Back to the Roots: Ancestral Origin and Mutual Fund Manager Portfolio Choice*

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ABSTRACT

We exploit variation in the ancestries of U.S. equity mutual fund managers to show that ancestry affects portfolio decisions. Controlling for fund firm location, we find that funds overweight stocks from their managers' ancestral home countries in their non-U.S. portfolio by 132 bps or 20.34% compared with their peers. Similarly, funds overweight industries that are comparatively large in their manager's ancestral home countries. Stocks linked to managers' ancestry do not outperform stocks in the same countries and industries but held by managers of other ancestries. This supports the notion that ancestry-linked investments are not informed but due to familiarity.

JEL classification: G11, G41.

Keywords: Culture, Home Bias, Mutual Funds, Portfolio Choice, Fund Managers

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Investor allocations are shown to be affected by home bias (French and Poterba (1991); Tesar and Werner (1995); Kang and Stulz (1997)) and local bias (Coval and Moskowitz (1999); Grinblatt and Keloharju (2001); Ivković and Weisbenner (2005); Seasholes and Zhu (2010)), i.e., the tendencies to invest the majority of a portfolio into domestic and, particularly, nearby firms. The academic literature, so far, has not found a consensus on whether information or familiarity is the channel through which individual investors prefer local equity. As Chevalier and Ellison (1999) point out, at least for professional investors, information should drive the preference for local stocks due to, for example, career concerns. In line with this idea, Coval and Moskowitz (2001) find evidence that mutual funds' local investing is informed. On the contrary, Pool, Stoffman, and Yonker (2012) show that US mutual fund managers exhibit a familiarity bias in their portfolio allocation decisions toward their home states which does not enhance investment performance. These studies all face the same empirical challenge: that is, how to identify securities that are familiar to the fund manager ex-ante, even though he or she does not have any informational advantage. Our unique data set allows us to address this challenge because we can plausibly separate portfolio choices due to familiarity from portfolio choices due to an informational advantage.

In this paper, we study investors' ancestral origins and inspect their long-lasting effect on portfolio formation. Exploiting that the U.S. is a nation of immigrants, we argue that fund managers are familiar with but are not better informed about firms headquartered in their ancestral home country. Specifically, we argue that a manager whose ancestors emigrated to the U.S. from another country, for example, Italy, is likely to be familiar with Italy's firms and prevailing industries. At the same time, such managers are unlikely to be informed about these firms and industries, especially if their ancestors emigrated several generations ago. To further strengthen our identification strategy, we focus only on managers socialized in the U.S. that is, if they are U.S. born or received at least one college degree from a U.S. institution. The motivation behind our identification strategy is twofold. Compared to ties to a home state, it is less likely that managers maintain active ties to their ancestral home country, particularly if they were socialized in the US, and their ancestors emigrated decades ago. Moreover, we can assume that the manager is the fund's main link to the ancestral home country. Other participants in the fund's investment and analysis process will likely be from other backgrounds that differ from the fund manager's ancestry.

We proceed in two steps to investigate the role of this ancestry-induced familiarity bias in portfolio decisions. First, we analyze whether managers overweight companies and industries from their ancestral home countries. Second, we examine whether such overweighting relates to the recency of the managers' connections to their ancestral home countries, measured as the number of generations since their ancestors immigrated to the U.S. We posit that managers are more familiar with ancestral home country companies and industries but that this familiarity does not offer an informational advantage. When choosing among stocks in the investment universe, managers may pick the more familiar ones. Due to "homophily" (Lazarsfeld and Merton (1954)), managers might associate their ancestral home country with positive attributes, and investing accordingly makes them feel good. Conversely, managers may have a more skeptical view on unfamiliar companies and industries. Further, an "availability heuristic" (Tversky and Kahneman (1973)) may create a mental shortcut that biases managers toward stocks associated with their ancestral home country. Last, managers may falsely perceive their ancestral connection as an informational advantage.

If managers are more familiar with companies and industries from their ancestral home countries, they should overweight them in their portfolio. We find that mutual fund managers invest more in stocks headquartered in their ancestral home countries than managers of comparable funds but of other ancestries. Within their non-U.S. equity portfolios, funds contain 20.34% more investment in the managers' ancestral home countries than expected. We label this pattern as "ancestral home country bias". Similarly, within their U.S. equity portfolios, funds favor industries that are comparatively large in the managers' ancestral home countries, overweighting the top 1 and 3 signature industries by 10.5% or 2.3%, respectively. We label this pattern as "ancestral industry bias". Our findings are robust to the inclusion of fund fixed effects, enabling us to identify the effect using within-fund variation only.

We investigate the drivers of the "ancestral home country bias" and "ancestral industry bias" in the cross-section. Our results reveal that less experienced managers put more weight on companies in their ancestral home countries, implying that these managers rely more on familiar investments. Additionally, overweighting of the ancestral home country companies and industries is more pronounced when managers' connection to their ancestral home countries is more recent. Interestingly, our results suggest a strongly persistent familiarity bias, as even managers with centuries-old connections to their ancestral home country exhibit this overweighting. When investigating the stocks that fund managers overweight, we find that ancestral biases are more pronounced for well-known and more available stocks. Ancestral home country overweighting is particularly strong for stocks that resemble national identity and have a long tradition.

To sharpen our inferences about whether ancestry reflects an informational advantage (e.g., through language), we study the performance related to overweighting ancestral home country stocks and industries. We follow Jagannathan, Jiao, and Karolyi (2022) and create as-if calendar-time portfolios that mimic mutual funds' allocations in stocks and industries associated with their managers' ancestral home country. The benchmark portfolio consists of stock holdings in these countries and industries held by funds in the same Morningstar category but whose managers have no ancestral ties. We find no positive outperformance of a constructed long-short fund-of-funds portfolio that buys the ancestry-linked portfolios and sells the benchmark portfolio. The results indicate that managers do not possess a superior ability to pick ancestry-linked stocks, supporting the familiarity hypothesis.

Our article contributes to the large strand of literature examining the impact of investors' experiences and values on portfolio decisions. Among other characteristics, age (Korniotis and Kumar (2011); Greenwood and Nagel (2009); Goetzmann and Kumar (2008)), political views (Hong and Kostovetsky (2012)), trading experience (Seru, Shumway, and Stoffman

(2010); Malmendier and Nagel (2011)), and patriotism (Morse and Shive (2011)) have all been found to affect portfolio decisions. Further, investors tend to prefer companies that are more closely located (Coval and Moskowitz (1999); Coval and Moskowitz (2001)), headquartered in their home state (Pool et al. (2012)), and held by their neighbors (Hong, Kubik, and Stein (2004); Shive (2010); Pool, Stoffman, and Yonker (2015)). More recent research shows that events in the managers' personal lives, such as wealth shocks, spill over to their professional decisions (Pool, Stoffman, Yonker, and Zhang (2019)). We add to this literature by providing evidence that an additional investor characteristic, namely ancestry, influences portfolio choice. Our results suggest that behavioral factors drive the preference for ancestral home country securities and industries, with less experienced investors relying on familiar stocks more heavily.

