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The Role of Domestic Industries in Foreign Portfolio Decisions

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Abstract: I analyze foreign portfolio decisions and performance of international mutual funds. In their foreign portfolios, funds overweight and concentrate in industries that are large in their home country. On the country level, they underweight countries with a different industry structure relative to home. This *Foreign Industry Bias* is concentrated in funds with a classical *Home Bias*. For those funds, *Foreign Industry Bias* is associated with superior performance and foreign stock picking is a significant contributor to that performance. Their foreign trades co-move with current home country and global industry returns and subsequently predict foreign stock returns. Both portfolio characteristics and performance are persistent at the one year horizon. Taken as a whole, the evidence supports the view that some funds successfully use domestically-rooted industry information when investing abroad and suggests that domestic industry structures proxy for the relative informational advantage enjoyed by different foreign investors.

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1. Introduction

The question of what drives international portfolio decisions is central in international finance because it is directly related to international risk sharing (e.g. Bekaert and Harvey (2000), Froot et al. (2001), Bekaert et al. (2002), Henry (2002)). While early research investigated the role of explicit barriers to foreign portfolio investment, the focus has shifted after most of those barriers were removed in the 1980s and 1990s. New determinants of foreign portfolio decisions, such as geographical or cultural proximity, gained prominence and were often interpreted as proxies for information flows (e.g. Portes and Rey (2005)). Yet, identifying the origins of such asymmetries remains a key challenge in linking information flows to international investment decisions. Simply put, it is difficult to trace what some investors know better than others. For example, geographic distance could measure the difficulty of collecting information or alternatively proxy for the similarity between firms to which a given piece of information applies.

In this paper, I empirically test one central hypothesis. I conjecture that the relative sizes of industries in the home country of investors proxy for information advantages when investing abroad. I view the industrial composition in the home country as an origin of asymmetric information and assume that the probability of an investor having an advantage when investing in a given industry is proportional to the relative size of that industry in his home country.

I use the dynamic model of international equity trading of Albuquerque et al. (2009) as a template and derive four empirical predictions. I test those predictions in a large universe of international mutual funds in the period 2001 to 2010. Two key characteristics make these funds exceptionally well qualified test investors. First, they have broad, pre-determined yet comparable investment styles. These geographically defined styles allow me to form an expectation about their international country exposures. Second, the funds are located around the world. Heterogeneous locations endow comparable funds with different home industry structures from which information or knowledge can be sourced.

As an example, consider two funds in the "Global Equity" style - one located in Germany, the other located in the US. My hypothesis predicts that the German fund has an advantage when investing in, say, automotive because this industry is relatively large in Germany. In contrast, the US fund is predicted to have an advantage in understanding, say, technology. Therefore, when both invest in Italy, the German fund is likely to focus on Italian automotive and the US fund on Italian technology.

Industrial structure has intuitive appeal as an origin of asymmetric information when it comes to cross-border investment because it has a clear fundamental anchor in the economy.

Industrial expertise is likely "portable" across borders because knowledge about e.g. technology and competition applies to firms worldwide. In addition, Kacperczyk et al. (2005) have shown in the domestic context that mutual funds that concentrate their holdings in few industries outperform those that do not. The authors interpret such behavior as an effort to exploit superior information. I expand on that idea by identifying the industries in which a given fund is likely to concentrate – the ones large at home.

To develop testable empirical predictions, I take guidance from theory. Albuquerque et al. (2009) develop a dynamic model of international equity trading that builds on Admati (1985) and Brennan and Cao (1997). In their model, there are multiple regions. Regional asset payoffs have both a local and a global component. All investors receive local and global public signals and additional local private signals about their home region payoffs. Finally, a fraction of investors from every region receives a global private signal. This signal is informative about the global component in payoffs and therefore useful for investing abroad. The payoff structure of assets combined with the non-symmetric information endowments generates predictions that can be taken to the data in the context of international mutual funds. To achieve that, I make two re-interpretations:

1. I interpret the "global" component in payoffs as industry specific.
2. I assume that the probability of a fund receiving a "private signal" about an industry component is proportional to the relative size of the industry in his home country.

Under those interpretations, that I discuss and justify in greater detail below, I make four predictions concerning foreign portfolio choice, performance, trading and persistence.

My first prediction is about foreign portfolio composition. If the domestic industry structure proxies for information advantages abroad, then funds will on average overweight industries that are large at home in their foreign investment decisions. This tendency can impact country allocations in two ways. First, foreign countries with a different industry structure relative to the home country are underweighted on average. Second, conditional on investing in a foreign country, informed funds have concentrated portfolios. The concentration is driven by a *Foreign Industry Bias (FIB)* towards large home industries. The intuition is that the bias against foreign assets is mitigated the more funds learn about the industry component in asset payoffs due to global private signals. Continuing with the stylized example from above, the German (US) fund is likely to have a foreign bias towards automotive (technology) because he is more likely to possess industry-specific knowledge in that industry.

To test the prediction, I run portfolio choice regressions and begin by showing that funds in general tend to overweight those industries in their foreign portfolios that are relatively large at home. For example, if a given industry is the largest in the fund's home country, it receives a 1.3%-points (t-statistic 2.00) higher foreign allocation on average controlling for other home and foreign industry characteristics. This is sizeable given an average absolute excess allocation of about 3%-points in the whole sample.

I then turn to country allocations and show that foreign countries with a different industry structure inside the investment style are, on average, underweighted. I measure *Industry Distance* as the sum of squared industry weight differences between two countries and show that the average portfolio allocation decreases by about 0.9%-points (t-statistic 2.41) per standard deviation of *Industry Distance*.

This effect is concentrated for funds with a classical *Home Bias*, where I define *Home Bias (HB)* as the excess allocation to the home country of the fund over the country allocation of all funds in the same style. Those funds underweight a given foreign country by 1.1%-points (t-statistic 3.24) per standard deviation of *Industry Distance*. Further, funds with a *Home Bias* also have a higher *Industry Concentration* and a higher *Foreign Industry Bias* in countries with a different industry structure relative to home, where I measure *Industry Concentration (ICI)* as a Herfindahl-Hirschmann Index over adjusted industry weights as in Kacperczyk et al. (2005) and *Foreign Industry Bias (FIB)* as the weighted sum of signed excess allocations where I weight foreign excess allocations on the industry level by the relative sizes of industries at home (details below). For example, for those funds, *Foreign Industry Bias* increases by 0.18 standard deviations (t-statistic 3.06) per standard deviation increase in *Industry Distance*. These effects are robust to the inclusion of a large set of known drivers of foreign portfolio decisions such as geographical distance (KM distance), cultural proximity (common language), economic ties (common currency), macro conditions (interest rate differentials, currency movements), capital structure (leverage), growth opportunities (book-to-market, capex), capital market conditions (market size, average firm size, past performance, liquidity) as well as observable and unobservable country and fund characteristics.

The result that domestic industry characteristics impact especially the foreign portfolio of funds with a classical *Home Bias* asks for a consistency check on domestic portfolios. In the model, *Home Bias* arises in the optimal portfolio choice because additional local private signals give investors a general advantage at home. Therefore, the first prediction can be qualified to apply primarily to funds with *Home Bias*. Intuitively, informed funds "max out" their holdings in their home market given their style constraint. The German (US) fund would invest as much as possible at home to exploit all his private signals. I therefore briefly turn to domestic portfolios.

On a descriptive level, the average *Home Bias* in the sample is about 6.7%. While the median fund has zero *Home Bias*, the funds at the lower (upper) quartile breakpoint have a -2%

(+10%) *Home Bias*. These figures are lower than the figures one might be familiar with from aggregate statistics but this is because funds have pre-determined geographical investment styles that put some constraint on their geographic exposure. More interestingly, when I investigate the industry composition of domestic portfolios, I find that profitability is the strongest predictor of domestic industry allocations, not size. This is consistent with the idea that relative size proxies for relative advantage but final decisions are driven by the quality of investment opportunities. In the two fund example, the German (US) fund would invest in domestic automotive (technology) only if the industry is profitable at home. Industries might be relatively large at home because of high quality firms or because of other reasons such as political support. Regardless of the reason, funds are more likely to learn about relatively large industries but optimally invest only in the best firms that could be located at home or abroad. Indeed, the most significant value-add from a thorough industry understanding might come to bear in the foreign portfolio where the investment opportunity set is large.

To capture the idea that industry knowledge is "domestically-rooted", I explicitly link foreign to domestic portfolio choices. I show that *Foreign Industry Bias* on the fund level has a strong positive association with both *Home Bias* and *Industry Concentration at home*. Naturally, the explanatory variables in that regression (*Home Bias* and *Industry Concentration at home*) are endogenous so I instrument both using home country industry characteristics. The instrumented regressions show a strong impact of domestic industries on foreign portfolio decisions.

In my second prediction, I turn to performance. If *Foreign Industry Bias* is driven by information, it should be associated with superior returns, especially for funds with a classical *Home Bias*. In the model, prices reveal fundamentals only gradually due to noise trading and learning. This makes foreign holdings of informed funds profitable on average.

To test the prediction, I aggregate *Foreign Industry Bias* to the fund level and show that funds with a positive *Home Bias* outperform by about 1% p.a. net of risk (t-statistic 4.47) per standard deviation of *Foreign Industry Bias*. This result is robust to various assumptions on the underlying factor model that is used to correct for risk (see details below) and various sample splits. For example, the result is concentrated in funds with above-median *Industry Concentration* and in those investment styles with the broadest scope in terms of expected country exposures. To complement the factor models, I perform holding decompositions in the spirit of Daniel et al. (1997) with an industry-benchmark portfolio. The decompositions confirm the result from the factor models and allow me to attribute about 50% of the aggregate effect to foreign stock picking within industries and about 11-15% to foreign industry timing.

The first two predictions are average statements about portfolio composition and performance. The dynamic nature of the model of Albuquerque et al. (2009) allows for a tighter test of the hypothesis that such behavior is information-driven by considering position changes over time – i.e. trading. The model offers distinct results on the foreign trading behavior of informed investors. The third prediction focuses on the co-movement of trades with current returns ("return chasing") as well as on the return predictability of trades.

In the model, learning about the global component in payoffs leads to "global return chasing" of informed investors. Prices display momentum because fundamental information is only gradually revealed. At the same time, due to learning, informed investors increase their foreign holdings gradually over time. This means that foreign trades are correlated both across assets and with contemporaneous returns in many countries. Intuitively, upon receiving a global private signal, our example funds would trade foreign automotive (technology). Since this signal is partially impounded into current prices, the foreign automotive (technology) trades of the German (US) fund co-move with current automotive (technology) returns in many countries, including German (US) automotive (technology) returns.

To investigate "global return chasing", I compute the correlation between foreign buy and sell transactions with various industry returns – industry returns in the destination country where the traded stock is located, in the home country and global industry returns – and indeed find a differential effect of return chasing when computed with respect to home country or global industry returns, but not when computed with respect to destination country industry returns where the stock is located. The correlation between trades and contemporaneous industry returns at home is about 2%-points higher for funds with *Home Bias* per standard deviation increase in *Foreign Industry Bias* and similarly when computed with respect to global industry returns. The effect is concentrated in the top-10 largest home industries where it reaches up to 4.5%-points (t-statistic 3.36). This seems consistent with the idea that "global private signals" should lead to "global return chasing" and may provide a channel by which information travels across borders.

The second aspect of the trading prediction is concerned with the return predictability of trades. If information is only gradually impounded into prices, then the trades over the current period should predict next period stock returns. Put differently: The Italian automotive (technology) trades of the German (US) fund should predict Italian automotive (technology) stock returns. I find that they do. For funds with *Home Bias*, the correlation between buy and sell trades and future foreign stock returns is 2%-points higher per standard deviation increase in *Foreign Industry Bias*. When I again only consider the top-10 home industries, the effect is stronger. This connects well to the results on "return chasing" as it helps to distinguish informed from uninformed trades and suggests that foreign trades of certain investors are information-driven.

The fourth and final prediction addresses persistence in portfolio choice and performance persistence. Informed funds should continue receiving “global private signals” for as long as their home country industry composition does not change drastically. This should induce persistence in their excess allocations as well as their performance. I sort funds into deciles based on *Foreign Industry Bias*, *Industry Concentration* or *Home Bias* and find that those funds in the highest current decile have the highest average future decile one year ahead. The relationship between average future deciles is strongly monotonic in current deciles. Persistence is not only limited to excess allocations. I sort funds into deciles based on various measures of previous year performance and indeed find performance persistence. Performance persistence is not only concentrated among the lower ranking funds but also among the currently high ranking funds. The persistence in performance ranks translates into statistically and economically significant performance differences one year ahead between the currently highest and lowest ranking funds of 3.3% p.a. net of risk and after expenses (t-statistic 2.14). This suggests that in the international context, investors may benefit by selecting funds based on current observables.

This study contributes to various strands of the international finance literature. A large literature investigates the determinants of foreign investment decisions. Some studies focus on firm or country characteristics at the investment destination (e.g. Kang and Stulz (1997), Ahearne et al. (2004), Gelos and Wei (2005), Covrig et al. (2006)) while others link investment and trading decisions to destination characteristics relative to the home country of investors (e.g. Grinblatt and Keloharju (2001), Chan et al. (2005), Massa and Simonov (2006), Ke et al. (2012)). To this, I add industry structure as a relevant dimension, positing that it serves as a proxy for informational advantages in international investment decisions. I thereby contribute to the debate on whether such foreign biases are familiarity-driven or the result of informational asymmetries. Both in the domestic and international context, researchers have debated whether “local” investors perform better than “non-locals” or foreigners. While some studies find superior performance in “local” or “close” investments (Kang and Stulz (1997), Coval and Moskowitz (1999, 2001), Hau (2001), Choe et al. (2005), Dvorak (2005)), others report no or negative implications of familiarity based investment; still others find that foreign trades have predictive power for domestic markets or even outperform domestic investors (see, for example, Seasholes & Zhu (2010) and Pool et al. (2012) on the first point and Froot et al. (2001) and Bailey et al. (2007) on the second). The findings here suggest that observable country characteristics (i.e. industry structure) proxy for relative information advantages among investors from different countries. Thus, I not only identify who is likely to be better informed but also the subset of assets in which the advantage is likely to be concentrated. This in turn suggests that some foreigners may outperform locals in certain stocks – namely stocks from industries large at home.

The paper proceeds as follows. In section 2, I develop the hypothesis, intuition and empirical predictions in more detail. The data, main variables and the sample are described in section 3. Section 4 presents the results of the portfolio choice regressions at the fund-industry or fund-country level and the results of the tests on the first prediction. Section 5 tests the second prediction on fund performance, while section 6 addresses the predictions on trading and persistence. I conclude in section 7.

2. Hypotheses

In this section, I develop my testable predictions in greater detail using the model of Albuquerque et al. (2009) as a template to articulate the main ideas. I provide a brief sketch of the model and then derive the testable predictions under my hypothesis that the relative sizes of domestic industries proxy for asymmetric information in foreign investment decisions.

2.A Model Summary

Albuquerque et al. (2009) develop a dynamic model of international equity trading. Its two central ingredients pertain to (1) the payoff structure of assets and (2) information endowments. I only give a brief overview of the model. Appendix A gives a more detailed summary.

The economy consists of a set of regions; every region has one asset that pays a terminal dividend. This terminal dividend is impacted by both a region-specific local factor and a global factor. The region-specific factors are uncorrelated across regions and the global factor impacts all assets in the economy. Every region is inhabited by investors and noise traders of equal sizes.

The information structure features public and private signals both about the local and global component of stock returns. Every investor receives both local and global public signals. In addition, every investor receives a local private signal that is relevant for his respective regional factor only. The first assumption is that investors start with background information in their local assets. That is, their prior beliefs are specified as if they had already observed a history of local private signals. This assumption gives locals an edge in their home assets over foreigners at the beginning of the economy.

Lastly, a fraction α of investors in every region also receives a global private signal about the global factor in stock returns. This makes the information endowments of investors non-symmetric.

The model is solved and interpreted from the perspective of US investors under the assumption that $\alpha^{US} > \alpha^{ROW}$, i.e. the fraction of informed investors who receive global private signals is larger in the US than in the rest of the world. The central results about foreign holdings, trades and performance are:

A. On average, US investors underweight foreign stocks if the initial advantage of locals is large. That is, informed US investors display a home bias.
B. On average, the bias against foreign assets is mitigated, the higher the fraction of US informed investors (α^{US} high) and the higher the precision of global private signals.
C. International stock prices display momentum. This is because prices are noisy and reflect public signal errors and liquidity trades next to fundamentals. Therefore, any innovation in fundamentals is only gradually impounded into prices. Over time, the price functions increasingly reflect fundamentals rather than signal errors because investors learn.
D. Foreign holdings of informed US investors are also increasing over time provided that the local advantage of foreigners is large and that the precision of global private signals is high. When this is true, US investors learn more about the global component because they update stronger. Therefore, their knowledge about foreign stocks catches up with foreign locals. This induces a sequence of foreign trades.

Learning of informed US investors about the global component in international stock prices therefore induces "global return chasing". Their foreign trades increasingly reflect their knowledge about the global component. This makes their trades (1) correlated across countries and (2) contemporaneously correlated with stock returns in many countries. Since prices reflect fundamental information only gradually, it makes foreign trades of US informed investors profitable.

2.B *<u>Empirical Predictions</u>*

The model of Albuquerque et al. (2009) provides a nice template for my empirical study with only a few re-interpretations to accommodate the role of domestic industries.

1. <u>The payoff structure:</u> I assume a payoff structure where the local factor is an asset specific factor and the global factor is an industry specific factor that applies to all stocks in the same industry.

2. <u>Recipients of global private signals:</u> I view countries as portfolios of industries and assume that the fraction of investors from a given country that receive global private signals about the industry component in payoffs is proportional to the relative size of the industry in that country. In other words, let c denote countries, i denote industries, $\alpha_{c,i}$ denote the fraction of investors from country c that receive global private signals about industry i and $\Omega_{c,i}$ the fraction of industry i in country c. I assume that

$$\alpha_{c,i} \propto \Omega_{c,i} \tag{1}$$

For any given individual fund from country c, $\alpha_{c,i}$ can be interpreted as the probability that the fund receives global private signals about industry i. This is the central hypothesis of the paper.

Under these assumptions (see further discussion below), I can directly formulate my empirical predictions. The first prediction is on the average foreign portfolio composition of funds.

<u>Prediction 1: Foreign Industry Bias:</u> In their foreign portfolio, funds on average overweight those industries large at home. On the country level, they underweight foreign countries with a different industry structure relative to home.

Prediction 1 follows from the average foreign asset holdings described by results A. and B. in the previous section (equation (21) in Appendix A). The higher the chance that a fund receives global private signals about a given asset, the lower the foreign bias against that asset. Therefore, in the portfolio of foreign assets, funds that receive global private signals overweight stocks from large home industries on average. On the country level, this leads to a heavier underweighting of foreign countries with a different industry structure relative to home.

