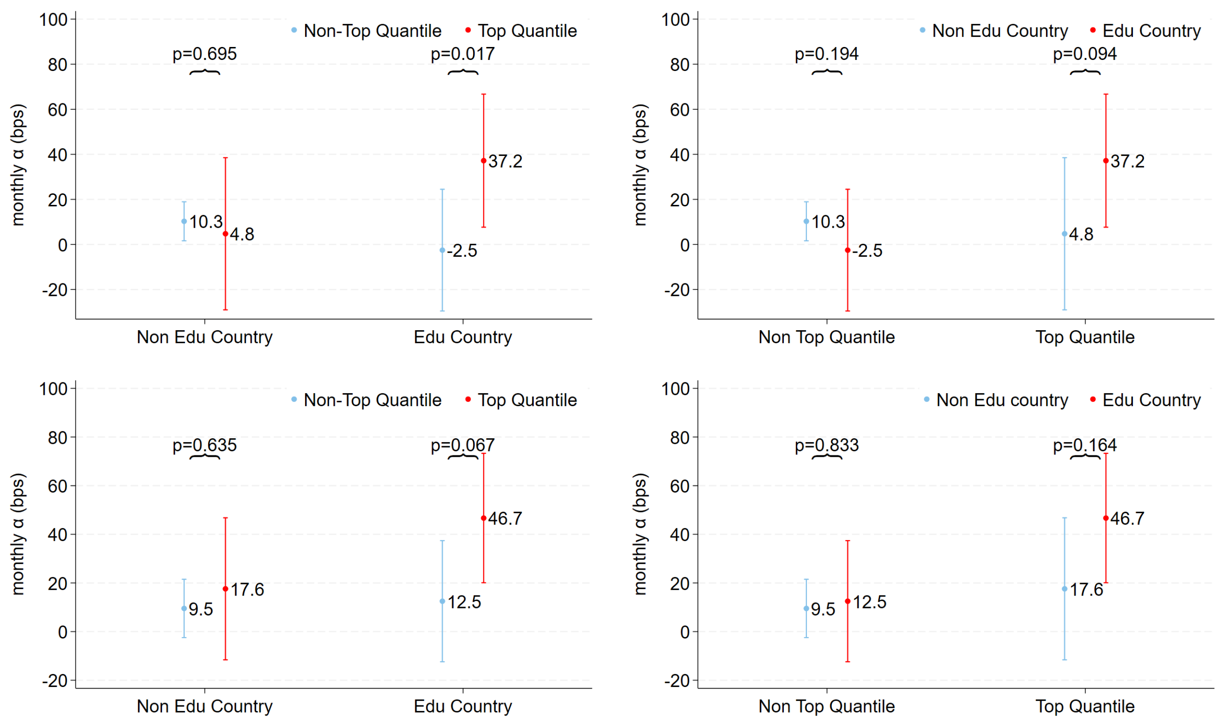


Figure 16: IR Measure Sorted Return

Notes: This figure provides portfolio α with modified IR measure sorting. The graph on the left top compares top VS non-top portfolio within either education country or non-education county with 5 factors. The graph on the right top compares education VS non-education portfolio within either top or non-top portfolio with 5 factors. The graph on the left bottom compares top VS non-top portfolio within either education country or non-education county with no factors. The graph on the right bottom compares education VS non-education portfolio within either top or non-top portfolio with no factors. The bars provide 95% confidence intervals.