More generally, we contribute to recent research focusing on the effects of culture on economic outcomes. Sociologists and anthropologists (e.g., Richerson and Boyd (2005)) have gathered a wide variety of field evidence linking culture and economic behavior. However, the concept of culture is broad, and the channels through which it may affect economic outcomes remain vague. Moreover, testable and refutable hypotheses are difficult to design (Guiso, Sapienza, and Zingales (2006)). In finance, several papers study the role of culture on savings rates and debt levels in a cross-country context (e.g., Christelis, Ehrmann, and Georgarakos (2017)), an approach that does not fully disentangle the roles of national institutions and economic conditions from cultural predispositions. Others contrast immigrants' savings rates with those of the native population (Haliassos, Jansson, and Karabulut (2017)), which gives rise to biases in the estimated results due to sample selection issues. We contribute to this literature by using a novel identification strategy that allows us to examine the effect of an investor's ancestry on portfolio decisions by separating it as much as possible from factors related to socialization and the economy. Our findings, which are consistent with prior literature linking cultural origin to personal choices (e.g., Giuliano (2007); Fernandez and Fogli (2009); Giavazzi, Petkov, and Schiantarelli (2019)), show that ancestry has a slowly diminishing but pervasive effect. Similar to Nguyen, Hagendorff, and Eshraghi (2018), we find that ancestry can affect not only personal decisions but entire organizations. Taken together, our paper contributes to documenting the pervasive effects of individuals' cultural preferences.

The remainder of the paper proceeds as follows. Section I describes the data set and data collection process and provides basic statistics. Section II examines whether funds overweight stocks and industries from their managers' ancestral home countries. Section III investigates the performance implications of such behavior. Section IV presents supplementary analyses, followed by Section V, which concludes the paper.

I. Data and Sample Construction

A. *Mutual Fund Sample*

Our initial sample contains the whole universe of U.S.-domiciled mutual funds covered by Morningstar from 1975 to 2017. We include defunct and active fund share classes to overcome a potential survivorship bias. We limit our sample to domestic and actively managed U.S.-equity funds (i.e., we exclude international funds, index funds, and funds that focus on bonds, commodities, and alternative assets). We do so for two main reasons. First, this approach improves comparability between investment managers. Second, we observe that U.S.-domiciled funds specializing in foreign equity are likely to be managed by managers who were not socialized in the U.S. In line with Jagannathan et al. (2022), we find that roughly 28% (52 of 188 identified individuals) of U.S.-domiciled foreign equity fund managers were not socialized in the U.S. Further, over 50% of these managers are first- or second-generation immigrants to the U.S., as defined later in the paper. For U.S. international equity funds, Jagannathan et al. (2022) document positive performance and flow implications when a fund's geographic mandate matches the fund manager's home country, which may be the reason why these funds hire these managers.[1] By focusing on U.S.-equity funds, we alleviate potential endogeneity concerns that managers are selected for their ancestry. Regarding ancestral country weightings, we also argue that compared to funds with a global or specific geographic mandate, any investment in non-U.S. equity by a fund focused on U.S. equity is a discretionary decision driven by the fund manager. The downside is that the fraction of the portfolio invested in non-U.S. equity is generally small for such funds.[2]

The sample is further restricted to include only those funds that were at least once managed by a single manager. This approach establishes a clean link between a fund manager's decisions and investment outcomes. Following the rationale of Agarwal, Ma, and Mullally (2018), we exclude cases where a solo manager runs more than four funds at the same time, as these managers are likely to be team managers.

For each fund passing the filters mentioned above, we obtain the fund manager names and the start and end dates of their management period at the respective fund via the Morningstar Direct Mutual Fund Database (MS Direct). This choice is in line with Patel and Sarkissian (2017), who show that the fund manager information provided by MS Direct is more accurate than the data provided by the CRSP Survivor-Bias-Free U.S. Mutual Fund Database. We restrict our sample to managers with at least 12 consecutive fund-month observations to evaluate investment decisions properly. We obtain data on a fund's Morningstar category and fund holdings from MS Direct. Country exposure is gathered directly from the portfolios reported by the fund companies and is calculated as the portion of the fund's holdings invested in securities headquartered in a certain country.[3] Most previous studies that analyze fund holdings have used the Thomson Reuters database as the source of holdings data. Yet, MS Direct data are much more complete and available in higher frequency, as shown in Elton, Gruber, and Blake (2011). Importantly, compared to Thom-

[1] Jagannathan et al. (2022) define a manager's home country according to the country where the manager earned his or her bachelor's degree.

[2] In our sample, roughly 5.1% of the average fund's total portfolio consists of non-U.S. equity.

[3] Morningstar classifies a security's location according to country of headquarters. We obtain similar results when we conduct our analyses using the country incorporation instead.

son Reuters, which includes only holdings identified by CUSIP, MS Direct data also include positions without CUSIP (i.e., primarily international equity).

From CRSP, we obtain additional information on fund share class characteristics, including returns, total net assets (TNA) under management, fees, age, fund families, location, and investment objectives. To establish a match between MS Direct and CRSP fund classes, we carefully follow the data appendix provided by Berk and Van Binsbergen (2015) and then proceed as in Pástor, Stambaugh, and Taylor (2015), who link fund share classes based on the fund ticker and CUSIP. We aggregate fund share class information at the fund-level by weighting the respective fund share classes with the corresponding TNA. Next, we link fund holding data from MS Direct with CRSP, Thomson Datastream, and Compustat and gather information on the individual stocks held. We initiate the following data collection process for the 2,357 fund managers who pass these criteria and whose funds were successfully matched.

B. Mutual Fund Manager Ancestry Information

We obtain information on the fund managers' ancestry from Census Bureau records, which are digitally available on Ancestry.com, the world's largest genealogy database. These census records contain detailed demographic information on all members of an individual household, most importantly places of birth. Due to U.S. Public Law 95-416 (92 Sta. 915, Oct. 5, 1978), individual decennial census records become publicly available 72 years after record collection. Our analyses, therefore, rely on the 1940 and earlier federal censuses as the most recently available at the time of writing. Consequently, and similar to Nguyen et al. (2018), who study bank CEO cultural origin, our exact approach to identify ancestral information depends on when a fund manager was born.