An important condition for the results in the model is the initial advantage of locals due to local private information. This generates underweighting of foreign stocks (i.e. home bias) in the first place. Therefore, the results of prediction 1 can be qualified.

<u>Prediction 1b:</u> Foreign Industry Bias is pronounced for funds with Home Bias.

Moving from portfolio choice to performance delivers the next predictions. If the global private signal view is correct, then holdings and trades of funds that receive such signals generate high performance. This is for two reasons. First, the holdings of informed funds reflect their relative advantages in foreign assets and their foreign trades are increasingly driven by global factors due to learning. Second, learning also implies that stock prices increasingly reflect fundamentals rather than signal errors. Therefore, holdings, trades and stock returns go hand-in-hand.

<u>*Prediction 2: Performance:*</u> *Foreign Industry Bias is associated with positive performance, especially for funds with a Home Bias.*

<u>*Prediction 3: Trading:*</u> *Foreign trades of funds with a Foreign Industry Bias display "global return chasing" and predict foreign stock returns.*

Predictions 2 and 3 help separating prediction 1 from an alternative framework in which portfolio choice is a manifestation of behavioral or familiarity biases. In such an alternative framework, there is likely no clear return implication. If *Foreign Industry Bias* is information driven, it should generate returns.

Prediction 3 exploits the dynamic context of the model. Learning about global factors introduces a correlation both between trades and contemporaneous returns and between trades and future returns. Since informed investors learn about the global component in payoffs, their foreign trades are correlated across countries and co-move with returns in many countries, including their home country. This defines "global return chasing" as a distinct characteristic of informed investors. Likewise, if trades are information driven, they predict future stock returns provided that this information will be impounded into prices going forward.

The final prediction is about persistence. Equation (1) is the central hypothesis of the paper. The probability of a given fund receiving global private signals about industry i is proportional to the relative size of the industry in his home country. Therefore, for as long as the industrial composition of countries does not change drastically, a given informed fund will continue receiving global private signals about the industry over time. This should induce persistence both in his portfolio choice and his performance.

<u>*Prediction 4: Persistence:*</u> *Portfolio choices and performance are persistent.*

2.C <u>Discussion</u>

I briefly discuss the main empirical assumptions I make and how the context of international mutual funds impacts my empirical strategy.

I make the simplifying assumption that asset payoffs have two components – an idiosyncratic component and an industry component. The advantage of foreigners comes via private signals about the industry component. These private signals could pertain to, for instance, information about technology or competition in the industry that affects all firms. There is a lively debate in the international literature on the components that drive global stock returns. While some early papers find conflicting evidence on the importance of industry components in global stock returns (e.g. Roll (1992), Heston and Rouwenhorst (1996), Griffin and Karolyi (1998)), recent studies identify industrial structure as an important determinant of international stock price co-movement (e.g. Dumas et al. (2003), Carrieri et al. (2004, 2008), Dutt and Mihov (Forthcoming)). I do not intend to actively contribute to this debate but assume that there is an industry component and that learning about this component can give foreigners an edge abroad. I justify this assumption with results that have established the link between industry and aggregate returns as well as the links between related industries when it comes to predictability and co-movement (e.g. Hou (2007), Hong et al. (2007), Cohen and Frazzini (2008), Menzly and Ozbas (2011)).

One generalization that the model of Albuquerque et al. (2009) makes is that all stocks have the same (unit) loading on the global factor. A strict interpretation would therefore posit that informed funds generate their performance abroad primarily by industry timing. A less strict interpretation could posit that global private signals are informative about developments in technology and competition and that informed funds not only understand these developments but are also able to identify those firms most capable of profiting from them. In the model, one could imagine e.g. a firm specific loading on the industry component. This would also open up some room to generate performance abroad by stock picking within industries.

My test investors are international mutual funds. These funds have pre-determined geographic investment styles but heterogeneous locations around the world. This provides a helpful identifying restriction. Investment styles are geographically defined and I view them as some form of “soft constraint” on the geographical exposures of funds. This allows me to form an expectation about the countries in which a fund should invest. In other words, style defines the investment opportunity set. Since the expectation is with respect to country allocations, but not industry allocations, a tension arises for those investors who indeed have an information advantage in some assets. Within the boundaries of the styles, these funds will deviate from a well-diversified portfolio in a predictable fashion, depending on their relative advantage. Relative advantages differ across comparable funds depending on their information endowments that are rooted in their domestic economy. Analyzing these deviations and associated performance implications is the empirical strategy I take.

I use the model of Albuquerque et al. (2009) as a template but there are other models of portfolio choice under asymmetric information that can deliver many of the predictions I make. For example, van Nieuwerburgh and Veldkamp (2009, 2010) model information and portfolio choice jointly and show that if some investors have an initial advantage in some assets, they may optimally specialize and learn only about those assets. Industrial composition in the home country of investors can be interpreted as a proxy for such an initial advantage along which investors specialize. In the international context, such specialization is valuable because (1) investors can expect to trade against other foreigners or locals that may not share the same advantages when they invest abroad and (2) the foreign pool of assets might be very large. Both reasons make specialization valuable. Such a view can provide predictions on portfolio choice, performance and persistence that are similar to the ones I investigate in this paper.

3. Data

3.A Data Sources

I employ multiple data sources. International mutual fund holdings are taken from the FactSet/LionShares database. FactSet/LionShares reports holdings of a large variety of investment vehicles from all around the world. Ferreira and Matos (2009) describe the database in detail. The dataset contains holdings as well as information on the firm in charge of managing the portfolios. Importantly, FactSet/LionShares not only reports the country in which a given fund is domiciled but also the country of residence of the management company. I define the 'home country' of the fund as the country of residence of its management company rather than its legal domicile. This avoids overweighting offshore locations that attract a lot of incorporations due to preferential tax treatment or other reasons. All distinct home countries are presented in panel F of Table 1 and are described in greater detail below. I obtain semi-annual holdings for all funds and complement them with international stock price data collected from Thomson-Datastream to which I apply the filters suggested in Ince & Porter (2006).[1]

Monthly fund returns are taken from the Morningstar-Direct database, section global open-ended funds. The link is provided by FactSet and complemented by comparing the actual fund names with a string comparison and then verified by hand. From Morningstar-Direct, I obtain monthly fund returns as well as control variables such as expenses and share-class information. I also obtain a classification that assigns funds into investment styles based on their geographic investment focus (e.g. "Global Equity" versus "Asia ex Japan Equity") as well as stock-characteristics for major styles (e.g. large-cap versus mid/small-cap). I use the Morningstar classification instead of self-declared fund benchmarks to infer the investment

[1] The key filters remove large returns that reverse in the next month, i.e. when r_t or r_{t+1} are greater than 400% but $(1 + r_t) * (1 + r_{t+1}) - 1 < 50\%$ then both are set to missing. Further returns that are stale for two successive periods and penny stocks with a price < 0.25 USD are set to missing. Finally, I treat as missing the returns that fall outside the 0.1% and 99.9% percentile ranges.

opportunity set of funds, similar to Cremers et al. (2011). This avoids the problem of funds strategically picking their benchmarks. Further, I use the style classification primarily to learn about the countries in which comparable funds invest (see details below). I subsequently focus on the within-country industry composition of portfolios and how industry weights of funds deviate from the representation of the industry in the local market which should make my choice of benchmark relatively robust with respect to measurement error.

To construct country-level industry structures as well as risk factors, I download accounting data for every firm in every country from the Worldscope database via Thomson-Datastream. I link firm-level accounting data to stock prices from Thomson-Datastream, aggregating multiple share classes of firms when necessary to ensure every firm only enters the calculations once per time period. I take the stock returns of the equity security flagged as "Major Security" in Datastream. In cases where it has multiple listings, I take the quote associated with its primary listing. I assign firms to countries based on the variable "Market" in Datastream.

In some specifications I include macro-level control variables. Monthly data on interest rate differentials and exchange rates are downloaded from Thomson Datastream. For the interest rate, I take the three-month interbank rate of the country when available, or alternatively a comparable three-month rate such as on government bonds. For exchange rates, I download the monthly rates of all currencies against the US dollar and compute cross-rates directly from those rates if necessary. Country-level macro variables such as GDP, GDP growth and population are taken from the IMF World Economic Outlook.

3.B Sample & Main Variables

I focus on international funds that have a broad mandate to invest in multiple countries and are classified as "Equity" in Morningstar. Since I require fund managers to have some discretion in their investment choices along the country and industry dimension, I drop all country funds that are dedicated to one country, either directly via their style or because they consistently only invest in one country (i.e. all funds in the styles "US Equity Large Cap Value", "Japan Equity", "UK Equity Large Cap" etc. are dropped). I also drop sector funds that are specialized in one particular industry. Finally I drop passive index funds and funds with less than 5 million USD assets under management. This leaves 13 distinct investment styles with international mandates. For each style, I determine the set of countries in which funds typically invest. The set comprises those countries in which all funds in the style invest at least 90%[2] of their TNA on average. I define the variable *Scope* as the number of countries in the investment focus of each

[2] Results are robust to this threshold, e.g. setting it at 75% delivers similar results.

style. The 13 distinct styles are presented in panel E of Table 1 and are described in greater detail below.

For every fund, I define a set of main variables. I use the following indices: j = fund, s = investment style, h = home country, c = investment destination country, i = industry and t = time. Variables denoted by ω refer to portfolio percentage-fractions chosen by the fund (i.e. choice variables), while variables denoted by Ω refer to percentage-fractions in terms of market capitalization of, for example, the destination country or the destination industry (i.e. country or industry characteristics). $CountyShare_{j,c,t}$ is the percentage-fraction of fund j allocated to country c at time t. Formally,

$$CountryShare_{j,c,t} = \omega_{j,c,t} \tag{2}$$

Likewise, the variable $IndustryShare_{j,i,t} = \omega_{j,i,t}$ is the percentage-fraction of fund j allocated to industry i at time t. $ForeignIndustryShare_{j,i,t}$ is the same variable, only taking foreign positions from the perspective of the fund into account. $HomeBias(HB)_{j,s,h,t}$ is defined as

$$HB_{j,s,h,t} = \omega_{j,s,h,t} - \mathrm{E}\left[\omega_{s,h}\right] \tag{3}$$

where $\omega_{\mathrm{j,s,h,t}}$ is the percentage-fraction of the fund allocated to his home country and $\mathrm{E}\left[\omega_{\mathrm{s,h}}\right]$ is estimated as the average percentage-fraction allocated to country h of all funds in style s. For the most part, I use $HB_{j,s,h,t}$ only as a conditioning variable when I analyze foreign portfolio decisions. To facilitate the economic interpretation, I work with a dummy variable

$$HasHB_{j,s,h,t} = \begin{cases} 1 & if\ HB_{j,s,h,t} > \overline{HB_{j,s,h,t}} \\ 0 & otherwise \end{cases} \tag{4}$$

A fund is defined as having a *HomeBias* if the value of $HB_{j,s,h,t}$ is above the mean in sample. The mean is about 6.7% (see panel B in table 1, more details below). The purpose of the variable is to separate those funds that overweight the home country relative to all funds in their style from those that underweight or stay approximately neutral. The exact definition of the threshold does not matter, the results are unaffected when, for example, defining terciles, setting it arbitrarily at 5% or directly using the original $HB_{j,s,h,t}$ variable in interactions. Such specifications are presented in robustness tests.

The main focus is on portfolio composition, especially along the industry dimension. I follow Kacperczyk et al. (2005) and define the country-level industry concentration of funds as

$$ICIinCountry_{j,c,t} = \sum_{i \in I(c)} \left(\omega_{j,i,c,t} - \Omega_{i,c,t}\right)^2 \tag{5}$$

While $ICIinCountry_{j,c,t}$ is informative, it does not allow for an identification of the industries that are over-/underweighted because excess allocations have lost their sign. As such, I define a measure of $ForeignIndustryBias$ as

$$FIBinCountry_{\mathrm{j,c,t}} = \sum_{\mathrm{i \in I(c)}} \left(\omega_{j,i,c,t} - \Omega_{i,c,t}\right) \times \Omega_{i,h,t} \tag{6}$$

where $\Omega_{h,i,t}$ is the share of industry i in the funds' home country h. The summation is taken over all industries in which country c has firms at time t and $\Omega_{h,i,t}$ is scaled to sum to one given the industry structure of country c. I compute country-level industry shares based on the market value of equity of all firms in the Worldscope database. Panel D of Table 1 presents the industry classification obtained from Datastream that is used in the construction of all industry related variables. The classification is quite granular and was previously used in an international setting by Bekaert et al. (2007, 2011).

$FIBinCountry_{j,c,t}$ measures the extent to which a fund over-/underweights industries that are large/small in his home country. Another interpretation, visualized by opening the brackets, would be the covariance of the funds' within country portfolio choice with his home industry structure corrected for the natural industry covariance of the two countries.

To obtain an aggregate measure of *ForeignIndustryBias (FIB)* on the fund level, I aggregate $FIBinCountry_{j,c,t}$ over all countries in the investment focus of the style (conditional on the fund investing there), excluding the home country of the fund.

$$FIB_{j,t} = \sum_{\mathrm{c \in C \neq h}} W_{c,t} \times FIBinCountry_{\mathrm{j,c,t}} \tag{7}$$

where $W_{c,t}$ is a weight given to country c. I construct three varieties of $FIB_{j,t}$ – equally weighted, weighted by the fund's TNA allocation to country c, and weighted by the market capitalization of country c. All measures deliver similar results. The baseline regressions use the equally weighted measures and results using the weighted measures are presented in the robustness tests. The variable $ICI_{j,t}$ aggregates the country-level $ICIinCountry_{j,c,t}$ in the same way.

The main distance variable I am interested in measures how different or similar the home country is in terms of industry composition relative to the investment destination countries of the fund. Define

$$IndustryDistance_{h,c,t} = \sum_{\mathrm{i \in I(h,c)}} \left(\Omega_{i,h,t} - \Omega_{i,c,t} \right)^2 \tag{8}$$

where the set $I(h,c)$ includes all industries in which either home country h or destination country c has firms. Industry shares are defined based on the market value of equity of all firms in Worldscope and based on sales as a robustness test.

3.C Control Variables – Investment Regressions

Further variables relating to the distance between fund location and investment destination are *KMDistance* as the distance in thousands of kilometers between country capitals. The variable is calculated from GPS coordinates obtained from the CIA World Factbook.[3] From the same source I establish if the two countries share an official language (common currency) and define *CommonLanguage* (*CommonCurrency*) as equal to one in this case to proxy for cultural affinity (economic ties). Since I perform the analysis on variables converted to US dollars, I need to control for confounding effects from interest rates and currency movements. To my knowledge, there is no established procedure in the mutual fund literature which is why I experiment with various controls. *IRDifferential* is the difference in the level of interest rates between the home country and the investment destination. I compute the difference on the short-term rate (3-month). *ChangeCrossRate* is the change in the exchange rate between the home country and investment destination, where positive values indicate a depreciation of the home currency vis-à-vis the destination currency over the period. The variable is computed from cross-rates that are calculated from all downloaded exchange rates relative to the US dollar. *FXChangetoUSD* is the same variable always for the home currency against the US dollar.

I also consider a set of variables that are structurally identical to the variable *IndustryDistance* but measure other dimensions along which two countries could be similar or different. *BTMDistance* is the squared difference of the average book-to-market ratio of firms in the country. It measures the average profile in terms of value versus growth firms in the country pair. *ROADistance*, *SizeDistance*, *CapextoSalesDistance*, *TurnoverDistance* and *GDPpcDistance* are constructed in the same fashion using the average ROA, the global size percentile, capital expenditure scaled by sales, stock market turnover and GDP per capita as relevant metrics along which two countries could be similar or different. Since I want to test *IndustryDistance* as a relevant dimension, these variables are designed to be other informative dimensions or possible falsification tests.

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[3] https://www.cia.gov/library/publications/the-world-factbook/

All country-level investment regressions include destination country fixed effects to control for time-invariant and unobservable country characteristics. Nevertheless, I include a set of time-varying country-level control variables. Variables used to capture broad macro and stock market development are *GDPpc* as the GDP per capita, and *MCAPbyGDP* as the ratio stock market capitalization divided by GDP. *PastCountryReturn* is the trailing one-year return on the stock market of the destination country to control for funds chasing high-performing markets. *CountrySize*, *CountryROS* and *CountryBTM* are the log of total market capitalization, average return-on-sales and book-to-market respectively. I construct a set of liquidity variables at the country level. *CountryAmihud* is the value weighted average of stock specific Amihud illiquidity measures, *CountryVolumebyMCAP* is the total trading volume divided by the market capitalization of the country, and *CountryZeroReturns* is the fraction of all daily returns that are exactly 0. All liquidity variables are computed monthly from daily price, return and volume data. I also include a set of home country characteristics such as *HomeCountrySize* (log of home market capitalization), *HomeCountryBTM* and *HomeCountryROS* as the average book-to-market and ROS respectively, as well as *HomeCountryIndustryConcentration* as a Herfindahl index over all industry weights in the home country. Unobserved home characteristics are in various specifications controlled via home country or even fund fixed effects. When I analyze industry allocations, I compute similar variables at the industry level, both domestic and foreign.

3.D Fund Performance & Fund Control Variables

For every fund, I compute various measures of performance and control variables. From Morningstar-Direct, I obtain monthly fund returns net of fees. I add back one-twelfth of the annual expense ratio to obtain fund returns gross of fees. Subtracting the risk-free rate from Kenneth French's website delivers excess fund returns.

I correct for risk using factor corrections. For every individual country with firms in the Worldscope database, I construct international Fama-French-Carhart factors using all firms in Worldscope, following closely the methodologies of Fama and French (1993) and Carhart (1997). I estimate fund performance using two sets of factor models – style specific ("local") and global factor models, each with 1, 3 or 4 factors. In the style specific models, fund returns are corrected using style factors that take weighted averages over all country-specific market / size / value / momentum factors in the investment focus of the style. For example, fund performance in the "Europe Equity Mid/Small Cap" style is corrected for risk using factors that are the weighted average of individual country factors in Europe. This is the direct extension to the standard approach in the US domestic literature in which US domestic funds are corrected for risk using US-based factors. Moreover, Griffin (2002) as well as Fama and French (2012) show that local factors deliver the best fit and the lowest intercepts in cross-country comparisons –

better than global factors. They are even superior to factor models that include local as well as global factors when it comes to out-of-sample performance. Cremers et al. (2011) take a similar approach.

To alleviate concerns about model misspecification, I present a variety of alternative factor corrections. First, I compute global factors that are weighted averages over all countries and do not vary by style. Second, Hunter et al. (2011) propose an "endogenous benchmark" model where a factor based on an equally weighted investment in all funds of the same investment style is added to the first stage regression. They show that adding such a fifth factor both reduces the average cross-sectional correlation of residuals across funds and improves fund selection, as it corrects for common investment strategies that may not be captured by standard factors. Third, in the spirit of Ferson and Harvey (1991), Ferson and Schadt (1996) and Ferson & Harvey (1999), I estimate conditional factor models using instruments that have been shown to improve conditional asset pricing tests such as the dividend yield, the credit spread and the yield spread.

Fund performance ("alpha") is calculated by first estimating factor loadings over the previous 36-month rolling window requiring at least 24 return observations and second computing the difference between actual returns and predicted returns using the estimated loadings. This filters out funds younger than two years and addresses potential incubation biases. For the conditional factor models, I estimate the first stage loadings in one pooled regression for every fund. In addition, I control for interest rates and currency effects on the right-hand side in the regressions using the variables introduced above, aggregated to the fund level. Again, I am not aware of an established procedure in the international mutual fund literature, but controlling for currency effects in this way seems intuitive as these effects are not specific to the investment style but rather to the fund's location (i.e. its home currency).

I perform a holdings-based analysis of performance to complement the factor-based approach. For every fund, I compute holdings returns using the semi-annual portfolio holdings. *HoldingsReturn* is defined as

$$HoldingsReturn_{\mathrm{j,t\rightarrow t+\tau}} = \sum_{\mathrm{k \in K}} \omega_{\mathrm{j,k,t}} \times \mathrm{R}_{\mathrm{k,t\rightarrow t+\tau}} \tag{9}$$

where $\omega_{\mathrm{j,k,t}}$ is the weight computed from the most recently published number of stocks held (adjusted for splits or other capital actions if necessary) multiplied by the last months' closing price, and $R_{k,t\rightarrow t+\tau}$ is the return of the stock over the next six months. I decompose *HoldingsReturn* in the spirit of Daniel et al. (1997) but with a style-specific industry benchmark portfolio. The benchmark portfolio of stock k is a value-weighted average of all stocks in the in same industry of stock k over the universe of stocks in which the fund invests conditional on its style. For example, the benchmark portfolio for an automotive stock when held in the "European Equity Large Cap" style consists of all automotive stocks in Europe. When the same stock is held in the "Global Equity" style, its benchmark portfolio consists of all global automotive stocks. Hence, the benchmark portfolios are style specific in order to control for the investment opportunity set the funds face when assessing, for example, stock-picking ability. The decomposition is then defined in the standard fashion as:

$$\begin{aligned} HoldingsReturn_{j,t\to t+\tau} \\ &= \sum_{k\in K} \omega_{j,k,t} \times (R_{k,t\to t+\tau} - R_{I-BM,t\to t+\tau}) \\ &+ \sum_{k\in K} (\omega_{j,k,t} - \omega_{j,k,t-\tau}) \times R_{I-BM,t\to t+\tau} \\ &+ \sum_{k\in K} \omega_{j,k,t-\tau} \times R_{I-BM,t\to t+\tau} \\ &= ICS_{j,t\to t+\tau} + ICT_{j,t\to t+\tau} + IAS_{j,t\to t+\tau} \end{aligned} \tag{10}$$

where *ICS ("Industry-Characteristic Selectivity")* measures stock picking within industries, *ICT ("Industry-Characteristic Timing")* measures industry timing and *IAS ("Industry-Average Style")* measures the average industry return. These variables are computed both for the entire portfolio as well as for the foreign sub-portfolio only.[4]

Prediction 3 analyzes foreign trading behavior via the correlation of trades with either contemporaneous industry or future stock returns. Only foreign trades are considered. The variable *ForeignCor(%Buy,LocalRet)* is defined as

$$ForeignCor(\%Buy, LocalRet)_{j,t} = Correlation(\%Buy_{j,k,c,i,t-\tau\to t}, R_{c,i,t-\tau\to t}) \tag{11}$$

where $\%Buy_{k,c,i,t-\tau\to t}$ is the percentage increase in the position of stock k in country c that belongs to industry i over the last six months, and $R_{c,i,t-\tau\to t}$ is the contemporaneous return of industry i in country c. This variable is then computed for buy, sell and total transactions. The correlation is computed with respect to local destination industry returns, home country industry returns, and global industry returns. I also use a condensed version, e.g. $ForeignTop10Cor(\%Buy, LocalRet)$, that only considers the top-10 industries in the home country of funds.

[4] Notice that stocks do not change industries in Worldscope, which is why the decomposition is written as it is.

Predictability is tested with similarly constructed variables that replace the contemporaneous industry return with the future stock return one or two quarters ahead after the most recent portfolio publication date. These variables again consider either all foreign trades or only foreign trades in the top-10 home industries. They are labeled, for example, *ForeignCor(%Buy,FutRet-1q)* for the correlation between the percentages of foreign purchases and one-quarter-ahead stock returns. As a robustness test, I compute correlations with simply buy/sell dummies instead of percentage increases/decreases.

Additional fund controls include *Fundsize* as the log of fund TNA, *Firmsize* as the log of 1 plus the TNA of all funds managed in the management company excluding the fund itself, *Age* as the fund age in years since inception, *Expenses* as the percentage annual expense ratio, *InstShareClass* as a dummy if the fund offers a share-class dedicated to institutional investors only, *ShareClasses* as the number of different share-classes of the fund, *Pastreturn* as the cumulative fund return over the trailing 12 months, *Volatility* as the annualized standard deviation of fund returns over the trailing 12 months, and *Turnover* computed from semi-annual holdings as the change in the position of every stock multiplied by the beginning of the period price and divided by fund TNA.

3.E *Descriptive Statistics*

Table 1 presents descriptive statistics on the sample. In Panel A, I give the number of funds in the sample as of December of each calendar year. The sample starts in 2001, with the first portfolio snapshots taken as of December 31, 2000, and ends in 2010. The sample size grows considerably for all but the last year in the sample, reaching a peak of 2763 distinct funds in 2009. In the last sample year, the number falls to 2114 funds, presumably in the aftermath of the financial crisis.

In Panel B, I report summary statistics on the fund level. The average fund in the sample has a 6.7% *HomeBias (HB)*. The median *HB* is 0, but the overall distribution is slightly skewed. The level of *HomeBias* is lower than, for example, in Hau and Rey (2008), who provide estimates of home bias from the predecessor database of FactSet/LionShares on the fund level. The difference is that they consider all funds from a given country and do not explicitly correct for the expected level of home investment given the investment style of the fund. *ForeignIndustryBias (FIB)* is a well-behaved symmetric variable, centered on 0. The average *IndustryConcentration* (*ICI)* is 36.7%, which is almost the same as the median (34,1%). The average fund in the sample has a TNA of 723.1 million USD and is managed in a firm that manages over 29 billion USD in mutual fund assets. From columns 2-5 of the panel, it is evident that the means are quite skewed due to a few large funds and a few large management companies. The average expense ratio is 1.7% p.a., somewhat higher than in the domestic US literature but comparable to the sample of multi-country funds in Cremers et al. (2011), and the average age is 11 years, somewhat younger than in the domestic US literature. All remaining fund variables seem to be broadly in line with other mutual fund studies. The average volatility of monthly fund returns is 18.6% annualized, average turnover is 64% over a semi-annual period, and the average gross-return is about 0.86% per month. Also consistent with the tenor in the mutual fund literature, the average 4-factor alpha is about 4.0 bp per month before fees and a negative 7.5 bp a month after fees.

In Panel C, I present a correlation matrix of the main fund-level variables over the entire sample. *HB* is positively correlated with both *FIB* (13%) and *ICI* (37%). *HB*, *FIB* and *ICI* are all positively correlated with both gross and net performance and negatively correlated with fund size. Panel D presents the industry classification employed. This is the same metric used by, for example, Bekaert et al. (2007, 2011). The metric is quite granular and covers 42 different industries.

In Panel E, I present the style classification as well as the sample evolution by style. The panel lists the 13 distinct Morningstar investment styles, which cover the global investment universe for international mandates. The styles are heterogeneous and include broad global mandates that span all major capital markets in the world, as well as more regional mandates that are narrower in scope. The mandates cover both developed and emerging markets. Columns 2 to 5 show the evolution of the sample over time according to style. The relative size per style in the sample is quite constant. Most styles grow in tandem with the aggregate for the first years in the sample and shrink in the last year.

The last two columns display the investment focus – i.e. the set of countries in which funds of that style typically invest – as well as the variable *Scope* that is a simple count of the countries to which the average fund in the style is expected to have exposure. The *Scope* is quite heterogeneous, ranging from two countries in the Latin America Equity style to 19 countries in the “Global Equity Mid/Small Cap” style.

About 47% of funds have a global investment mandate – they are part of one of the three “Global Equity” styles. These funds invest primarily in developed equity markets in North America, Europe and Asia (see column 6). The second biggest group consists of European focused styles. They make up about 35% of the sample. In those styles, funds focus on developed European equity markets. The remaining part of the sample focusses on Emerging Markets (11%) and mostly developed Asia (7%).

Finally, Panel F of Table 1 summarizes the geographic distribution of funds around the world. The location of the fund is defined as the location of its management company that is in charge of managing the portfolio and taking investment decisions. Almost 20% of funds are managed from the US and about 70% of funds are managed from Europe. As the table illustrates, the European funds are managed primarily in the main capital markets of Europe with the UK contributing the largest share (16% of the total sample), followed by France (11%) and Germany (8%). About 6% of all funds are managed from Asia. Important for this study, very few funds are managed from offshore locations that are known to attract fund incorporations due to preferential tax treatment but few other industries. To the contrary, the vast majority of funds are situated in countries that also have developed industrial structures.

4. Industry and Country Allocations

In this section, I present portfolio choice regressions that analyze both industry and country allocations of the sample of global mutual funds. The observational level is the portfolio choice variable for a given fund at a given point in time, either at the industry or the country level. All regressions are run at the semi-annual frequency. The results presented in subsections 4.A-4.C constitute the test of the first prediction on *ForeignIndustryBias*.

4.A Industry Regressions

I begin by decomposing the portfolios of funds along the industry dimension. In Table 2, I present panel regressions where the dependent variable is *IndustryShare* (or alternatively *ExIndustryShare*), i.e. the percentage of the portfolio invested in industry i (in excess of its market capitalization). The regression equation is

$$(Ex)Ind.Share_{j,i,t} = \beta_1 A_{h,i,t} + \beta_2 B_{s,i,t} + \beta_3 C_{h,t} + \beta_4 D_{j,t} + \alpha_t + \alpha_i + \alpha_h + \epsilon_{j,i,t} \tag{12}$$

where the vector $A_{h,i,t}$ contains a set of home industry characteristics such as its percentage share in the domestic market capitalization (*HomeCtryIndustryShare*), its size, profitability, growth opportunities and leverage. The vector $B_{s,i,t}$ has the same characteristics but for the remaining foreign part of industry i. The estimation further includes the vectors $C_{h,t}$ of home country characteristics, $D_{j,t}$ of fund characteristics, all of which are defined in the previous section but unreported for brevity as well as time, industry and home country fixed effects. As a baseline, I consider the top-20 industries in each investment style measured by their market capitalization. Inference is calculated from standard errors clustered along the home country-industry pair dimension.

Columns 1 and 2 of Table 2 consider the total fund portfolio. The dependent variable in column 1 is *IndustryShare*, in column 2 it is *ExIndustryShare*. The results show that the relative size of the industry at home is a significant determinant of the overall industry composition of funds. An industry with a 10% weight in the domestic economy is associated with about a 1.1% excess allocation (t-statistic 3.44) in the total portfolio (column 2). This is economically sizeable given an average absolute excess allocation of about 3% in the sample.

In columns 3 to 6, I only consider the foreign sub-portfolio. In all regressions, the relative size of a given industry at home is a strong determinant of foreign industry allocations. When a given industry is the largest in the home country of the fund, it receives on average a 1.3% (t-statistic 2.00) higher allocation in the foreign portfolio (column 4). A domestic industry with a 10% weight receives an average excess allocation of almost 1% (t-statistic 2.27) in the foreign portfolio (column 5). Limiting the sample to the top-10 industries in style only (column 6) does not affect the result.

From these columns it is also clear that the relative size of the industry at home is the strongest predictor of foreign allocations. In columns 3 and 4, where the dependent variable is *ForeignIndustryShare*, foreign industry characteristics such as size (+), profitability (+), leverage (-) and book-to-market (-) are significant determinants. All except profitability lose significance in columns 5 and 6 where the dependent variable is *ExForeignIndustryShare* that only considers excess allocations. These regressions already capture a good part of the idea that the relative sizes of industries at home proxy for expertise once funds invest abroad, where they face a large opportunity set of stocks as opposed to a potentially limited opportunity set of stocks when they invest at home.

4.B *Country Allocations*

If foreign fund portfolios show an industry bias towards large home industries, then countries with an industry structure different from the home country are likely to receive lower allocations on average. I test this prediction by slicing the fund portfolios along the country – rather than the industry – dimension, and running semi-annual fund-country investment regression of the form

$$(Ex)CountryShare_{j,c,t} = \beta_1 A_{h,c,t} + \beta_2 B_{c,t} + \beta_3 C_{j,t} + \alpha_t + \alpha_c + \left(\alpha_j\right) + \epsilon_{j,c,t} \tag{13}$$

where the vector $A_{h,c,t}$ contains measures of distance between the country pair *h*-*c*, such as *IndustryDistance*, *KMDistance*, etc., the vector $B_{c,t}$ contains destination country characteristics of country c and $C_{j,t}$ contains fund characteristics. The regressions include all countries in the investment focus of the style. That is, the regressions are unconditional on the fund investing in country c. Inference is calculated from standard errors that allow for clustering along the country-pair dimension. There are 851 distinct location–destination country pairs in the sample.

Table 3 presents the results. The main variable of interest is *IndustryDistance*, it has a mean (median) of 0.11 (0.09) and a standard deviation of (0.09) and its coefficient is predicted to be negative and significant. All regressions include destination country fixed effects. Indeed, the estimate in column 1 suggests that foreign countries are underweighted by 0.1*0.09=0.9% points (t-statistic 2.41) per standard deviation of *IndustryDistance*. From column 2 onwards, I condition on funds with a *HomeBias* by interacting the distance variable with the dummy *HasHB*. The regression shows that the effect is concentrated in funds with a *HomeBias*. Naturally, funds with a *HomeBias* need to underweight foreign countries on average. The results show that they underweight countries with a different industry structure (relative to home) more. This effect is robust to the inclusion of a large set of controls, as well as fund fixed effects (column 3) or defining *IndustryDistance* in terms of sales rather than the market value of equity which may be closer to output (column 4). In column 5, I present the full specification that also interacts other distance variables with the variable *HasHB*. The result on *IndustryDistance* is robust: funds with a positive *HomeBias* underweight a foreign country by almost 1.1% points (t-statistic 3.24) per standard deviation of *IndustryDistance*.[5] These funds simultaneously display a preference for foreign countries that are geographically close and share a common language or currency. Foreign countries that not only have a different industry structure but are also geographically distant are generally underweighted too.

The estimation also interacts *HasHB* with the other distance variables. The effects are largely statistically insignificant or, when significant, economically small. The coefficients are not reported here to conserve space. An exception is the interaction with the variable *SizeDistance*. Funds with *HomeBias* also show a preference for countries whose firms are equally small or large, suggesting that preferences along the “small cap/large cap” dimensions potentially exist. In column 6, I replace the dependent variable *CountryShare* with *ExCountryShare* which subtracts the expected allocation based on market capitalization of the

[5] Notice that in some specifications, the level effect on *HasHB* is positive and significant. This means that if a perfect foreign replica in terms of industry structure existed, funds with a *Home Bias* would like to overweight that foreign country. This is sensible in light of the fact that the funds actually display a *Home Bias*.

destination country directly. The results are robust. In Table 11, I present further robustness tests where I use the raw *HB* variable instead of the *HasHB* dummy. I also experiment with home country fixed effects instead of fund fixed effects and split the sample into the pre-crisis period (2001-2007) and the crisis period (2008-2010). The results are generally robust to these specifications.

4.C Foreign Industry Bias and Industry Concentration

The results on industry and country allocations give tentative support to the first prediction: funds tend to display a tilt towards large home industries in their foreign portfolio decisions. This leads to a larger underweighting of foreign countries with a different industry structure relative to home. The effect is concentrated in funds that simultaneously display a classical *HomeBias*. It remains to be shown that, conditional on investing in a given country, funds concentrate and tilt their within-country portfolios towards large home industries.

To illustrate that this is indeed the case, I re-run regression (13), replacing the dependent variable with *FIBinCountry* or *ICIinCountry*. The regressions are now conditional on the fund investing in country *c*. Table 4 presents the results, beginning with the variable *ICIinCountry*. Funds with a classical *HomeBias* show a significantly higher industry concentration in foreign countries with a different industry structure from home. The results are again robust to the inclusion of many control variables, fund fixed effects, as well as alternative definitions of *IndustryDistance*. Column 3 presents the full specification with all interactions (only selected are reported). The effect of *IndustryDistance* on portfolio concentration is robust and other variables of distance go in the expected direction. For example, in countries with a common language or currency, funds with a *HomeBias* display a lower level of industry concentration, whereas in geographically distant countries industry concentration is higher.

While this result is suggestive, analyzing which industries drive the concentration result may help to clarify the investment behavior. The variable *FIBinCountry* weights the industry-level over- or under-investment by the relative size of the same industry at home. If industry concentration on the country level correlates with the size of the industry at home, then *FIBinCountry* is magnified, confirming that the industry concentration is driven by a tilt towards large home industries. This analysis is carried out in the remaining columns of table 4. Indeed, in structurally different countries, funds with a *HomeBias* overweight large home industries more. The point estimates in column 6 imply that this mimicking behavior increases by (0.0473*0.1) = 0.0045 (t-statistic 3.06), or about 0.18 standard deviations per standard deviation increase in the variable *IndustryDistance*. The variable *HasHB* has a negative and significant level effect. That is to say that, if a perfect foreign replica of the home country existed, funds with a *HomeBias* would show less mimicking behavior in terms of *ForeignIndustryBias*, which may be intuitive as no over-/underweighting on the industry level is necessary to build a country portfolio with industry similarity to the home country. The mimicking behavior increases with *IndustryDistance*. A one standard deviation increase in *IndustryDistance* hence already compensates for about 74% of the level effect of *HasHB*. While some of the remaining interactions are statistically significant, for example the overweighting of large home industries increases with geographic distance, they are economically negligible.

4.D The Domestic Portfolio and the Determinants of Foreign Industry Bias

The results in Tables 3 and 4 are pronounced for those funds that display a classical *HomeBias*. While domestic portfolio choices are not the primary concern of this paper, the results nevertheless provide an opportunity for a consistency check by linking foreign to domestic investment decisions. After all, if foreign portfolio decisions are impacted by domestically-rooted industry knowledge, it is natural to expect some effect on the domestic choices of funds as well. Likewise, in the model, informed investors display *HomeBias* due to local private signals.