For fund managers born before 1940, we can retrieve ancestry information directly from the 1940 census records. We first locate the fund managers' census records and obtain information on them and their parents, specifically their respective places of birth. If the fund manager or the father was born outside the U.S., we stop our search. If the fund manager's father was born in the U.S., we start a new search using the father's census information (i.e., name, birth year, location of birth, and spouse's name). We then use earlier census records, for example, from 1920 or 1900, to identify information on the fund manager's grandfather. If the grandfather was born in the U.S., we search earlier generations of the fund manager's ancestors as far back as data availability allows. For the fund managers born in or after 1940, we first identify their youngest direct paternal relative who was born before 1940 and whose census records are accessible.[4] Once we identify that person, we can create the fund manager's paternal family tree. We then follow the same procedure as above to locate the ancestors in the census data.

We classify a fund manager as a first-generation immigrant if he or she was born outside the U.S. If the fund manager's father was born outside the U.S., the fund manager is treated as a second-generation immigrant from the country where his or her father was born. If the fund manager's grandfather was born outside the U.S., the fund manager is treated as a third-generation immigrant from the country in which his or her grandfather was born, and so on. We rely on the fund manager's paternal ancestry because mothers usually change their surname following marriage, making it difficult to apply our search algorithm to identify the fund manager's maternal ancestry.[5] Cross-cultural intermarriages were rare among immigrants to the U.S. in the early 20th century (Kalmijn (1999); Pagnini and Morgan (1990)). Thus, a fund manager's maternal ancestral background should only rarely differ from the paternal one. Nguyen et al. (2018) report only 15% of bank CEOs as having a mixed ancestry. Therefore, we argue that we can reasonably identify a fund manager's ancestry based on his or her paternal ancestry. We also drop observations for which the fund manager's ancestry is clearly mixed (i.e., each parent emigrated from a different country).

To ensure that we correctly identify the fund managers and their ancestors in the census,

[4]In our sample, either the fathers or grandfathers of all fund managers were born before 1940, so their census records are potentially available.

[5]Importantly, difficulties in finding female managers' ancestors do not bias our sample toward male managers. Our sample of identified managers contains 9.6% females, compared to 10.1% in the total sample.

we follow a structured process similar to Chuprinin and Sosyura (2018):

We start our data collection process by obtaining the fund manager's education and employment histories from their biographies in MS Direct and Bloomberg Executive Profiles. We also search LinkedIn.com, university alumni publications, and university yearbooks available at Ancestry.com to complement the education data. We verify these data against the information provided in the annual editions of Nelson's Directory of Investment Managers, which we use to establish the fund manager's age in many cases. For the remaining managers, we either obtain data on age from fund-related sources (e.g., fund registration filings available from the SEC and fund firm websites), or we approximate age based on the date of college graduation.

We next search for the most comprehensive version of the manager's name (e.g., including full middle names and suffixes like Jr., Sr., or III). In most cases, we find this information using investment advisor and broker registration records from the Financial Industry Regulatory Authority (FINRA). These records include currently and previously registered investment advisers and brokers who underwent industry registration and licensing processes. Due to their official nature, these records often include the most comprehensive manager names. We confirm the match with FINRA by comparing the manager's employment history.

Based on full name and age, we then conduct a nationwide search for the fund managers using Intelius.com, a commercial public records database. Notably, the full name uniquely identifies managers in our sample, regardless of age. A potential match is preliminarily confirmed if it fulfills any of the following criteria: (i) the individual's Intelius employment records contain one of the fund manager's employers; (ii) the individual's email addresses in Intelius include a domain of the manager's employer, for example, @blackrock.com; (iii) the individual's voter registration record lists occupations such as "portfolio manager" or "investment adviser"; (iv) at least one of the individual's addresses in Intelius coincides with a business address of the manager's employer. We confirm the date of birth from Intelius by accessing city and area directories via Ancestry.com. City and area directories usually contain an individual's exact location and time of residence, as well as the date of birth. We compare this information with other information linked to the fund manager (e.g., places and dates of study, current and past work addresses, and personal addresses obtained from Facebook.com, LinkedIn.com, or the CFA Institute membership directory).

We follow the three-step algorithm in Chuprinin and Sosyura (2018) and identify the manager's parents by sequentially searching birth, marriage, and death records on Ancestry.com. We obtain a manager's birth record using the full name and exact date of birth. As each state's health department issues birth records, details such as name, birth date, and birthplace can vary and may be available for both (e.g., Texas), one (e.g., California), or neither (e.g., Pennsylvania) of the parents.

For birth records that do not provide parents' full names, we search the marriage records using the manager's full name and date of birth. Depending on the state where the marriage was recorded, some marriage certificates provide the names of the bride's and groom's parents. We establish a unique match by checking the bride's and groom's names and birth dates. In most cases, we can identify the manager's spouse through property records on Intelius. We verify the spouse's name by searching documents that connect the fund manager to the spouse (e.g., fund manager biographies, interviews, and charity event reports). If the marriage records do not contain the parents' names, we search for them in engagement and marriage announcements using Newspapers.com, the largest online newspaper archive, with more than $11,000$ digitized newspapers from the $1700s$-$2000s$, including small local newspapers.

For cases where we cannot identify parents or other household members, we search death records using the manager's full name and date of birth. If we identify a deceased fund manager, we obtain their obituaries from Newspapers.com and Legacy.com, an obituary database. These records usually mention the manager's direct family, including parents and siblings.

For the remaining managers, we search for their parents' obituaries. For most managers in our sample, either one or both parents are deceased. If we identify managers and their spouses as the surviving family members, usually mentioned in obituaries, we can map out the fund manager's immediate family. Additionally, Intelius links other individuals to the fund manager based on prior and current residential addresses. We consider those individuals as potential relatives if they have the same last name as the fund manager. We verify potential relatives by searching documents that connect the fund manager to these individuals (e.g., fund manager biographies and interviews).

In total, we find ancestry information for 1,224 of 1,756 fund managers born in or after 1940. Combined with 125 of 141 fund managers born before 1940, this yields a sample of 1,349 fund managers. The main advantage of our approach is twofold. First, we obtain precise information on the manager's immigrant generation. Second, we can accurately determine the location of a fund manager's ancestors. Many contemporaneous articles (Du, Yu, and Yu (2017); Pan, Siegel, and Wang (2017)) consider only surnames to identify ancestry, which may lead to false conclusions because many surnames (e.g., Baron) have various origins. The disadvantage of our approach is that we lose fund manager observations for which we cannot precisely identify the ancestors. By including only managers in our sample whose ancestry we can identify, we minimize selection bias when comparing them to each other.