In panel A of Table 5, I first analyze the industry composition of domestic portfolios. I re-estimate the specification of equation (12) with *(Ex)HomeIndustryShare* as the dependent variable. My first observation is that the relative size of the industry abroad (the variable *ForeignCtryIndustryShare*) has no significant impact on domestic industry allocations, which may be seen as a falsification test. The most robust predictor of domestic excess allocation is the profitability of the industry at home (the variable *HomeCtryIndustryROS* in all columns). While the size of the industry is significantly positive for raw allocations, it becomes insignificant when excess allocations are considered. Consequently, the average domestic sub-portfolio is tilted towards the "best" domestic industries, not necessarily the largest. This seems consistent with the idea that relative size proxies for relative advantage but investment decisions are ultimately driven by quality.

An industry in a given country might be large because of high-quality firms (e.g. technology clusters) or for other reasons such as subsidies or political support. The idea that local investors have an advantage in understanding that industry is true regardless of the reason why the industry is relatively large. Their decision to invest domestically in that industry, however, is not. If indeed the industry is large for quality-unrelated reasons, then domestic investors that source information locally may pick domestic firms in other industries that constitute the best investment opportunity. In that sense, the advantage stemming from the relative size of domestic industries comes into full effect only in the foreign choices where the industry-level opportunity set of stocks is potentially far less restricted.

To make the consistency between domestic and foreign portfolio choices as a function of domestic industries more explicit, I estimate the determinants of *ForeignIndustryBias* at the fund level in the following specification.

$$\begin{gathered} FIB_{j,t} = \beta_1 HB_{j,t} + \beta_2 ICIatHome_{j,t} + \beta_3 C_{j,t} + \alpha_t + \alpha_s + \epsilon_{j,t} \\ HB_{j,t} = \gamma_1 A_{h,t} + \widehat{\epsilon_{j,t}} \\ ICIatHome_{j,t} = \gamma_2 A_{h,t} + \widehat{\widehat{\epsilon_{j,t}}} \end{gathered} \tag{14}$$

The investment strategy of informed investors requires consistent behavior at home and abroad. The main variable of interest is *ForeignIndustryBias (FIB)* that is modeled as being related to domestic choices, captured by *HomeBias (HB)* and *IndustryConcentrationatHome (ICIatHome)*. Naturally, these two explanatory variables are endogenous but the analysis so far suggests a set of instruments for both – home country characteristics. Panel B of Table 5 presents this two-stage least square estimation where *HB* and *ICIatHome* are instrumented using home country characteristics. Columns 1 and 2 present the first stage regressions. Indeed, home industry characteristics are strong determinants of domestic investment behavior. The specification tests at the bottom of the table indicate that the set of instruments is strong. Column 3 presents the instrumented second stage regression. Once instrumented, both *HB* and *ICIatHome* are strong determinants of *ForeignIndustryBias*. For comparison, Column 4 presents an estimate of the first equation of system (14) without instrumenting *HB* and *ICIatHome* in which case the positive relation between domestic and foreign portfolio choices is noisy.

Overall, the predictions on *ForeignIndustryBias* are strongly supported in the data. Domestic characteristics seem to feed through to foreign investment decisions along the industry dimension.

5. *Foreign Industry Bias* and Performance

While the results of the previous section support the first prediction on *ForeignIndustryBias*, it is difficult to assess the motivation for such behavior from portfolio choice regressions alone. Investing based on industry characteristics may equally be a manifestation of a familiarity bias instead of an information-related phenomenon. An analysis of performance is needed to separate the two, which is the purpose of this section. I first focus on performance attribution using a factor-model approach, and subsequently complement the results with holding decompositions. Together this constitutes the test on the second prediction.

5.A Performance Attribution with Factor Models

The second prediction posits positive return implications of *ForeignIndustryBias*. I test the prediction by running performance regressions of the form

$$Return_{j,t} = \beta_1 HasHB_{j,t} + \beta_2 FIB_{j,t} + \beta_3 HasHB_{j,t} \times FIB_{j,t} + \beta_4 C_{j,t} + \alpha_t + \alpha_s + \epsilon_{j,t} \qquad (15)$$

where $Return_{j,t}$ is measured monthly either using raw fund returns or "alpha" from factor models. *HasHB* and *FIB* are measured as of June and December each calendar year and then used for the entire six month period that follows. The vector $C_{j,t}$ contains fund controls including home country characteristics and average distance measures between the fund location and its investment opportunities (e.g. *KMDistance* is now the average distance in thousands of kilometers between the fund and all destination countries).

Table 6 presents the results from the factor corrections. The regressions are run at monthly frequency and estimated using the procedure of Fama and MacBeth (1973) with standard errors corrected for serial dependence with 3 lags. The baseline specification that uses style specific four factor models (regional or "local" factors in fact) is presented in panel A. The main coefficient of interest is β_3 that is positive and significant at the 1% level in the full specification (column 4) as predicted. The level effect β_1 is negative for funds with no *HomeBias*. This is intuitive as it should be regarded as an inconsistency in the theoretical framework where *ForeignIndustryBias* is an information-related phenomenon that has implications for the entire portfolio. Funds that are inconsistent in the domestic portfolio but mimic the home industry structure in foreign holdings underperform.[6] But the interaction in the full specification (column 4) clearly dominates that effect. The estimates suggest that a fund with a one standard deviation *FIB* but no *HomeBias* underperforms a fund with *HomeBias* and the same level of *FIB* by 9 bp a month, or slightly more than 1% p.a. net of risk. This result is robust to a large range of controls. In column 5, I add an interaction of *HasHB* with the variable *ICI*. While the effect is positive, it is not statistically significant. In column 6, I use the raw *HB* variable which delivers the same result. From the other distance variables in column 6, geographic distance is associated with negative performance. A one standard deviation increase corresponds to a negative effect of

[6] Or equivalently, those funds that have no *HomeBias* and a negative *ForeignIndustryBias* are not the worst funds in the sample. In light of the hypotheses, these funds at least do not display an inconsistent investment behavior and might generate performance in different manners or simply provide diversification to their (local) investors.

about 2 bp a month. Perhaps surprisingly, *CommonCurrency* has a negative association with fund performance. A one standard deviation increase in *CommonCurrency* implies a negative 4 bp a month performance effect net of risk.

In the remaining panels of Table 6, I assess the robustness of the factor models. In panel B, I begin by measuring performance against global factors that do not differ by style. If markets were perfectly integrated, these factors would be more appropriate than "local" factors. In column 2, I use an estimate of alpha that is computed from net-of-fee returns rather than before-fee returns (expenses are always among the control variables). In columns 3 and 4, I implement the "endogenous benchmark" model of Hunter et al. (2011), which adds an additional "peer factor" to the first stage regression. I use both value- and equally-weighted peer factors. This model is designed to capture common investment strategies that standard factors may omit. In columns 5 and 6, I estimate conditional alphas. Column 5 uses the style-specific dividend yield, as well as the yield spread of long-term over short-term treasuries, and the credit spread of Moody's BAA – Moody's AAA rated bonds as instruments. Column 6 replaces the style-specific dividend yield with the US dividend yield. In all specifications, the main result of a positive effect of *FIB* for funds with *HB* is robustly significant.

In panel C, I present sample splits, again using the baseline specification of panel A. Columns 1 and 2 show that the effect is concentrated in the subset of funds with above-median levels of industry concentration, as expected. In this specification, the performance effect is exclusively on *FIB,* and the absolute magnitude of the interaction effect is 2.5 times the magnitude of the level effect. Columns 3 and 4 split the sample along the time series dimension. Column 3 only considers the 2001-2007 period before the financial crisis, and column 4 the remaining years from 2008-2010. The effect is present in both samples, but slightly stronger for the crisis years. Finally, in columns 5 and 6, I split the sample into those styles with a wide investment scope and those with a narrow scope. A style is defined to have a wide scope if the number of countries to which funds are expected to have exposure is above the median in the sample. The effect of *FIB* is concentrated in styles with a wide scope, consistent with the idea that in such styles "global private signals" are particularly valuable because the foreign investment opportunity set is very large, permitting maximum flexibility in portfolio choice.

In Table 12, I present further robustness tests on the factor regression. I estimate the regression in a panel with two-dimensional clustering along the fund and time dimension. I use weighted versions of *FIB* as described in the data section, and truncate the sample along the top and bottom 5% for the variable *HB* to mitigate outlier concerns for funds with extreme deviations. I add home country fixed effects and subsequently drop different funds and investment styles from the sample. None of these tests affects the main result.

5.B *Performance Attribution with Holding Decompositions*

The factor models in the previous subsection give tentative support to the second prediction. However, factor models can only be a partial test of the prediction for various reasons. First, they do not allow for a detailed investigation into what parts of the portfolio generate the result, as only one time-series of fund returns is available. Holding decompositions can help assess, for example, stock-picking ability before expenses and transaction costs, and, for the purpose of this study, allow for a separate analysis of the total portfolio and the foreign sub-portfolio. Second, factor models are subject to the critique of benchmark misspecification. Benchmark misspecification is already a concern in the domestic literature, and, if anything, is more pressing in the international context where there is little agreement on the appropriate factor model to describe stock returns worldwide, not to mention the common trading strategies and associated risks that investors follow.

To complement the factor models of the previous subsection, I now perform a holding decomposition in the spirit of Daniel et al. (1997) for both the total fund portfolio and the foreign sub-portfolio only. Since industrial structure is singled out as a candidate source of information, I pick an industry portfolio as the benchmark for every stock. The decomposition is shown in equation (10). The different components are estimated from semi-annual holdings over the next half-year period, and the regressions are run at semi-annual frequency. The model is thus

$$HR_{j,t+\tau} = \beta_1 HasHB_{j,t} + \beta_2 FIB_{j,t} + \beta_3 HasHB_{j,t} \times FIB_{j,t} + \beta_4 C_{j,t} + \alpha_{t+\tau} + \alpha_s + \epsilon_{j,t+\tau} \quad (16)$$

where $HR_{j,t+\tau}$ refers to the various measures of holdings return and τ is the subsequent semi-annual period. The equation is estimated in a panel regression with two-dimensional clustering along the fund and time dimensions.

Table 7 presents the results. In columns 1 to 4, I consider the entire fund portfolio, in columns 5 to 8, only the foreign sub-portfolio. The regressions on the total holdings return (column 1) or the foreign holdings return (column 5) show a similar pattern compared to the factor models. The level effect of *FIB* is negative and the interaction of *HasHB* and *FIB* is strongly positive and significant. In the foreign sub-portfolio, this interaction effect dominates the level effect of *FIB*. From the foreign holdings return in column (6), a differential performance effect of about 10 bp per semi-annual period can be attributed to *FIB*. The decomposition into stock picking (columns 2 or 6), industry timing (columns 3 or 7), and average industry returns (columns 4 or 8) are now informative. The positive differential effect is heavily concentrated in foreign stock-picking ability (column 6). The differential effect of *FIB* now amounts to 27 bp per half-year or 55 bp per year (t-statistic 2.39), which allows me to attribute about 50% of the performance result from the factor models to superior foreign stock picking within industries. There is some evidence of better foreign industry timing of funds with *FIB* as well as for funds with high *IndustryConcentration (ICI)*, regardless of the mediating effect of *HomeBias* (column 7). The economic effect amounts to about 11 bp (15 bp) a year per standard deviation of *FIB* (*ICI*) or about 11-15% of the aggregate fund effect. The residual in columns 4 and 8 shows a more negative average industry return, the higher the *FIB*.

6. Trading and Persistence

While the results on the first two predictions give tentative support to the hypothesis that foreign investment decisions are linked to domestic industry characteristics and that this link identifies an information asymmetry, they are both average statements. A test of whether these results are likely information-driven can be strengthened along two dimensions. First, analyzing position changes over time provides a tighter test of the main predictions than tests on average quantities, because, for example, the arrival of new information over time should trigger portfolio changes, i.e. trading. In fact, the dynamic model of Albuquerque et al. (2009) has distinctive results on the foreign trading behavior of informed investors that can be exploited empirically. Second, industry structures are slow-moving. Hence, informed funds should continue to receive "global private signals" for as long as the domestic industry structure does not change drastically. This should induce persistence. Exploring both dimensions is the purpose of this section.

6.A Global Return Chasing

In the model, the presence of noise trading as well as learning induces both momentum in international stock returns and a sequence of trades of informed investors. Signal realizations are only gradually impounded into prices. This generates momentum. Learning about the global component in payoffs leads informed investors to perform a sequence of trades. This generates "global return chasing". Foreign trades of informed investors are correlated across assets and contemporaneously with returns of many stocks. This differentiates "global return chasing" from classical "return chasing" in the sense of Brennan and Cao (1997). There, "return chasing" is a phenomenon attributed to uninformed foreign investors that over-react to public signals.

If *ForeignIndustryBias* is interpretable as some funds investing internationally based on "global private signals" about industries, then their foreign trades should co-move with industry returns world-wide, including industry returns in their home country. This is the first aspect of the third prediction on trading.

I compute measures of return chasing as described in equation (11). These measures are simple correlations between buy (sell) trades with different industry returns associated with the stock that is traded over the trading period. The returns are destination country industry returns, home country industry returns, or global industry returns. I focus on a differential effect – are the foreign trades of funds with *ForeignIndustryBias* more responsive to home country and global industry returns relative to other funds?[7]

In Table 8, I present the results using different horizons for contemporaneous returns (one or two quarters) for both the entire foreign portfolio and only those foreign positions whose stocks are in one of the industries that constitute the top-10 by market capitalization at home. In panel A, the first three columns illustrate that there is no differential effect associated with *FIB* when it comes to traditional return chasing with respect to destination country industry returns (the coefficients on the variable $HasHB \times FIB$ are insignificant in those columns). If anything, funds with *HB* show less traditional return chasing. In contrast, columns 3 to 6 show a very strong differential effect of global return chasing for funds with both *HomeBias* and *ForeignIndustryBias*. Foreign trading of those funds is more sensitive to domestic industry returns – they tend to buy (sell) in foreign industries when the corresponding home industry has high (low) current returns. The same is also true when return chasing is computed with respect to global industry returns. Here the effect is concentrated in buy transactions.

In panels B and C of the same table, I focus on transactions in those industries that are among the top-10 in terms of market capitalization at home. In panel B, contemporaneous returns are calculated over the last quarter; in panel C over the last 6 months. If the likelihood of receiving "global private signals" is proportional to the relative industry size, then global return chasing" should be pronounced for those transactions. I find that this is indeed the case. For example, the point estimates in panel C, column 4 imply that the correlation between foreign purchases and domestic industry returns is almost 4.5% points higher (t-statistic 3.36) per standard deviation of *ForeignIndustryBias* for funds that have a *HomeBias*. The economic magnitudes implied by columns 5 to 8 of the same table are of similar magnitude, ranging typically between 2.5%-4% points per standard deviation of *ForeignIndustryBias*. To my knowledge, this is the first study to document global returns chasing in a defined subset of investors.

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[7] The country level investment regressions in section 3 contain as a control variable the trailing 12 month return of the destination country. The (unreported) coefficient on that variable in table 3 is strongly positive and significant, i.e. countries with high past performance indeed receive higher allocations which can be interpreted as traditional return chasing.

6.B Return Predictability

Informed trading should predict future stock returns. The previous section has shown that trading co-moves more with domestic and global industry returns for funds that show both *HomeBias* and *ForeignIndustryBias*. I now analyze whether these trades predict future stock returns better than do trades of other funds. This is the second aspect of the trading prediction that I explore.

The tests are similar to those used in the previous subsection. As the dependent variable, I simply use the correlation between trades and future stock returns. As a horizon, I choose returns one and two quarters ahead, and I again present the measures both for all foreign trades and for the trades in those industries that make up the top-10 at home.

These predictive regressions are presented in table 9. Panel A considers all foreign trades, panel B only the top-10 home industries. This last piece of evidence shows that, indeed, the trades of funds with both *HomeBias* and *ForeignIndustryBias* have a higher correlation with future stock returns than those of other funds. When the entire portfolio is considered, the effects are about equally strong for buy and sell trades and the result is concentrated in the one quarter horizon. When only foreign trades in the top-10 home industries are considered (panel B), the effect is considerably stronger and has power even two quarters ahead. In terms of economic significance, per standard deviation increase in *ForeignIndustryBias*, the correlation of buy transactions with six-months-ahead stock returns is about (0.96*0.026) = 2.5% points higher (t-statistic 2.60) for funds that have *HomeBias*. This effect is entirely attributable to *Foreign Industry Bias* and therefore supports the prediction.

6.C Persistence

The final prediction that I investigate is concerned with persistence. In the context of this paper, persistence has two aspects. First, slow-moving industry structures should induce persistent portfolio choices. Second, provided that this impact is information-driven, fund performance should be persistent, too.

To test for persistence in portfolio choice, I sort funds into deciles based on portfolio choice variables every June and December and then track the average future deciles for each current decile group. In panel A of Table 10, I present results for a future horizon of one year. Results at the six-month horizon are similar but unreported for brevity. The table presents the average rank one year ahead in excess of the expected rank under the null of no persistence (i.e. average future rank – (10+1)/2). The sorting variable is given in the first column for every row. There is strong persistence in excess allocations and the average future ranks are strongly monotonic in current ranks. For example, funds that are currently ranked in the highest (lowest) *ForeignIndustryBias* decile tend to have an average *ForeignIndustryBias* decile of 8.3 (2.3). Results for *IndustryConcentration* and *HomeBias* are similarly persistent and monotonic.

In panel B, I document performance persistence. I sort funds based on various measures of previous year performance (net of style returns, alpha, before or after fees) and again track the average future performance rank in excess of the unconditional average rank. Columns 1 to 10 illustrate that there is performance persistence, and that performance persistence is not only concentrated among poor-performing funds. There appears to be positive performance persistence in the two highest deciles in the sample and this persistence translates into statistically and economically significant return differences. Column 11 presents the future return differences between the currently highest and lowest ranking funds (a hypothetical long-short) implied by the persistence in ranks. When four factor alpha is the measure of performance, this difference is a significant 3.3% p.a., even net of expenses.

The result on performance persistence is particularly interesting, both in light of the model of Berk and Green (2004) and the empirical evidence on mutual fund persistence in the domestic context (e.g. Grinblatt and Titman (1992), Brown and Goetzmann (1995), Elton et al. (1996), Carhart (1997), Bollen and Busse (2005), Berk and Tonks (2008), Busse et al. (2012)). Berk and Green (2004) present strong theoretical arguments against performance persistence at the fund level, based on the underlying assumptions that capital provision by investors is perfectly competitive and that there are diseconomies of scale to fund management. In this case, fund flows equilibrate expected fund performance going forward such that there is no performance persistence. The empirical literature has found conflicting evidence on performance persistence in domestic mutual funds. For the most part, performance persistence is either concentrated among poor-performing funds or restricted to short time periods when it is indeed found among high-performing funds. The finding that performance persists at the annual horizon in the international context calls for more detailed investigation, which I leave for future work.

7. Concluding Remarks

This study has shown that domestic industry structure is a significant determinant of foreign investment decisions of global mutual funds. Some funds display a *Foreign Industry Bias* by concentrating in those foreign industries that are large in their home country. This behavior is associated with superior performance; the trading decisions of such funds are consistent with the behavior of informed investors in models of portfolio choice under asymmetric information. This suggests that domestic industry structure may serve as a proxy for the relative industrial expertise of local investors when investing abroad. Thus, I interpret the domestic industry composition as a source of informational advantages, useful for foreign investment decisions.

This view contributes to the international finance literature in various ways. For example, the literature has debated if local investors outperform foreign investors with mixed results. The evidence I present allows for the possibility that foreigners outperform locals in some stocks but potentially underperform in others. In assessing this question, my results suggest that one needs to account for the identities of traders and the set of assets that are traded when performing such tests. In this framework, it matters who trades in what stocks.

On a broader scale, this study opens avenues for future research. One such avenue could explore the information content of foreign stock prices as a function of the identities of foreigners that trade in the market. If industry-level trading in a country is dominated by foreigners from countries where the same industry is relatively large, I would predict that the information content of stock prices is higher. A second avenue could investigate the link between return chasing and return predictability in greater detail on the country level. Lead-lag relationships between industries and aggregate stock markets have been explored in the domestic literature, and the findings here seem to indicate that such relationships can be detected in the international context as well as a function of foreign trading. The strength of such relationships should be tightly linked to the identities of foreign trades. Such an analysis might provide new insights on how industry information travels across borders.

Finally, the results on performance persistence call for a more detailed analysis into the nature of competition in the international mutual fund industry. It is rare for mutual fund studies to find performance persistence among the best performing funds at the one year horizon. In the domestic literature, persistence is usually either limited to short horizon periods or clustered among the worst performing funds. I document positive persistence that is significant even net of expenses, which is an interesting lead. A detailed investigation of persistence could analyze the barriers that prevent flows from equilibrating expected fund performance. I leave those avenues for future work.

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Appendix A: A Sketch of Albuquerque et al. (2009)

Albuquerque et al. (2009) develop a dynamic model of international equity trading that builds on the static model of Admati (1985) and the dynamic model of Brennan and Cao (1997). In their model, trading takes place over T periods in n securities that they interpret as regional stock indices that are indexed by j. Every region is populated by both investors and liquidity traders in equal masses of $1/n$. Investors have CARA utility over terminal wealth and start out with some initial holdings in all assets. The presence of liquidity traders precludes prices from being fully revealing.

The model has two key ingredients. First, assets have a terminal payoff that is subject to both local (i.e. region specific) and global factors. In particular, the terminal payoff of asset j is

$$U_j = \mu + U_j^l + U^g \tag{17}$$

where $\mu > 0$ is the mean payoff, U_j^l is the local component specific to region j and U^g is the global component that is common across all assets. Local factors are uncorrelated across regions.

Second, the information structure features public and private signals both about the local and global components of asset payoffs. Signal shocks are normally distributed and uncorrelated both in the cross-section and the time-series. All investors observe both local and global public signals of the forms

$$\begin{aligned} y_{t,j} &= U_j + v_{t,j} \quad j = 1, \dots, n \\ y_t^g &= \frac{1}{n}\sum_{j=1}^{n} U_j + v_t^g \end{aligned} \tag{18}$$

where the two shocks have precisions q_l and q_g respectively.

In addition to public signals, every investor i in region j receives a local private signal

$$z_{t,j}(i) = U_j + \epsilon_{t,j}(i), \;\; j = 1, \dots, n; \;\; i \in [0,1/n] \tag{19}$$

where the shocks have precision p_l. Investors in region j are assumed to start out with background information about the dividend in their home region. This background information is encoded into their prior beliefs that are assumed to equal posterior beliefs of investors that have already observed a history of t_0 local private signals. This assumption of a local information advantage ultimately generates home bias.

Finally, a fraction α_j of investors in every region obtains an additional global private signal of the form

$$z^g_{t,j}(i) = \frac{1}{n}\sum_{j=1}^{n} U_j + \epsilon^g_{t,j}(i) \;\; j = 1, \dots, n; \;\; i \in [0, \alpha_j] \tag{20}$$

with precision p_g. The presence of some investors that receive global private signals makes information endowments non-symmetric.

Equilibrium in the economy is defined as sequences of price processes $\{P_t\}$ and asset demands $\{A_t(i)\}$ such that investors maximize expected utility given prices and conditioning information and such that markets clear.

The authors are interested in studying the aggregate international equity flows of US investors. They therefore define the United States as a fraction ν of the n regions. The second key assumption is that the fraction of investors that receive global private signals is higher in the US then in the rest of the world - that is $\alpha^{US} > \alpha^{ROW}$ where $\alpha_j = \alpha^{US} \; \forall \; j \in \nu$ for simplicity. Their proposition 1 (equations (16) and (17)) characterizes prices and holdings as functions linear in fundamentals, errors in public signals and liquidity trades.

The main focus of this paper is on the implications for holdings, trades and performance of investors that receive global private signals. I do not reproduce the full expressions for prices and holdings here but focus on the key properties.

First, under the given information structure, average per capita holdings in any foreign asset for a US investor is given by equation (19) in their paper. It is

$$E\left[A^{US}_{t,j}\right] = \mu_X + \frac{1}{nk_t}\left((\alpha^{US} - \alpha)p_g t - p_l(t + t_0)\right)\mu_X \tag{21}$$

where μ_X are the average liquidity trades (which in the absence of signals would be absorbed in equal amounts by all investors), α is the world-wide fraction of investors that receive global private signals and k_t is a quantity that characterizes the average total knowledge about local and global factors. The important part of the expression is the bracketed term that describes the trade-off between global and local information in foreign assets. When

$$(\alpha^{US} - \alpha)p_g t < p_l(t + t_0) \tag{22}$$

the information advantage of foreigners in their home asset is larger than the advantage of informed US investors generated by observing global private signals. In such cases, US investors display home bias by underweighting foreign stocks. At the same time, the bias against foreign stocks is mitigated if α^{US} is large.

Next, consider the dynamic behavior of US holdings and prices induced by global private signals. Both quantities are driven by liquidity trades, fundamentals as well as aggregate errors in public signals. Aggregate errors in private signals cancel out. For example, when the local factor U^l is high, the asset price increases but not fully as prices contain noise. The price increase takes place over several periods because prices increasingly reflect fundamentals due to learning and are less and less impacted by signal errors. The same is true for the global factor. A high global factor U^g is only partially reflected in current prices due to noise. However, over time, investors learn more and the prices increasingly reflect fundamentals. As such, learning about global factors introduces momentum in international stock prices because the true value of fundamentals is only gradually revealed.

What is the dynamic effect on US foreign holdings in such situations? Foreign positions of US investors are gradually increasing over time for high values of the global factor if their demand functions increased the weight on the global factor over time. The authors show that this is indeed true provided that two conditions are met. First, the initial advantage of foreigners needs to be large (high t_0) and second, the precision of global private signals needs to be large (high p_g). When this is the case, US investors learn more about global factors because (1) they update stronger due to the initial disadvantage in local assets and (2) their global private signals are useful given that everybody can learn from public signals and prices.

These results have implications for the foreign trading behavior of US investors. First, US investors demand in foreign assets increases over time due to learning about global factors while, at the same time, fundamentals are increasingly reflected in prices. This means that US foreign trades "chase" returns in many countries. In other words, US foreign trades should exhibit a contemporaneous correlation with returns in many countries. It also means that the trades over a given time period can predict foreign returns because, as time progresses, foreign prices increasingly reflect fundamentals.

Table 1: Descriptive Statistics

The table presents summary statistics on the sample of international funds. Panel A presents the number of funds in the sample as of December of each calendar year. Panel B presents summary statistics on the fund level. Variables are as defined in section 3. Panel C presents a correlation matrix for the main variables on the fund level where * indicate statistical significance at the 5% level. Panel D presents the Thomson-Datastream industry classification employed. Panel E shows the Morningstar style classification, the evolution of the sample composition in terms of number of funds per style as well as style characteristics. Panel F shows the number of distinct funds per fund location country where fund location is defined as the country of residence of the management company that manages the portfolio.

Panel A: Number of Funds in Sample

	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
# of Funds	683	1364	1698	1978	2193	2304	2432	2603	2665	2763	2114

Panel B: Descriptive Statistics on the Fund Level

	Mean	**StD**	**P25**	**P50**	**P75**
HomeBias (HB-%)	6.710	22.230	-2.105	0.000	10.250
ForeignIndustryBias (FIB)	0.001	0.026	-0.011	0.000	0.010
IndustryConcentration (ICI)	0.367	0.195	0.228	0.341	0.473
FundTNA (mUSD)	723.1	3501.4	33.56	100.9	364.3
FirmTNA (mUSD)	29704.6	121089.0	1117.9	5864.3	20411.7
Expenses (% p.a.)	1.714	0.658	1.320	1.650	2.020
ShareClasses	2.181	2.000	1	1	2
InstShareClass	0.014	0.120	0	0	0
Age (years)	10.99	7.756	5.772	9.341	13.95
Volatility (% p.a.)	18.62	8.559	11.97	16.99	23.28
Turnover (% semi-annually)	63.91	114.7	29.47	44.93	63.95
GrossReturn (% p.m.)	0.863	6.225	-2.410	1.367	4.636
4F Alpha (% p.m.)	0.040	2.269	-1.154	-0.035	1.136
NetReturn (% p.m.)	0.719	6.216	-2.550	1.225	4.485
4F Alpha (Net, % p.m.)	-0.075	2.263	-1.265	-0.141	1.029

Panel C: Correlation Matrix of Selected Variables

	HB	*FIB*	*ICI*	*FundTNA*	*FirmTNA*	*Expenses*	*Share Classes*	*InstShare Class*	*Age*	*Volatility*	*Turnover*	*4F Alpha*	*4F Alpha (Net)*
HB	1												
FIB	0.132*	1											
ICI	0.365*	-0.062*	1										
FundTNA	-0.084*	-0.027*	-0.064*	1									
FirmTNA	-0.072*	0.001	-0.053*	0.183*	1								
Expenses	0.031*	-0.076*	0.109*	-0.077*	-0.044*	1							
ShareClasses	-0.221*	-0.060*	0.006*	0.213*	0.189*	0.024*	1						
InstShareClass	-0.083*	-0.010*	-0.002	0.000	0.015*	-0.019*	0.257*	1					
Age	0.022*	0.050*	-0.099*	0.087*	0.045*	-0.068*	0.055*	0.012*	1				
Volatility	0.082*	0.022*	-0.017*	-0.020*	0.027*	0.004	0.030*	0.019*	0.023*	1			
Turnover	-0.075*	-0.008*	-0.024*	0.038*	0.021*	0.008*	0.049*	0.030*	-0.025*	0.010*	1		
4F Alpha	0.029*	0.015*	0.012*	0.010*	-0.001	0.002	0.002	-0.001	-0.004	0.055*	-0.007*	1	
4F Alpha (Net)	0.029*	0.016*	0.010*	0.012*	-0.001	-0.016*	-0.001	-0.002	-0.004	0.044*	-0.007*	0.999*	1

Panel D: Industry Classification

Aerospace & Defense	Forestry & Paper	Mobile Telecommunications
Alternative Energy	Gas, Water & Multiutilities	Nonlife Insurance
Automobiles & Parts	General Industrials	Oil & Gas Producers
Banks	General Retailers	Oil Equipment & Services
Beverages	Health Care Equipment & Service	Other Equities
Chemicals	Household Goods & Home	Personal Goods
Construction & Materials	Construction	Pharmaceuticals & Biotechnology
Electricity	Industrial Engineering	Real Estate Investment & Services
Electronic & Electrical Equipment	Industrial Metals & Mining	Real Estate Investment Trusts
Equity Investment Instruments	Industrial Transportation	Software & Computer Services
Financial Services (Sector)	Leisure Goods	Support Services
Fixed Line Telecommunications	Life Insurance	Technology Hardware & Eqmt.
Food & Drug Retailers	Media	Tobacco
Food Producers	Mining	Travel & Leisure

Panel E: Style Classification

	Sample Evolution (Number of Funds, end-of-year)				**Style Characteristics**	
	2002	*2005*	*2008*	*2010*	*Investment Focus*	*Scope*
Africa Equity	15	21	30	35	ZA, UK, TR, EG	4
Asia Equity	61	71	77	43	JP, HK, AU, KR, SG, TW	6
Asia ex Japan Equity	104	131	154	108	HK, KR, TW, AU, SG, CN, MY, IN	8
Emerging Markets Equity	120	146	187	169	BR, TR, KR, RU, TW, HK, PL, ZA, MX, CN, IN, CZ, VE, HU, MY, US	16
Europe Equity Large Cap	276	383	422	282	FR, DE, UK, CH, IT, NL, ES, SE, FI, BR, HK	11
Europe Equity Mid/Small Cap	45	75	94	51	DE, FR, UK, IT, CH, NL, ES, SE, FI, NO, TR, AT	12
Global Equity	168	228	293	250	US, JP, UK, FR, SE, BR, DE, CA, CH, HK, NL, IT, AU, ES, KR, FI	16
Global Equity Large Cap	514	676	738	649	US, JP, UK, FR, DE, CH, BR, NL, IT, HK, ES, CA, SE, AU, FI	15
Global Equity Mid/Small Cap	56	86	106	97	US, JP, UK, DE, FR, CA, CH, BR, AU, HK, SE, NL, FI, ES, IT, KR, TR, NO, SG	19
Islamic Equity	0	0	3	4	MY, US, ZA, UK, JP, BR, FR	7
Latin America Equity	28	32	33	26	BR, MX	2
Other Asia Equity	1	5	8	3	MY, TH, SG, ID, PH	5
Other Europe Equity	310	450	520	397	FR, IT, ES, SE, CH, DE, NL, FI, NO, RU, BE, TR, DK, PL	14
Total	*1698*	*2304*	*2665*	*2114*	*Median*	*11*

Panel F: Fund Locations

Fund Location	**Region**	**Number of Funds**	**Percentage of Sample**
US	North America	760	19,64%
UK	Europe	607	15,69%
France	Europe	431	11,14%
Germany	Europe	309	7,99%
Spain	Europe	267	6,90%
Sweden	Europe	171	4,42%
Italy	Europe	158	4,08%
Canada	North America	142	3,67%
Denmark	Europe	134	3,46%
Switzerland	Europe	119	3,08%
Austria	Europe	96	2,48%
Norway	Europe	87	2,25%
Belgium	Europe	82	2,12%
Singapore	Asia Pacific	70	1,81%
Hong Kong	Asia Pacific	66	1,71%
Finland	Europe	64	1,65%
Netherlands	Europe	59	1,52%
South Africa	Africa	49	1,27%
Taiwan	Asia Pacific	49	1,27%
Ireland	Europe	45	1,16%
Portugal	Europe	26	0,67%
Malaysia	Asia Pacific	25	0,65%
Estonia	Europe	12	0,31%
Japan	Asia Pacific	10	0,26%
Omitted Countries (<10 funds)	Australia, Luxembourg, Lithuania, Greece, Poland, Liechtenstein, Thailand, Croatia, Latvia, Mexico, Bermuda, Argentina		

Table 2: Industry Allocations

The table presents semi-annual investment regressions at the fund-industry level. The top-20 industries per style in terms of market capitalization are considered except for column 6 that limits the regression to the top-10 industries per style. The dependent variables are *IndustryShare* or *ExIndustryShare* that measure the percentage (excess) allocation per industry. Columns 1 and 2 consider the entire portfolio, columns 3 to 6 only the foreign sub-portfolio. Explanatory variables include home industry, foreign industry, fund and home country characteristics (unreported), which are defined in section 3. All specifications include time, industry and home country fixed effects. * / ** / *** denote statistical significance at the 10% / 5% / 1% level computed from standard errors clustered along the home country-industry pair dimension.