C. Sample Composition

Panel A of Table I reports the average monthly composition of our sample grouped by Morningstar category. On average, we observe 189 funds per month or 70.84% of the funds and 80.09% of TNA of all solo-managed U.S. equity funds covered by the Morningstar/CRSP intersection. The largest Morningstar category in our sample, by the number of funds and aggregate TNA, is Large Growth, with an average of 54 funds each month and an average aggregate TNA of $138 billion. The smallest category in our sample funds is Small Value, with an average of 8 funds each month and a monthly aggregate TNA of $2 billion.

Panel B of Table I shows summary statistics of fund and manager characteristics. In our sample, the average (median) fund has a TNA of \$1.26 billion (\$0.17 billion). The median solo manager is 48 years old, served at the fund for almost 4 years, and has 7 years of portfolio management experience. More than 36% of our monthly observations include managers with an Ivy League degree.

Table II shows the ancestral dispersion of managers in our sample. We report the average immigrant generation and the relative number of solo managers per country of ancestry. The fund managers' ancestries are relatively dispersed across the globe. Nevertheless, most fund managers can trace their ancestry to Germany, the United Kingdom, Ireland, Russia, Italy, and Poland. The numbers only partly align with data from the 2010 American Community Survey (ACS), in which U.S. households provide information about their self-identified ancestry.[6] Fund managers with German and the U.K. ancestry are overrepresented, compared to the overall U.S. population. Managers with Hispanic ancestry are heavily underrepresented. Similarly, we identify only 0.7% of managers as African Americans. Yet, since their exact ancestry information is not available in the census records, they are not represented in our sample. At least with regards to gender, it is well known that diversity in portfolio management is limited (Niessen-Ruenzi and Ruenzi (2019)).

II. Do Funds Overweight Stocks and Industries from their Managers' Ancestral Home Countries?

If fund managers exhibit a familiarity bias towards their ancestral home countries, we should observe that they place more weight on companies headquartered and industries more prevalent in these countries. In the unlikely case that information drives the ancestral home country overweighting, we also should observe underweighting whenever the information is negative.

[6]We choose the 2010 ACS because the date is close to the median date in our sample.

A. *Ancestral Home Country Bias*

We begin by analyzing aggregate foreign portfolio allocations dependent on the manager's ancestral home country. Table III compares average allocations at the country level and is based on all non-U.S. holdings of all funds in our sample. Every cell displays average allocations (in percentage of non-U.S. holdings) to a certain country, conditional on whether the respective fund manager has ancestors from that country ($Home$) or not ($Foreign$). Additional columns show how these average allocations change across fund managers' immigrant generations.

Comparing the sample means between $Home$ and $Foreign$ across all generations, we find a positive and statistically significant difference for most countries. Except for Poland, every difference is positive, indicating that fund managers overweight countries associated with their ancestry. To preliminarily explore whether our results are driven by specific information a fund manager may have about the ancestral home country, we analyze the overweighting for different immigrant generations. The differences between $Home$ and $Foreign$ remain positive and remarkably stable for most countries, even among seventh- to ninth-generation fund managers and beyond. This finding indicates that our results do not merely reflect the standard home bias. Later in this paper, we show that the result on the relationship between fund managers' ancestry and their country weightings remains unaltered after controlling for several other factors, such as time, fund, and manager characteristics. We label this novel form of home bias "ancestral home country bias".

For the further empirical analysis of home-country stock overweighting, we closely follow Pool et al. (2012), who study U.S. fund managers' home state bias. We start by analyzing the portfolio weight that fund managers put on their ancestral home countries. We estimate various forms of the regression equation

$$w_{i,c,t} = \alpha + \beta MgrHmCountry_{i,c,t} + \delta MorningstarBMWt_{i,c,t} + \Gamma' Controls_{i,c,t} + \epsilon_{i,c,t}, \quad (1)$$

where $w_{i,c,t}$ is the weight in fund i's non-U.S. portfolio of firms headquartered in country c during month t; $MgrHmCountry_{i,c,t}$ is a dummy that equals one if the fund manager of fund i in month t originates from country c; $MorningstarBMWt_{i,c,t}$ is the average non-U.S. portfolio weight in country c of all funds within the same Morningstar category as fund i during month t, and $Controls_{i,c,t}$ is a vector of control variables.[7] If fund managers overweight their ancestral home country in the non-U.S. part of their portfolios, we should find β to be positive and statistically significant. All fund-month observations in our sample have only one manager; thus, β measures the average ancestral home country bias per fund and per manager.

In Table IV, we report results from the OLS estimation of various forms of equation (1). In column 1, only $MgrHmCountry$ and a constant are included in the regression. The sum of $MgrHmCountry$ and the intercept equals the average weight of the non-U.S. portfolio that a fund manager invests in his or her ancestral home country. We estimate that 7.81% of mutual funds' non-U.S. portfolios are allocated to companies headquartered in the ancestral home countries of their managers.

By adding $MorningstarBMWt$ in column 2, we control for the average portfolio weight that funds in the same Morningstar category allocate to a given country during each month. The $MorningstarBMWt$ coefficient is one and highly significant. When including this benchmark, the intercept becomes statistically indistinguishable from 0, and we can explain much of the portfolio weight variation across funds. This result helps confirm that we are using the correct benchmark. Our coefficient estimate on $MgrHmCountry$ shrinks to 1.32 but remains significant at the 1% level. Within funds' non-U.S. portfolios, the average fund

[7]Importantly, we consider only those managers and those country exposures that potentially allow for an ancestral home country bias (i.e., where a match between the manager's ancestral home country and the fund's country exposure is at all possible). For example, we drop fund equity exposure toward Chile because no fund manager in our sample has ancestors from Chile. Similarly, we do not include managers whose ancestors are from Papua New Guinea because there is no fund with such equity exposure in our Morningstar holding data. Consequently, the following 40 countries are part of the funds' non-U.S. portfolios: Albania, Argentina, Australia, Austria, Belgium, Brazil, Canada, China, Czech Republic, Denmark, Egypt, France, Germany, Greece, Hungary, India, Ireland, Israel, Italy, Japan, Latvia, Mexico, Netherlands, Norway, Philippines, Poland, Portugal, Russia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Turkey, and the United Kingdom.

manager overweights stocks from his or her ancestral home country by 132 bps compared with other solo managers managing funds in the same Morningstar category. Taken together, columns 1 and 2 indicate that the expected country weight without any home bias is 6.49% (=7.81% − 1.32%), meaning that the average fund manager overweights his or her ancestral home country by 20.34% (=132/649).