	Total Portfolio		**Foreign Portfolio**			
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*Industry Share*	*ExIndustry Share*	*Foreign Industry Share*	*Foreign Industry Share*	*ExForeign Industry Share*	*ExForeign Industry Share*
HomeCtryIndustryShare	0.1800***	0.1086***	0.0818*		0.0956**	0.0968**
	(5.16)	(3.44)	(1.80)		(2.27)	(2.13)
LargestHomeIndustry				0.0125**		
				(2.00)		
HomeCtryIndustrySize	-0.0003	0.0000	-0.0014	-0.0002	-0.0012	-0.0013
	(-0.34)	(0.07)	(-1.61)	(-0.27)	(-1.59)	(-1.19)
HomeCtryIndustryROS	0.0001	0.0001	0.0001	0.0001	0.0001	0.0003
	(0.78)	(0.69)	(1.04)	(1.03)	(0.77)	(1.14)
HomeCtryIndustryBTM	-0.0011*	-0.0005	-0.0014**	-0.0013*	-0.0008	-0.0007
	(-1.93)	(-1.05)	(-2.14)	(-1.95)	(-1.44)	(-0.78)
HomeCtryIndustryLeverage	0.0000	0.0029	0.0012	0.0006	0.0024	0.0064
	(0.01)	(0.68)	(0.23)	(0.11)	(0.50)	(0.91)
ForeignCtryIndustryShare	0.3479**	-0.0677				
	(2.46)	(-0.72)				
ForeignCtryIndustrySize	0.0051	0.0126***	0.0197***	0.0179***	-0.0003	-0.0042
	(1.39)	(3.85)	(5.63)	(5.53)	(-0.11)	(-0.82)
ForeignCtryIndustryROS	0.0201**	0.0304***	0.0220**	0.0199*	0.0265***	0.0203
	(2.49)	(3.67)	(2.04)	(1.85)	(2.65)	(1.54)
ForeignCtryIndustryBTM	-0.0187***	0.0131**	-0.0215***	-0.0227***	-0.0054	-0.0163
	(-3.08)	(2.48)	(-2.59)	(-2.85)	(-0.82)	(-1.56)
ForeignCtryIndustry	-0.0345**	0.0226	-0.0466***	-0.0514***	-0.0086	0.0038
Leverage	(-2.11)	(1.33)	(-2.87)	(-3.04)	(-0.49)	(0.15)
Unreported Variables	Fund & Home Country Controls					
Fixed Effects	Time, Industry & Home Country					
Industries in Regression	Top-20	Top-20	Top-20	Top-20	Top-20	Top-10
Observations	784210	784210	782486	782486	782486	394179
Adjusted R^2	0.22	0.03	0.17	0.17	0.03	0.05

Table 3: Country Allocations

The table presents semi-annual unconditional investment regressions at the fund-country level. The dependent variables are *CountryShare* or *ExCountryShare* that measure the percentage (excess) allocation per country. Explanatory variables include measures of distance between home and investment destination as well as (unreported) destination, home country and fund characteristics which are defined in section 3. All specifications include time and country fixed effects, columns 3-6 add fund fixed effects. * / ** / *** denote statistical significance at the 10% / 5% / 1% level computed from standard errors clustered along the country-pair dimension.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:			*CountryShare*			*ExCountry Share*
IndustryDistance	-0.1033**	0.0201	0.0762*		0.1307***	0.1436***
	(-2.41)	(0.50)	(1.69)		(2.96)	(3.60)
IndustryDistance (Sales)				0.1784**		
				(2.43)		
HasHB		0.0406*	0.0451***	0.0793***	0.0085	0.0118
		(1.74)	(2.63)	(3.33)	(0.57)	(0.77)
*IndustryDistance * HasHB*		-0.3790***	-0.4182***		-0.2442***	-0.2367***
		(-2.87)	(-2.89)		(-3.24)	(-3.14)
*IndustryDistance (Sales) * HasHB*				-0.8033***		
				(-3.54)		
CommonLanguage	0.0121	0.0123	0.0128	0.0117	-0.0203	-0.0174
	(1.53)	(1.62)	(1.58)	(1.52)	(-1.63)	(-0.92)
KMDistance	-0.0003	-0.0006	0.0028	0.0026	0.0052*	0.0051*
	(-0.22)	(-0.39)	(1.10)	(1.07)	(1.96)	(1.76)
CommonCurrency	0.0074	0.0060	0.0072	0.0081	-0.0206*	-0.0223*
	(1.26)	(1.03)	(0.75)	(0.84)	(-1.67)	(-1.89)
ChangeCrossRate	0.0101**	0.0082*	0.0110**	0.0104**	0.0098**	0.0176***
	(2.20)	(1.78)	(2.07)	(2.01)	(2.12)	(3.10)
IRDifferential	-0.0008	-0.0009	-0.0015**	-0.0016**	-0.0015**	-0.0006
	(-0.95)	(-1.05)	(-2.11)	(-2.49)	(-2.42)	(-0.84)
FXChangetoUSD	-0.0108	-0.0128	-0.0184**	-0.0191**	-0.0166**	-0.0208**
	(-1.19)	(-1.43)	(-2.29)	(-2.48)	(-2.35)	(-2.53)
BTMDistance	-0.0000	0.0000	0.0002	0.0002	0.0005**	0.0004
	(-0.14)	(0.02)	(0.93)	(1.04)	(2.29)	(1.48)
ROADistance	0.0002*	0.0002*	0.0003**	0.0002**	0.0002*	0.0003*
	(1.84)	(1.77)	(2.06)	(2.08)	(1.84)	(1.86)
SizeDistance	0.0000	0.0000	-0.0000	-0.0000	0.0000	0.0000
	(0.10)	(0.22)	(-0.29)	(-0.11)	(1.17)	(1.61)
CapextoSalesDistance	0.0000	0.0000	0.0001*	0.0000	0.0001***	0.0001**
	(0.27)	(0.16)	(1.72)	(1.49)	(2.70)	(2.25)
TurnoverDistance	-0.0270	0.0084	-0.1512	-0.2102	0.2660	0.8440*
	(-0.06)	(0.02)	(-0.36)	(-0.52)	(0.61)	(1.92)
GDPpcDistance	-0.0000***	-0.0000**	-0.0000**	-0.0000**	-0.0000***	-0.0000***
	(-2.77)	(-2.54)	(-2.38)	(-2.51)	(-2.80)	(-3.11)
HomeCountry	0.0993**	0.0960**	0.1009***	0.0949***	0.0889***	0.0892***
	(2.52)	(2.53)	(2.90)	(2.80)	(2.85)	(2.76)
*HasHB * KMDistance*					-0.0049**	-0.0056**
					(-2.36)	(-2.52)
*HasHB * CommonLanguage*					0.1037***	0.1031***
					(4.35)	(4.29)
*HasHB * CommonCurrency*					0.1066***	0.1057***
					(4.41)	(4.25)
*HasHB * SizeDistance*					-0.0001***	-0.0001***
					(-2.82)	(-3.01)
*IndustryDistance * KMDistance*					-0.0223***	-0.0270***
					(-3.69)	(-4.50)
					Additional interactions estimated but unreported	
Unreported Variables	Destination Country, Home Country & Fund Controls, Time & Country Fixed Effects					
Fund Fixed Effects	No	No	Yes	Yes	Yes	Yes
Observations	552636	552636	552636	552636	552636	552636
Adjusted R^2	0.23	0.24	0.31	0.32	0.38	0.34

Table 4: Within-country Portfolio Allocations

The table presents semi-annual investment regressions at the fund-country level conditional on investing. The dependent variables are *ICIinCountry* or *FIBincountry* that measure the industry concentration or home industry weighted industry deviations on the country level. Explanatory variables include measures of distance between home and investment destination as well as (unreported) destination, home country and fund characteristics which are defined in section 3. All specifications include time, country and fund fixed effects. * / ** / *** denote statistical significance at the 10% / 5% / 1% level computed from standard errors clustered along the country-pair dimension.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:		*ICIinCountry*			*FIBinCountry*	
IndustryDistance	-0.2618***		-0.2930***	-0.0094		0.0136
	(-2.98)		(-2.78)	(-0.68)		(0.73)
IndustryDistance (Sales)		-0.0398			-0.0088	
		(-0.57)			(-0.47)	
HasHB	-0.0461**	-0.0676***	-0.0002	-0.0050***	-0.0044***	-0.0064***
	(-2.07)	(-2.76)	(-0.01)	(-3.14)	(-2.94)	(-2.75)
*IndustryDistance * HasHB*	0.6035***		0.3374**	0.0533***		0.0473***
	(2.65)		(2.51)	(3.35)		(3.06)
*IndustryDistance (Sales) * HasHB*		0.8880***			0.0499***	
		(3.37)			(3.43)	
CommonLanguage	-0.0484***	-0.0459***	-0.0318	-0.0079***	-0.0079***	-0.0068*
	(-3.48)	(-3.37)	(-1.28)	(-3.00)	(-2.98)	(-1.91)
KMDistance	-0.0045	-0.0044	-0.0073	-0.0000	-0.0000	0.0004
	(-1.14)	(-1.14)	(-1.59)	(-0.02)	(-0.06)	(0.94)
CommonCurrency	-0.0290**	-0.0340***	0.0068	-0.0053	-0.0054	-0.0051
	(-2.54)	(-2.98)	(0.33)	(-1.59)	(-1.61)	(-1.22)
ChangeCrossRate	0.0076	0.0116	0.0087	-0.0035	-0.0034	-0.0032
	(0.49)	(0.79)	(0.58)	(-1.52)	(-1.49)	(-1.45)
IRDifferential	0.0003	0.0004	0.0005	0.0002	0.0002	0.0002
	(0.18)	(0.24)	(0.34)	(0.99)	(0.98)	(0.98)
FXChangetoUSD	0.0203	0.0154	0.0180	0.0054	0.0054	0.0052
	(0.78)	(0.61)	(0.71)	(1.31)	(1.31)	(1.29)
BTMDistance	-0.0000	0.0002	-0.0005	0.0002**	0.0002**	0.0002**
	(-0.04)	(0.23)	(-0.60)	(2.54)	(2.57)	(2.02)
ROADistance	-0.0004	-0.0004	-0.0004	0.0000	0.0000	0.0000
	(-1.59)	(-1.57)	(-1.37)	(1.08)	(1.04)	(1.52)
SizeDistance	0.0000**	0.0000*	0.0000	-0.0000	-0.0000	-0.0000
	(2.06)	(1.78)	(1.09)	(-0.67)	(-0.69)	(-1.11)
CapextoSalesDistance	-0.0000	-0.0000	-0.0001	0.0000	0.0000	0.0000
	(-0.42)	(-0.46)	(-1.39)	(0.44)	(0.45)	(1.12)
TurnoverDistance	-0.3727	-0.1398	-0.1809	0.0955	0.1049	0.0931
	(-0.52)	(-0.19)	(-0.23)	(0.72)	(0.79)	(0.67)
GDPpcDistance	0.0000***	0.0000***	0.0000***	-0.0000*	-0.0000*	-0.0000
	(5.34)	(5.36)	(5.41)	(-1.70)	(-1.66)	(-1.57)
HomeCountry	-0.0265	0.0031	-0.0086	-0.0015	-0.0017	-0.0001
	(-0.73)	(0.08)	(-0.19)	(-0.41)	(-0.40)	(-0.01)
*HasHB * KMDistance*			0.0075**			0.0006**
			(2.35)			(2.25)
*HasHB * CommonLanguage*			-0.0913***			0.0005
			(-3.75)			(0.17)
*HasHB * CommonCurrency*			-0.1156***			-0.0012
			(-3.90)			(-0.56)
*HasHB * SizeDistance*			0.0001**			0.0000
			(2.23)			(1.47)
*IndustryDistance * KMDistance*			0.0239*			-0.0051**
			(1.81)			(-2.09)
Additional interactions estimated but unreported			Yes			Yes
Unreported Variables	Destination Country, Home Country & Fund Controls					
Fixed Effects	Time, Country & Fund					
Observations	377539	377539	377539	377539	377539	377539
Adjusted R^2	0.33	0.33	0.34	0.14	0.14	0.15

Table 5: The Domestic Portfolio and the Determinants of *Foreign Industry Bias (FIB)*

The table analyses the domestic portfolios of funds and its impact on *Foreign Industry Bias*. Panel A presents semi-annual fund-industry level regressions as in table 2 but limited to domestic portfolios. The specification is as in table 2. Panel B presents two-stage least square semi-annual investment regressions at the fund level. Columns 1 and 2 are first-stage regressions of the second stage endogenous variables *HB* and *ICIatHome* that are instrumented via home country characteristics. Column 3 estimates the determinants of *FIB* instrumenting *HB* and *ICIatHome* while column 4 presents the second stage without instrumenting *HB* and *ICIathome*. Explanatory variables include home country and fund characteristics as well as style and time fixed effects. * / ** / *** denote statistical significance at the 10% / 5% / 1% level computed from standard errors clustered along the fund & time dimensions.

Panel A : Domestic Industry Allocations

	Domestic Portfolio	
Dependent Variable:	(1) *HomeIndustry Share*	(2) *ExHomeIndustry Share*
HomeCtryIndustrySize	0.0187***	-0.0006
	(9.69)	(-0.62)
HomeCtryIndustryROS	0.0015***	0.0006*
	(2.78)	(1.75)
HomeCtryIndustryBTM	0.0001	0.0001
	(0.08)	(0.15)
HomeCtryIndustryLeverage	-0.0035	0.0054
	(-0.29)	(0.63)
ForeignCtryIndustryShare	-0.2156	0.3043
	(-0.62)	(1.33)
ForeignCtryIndustrySize	-0.0183	-0.0052
	(-1.43)	(-0.56)
ForeignCtryIndustryROS	0.0023	0.0071
	(0.09)	(0.32)
ForeignCtryIndustryBTM	-0.0524***	0.0010
	(-3.15)	(0.07)
ForeignCtryIndustryLeverage	-0.0765	-0.0002
	(-1.57)	(-0.00)
Unreported Variables	Fund & Home Country Controls	
Fixed Effects	Time, Industry & Home Country	
Industries in Regression	Top 20	Top 20
Observations	587198	587198
Adjusted R^2	0.12	0.01

Panel B: The Determinants of Foreign Industry Bias

	First Stage Regression		Second Stage Regression	
			Instrumented (2SLS)	**NOT Instrumented**
	(1)	(2)	(3)	(4)
Dependent Variable:	*HB*	*ICIatHome*	*FIB*	*FIB*
HB			0.0468***	0.0168***
			(6.07)	(4.13)
ICIatHome			0.0455***	-0.0000
			(3.65)	(-0.04)
HomeIndustryConcentration	-1.0709***	1.3746***		
	(-5.40)	(4.20)		
HomeCountrySize	-0.0595***	0.0120		
	(-10.28)	(1.42)		
HomeCountryROS	0.8384***	-1.2650***		
	(4.03)	(-3.95)		
HomeCountryLeverage	0.3694***	-0.3116**		
	(3.71)	(-2.35)		
HomeCountryBtM	-0.0403	-0.3460***		
	(-1.01)	(-4.20)		
HomeCountryPastReturn	0.0213	-0.1231		
	(0.58)	(-1.36)		
Fundsize	-0.0111***	0.0013	0.0002	-0.0002
	(-4.54)	(0.41)	(0.58)	(-1.06)
Firmsize	-0.0022	0.0024	0.0003	0.0003*
	(-1.40)	(1.27)	(1.63)	(1.82)
Age	0.0019***	-0.0026***	0.0002***	0.0001***
	(4.02)	(-4.72)	(3.19)	(2.79)
Expenses	-0.3428	1.6816**	-0.3454***	-0.2805***
	(-0.55)	(2.47)	(-4.11)	(-3.44)
Pastreturn	0.1606***	0.0819*	-0.0145*	-0.0057
	(2.97)	(1.77)	(-1.88)	(-0.82)
InstShareClass	-0.0232	0.0716	-0.0005	0.0018*
	(-1.17)	(1.70)	(-0.26)	(1.68)
ShareClasses	-0.0080***	0.0072**	-0.0001	-0.0001
	(-4.67)	(2.14)	(-0.53)	(-0.89)
Volatility	0.4165***	0.1396	-0.0061	0.0141
	(3.20)	(1.25)	(-0.49)	(1.43)
Turnover	-0.0082***	0.0052*	0.0003	0.0002**
	(-5.30)	(1.80)	(1.43)	(2.33)
Fixed Effects	Time & Style			
Observations	30398	30398	30398	30398
Adjusted R^2	0.3446	0.1946		0.1437
F-test	28.6028	15.0362		
p-value	0.0000	0.0000		
AP-F-test (Weak ID)	31.7681	16.6428		
AP-Chi^2 (Under ID)	167.0408	87.5100		
p-value	0.0000	0.0000		

Table 6: Performance Effects of *Foreign Industry Bias (FIB)* – Factor Models

The table presents monthly Fama-MacBeth regressions on fund performance. Panel A presents the baseline specification where fund performance is estimated with style-specific factor models, panel B presents results from alternative factor models while panel C presents sample splits. Explanatory variables are as defined in section 3. All regressions include (unreported) style fixed effects. * / ** / *** denote statistical significance at the 10% / 5% / 1% level computed from standard errors that correct for serial dependence with the Newey-West procedure allowing for 3 lags.

Panel A: Baseline

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*Grossret-RF*	*1F Alpha*	*4F Alpha*	*4F Alpha*	*4F Alpha*	*4F Alpha*
FIB	-2.7923***	-3.0228***	-2.1140***	-2.2664***	-2.3479***	-2.0652***
	(-4.26)	(-4.61)	(-3.37)	(-3.65)	(-3.71)	(-3.44)
HasHB	0.0230	0.0046	0.0508	0.0688**	0.0389	
	(0.71)	(0.13)	(1.48)	(2.15)	(0.80)	
*HasHB * FIB*	2.0677**	2.0462**	3.1802***	2.8984***	3.0246***	
	(2.34)	(2.22)	(3.83)	(4.28)	(4.47)	
ICI				-0.0118	-0.0511	-0.0548
				(-0.15)	(-0.58)	(-0.73)
*HasHB * ICI*					0.0782	
					(0.89)	
HB						0.2754**
						(2.05)
*HB * FIB*						5.0467***
						(3.89)
*HB * ICI*						-0.1123
						(-0.65)
HomeIndustryConcentration				-0.4081	-0.4211	-0.3143
				(-0.87)	(-0.90)	(-0.69)
LogHomeMCAP				-0.0259	-0.0263	-0.0168
				(-1.40)	(-1.42)	(-0.94)
KMDistance				-0.0062	-0.0063	-0.0075*
				(-1.40)	(-1.41)	(-1.69)
CommonLanguage				-0.0515	-0.0514	-0.0462
				(-0.97)	(-0.97)	(-0.90)
CommonCurrency				-0.2311**	-0.2292**	-0.2100*
				(-2.11)	(-2.10)	(-1.94)
DeltaFXtoUS				-0.7986	-0.7914	-0.7084
				(-1.55)	(-1.52)	(-1.33)
DiffIR				0.0162	0.0162	0.0165
				(1.30)	(1.30)	(1.31)
Fundsize	0.0046	0.0080	-0.0039	-0.0020	-0.0021	-0.0020
	(0.79)	(1.34)	(-0.63)	(-0.33)	(-0.36)	(-0.34)
Firmsize	0.0031	0.0024	0.0048*	0.0072**	0.0073**	0.0068**
	(1.18)	(0.93)	(1.69)	(2.54)	(2.56)	(2.44)
Age	-0.0009	-0.0012	-0.0005	-0.0009	-0.0009	-0.0012
	(-1.00)	(-1.32)	(-0.49)	(-0.98)	(-0.98)	(-1.28)
Expenses	1.0668	1.1193	1.0998	1.8071	1.8347	1.9512
	(0.97)	(0.87)	(0.74)	(1.38)	(1.40)	(1.52)
Pastreturn	2.2030***	1.9305***	-0.0526	-0.1281	-0.1195	-0.1190
	(4.47)	(4.02)	(-0.10)	(-0.24)	(-0.23)	(-0.23)
InstShareClass	0.0215	0.0251	0.0060	0.0055	0.0058	0.0071
	(0.62)	(0.72)	(0.18)	(0.18)	(0.19)	(0.24)
ShareClasses	0.0062	0.0095*	-0.0034	-0.0026	-0.0027	-0.0020
	(1.14)	(1.78)	(-0.69)	(-0.73)	(-0.74)	(-0.57)
Volatility	1.2325	-0.0562	0.8103	1.0831	1.0572	1.0809
	(0.65)	(-0.04)	(0.67)	(0.91)	(0.89)	(0.92)
Turnover	-0.0024	0.0004	-0.0088	-0.0076	-0.0075	-0.0072
	(-0.28)	(0.05)	(-0.80)	(-0.69)	(-0.69)	(-0.68)
Unreported Variables	Style Fixed Effects					
Observations	236718	236718	236718	236516	236516	236516
R^2	0.46	0.36	0.32	0.35	0.35	0.35