Although we focus on U.S.-domiciled funds, not all fund firms are headquartered in the U.S. If fund firms are more likely to hire managers who are culturally close to the fund firm's headquarters location, part of the ancestral home country overweighting could be driven by local equity preference, as in Coval and Moskowitz (1999). To control for this, we include the fund firm's location in column 3 as a dummy variable, $MFHQCountry$, that equals one if the firm of fund i is headquartered in country c during month t and zero otherwise. The coefficient estimate on $MgrHmCountry$ only slightly decreases to 131 bps and remains highly statistically significant.

In column 4, we add fund-fixed effects to our model and identify our β solely from within-fund variation. The coefficient estimate on $MgrHmCountry$ is almost unaltered and remains highly statistically significant. Last, in column 5 of Table IV, we implement a high econometric hurdle and estimate the model with fund-country fixed effects. In doing so, we control for the average weight of each fund in each country. Hence, our $MgrHmCountry$ coefficient is estimated from within-fund variation in managers' ancestral home countries. The coefficient estimate on $MgrHmCountry$ reduces to 86 bps and remains statistically significant.

How does ancestral home country bias compare with other portfolio tilts found in the literature? In column 3, we implicitly test for a local equity preference of mutual fund firms based on the country in which they are headquartered. Compared with Coval and Moskowitz (1999), who document such a preference within the U.S., our results suggest a positive but statistically insignificant preference on an international level.

As reported in column 3, we find an average ancestral home country tilt of 20.34% for the average fund manager in our sample.[8] The relative magnitude of this tilt tends to be slightly higher than the effects of fund managers' home states, political values, and college networks found within funds' U.S. equity portfolios. Pool et al. (2012) document that the average fund overweights its managers' home states by 18.8%. Hong and Kostovetsky (2012) show that Democratic managers underweight politically sensitive industries by 19%. Cohen, Frazzini, and Malloy (2008) find that fund managers overweight companies to whose top executives they are connected to through their education network by 10% to 14%.

For comparison, we try to infer the managers' ancestral home countries by implementing the NamePrism nationality classification algorithm of Ye, Han, Hu, Coskun, Liu, Qin, and Skiena (2017), which is based solely on full names. For each manager, we classify the country with the highest probability score as the manager's ancestral home country. In Table V, we rerun the OLS estimations of Table IV on the same sample of funds, but we replace the $MgrHmCountry$ dummy with $MgrHmCountryAlgo$, another dummy that equals one if the fund manager of fund i in month t originates from country c according to NamePrism.[9] Across specifications from columns 2 to 5, the $MgrHmCountryAlgo$ coefficient is positive but insignificant, indicating that the average fund manager does not overweight stocks from his or her algorithm-inferred ancestral home country. This result supports our careful approach in identifying ancestry and implies that name-based nationality classification tools, as in Du et al. (2017) and Pan et al. (2017), should be viewed with caution.

[8] In an unreported table, we rerun the OLS estimations of Table IV for a subsample of U.S. international equity funds. Unsurprisingly and in line with Jagannathan et al. (2022), we find an even more pronounced ancestral home country bias of nearly 30%.

[9] NamePrism is trained on a set of 74 million labeled names from 118 countries. Similar to our analysis in Table IV, we consider only those managers for whom a match between the name-based ancestral home country and the funds' country exposure is at all possible. The following 19 countries are part of the funds' non-U.S. portfolios: China, Denmark, France, Germany, Greece, Indonesia, Italy, Japan, Norway, Pakistan, Philippines, Portugal, South Africa, South Korea, Spain, Sweden, Turkey, United Kingdom, and Vietnam. Due to the different number of countries, direct comparisons between the coefficient magnitudes in Table IV and Table V are not possible.

B. *Ancestral Industry Bias*

Although the ancestral home country overweighting we find has high relative and statistical significance, its absolute economic magnitude is arguably limited. This result is not surprising, as we consider only U.S. equity funds that naturally have a small proportion invested in non-U.S. equity. To address these concerns, this subsection presents results on the impact of fund managers' ancestry on the comparably larger proportion invested in U.S. equity. We conduct a similar analysis as in the previous subsection but instead focus on industry overweighting within the funds' U.S. equity portfolios. Limiting the sample to U.S. equity holdings ensures that any industry bias we may observe is no country bias in disguise.

We start this analysis by closely following Schumacher (2018), who studies industry allocations of mutual funds. We assign every firm in the funds' U.S. portfolios to one of 45 industries based on the Datastream Industry Classification Benchmark (ICB).[10] We further assign every firm available in Datastream to an industry based on the ICB and to a country based on the primary listing location of the stock. We then create an ancestral industry bias metric. This metric indicates whether funds overweight in their portfolio of U.S. stocks the industries that are most prevalent in their managers' ancestral home country. We first define

$$Aggregated\ Excess\ Industry\ Weight_{c,s,t} = \frac{1}{I(c)} \sum_{i=1}^{I(c)} (w_{i,s,t} - w_{b,s,t}), \tag{2}$$

where $w_{i,s,t} - w_{b,s,t}$ is the difference between fund i's weights in industry s at time t and average benchmark b weights in the same industry s during the same time t. Benchmark b weights are calculated as averages across all funds with managers who do not have ancestors from country c. $I(c)$ denotes the set of funds managed in time t by managers who have ancestors from country c.

To identify the most prevalent industries within each ancestral home country, we focus on

[10] Bekaert, Harvey, Lundblad, and Siegel (2007, 2011) also use the ICB in an international setting. In unreported robustness tests, we assign firms to industries according to the Fama-French 12 or 49 industry classifications based on 4-digit SIC codes.

the largest, three largest, and five largest industries in terms of market share when compared to the global average.[11] The assumption behind this approach is that fund managers may be less familiar with the general industry structure and more familiar with the signature industries in their ancestral home countries. Specifically, we define

$$Excess\ Home\ Industry\ Market\ Share_{c,s,t} = \frac{MV_{c,s,t}}{MV_{c,t}} - \frac{MV_{g,s,t}}{MV_{g,t}}, \tag{3}$$

that is, the difference between the market share of industry s in ancestral home country c at time t, and the global g market share of the same industry s at the same time t. MV denotes the market value of equity, and global g market share is based on market values in the world market portfolio excluding country c.

We assign ranks to each industry s in country c at time t according to the industry's *Excess Home Industry Market Share*. Finally, we calculate the average *Aggregated Excess Industry Weight* for the largest, three largest, and five largest industries. The resulting ancestral industry bias measure increases if funds overweight comparably large industries of their managers' ancestral home countries and analogously decreases if funds underweight such industries.

Figure 1 dissects our bias measure across ancestral home countries and the number of generations since the fund manager's family immigrated to the U.S.[12] For the largest ancestral home country industry, the bias is sizeable, positive, and statistically significant across a large spectrum of fund manager ancestry. The bias lessens for the three largest or five largest industries and is more pronounced for fund managers whose connection to the ancestral home country is more recent. On average, funds overweight the largest and three largest ancestral home industries of their fund managers by 10.5% and 2.3%, respectively. The bias vanishes almost completely for the five largest industries. Managers who are first- to

[11] We apply the filters suggested in Ince and Porter (2006) to the international stock price information from Thomson Datastream.

[12] For illustrative purposes, the average *Aggregated Excess Industry Weights* are expressed in percentages by dividing them by the average benchmark weights in the respective industries.

third-generation immigrants overweight the largest, three largest, and five largest ancestral home industries by 24.7%, 8.9%, and 7.1%, respectively.

Compared to Schumacher (2018), who finds that international mutual funds overweight the top 1, 3, and 5 domestic industries abroad by 68%, 51%, and 39%, respectively, the bias we uncover is of much lower economic magnitude. An ancestral home industry bias may largely reflect familiarity-based motives, whereas evidence suggests that specialized learning motives contribute to the bias in Schumacher (2018). In Section III, we formally test whether investment and performance patterns are consistent with the information and familiarity hypotheses.

For the further empirical analysis of home industry overweighting, we slightly adjust the empirical setup used in the previous subsection. We estimate various forms of the regression equation

$$\begin{aligned} w_{i,s,t} = \alpha &+ \beta_1 Rank1HmIndustry_{i,s,t} + \beta_2 Rank2HmIndustry_{i,s,t} \\ &+ \beta_3 Rank3HmIndustry_{i,s,t} + \beta_4 Rank4HmIndustry_{i,s,t} \\ &+ \beta_5 Rank5HmIndustry_{i,s,t} + \delta MorningstarBMW_{i,s,t} \\ &+ \Gamma' Controls_{i,s,t} + \epsilon_{i,s,t}, \end{aligned} \tag{4}$$

where $w_{i,s,t}$ is the weight in fund i's U.S. portfolio of firms in industry s at time t; $Rank1HmIndustry_{i,s,t}$, $Rank2HmIndustry_{i,s,t}$, and so on, are dummies that equal one if industry s in time t is ranked first, second, and so on, according to equation (3), in the ancestral home country of fund i's manager; $MorningstarBMWt_{i,s,t}$ is the average U.S. portfolio weight in industry s of all funds within the same Morningstar category as fund i during month t; and $Controls_{i,s,t}$ is a vector of control variables. If fund managers overweight comparably large industries in their ancestral home countries within their U.S. portfolios, then we should find β_1, β_2, and so on, to be positive and statistically significant. Again, all fund-month observations in our sample have only one manager, β_1, β_2, and so on, so we measure the average ancestral industry bias per fund and per manager.

In Table VI, we report results from the OLS estimation of various forms of equation (4). For each specification, we also show results for the subsample of fund managers who are first- to third-generation immigrants. In specification (1), only $Rank1HmIndustry$, $Rank2HmIndustry$, and so on, and a constant are included in the regression. The sum of each $Rank1HmIndustry$, $Rank2HmIndustry$, and so on, and the intercept equals the average weight within funds' U.S. portfolios that managers assign to the industry ranked first, second, and so on, in their ancestral home countries. We estimate that 4.67%, 3.19%, 2.63%, 2.57%, and 2.32% within mutual funds' U.S. portfolios are respectively allocated to industries ranked first, second, third, fourth, and fifth in the ancestral home countries of their managers. These weights exceed the average industry weight of 2.12%, indicating that the top industries in the managers' ancestral home countries also are among the larger industries within the U.S.

By adding $MorningstarBMWt$ in specification (2), we control for the average portfolio weight that funds in the same Morningstar category allocate to a given industry during each month. $MorningstarBMWt$ serves as a good benchmark, as the coefficient of one is highly statistically significant, the intercept becomes statistically indistinguishable from zero, and we can explain much of the portfolio weight variation across funds. Except for $Rank1HmIndustry$, coefficient estimates shrink to nearly zero and lose their significance, implying that in the funds' U.S. portfolios, the average fund manager overweights only the first-ranked ancestral home industry. The overweight is 17 bps (significant at the 5% level), compared with other solo managers managing funds in the same Morningstar category. Taken together, specifications (1) and (2) indicate that the expected first-ranked industry weight, without any ancestral industry bias, is 4.50% (=4.67% − 0.17%), meaning that the average fund manager overweights the first-ranked industry by 3.78% (=17/450). When restricting the sample to fund managers who are first- to third-generation immigrants, the overweighting grows to 10.07% (=46/457) and is significant at the 1% level. Additionally, these managers also significantly overweight the second- and third-ranked industries of their ancestral home country by 7.62% (=25/328) and 7.51% (=19/2.53), respectively (significant at the 10% level).

In specification (3), we add fund-fixed effects to our model and identify our β solely from within-fund variation. This way, we mitigate concerns that the ancestral industry overweighting could be driven by fund firms' specialized learning motive, as in Schumacher (2018). Following the same argument as in the previous subsection, fund firms may be more likely to hire managers who are culturally close to the fund firm's country of headquarters. The coefficient estimate on $Rank1HmIndustry$ only slightly decreases to 16 bps, whereas the other coefficient estimates remain almost unaltered. Last, in specification (3) of Table IX, we estimate the model with fund-industry fixed effects to control for the average weight each fund has in each industry. Hence, coefficients on $Rank1HmIndustry$, $Rank2HmIndustry$, and so on, are estimated from within-fund variation in managers' ancestral home industries. The coefficient estimate on $Rank1HmIndustry$ reduces to 4 bps and loses its significance. However, fund managers who are first- to third-generation immigrants still significantly overweight the first- and second-ranked industry of their ancestral home country. The relative magnitude of the ancestral home industry bias tends to be low, compared with other portfolio tilts in the literature (see the previous subsection).[13]

C. Changes in Overweighting around Manager Turnover

In Table IV and Table VI, we use a regression framework to show that funds overinvest in countries and industries associated with their managers' ancestral background. To establish a cleaner link, we next investigate changes in portfolio allocations around manager turnover. For example, if managers tilt fund holdings toward ancestral home countries and industries, we should find that new managers start increasing the fund's allocation in that direction while

[13]We again rerun the OLS estimations of Table VI on the same sample of funds, inferring the managers' ancestral home countries via the algorithm by Ye et al. (2017). Coefficient estimates on $Rank1HmIndustry$, $Rank2HmIndustry$, and so on, are statistically indistinguishable from zero across specifications (2) to (4).

also decreasing holdings in the previous managers' ancestral home countries and industries.