Panel B: Alternative Factor Models

Dependent Variable:	(1) 4F Alpha (Global)	(2) 4F Alpha (Net)	(3) End.BM Alpha (VW)	(4) End.BM Alpha (EW)	(5) C-Alpha (Style DY)	(6) C-Alpha (US DY)
FIB	-1.6387***	-2.0976***	-1.7202***	-1.5734***	-1.2136***	-1.2368***
	(-3.91)	(-3.50)	(-3.25)	(-3.58)	(-2.81)	(-2.97)
HB	0.2270**	0.2255**	0.2566***	0.2199**	0.0072	0.0250
	(2.59)	(2.42)	(2.74)	(2.22)	(0.09)	(0.32)
*HB * FIB*	3.2042**	4.8610***	4.0308***	3.2886***	2.4396**	2.2037**
	(2.59)	(3.62)	(3.44)	(2.79)	(2.42)	(2.23)
ICI	-0.0018	-0.0744	-0.0874	-0.0238	-0.0479	-0.0508
	(-0.02)	(-1.06)	(-1.27)	(-0.36)	(-0.80)	(-0.85)
HomeIndustryConcentration	-0.0917	-0.3176	-0.2581	0.0037	-0.1740	-0.1271
	(-0.21)	(-0.69)	(-0.56)	(0.01)	(-0.40)	(-0.29)
LogHomeMCAP	-0.0072	-0.0170	-0.0183	-0.0003	0.0062	0.0068
	(-0.43)	(-0.96)	(-1.02)	(-0.02)	(0.36)	(0.39)
KMDistance	-0.0084*	-0.0078*	-0.0069	-0.0041	0.0037	0.0019
	(-1.89)	(-1.72)	(-1.60)	(-0.89)	(0.87)	(0.45)
CommonLanguage	-0.0269	-0.0466	-0.0534	-0.0162	0.0482	0.0469
	(-0.48)	(-0.90)	(-1.01)	(-0.33)	(1.11)	(1.06)
CommonCurrency	-0.2183*	-0.2191**	-0.2011**	-0.1324	0.0311	0.0287
	(-1.96)	(-2.02)	(-2.02)	(-1.28)	(0.30)	(0.27)
DeltaFXtoUS	-0.5628	-0.7198	-0.6498	-0.8324*	-0.6793	-0.6648
	(-1.11)	(-1.35)	(-1.36)	(-1.72)	(-1.63)	(-1.52)
DiffIR	0.0221*	0.0167	0.0040	0.0098	-0.0048	-0.0027
	(1.81)	(1.33)	(0.33)	(0.72)	(-0.48)	(-0.27)
Unreported Variables	Fund-level Controls, Style Fixed Effects					
Standard Errors	Newey-West corrected with 3 lags					
Observations	236516	236516	236511	236516	235602	235602
R^2	0.43	0.35	0.18	0.15	0.35	0.35

Panel C: Sample Splits

	ICI		**Time Series Split**		**Investment Scope**	
	High	***Low***	***2001-2007***	***2008-2010***	***Wide***	***Narrow***
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*4F Alpha*	*4F Alpha*	*4F Alpha*	*4F Alpha*	*4F Alpha*	*4F Alpha*
FIB	-2.0654***	-2.2264***	-2.4374***	-1.2724	-2.3535***	-1.5519**
	(-2.74)	(-3.22)	(-3.17)	(-1.50)	(-3.51)	(-2.13)
HB	0.1562	0.2824**	0.1677	0.3563**	0.2212**	0.0440
	(1.65)	(2.09)	(1.48)	(2.29)	(2.19)	(0.27)
*HB * FIB*	4.9196***	1.2194	4.2339**	6.3218***	4.9078***	1.8245
	(3.15)	(0.26)	(2.53)	(2.98)	(3.87)	(0.47)
ICI	0.1778*	-0.3377**	-0.2068***	0.2415*	-0.1208	0.1348
	(1.85)	(-2.59)	(-2.97)	(2.00)	(-1.46)	(1.56)
HomeIndustryConcentration	-0.6923	0.1944	0.1494	-1.4545	-0.3907	-0.4011
	(-1.04)	(0.38)	(0.33)	(-1.43)	(-0.61)	(-1.01)
LogHomeMCAP	-0.0089	-0.0177	-0.0165	-0.0196	-0.0328	0.0143
	(-0.39)	(-0.94)	(-0.83)	(-0.54)	(-1.18)	(0.91)
KMDistance	-0.0047	-0.0053	-0.0059	-0.0118	-0.0075	-0.0123**
	(-0.56)	(-0.96)	(-1.16)	(-1.33)	(-0.64)	(-2.24)
CommonLanguage	-0.1354*	-0.0052	-0.0488	-0.0441	-0.0563	0.0664
	(-1.66)	(-0.08)	(-0.81)	(-0.43)	(-0.90)	(0.79)
CommonCurrency	-0.2885**	-0.1794*	-0.1513	-0.3826	-0.3734***	-0.0043
	(-2.08)	(-1.79)	(-1.31)	(-1.61)	(-2.63)	(-0.05)
DeltaFXtoUS	-0.8447	-0.6968	-0.8348	-0.4570	-0.9424	-0.6166
	(-1.11)	(-1.12)	(-1.23)	(-0.54)	(-1.40)	(-0.68)
DiffIR	0.0368*	0.0114	-0.0101	0.0800***	-0.0105	0.0389***
	(1.94)	(0.96)	(-0.90)	(3.72)	(-0.46)	(2.68)
Unreported Variables	Fund-level Controls, Style Fixed Effects					
Standard Errors	Newey-West corrected with 3 lags					
Observations	117689	118827	148883	87633	164498	72018
R^2	0.31	0.44	0.35	0.35	0.31	0.41

Table 7: Performance Effects of *Foreign Industry Bias (FIB)* – Holding Decompositions

The table presents decompositions of holding returns. Holding returns are computed from semi-annual holdings and decomposed following Daniel et al. (1997) with a style-specific industry benchmark. Columns 1-4 consider entire fund portfolios, columns 5-8 only foreign sub-portfolios. Explanatory variables are as defined in section 3. All regressions include (unreported) fund-level controls, style and time fixed effects. * / ** / *** denote statistical significance at the 10% / 5% / 1% level computed from standard errors that are clustered along the fund and time dimensions.

	All Positions				**Foreign Positions Only**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	*Holdret*	*I-CS*	*I-CT*	*I-AS*	*Foreign Holdret*	*Foreign I-CS*	*Foreign I-CT*	*Foreign I-AS*
FIB	-17.4631***	-7.7465**	1.3499	-11.0665***	-18.2374***	-9.2724***	2.1733*	-11.1726***
	(-4.69)	(-2.25)	(1.24)	(-3.25)	(-5.01)	(-2.87)	(1.67)	(-3.23)
HasHB	0.0932	0.0559	0.0066	0.0307	-0.1748	-0.1185	0.0078	-0.0645
	(0.45)	(0.34)	(0.30)	(0.43)	(-1.14)	(-0.93)	(0.24)	(-0.77)
*HasHB * FIB*	11.7952**	9.5676*	-1.8401	4.0678	21.9816***	19.7798**	-0.9647	2.6277
	(2.26)	(1.92)	(-1.60)	(0.89)	(3.05)	(2.39)	(-0.39)	(0.45)
ICI	0.2521	-0.3765	0.2382**	0.3904	0.5027	-0.8579	0.3707**	0.9919**
	(0.37)	(-0.77)	(2.05)	(1.46)	(0.58)	(-1.21)	(2.50)	(2.40)
HomeIndustryConcentration	-2.0442	2.0782	-0.5427	-3.5798	3.2769	3.5129	-1.1645	0.9138
	(-0.45)	(0.68)	(-1.08)	(-1.59)	(0.70)	(1.00)	(-1.54)	(0.44)
LogHomeMCAP	-0.1366	0.0061	-0.0326**	-0.1100	0.1516	0.1567	-0.0585***	0.0550
	(-0.88)	(0.06)	(-1.98)	(-1.59)	(0.83)	(1.16)	(-2.96)	(0.72)
KMDistance	-0.0442	-0.0127	0.0091	-0.0407	-0.0668*	-0.0398	0.0034	-0.0282
	(-1.26)	(-0.30)	(1.00)	(-1.04)	(-1.90)	(-0.84)	(0.30)	(-0.69)
CommonLanguage	0.2749	0.1855	0.0830	0.0064	0.6718**	0.5514*	0.1019	0.0176
	(0.97)	(0.65)	(1.04)	(0.03)	(2.16)	(1.89)	(1.24)	(0.09)
CommonCurrency	-2.5928**	-1.4293**	0.1506	-1.3141**	-1.6310*	-1.0662	-0.0239	-0.5480
	(-2.35)	(-2.00)	(1.26)	(-2.23)	(-1.68)	(-1.62)	(-0.15)	(-1.13)
DeltaFXtoUS	-1.0295	1.0856	0.5548*	-2.6700	-4.6876*	-2.2581	0.9585***	-3.3764*
	(-0.50)	(0.61)	(1.73)	(-1.60)	(-1.69)	(-0.98)	(3.45)	(-1.86)
DiffIR	-0.0828	0.0382	-0.0312	-0.0898	0.0510	0.1063	-0.0371	-0.0193
	(-0.37)	(0.18)	(-1.30)	(-1.11)	(0.25)	(0.51)	(-1.43)	(-0.22)
Unreported Variables	Fund-level Controls, Time & Style Fixed Effects							
Standard Errors	2-way Cluster at the Fund & Time Dimensions							
Observations	38065	38065	38065	38065	38065	38064	38046	38046
Adjusted R^2	0.87	0.15	0.12	0.92	0.85	0.12	0.09	0.91

Table 8: Return Chasing in Foreign Trades

The table presents regressions on return chasing, decomposed into buy and sell transactions at the semi-annual frequency. The dependent variables are the correlation of foreign trading with industry returns of the traded stock. In Panel A, all foreign trades are considered with contemporaneous returns measured over the last quarter. Panel B only considers foreign trades in those industries that are among the top-10 by market capitalization at home and panel C measures contemporaneous returns over the last 6 months. Columns 1-3 compute return chasing with respect to industry returns in the destination country where the stock is located, column 4-6 with respect to home country industry returns and columns 7-9 with respect to world industry returns. Explanatory variables are as defined in section 3. All regressions include (unreported) fund-level controls, style and time fixed effects. * / ** / *** denote statistical significance at the 10% / 5% / 1% level computed from standard errors that are clustered along the fund and time dimensions.

Panel A: Correlation of Percentage Position Changes with Contemporaneous Quarterly Industry Returns

	DESTINATION Industry Returns			**HOME Industry Returns**			**WORLD Industry Returns**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:	*Foreign Cor(%Buy, LocalRet-1q)*	*Foreign Cor(%Sell, LocalRet-1q)*	*Foreign Cor(%Trade, LocalRet-1q)*	*Foreign Cor(%Buy, HomeRet-1q)*	*Foreign Cor(%Sell, HomeRet-1q)*	*Foreign Cor(%Trade, HomeRet-1q)*	*Foreign Cor(%Buy, WorldRet-1q)*	*Foreign Cor(%Sell, WorldRet-1q)*	*Foreign Cor(%Trade, WorldRet-1q)*
FIB	-0.0110	0.0111	-0.0747	0.0790	-0.0061	0.0196	0.0078	0.0081	-0.0518
	(-0.13)	(0.14)	(-0.73)	(0.69)	(-0.08)	(0.17)	(0.11)	(0.09)	(-0.66)
HasHB	-0.0081**	-0.0063**	-0.0093***	-0.0050	-0.0027	-0.0049	-0.0063*	-0.0015	-0.0054
	(-2.02)	(-2.52)	(-3.01)	(-1.42)	(-0.76)	(-1.19)	(-1.81)	(-0.47)	(-1.53)
*HasHB * FIB*	-0.2413	-0.1336	0.0619	0.5421**	0.5246**	0.7165***	0.5817**	0.2716	0.7652***
	(-0.92)	(-0.62)	(0.28)	(2.26)	(2.40)	(3.07)	(2.32)	(1.23)	(3.26)
ICI	-0.0287*	-0.0233	-0.0524***	0.0267***	0.0280***	0.0239***	-0.0050	0.0067	-0.0110
	(-1.93)	(-1.36)	(-2.62)	(2.81)	(3.02)	(2.83)	(-0.39)	(0.48)	(-0.74)
HomeIndustry	-0.0400	-0.0765	-0.0761	-0.0191	0.0020	0.0183	-0.0381	-0.0237	0.0026
Concentration	(-0.49)	(-1.06)	(-1.18)	(-0.33)	(0.03)	(0.34)	(-0.56)	(-0.49)	(0.05)
LogHomeMCAP	0.0027	0.0029	0.0020	0.0022	0.0015	0.0025	0.0006	0.0001	0.0009
	(0.99)	(1.33)	(0.78)	(1.20)	(0.67)	(1.48)	(0.30)	(0.11)	(0.45)
KMDistance	-0.0008	0.0007	0.0010	-0.0013**	-0.0014*	-0.0011	-0.0013**	0.0002	0.0003
	(-0.82)	(0.64)	(0.79)	(-2.01)	(-1.76)	(-1.45)	(-1.96)	(0.36)	(0.32)
CommonLanguage	0.0009	-0.0095	0.0073	-0.0005	-0.0084	-0.0039	-0.0068	-0.0054	0.0054
	(0.16)	(-1.42)	(1.08)	(-0.12)	(-1.50)	(-0.76)	(-1.15)	(-0.96)	(0.90)
CommonCurrency	0.0004	-0.0046	0.0049	0.0018	0.0024	0.0116	-0.0085	-0.0084	-0.0013
	(0.03)	(-0.35)	(0.34)	(0.14)	(0.22)	(1.13)	(-0.76)	(-0.87)	(-0.11)
DeltaFXtoUS	0.0233	0.0096	0.0266	-0.0084	0.0277	0.0018	0.0119	-0.0075	0.0039
	(0.80)	(0.37)	(0.81)	(-0.39)	(1.00)	(0.06)	(0.41)	(-0.29)	(0.15)
DiffIR	-0.0001	-0.0014	-0.0001	0.0014	0.0002	0.0012	-0.0025	-0.0031***	-0.0025**
	(-0.08)	(-0.82)	(-0.03)	(0.84)	(0.11)	(0.70)	(-1.60)	(-3.06)	(-2.18)
Unreported Variables	Fund-level Controls, Time & Style Fixed Effects								
Standard Errors	Clustered at the Fund & Time Dimensions								
Observations	37133	38441	38614	36990	38374	38551	37141	38434	38604
Adjusted R^2	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.02	0.01

Panel B: Top-10 Home Industries Only

	DESTINATION Industry Returns			HOME Industry Returns			WORLD Industry Returns		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:	*Foreign Top10Cor (%Buy, LocalRet)*	*Foreign Top10Cor (%Sell, LocalRet)*	*Foreign Top10Cor (%Trade, LocalRet)*	*Foreign Top10Cor (%Buy, HomeRet)*	*Foreign Top10Cor (%Sell, HomeRet)*	*Foreign Top10Cor (%Trade, HomeRet)*	*Foreign Top10Cor (%Buy, WorldRet)*	*Foreign Top10Cor (%Sell, WorldRet)*	*Foreign Top10Cor (%Trade, WorldRet)*
FIB	0.1042	-0.0590	0.0541	0.1245	-0.3323***	-0.1423	0.1823	-0.1346	0.1553
	(0.89)	(-0.42)	(0.32)	(1.04)	(-3.28)	(-1.21)	(1.50)	(-1.02)	(1.27)
HasHB	-0.0137**	-0.0046	-0.0069	-0.0033	0.0019	0.0047	-0.0069	0.0049	-0.0010
	(-2.36)	(-1.03)	(-1.39)	(-0.71)	(0.42)	(0.80)	(-1.34)	(1.25)	(-0.21)
*HasHB * FIB*	-0.1919	-0.0328	0.0395	0.8143**	1.0123***	0.9547***	1.1890***	0.8593***	1.1025***
	(-0.60)	(-0.12)	(0.15)	(2.32)	(3.43)	(2.85)	(3.07)	(3.10)	(3.38)
ICI	-0.0326	-0.0362*	-0.0698***	0.0594***	0.0389**	0.0400**	0.0277*	0.0468***	0.0248
	(-1.48)	(-1.91)	(-2.62)	(3.93)	(2.39)	(2.42)	(1.85)	(2.96)	(1.43)
Unreported Variables	Controls, Time & Style Fixed Effects								
Standard Errors	Clustered at the Fund & Time Dimensions								
Observations	34205	37078	37598	34167	37018	37470	34171	37023	37473
Adjusted R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Panel C: Top-10 Home Industries Only with Semi-Annual Industry Returns

	DESTINATION Industry Returns			HOME Industry Returns			WORLD Industry Returns		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:	*Foreign Top10Cor (%Buy, LocalRet-2q)*	*Foreign Top10Cor (%Sell, LocalRet-2q)*	*Foreign Top10Cor (%Trade, LocalRet-2q)*	*Foreign Top10Cor (%Buy, HomeRet-2q)*	*Foreign Top10Cor (%Sell, HomeRet-2q)*	*Foreign Top10Cor (%Trade, HomeRet-2q)*	*Foreign Top10Cor (%Buy, WorldRet-2q)*	*Foreign Top10Cor (%Sell, WorldRet-2q)*	*Foreign Top10Cor (%Trade, WorldRet-2q)*
FIB	0.1218	0.0759	0.1107	0.0913	-0.0906	0.0959	0.2767**	0.0769	0.2539
	(0.86)	(0.44)	(0.55)	(0.71)	(-0.73)	(0.64)	(2.32)	(0.56)	(1.61)
HasHB	-0.0170***	-0.0094***	-0.0155***	0.0105*	0.0137**	0.0116*	-0.0013	0.0063*	-0.0019
	(-2.81)	(-2.66)	(-3.46)	(1.77)	(2.36)	(1.92)	(-0.20)	(1.66)	(-0.38)
*HasHB * FIB*	0.0973	0.4805*	0.5267*	1.3103***	0.8611***	1.1384***	1.0252**	0.8070***	1.2332***
	(0.30)	(1.65)	(1.70)	(3.36)	(3.35)	(2.78)	(2.17)	(3.18)	(3.72)
ICI	-0.0528***	-0.0164	-0.0611**	0.0446**	0.0474***	0.0431**	0.0043	0.0397***	0.0167
	(-2.70)	(-0.86)	(-2.51)	(2.42)	(3.04)	(2.27)	(0.29)	(3.08)	(1.02)
Unreported Variables	Fund-level Controls, Time & Style Fixed Effects								
Standard Errors	Clustered at the Fund & Time Dimensions								
Observations	34200	37077	37597	34167	37018	37470	34171	37023	37473
Adjusted R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table 9: Foreign Trading and Return Predictability

The table presents regressions on return predictability of trades, decomposed into buy and sell transactions at the semi-annual frequency. The dependent variables are the correlation of trading with future destination stock returns. In Panel A, all foreign trades are considered. Panel B only considers foreign trades in those industries that are among the top-10 by market capitalization at home. Columns 1-3 compute return predictability over the next quarter, columns 4-6 over the next two quarters. Explanatory variables are as defined in section 3. All regressions include (unreported) fund-level controls, style and time fixed effects. * / ** / *** denote statistical significance at the 10% / 5% / 1% level computed from standard errors that are clustered along the fund and time dimensions.