Table VII displays mutual funds' average excess portfolio weights on companies in their former and new managers' ancestral home countries one year prior to and one year following manager turnover. Excess weights are calculated as a fund's non-U.S. portfolio weight allocated to its manager's ancestral home country minus the average Morningstar benchmark non-U.S. portfolio weight in that country. The table shows that funds significantly overweight their outgoing manager's home country by 154 bps prior to turnover (significant at the 10% level). After turnover, this overweighting becomes a statistically insignificant underweighting of -23 bps. When the incoming manager starts managing the fund, the excess portfolio weight in the new manager's home country slightly increases by 15 bps. Notably, the decrease in the abnormal weight allocated to the outgoing manager's home country is much greater than the increase in that of the incoming manager. Asymmetric portfolio weight changes around manager turnovers also are documented in Cohen et al. (2008) and Pool et al. (2012). The asymmetry we observe is consistent with the view that new managers may have an incentive to quickly "clean the house" during a short grace period granted by the fund firm (e.g., Jin and Scherbina (2011)). The total turnover effect is indicated by the difference-in-differences estimate (i.e., the difference between the changes in excess weights reported in the last column of Table VII). The magnitude of this estimate is 193 bps (significant at the 5% level) and corresponds to that reported in specification (3) of Table III.

Regarding ancestral home industry overweighting, results point in a similar direction but are barely statistically significant. Table VIII reports mutual funds' average excess weights toward the largest industry in the former and new managers' ancestral home industry, respectively, at one year prior to and one year following manager turnover, as well as the difference in excess weights. Excess weights are calculated as a fund's U.S. portfolio weight in the manager's largest ancestral home industry minus the average Morningstar benchmark U.S. portfolio weight in that industry. The total turnover effect is 17 bps and significant at the 10% level. The effect's magnitude aligns with that reported in specification (2) of Table VI.

D. Fund Characteristics

By investigating which types of funds demonstrate the most overweighting, we can further understand what drives the ancestral home country and industry biases. Specifically, we test whether the overweighting differs across fund investment styles and fund resources. We first test for differences in overweighting across fund investment styles by interacting $MgrHmCountry$ and $Rank1HmIndustry$ with dummies that indicate a fund's Morningstar style (i.e., value, growth, small-cap, and large-cap). If the interaction coefficients differ significantly from zero, we can conclude that there are differences in ancestral home country and industry overweighting across fund styles.

Table IX reports the corresponding regression results for the ancestral home country bias. As the baseline model, we use the specification from column 3 of Table III. In column 1, we test for differences in ancestral home country weightings across value, growth, and blend funds. The interaction term coefficients of $MgrHmCountry \times Value$ and $MgrHmCountry \times Growth$ do not differ statistically from zero, indicating that managers do not overweight their ancestral home countries differently across these fund types. In column 2, we test for differences across fund investment objectives regarding size. We find that ancestral home country bias is increasing with a fund's size objective, being lowest for small-cap funds. However, the only significant difference is between large-cap and mid-cap fund styles. Managers of large-cap funds may easily build non-U.S. exposure through American depositary receipts, which are predominantly large-cap companies (Eun, Huang, and Lai (2008)). These fund managers may be able to pick from a variety of stocks headquartered in different countries, whereas other criteria may restrict the geographical scope when picking small and mid-cap non-U.S. stocks.

As Pool et al. (2012) note, smaller funds and funds from smaller families are likely to have fewer resources to conduct their investment analyses. These funds may therefore rely more on their managers' ideas, leading to more biased investment decisions. We find the opposite to be true in our sample. In column 3, we test for differences in ancestral home country bias across different fund family sizes. We group fund families into quintiles according to their TNA.[14] The estimated interaction term coefficient of $MgrHmCountry \times FamTNAQuin$ is -21 bps and significant at the 10% level. This result implies that funds belonging to fund families in the largest TNA quintile tend to overweight their managers' ancestral home countries by 151 bps, compared to only 67 bps for funds belonging to the smallest fund families. In contrast to the national investment context of Pool et al. (2012), more resources might enable a potentially biased manager to choose among a variety of foreign stocks in the first place. In column 4, we create $FundTNAQuin$ as a measure of fund resources, which is constructed analogously to $FamTNAQuin$ using fund TNA. The estimated coefficient on $MgrHmCountry \times FundTNAQuin$ also is negative, and it is significant at the 5% level, suggesting that smaller funds exhibit less ancestral home country bias. Column 5 of Table V shows that only the fund size effect holds when all fund style variables are included in the same regression.

Table X reports results of the ancestral industry bias across fund investment style and fund resources. As the baseline model, we use a specification similar to (2) Gen. 1-3 of Table VI but instead focused on the most prevalent ancestral home country industry. The coefficient estimates on the interactions with $Value$ and $Growth$ in column 1 and with $SmallCap$ and $LargeCap$ in column 2 are not statistically different from zero, indicating that there is no difference in the weight that managers place on the top ancestral home industry across these funds. Coefficients on interaction terms involving $FamTNAQuin$ in column 3 and $FundTNAQuin$ in column 4 also are statistically indistinguishable from zero but point toward more pronounced bias for smaller funds and fund families, as suggested

[14]Quintiles are based on monthly TNA obtained from CRSP. The variable $FamTNAQuin$ is equal to the fund family's TNA quintile in a certain month minus one. This way, we can interpret the coefficient on $MgrHmCountry$ as the ancestral home country overweighting by funds in the largest family size quintile.

by Pool et al. (2012). Results remain unaltered in column 5, which includes all fund style variables.

E. Manager Characteristics

In this section, we investigate which types of managers display more pronounced ancestral biases. We analyze whether managers' age, experience, immigrant generation, or education are associated with ancestral home country or industry bias. We estimate the regressions in equation (1) and (4) using a conservative within-fund specification and interact various dummy variables with $MgrHmCountry$ and $Rank1HmIndustry$, respectively.[15] If investments based on familiarity substitute for informed investments, then we should observe that managers with less experience, closer ties to the ancestral home country, and less education overweight their ancestral home countries more heavily.