Panel A : All Foreign Positions

	1 Quarter Horizon			**2 Quarter Horizon**		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*Foreign Cor(%Buy, FutRet-1q)*	*Foreign Cor(%Sell, FutRet-1q)*	*Foreign Cor(%Trade, FutRet-1q)*	*Foreign Cor(%Buy, FutRet-2q)*	*Foreign Cor(%Sell, FutRet-2q)*	*Foreign Cor(%Trade, FutRet-2q)*
FIB	-0.1304*	-0.0322	-0.1456	-0.1785**	-0.1036	-0.1838**
	(-1.69)	(-0.31)	(-1.31)	(-2.23)	(-1.36)	(-2.18)
HasHB	0.0009	0.0042	0.0037	0.0031	0.0023	0.0038
	(0.30)	(1.20)	(1.06)	(0.92)	(0.71)	(0.95)
*HasHB * FIB*	0.5992*	0.4968**	0.8200***	0.6141	0.5629**	0.7625*
	(1.85)	(2.19)	(3.02)	(1.62)	(2.22)	(1.95)
ICI	0.0313***	0.0184*	0.0264**	0.0354**	0.0339***	0.0287**
	(3.31)	(1.70)	(2.40)	(2.22)	(2.85)	(2.10)
HomeIndustryConcentration	-0.1336**	-0.0239	-0.0645	-0.1371***	-0.0256	-0.0481
	(-2.41)	(-0.36)	(-0.93)	(-2.68)	(-0.42)	(-0.77)
LogHomeMCAP	-0.0034*	0.0001	-0.0007	-0.0034*	-0.0004	-0.0011
	(-1.68)	(0.03)	(-0.29)	(-1.83)	(-0.21)	(-0.57)
KMDistance	-0.0006	0.0002	0.0003	-0.0015*	-0.0003	-0.0006
	(-0.80)	(0.28)	(0.38)	(-1.68)	(-0.39)	(-0.65)
CommonLanguage	-0.0010	-0.0076	-0.0055	-0.0030	-0.0032	-0.0024
	(-0.21)	(-1.63)	(-1.01)	(-0.46)	(-0.55)	(-0.34)
CommonCurrency	-0.0249*	-0.0155	-0.0251	-0.0225*	-0.0172	-0.0229*
	(-1.86)	(-1.23)	(-1.45)	(-1.89)	(-1.50)	(-1.72)
DeltaFXtoUS	0.0454*	-0.0103	0.0201	0.0051	-0.0308	-0.0231
	(1.75)	(-0.44)	(0.63)	(0.19)	(-1.09)	(-0.67)
DiffIR	0.0005	0.0010	0.0006	0.0005	-0.0006	-0.0002
	(0.36)	(0.76)	(0.45)	(0.29)	(-0.51)	(-0.13)
Unreported Variables	Fund-level Controls, Time & Style Fixed Effects					
Standard Errors	Clustered at the Fund & Time Dimensions					
Observations	37139	38433	38617	35256	36514	36675
Adjusted R^2	0.01	0.02	0.01	0.01	0.02	0.01

Panel B: Foreign Positions in Top-10 Home Industries Only

	1 Quarter Horizon			**2 Quarter Horizon**		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*Foreign Top10Cor(%Buy, FutRet-1q)*	*Foreign Top10Cor(%Sell, FutRet-1q)*	*Foreign Top10Cor(%Trade, FutRet-1q)*	*Foreign Top10Cor(%Buy, FutRet-2q)*	*Foreign Top10Cor(%Sell, FutRet-2q)*	*Foreign Top10Cor(%Trade, FutRet-2q)*
FIB	0.0649	0.2307*	0.1050	-0.1671	0.0794	-0.0522
	(0.53)	(1.85)	(0.72)	(-0.90)	(0.63)	(-0.28)
HasHB	0.0011	0.0033	0.0008	0.0067	0.0016	0.0060
	(0.16)	(0.64)	(0.13)	(0.97)	(0.34)	(0.94)
*HasHB * FIB*	0.8417***	0.5039*	0.8859***	0.9558***	0.3068	0.9977***
	(2.65)	(1.77)	(3.42)	(2.60)	(1.12)	(2.74)
ICI	0.0576***	0.0395***	0.0651***	0.0415**	0.0472***	0.0620***
	(3.28)	(3.69)	(4.53)	(2.05)	(3.65)	(3.79)
HomeIndustryConcentration	-0.2552**	-0.2158***	-0.1954**	-0.0874	-0.1248	-0.0196
	(-2.17)	(-2.76)	(-1.96)	(-0.83)	(-1.30)	(-0.21)
LogHomeMCAP	-0.0052*	-0.0057**	-0.0039	-0.0010	-0.0030	0.0004
	(-1.69)	(-2.05)	(-1.29)	(-0.34)	(-0.93)	(0.12)
KMDistance	0.0005	-0.0009	0.0011	-0.0008	-0.0007	0.0003
	(0.37)	(-0.75)	(0.72)	(-0.58)	(-0.94)	(0.26)
CommonLanguage	0.0046	-0.0064	0.0117	-0.0158	-0.0105	-0.0047
	(0.56)	(-0.76)	(1.51)	(-1.47)	(-1.49)	(-0.60)
CommonCurrency	-0.0188	-0.0232	-0.0080	-0.0158	-0.0297*	-0.0113
	(-1.29)	(-1.17)	(-0.37)	(-1.15)	(-1.68)	(-0.77)
DeltaFXtoUS	0.0853**	0.0283	0.0648	0.0518	0.0057	0.0496
	(2.56)	(0.43)	(1.19)	(0.90)	(0.10)	(0.89)
DiffIR	0.0026	0.0002	0.0032	0.0008	-0.0024	-0.0005
	(1.02)	(0.11)	(1.21)	(0.31)	(-1.36)	(-0.25)
Unreported Variables	Fund-level Controls, Time & Style Fixed Effects					
Standard Errors	Clustered at the Fund & Time Dimensions					
Observations	34277	37132	37686	32551	35292	35787
Adjusted R^2	0.01	0.02	0.01	0.01	0.01	0.01

Table 10: Persistence in Portfolio Choice and Performance

This table presents fund-level sorts on either excess allocations (panel A) or performance (panel B). Every June and December, funds are sorted into deciles on the variable indicated in the first column of the tables. The next ten columns present the average future rank of all funds in each group one year ahead adjusted for the average rank under the null of no persistence (i.e. Future Rank – 5.5). In panel A, the portfolio characteristics are as of June and December when the sort is performed. In panel B, funds are sorted on the prior one year performance measured by the variable indicated in the first column. The final columns in panel B also presents the differences in returns implied by the rank analysis of the preceding ten columns. * / ** / *** indicate significance at the 10% / 5% / 1% level.

Panel A: Persistence in Portfolio Choice

Horizon: 12 months	*Future Rank – E[Future Rank | No Persistence]*									
Current Rank	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Foreign Industry Bias	-3.1495***	-1.9868***	-1.2483***	-0.6371***	-0.1101***	0.3289***	0.6685***	1.2544***	1.9246***	2.7814***
	(-61.41)	(-36.26)	(-23.49)	(-12.68)	(-3.04)	(7.37)	(11.13)	(19.40)	(39.29)	(30.24)
Industry Concentration	-3.5527***	-2.6894***	-1.7919***	-1.0830***	-0.4357***	0.2900***	0.8721***	1.6484***	2.5085***	3.7219***
	(-73.46)	(-78.64)	(-41.52)	(-25.29)	(-9.14)	(8.91)	(22.49)	(40.52)	(51.62)	(138.72)
Home Bias	-4.3888***	-2.9165***	-1.8452***	-1.1921***	-0.5640***	0.0293	0.8014***	1.8664***	3.1336***	4.2481***
	(-265.02)	(-34.53)	(-36.01)	(-21.63)	(-8.31)	(0.99)	(15.09)	(32.83)	(75.01)	(161.41)

Panel B: Performance Persistence

Horizon: 12 months	*Future Rank – E[Future Rank | No Persistence]*										*% p.a.*
Current Rank	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(10)-(1)
Return-Style BEFORE Fees	-1.1470***	-0.7094***	-0.5944***	-0.3949***	-0.1979**	0.0596	0.2614**	0.4786**	0.8135***	1.0841**	5.4189***
	(-3.92)	(-3.42)	(-3.90)	(-3.65)	(-2.41)	(0.68)	(2.48)	(2.83)	(3.71)	(2.64)	(3.59)
4F Alpha BEFORE Fees	-0.1721	-0.1559	-0.2872*	-0.3087***	-0.3926***	-0.3915***	-0.1079	0.1362	0.4177*	0.8360**	3.2362*
	(-0.58)	(-0.68)	(-2.02)	(-3.58)	(-4.12)	(-4.15)	(-0.89)	(0.85)	(1.96)	(2.76)	(1.94)
4F Alpha AFTER Fees	-0.2336	-0.1964	-0.2239	-0.3181***	-0.3016***	-0.3813***	-0.0823	0.0979	0.4071*	0.8185**	3.3196**
	(-0.80)	(-0.84)	(-1.40)	(-4.50)	(-3.09)	(-3.63)	(-0.67)	(0.61)	(1.97)	(2.77)	(2.14)

Table 11: Robustness Tests – Portfolio Choice Regressions

The table presents robustness tests on the investment regressions of tables 3 and 4. All regressions use the raw measure of *HB* and details are as in the table or as above.

Dependent Var.:	*CountryShare*				*ICIinCountry*				*FIBinCountry*			
Specification	**Baseline**	**Home F.E.**	**2001-07**	**2008-10**	**Baseline**	**Home F.E.**	**2001-07**	**2008-10**	**Baseline**	**Home F.E.**	**2001-07**	**2008-10**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IndustryDistance	0.1498***	0.1392***	0.0621	0.1658**	-0.3006***	-0.2736**	-0.0834	-0.1886	0.0181	0.0156	0.0252	-0.0060
	(3.10)	(2.97)	(1.44)	(2.41)	(-2.88)	(-2.53)	(-0.79)	(-1.40)	(0.99)	(0.89)	(1.23)	(-0.26)
HB	0.0385	0.0313	0.0253	0.0972**	0.1991**	0.1822**	0.1118	0.0129	-0.0185***	-0.0176**	-0.0142	-0.0101
	(0.74)	(0.79)	(0.62)	(2.06)	(2.30)	(2.48)	(1.45)	(0.14)	(-2.75)	(-2.25)	(-1.54)	(-1.00)
*IndustryDistance **	-0.5347***	-0.5725***	-0.4675***	-1.0068***	0.8098**	0.9190**	0.6352	2.2140***	0.1167***	0.1457***	0.1339***	0.2004**
HB	(-2.97)	(-3.25)	(-2.83)	(-3.86)	(2.17)	(2.03)	(1.46)	(3.45)	(2.89)	(3.26)	(3.33)	(2.54)
CommonLanguage	-0.0007	0.0047	0.0013	0.0206	-0.0456*	-0.0525**	-0.0355	-0.0427	-0.0067**	-0.0062*	-0.0116***	-0.0073*
	(-0.05)	(0.31)	(0.09)	(1.27)	(-1.74)	(-1.96)	(-1.20)	(-1.48)	(-2.11)	(-1.78)	(-2.77)	(-1.72)
KMDistance	0.0026	0.0004	-0.0009	-0.0005	-0.0036	0.0016	0.0055**	0.0026	0.0005	0.0005	0.0008	0.0008*
	(1.26)	(0.19)	(-0.68)	(-0.34)	(-1.00)	(0.53)	(2.08)	(1.02)	(1.30)	(1.18)	(1.60)	(1.81)
CommonCurrency	0.0017	0.0015	-0.0051	0.0061	-0.0195	-0.0356*	-0.0075	-0.0945***	-0.0049	-0.0016	0.0022	0.0013
	(0.15)	(0.15)	(-0.50)	(0.62)	(-1.01)	(-1.82)	(-0.35)	(-4.00)	(-1.25)	(-0.43)	(0.61)	(0.28)
ChangeCrossRate	0.0052	0.0059	-0.0129***	0.0056*	0.0157	0.0159	0.0700***	0.0025	-0.0030	-0.0033	-0.0083*	-0.0004
	(1.50)	(1.56)	(-2.71)	(1.79)	(1.18)	(1.13)	(3.86)	(0.17)	(-1.33)	(-1.37)	(-1.94)	(-0.18)
IRDifferential	-0.0017***	-0.0017***	-0.0007	0.0019	0.0008	0.0017	0.0002	0.0033	0.0002	0.0002	-0.0001	0.0000
	(-2.69)	(-2.83)	(-0.77)	(1.20)	(0.52)	(1.11)	(0.11)	(1.35)	(1.02)	(0.94)	(-0.22)	(0.06)
FXChangetoUSD	-0.0118**	-0.0088	0.0160	-0.0036	0.0164	0.0297	-0.0246	0.0180	0.0052	0.0053	0.0090	-0.0009
	(-2.07)	(-1.35)	(1.44)	(-0.46)	(0.69)	(1.12)	(-0.86)	(0.90)	(1.27)	(1.27)	(1.48)	(-0.22)
BTMDistance	0.0005**	0.0005**	-0.0001	0.0006**	-0.0002	-0.0003	-0.0003	0.0006	0.0002**	0.0002**	0.0002	0.0001
	(2.22)	(2.29)	(-0.32)	(2.12)	(-0.23)	(-0.41)	(-0.29)	(1.02)	(2.28)	(2.01)	(0.99)	(0.49)
ROADistance	0.0001*	0.0001	0.0003**	0.0002***	-0.0003	-0.0003	-0.0005	-0.0002	0.0000	0.0000	-0.0000	0.0000
	(1.77)	(1.60)	(2.51)	(3.41)	(-1.53)	(-1.41)	(-1.65)	(-1.64)	(1.02)	(1.07)	(-0.60)	(1.18)
SizeDistance	0.0000	0.0000*	0.0000**	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(1.55)	(1.66)	(2.20)	(1.52)	(1.06)	(0.66)	(0.82)	(0.97)	(-1.14)	(-1.11)	(-1.34)	(-1.51)
CapextoSales	0.0001***	0.0001***	0.0001***	0.0000	-0.0001	-0.0001	0.0002*	0.0003***	0.0000	0.0000	-0.0000**	-0.0000
Distance	(3.68)	(3.60)	(2.76)	(0.46)	(-1.32)	(-1.07)	(1.78)	(4.06)	(0.74)	(0.91)	(-2.19)	(-1.04)
TurnoverDistance	0.0424	0.0763	-0.3266	1.4980**	-0.4063	-0.4094	-1.0371*	-1.0360	0.0889	0.0572	0.0459	0.0477
	(0.10)	(0.18)	(-0.76)	(2.26)	(-0.62)	(-0.60)	(-1.82)	(-0.58)	(0.68)	(0.47)	(0.42)	(0.11)
GDPpcDistance	-0.0000***	-0.0000***	-0.0000**	-0.0000***	0.0000***	0.0000***	0.0000	0.0000***	-0.0000	-0.0000*	-0.0000	-0.0000
	(-3.22)	(-3.64)	(-2.42)	(-3.32)	(5.43)	(4.45)	(1.16)	(3.80)	(-1.60)	(-1.81)	(-0.76)	(-1.17)
HomeCountry	0.0789***	0.0709**	0.0720**	0.0602**	0.0119	0.0301	0.0135	0.0885**	0.0003	-0.0025	0.0001	-0.0024
	(2.97)	(2.49)	(2.53)	(2.03)	(0.29)	(0.71)	(0.29)	(1.98)	(0.07)	(-0.59)	(0.02)	(-0.41)
Unreported Var.	Destination Country & Fund Controls, Remaining Interactions with Distance Variables, Country & Time Fixed Effects											
Fund F.E.	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No
Observations	552636	552636	358528	194108	377539	377539	243857	133682	377539	377539	243857	133682
Adjusted R^2	0.44	0.38	0.35	0.43	0.35	0.19	0.19	0.19	0.15	0.07	0.07	0.06

Table 12: Robustness Tests – Factor Models

The table presents robustness tests on the factor models of table 6. Column 1 estimates a panel-regression with style and time fixed effects where inference is calculated from standard errors clustered along the fund and time dimensions. Columns 2-10 estimated Fama-MacBeth regressions. Columns 2-3 use weighted versions of *FIB*, column 4 truncates *HB* at the bottom and top 5%, column 5 adds home country fixed effects and the remaining columns drop selected funds or styles. All other specifications are as above.

	OLS	**Weighted FIB**		**Trun-cating HB**	**Home Fixed Effects**	**Dropping narrow funds**	**Dropping EM styles**	**Dropping Europe styles**	**Dropping "Other Europe"**	**Dropping Global styles**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:	*4F Alpha*	*4F Alpha*	*4F Alpha*	*4F Alpha*	*4F Alpha*	*4F Alpha*	*4F Alpha*	*4F Alpha*	*4F Alpha*	*4F Alpha*
FIB	-0.2391			-2.4938***	-2.3731***	-2.2394***	-2.3184***	-2.1327***	-1.2083***	-2.5319***
	(-0.35)			(-3.87)	(-3.44)	(-3.84)	(-3.12)	(-3.47)	(-2.99)	(-2.63)
HB		0.1697*	0.1441	0.1547*	0.1327	0.1544*	0.2110**	0.2588**	0.2019**	0.1726
		(1.82)	(1.54)	(1.70)	(1.60)	(1.84)	(2.24)	(2.61)	(2.56)	(1.16)
*HB * FIB*				9.1915***	4.7290***	3.8848***	5.0732***	4.7256***	3.7260**	5.9739**
				(4.00)	(3.67)	(2.68)	(3.52)	(3.83)	(2.32)	(2.47)
ICI	0.0625			-0.0708	-0.0078	-0.0636	-0.0648	-0.1165	0.0987	-0.1370
	(0.87)			(-1.02)	(-0.12)	(-0.89)	(-0.87)	(-1.49)	(1.62)	(-1.51)
HasHB	0.0530									
	(1.60)									
*HasHB * FIB*	2.8142**									
	(2.46)									
PS-FIB		-1.5420***								
		(-3.14)								
*HB * PS-FIB*		4.5088***								
		(3.38)								
PS-ICI		0.0865								
		(1.05)								
MV-FIB			-1.3627**							
			(-2.52)							
*HB * MV-FIB*			5.3275***							
			(3.69)							
MV-ICI			0.0893							
			(1.00)							
Unreported Variables					Control variables and Style Fixed Effects					
Add. Fixed Effects	Time				Home					
Standard Errors	2D Cluster Fund / Time					Newey-West corrected with 3 lags				
Observations	236516	236516	236516	212150	236516	227306	207852	191675	193470	130619
R^2	0.08	0.35	0.35	0.35	0.39	0.35	0.27	0.37	0.37	0.43