Table XI reports the regression results for ancestral home country bias across fund manager characteristics. In columns 2 and 3, we interact $MgrHmCountry$ with two measures of manager experience, $MgrAge$ and $MgrExperience$. The former indicates whether the manager is older than the median manager, and the latter indicates whether the manager has more fund management experience than the median manager in the respective time period. Manager age does not affect managers' ancestral home country bias, but fund management experience has a sizable and statistically significant effect of -106 bps (significant at the 10% level), suggesting that overweighting of home-country stocks is concentrated among managers who are relatively early in their careers. In columns 2 and 3, we interact $MgrHmCountry$ with two measures of home-country tie strength. $MgerGeneration$ equals the manager's immigrant generation (as defined in Section 1) minus one and $MgrCollCountry$ is a dummy that equals one if the manager's undergraduate degree is from a college in country c. Lending support to our conjecture, the estimated interaction term coefficient of $MgrHmCountry \times MgerGeneration$ is -46 bps and significant at the 1% level. Results imply that the ancestral

[15]We use only solo-managed observations; thus fund-month observations are equivalent to manager-month observations, and we can include interactions with manager-specific characteristics.

home country bias remains high in magnitude for managers with a long, multi-generational family history in the U.S. but decreases across immigrant generations. First-generation immigrant managers overweight their ancestral home countries by 263 bps, compared to 33 bps for sixth-generation immigrant managers. The coefficient on $MgrHmCountry \times MgrCollCountry$ is positive and large in magnitude but statistically insignificant.

Finally, in columns 6 and 7, we test whether quality of education affects a manager's ancestral home country bias. We first interact $MgrHmCountry$ with $MgrIvy$, which is a dummy equal to one if the manager has an Ivy League degree. Contrary to expectations, the estimate on the interaction is positive, albeit insignificant. $MgrIvy$ also may capture managers' tendency to attach more value to family history. Therefore, in column 7, we also interact $MgrHmCountry$ with $MgrMBA$, which is a dummy that equals one if the manager holds an MBA. The estimated interaction term coefficient of $MgrHmCountry \times MgrMBA$ is negative but not statistically different from zero. Taken together, there is no evidence that better-educated managers exhibit less bias. As shown in column 8, results that more experienced managers and managers whose ancestors emigrated more recently have significantly lower biases continue to hold when including both experience and home-country tie strength measures in the same regression.

Table XII reports results for ancestral home industry bias across manager characteristics. We adjust specification (4) Gen. 1-3 of Table VI to focus on the largest industry of the ancestral home country. The coefficient estimates on the interactions with $MgrAge$ and $MgrExperience$ in columns 1 and 2 do not differ statistically from zero, indicating that manager age and experience do not affect managers' bias toward the largest ancestral home industry. The estimated interaction term coefficient of $Rank1HmIndustry \times MgrGeneration$ is -13 bps and significant at the 10% level, implying that ancestral home industry overweighting vanishes after three immigrant generations. Results in columns 5 and 6 suggest that quality of education has no effect on ancestral home industry overweighting.

To shed light on the pervasiveness of observed ancestral home country bias across different cultural origins, we interact $MgrHmCountry$ with dummies indicating the manager's home country (e.g., UK, which equals one when the manager has ancestors from the United Kingdom). Results in Table XIII suggest that the ancestral home country bias is not concentrated among managers from a specific cultural background.[16] However, the estimated coefficient of $MgrHmCountry \times Russia$ is -105 bps (significant at the 5% level), indicating that managers of Russian descent exhibit no bias.

F. Stock Characteristics

Next, we investigate which types of stocks managers overweight from their ancestral home countries and industries. We posit that our observed overweighting is based on familiarity, in the sense that when choosing among similar stocks, managers' ancestry may tip the scale in favor of the ancestral home country and industry stock. If information or a perceived informational advantage drives our results, we would expect that fund managers mainly overweight lesser known and less available stocks from their ancestral home countries and industries.

To analyze how stock characteristics relate to managers' ancestral home country and industry overweighting, we follow Pool et al. (2012) and use a regression similar to column 3 of Table IV and column 2 Gen. 1-3 of Table VI, with monthly fund-stock observations, respectively. We form subsamples based on certain stock characteristics that correlate with stock availability, firm size, and national identity. Compared to estimating interaction terms, subsamples allow for easy interpretation of relative differences in home-country overweighting. We estimate

$$w_{i,k,t} = \alpha + \beta MgrHmCountry_{i,k,t} + \delta MorningstarBMWt_{i,k,t} + \Gamma' Controls_{i,k,t} + \epsilon_{i,k,t}, \quad (5)$$

[16]In unreported analyses, we find analogous results for ancestral home industry bias.

and

$$w_{i,k,t} = \alpha + \beta Rank1HmIndustry_{i,k,t} + \delta MorningstarBMWt_{i,k,t} + \Gamma' Controls_{i,k,t} + \epsilon_{i,k,t}, \quad (6)$$

where $w_{i,k,t}$ is the weight in fund i's non-U.S. portfolio of stock k during month t. For each fund-month, we include all stocks within a fund's investment universe (i.e., stocks held by at least one fund in the same nine-box Morningstar category).

Table XIV reports the ancestral home country bias across stock characteristics. Column 1 shows regression results for the full sample. The excess holding in home countries is 14 bps, representing a 24.10% overweighting when compared to the average stock weight of 59 bps. The relative overweighting is consistent with our previous estimates.

In columns 2 and 3, the sample is split into securities that are traded and not traded on U.S. exchanges, respectively. Results show that home-country stock overweighting is present in both subsamples, but the relative overweighting of U.S. exchange traded stocks is more pronounced (28.38% vs. 16.38%). Columns 4 and 5 show similar results when splitting the sample into securities that are included and not included in a national stock market index, respectively (32.36% vs. 21.71%).

Sample splits in columns 6 to 9 try to capture a stock's association with a certain country. We argue that overweighting should be larger for stocks that reflect national identity, as suggested in Morse and Shive (2011). In columns 6 and 7, we report results for stocks whose names either contain or do not contain references to certain countries or variations thereof (i.e., "patriot stocks" vs. "non-patriot stocks").[17] Compared to the benchmark weights, overweighting is much higher for the patriot stocks (71.16% vs. 20.27%). Notably, the mean weights of patriot and non-patriot stocks are nearly identical, implying that we do not merely pick up potential firm size or availability effects.

Regressions in columns 8 and 9 are estimated for samples split by the median year of incorporation. More traditional stocks incorporated before the median year of incorporation

[17] For example, "United Kingdom", "British", "Great Britain", and "Royal".

("heritage stocks") may be more likely to be associated with a certain country. Results indicate that the relative overweighting is higher for heritage stocks (29.77% vs. 23.00%).

Table XV displays the ancestral home industry bias across stock characteristics and provides a similar picture. Regression results for the full sample in column 1 show excess holdings of 10.55% in ancestral home industry stocks, consistent with our previous estimates. We split the sample along several dimensions that are correlated with size: SP500 inclusion, sales, analyst coverage, and selling, general, and administrative expenses (SG&A). For the latter three, we form subsamples of stocks that are above and below the median value of the respective characteristic each month. Overweighting of ancestral home industry stocks is positive and statistically significant in most subsamples. However, relative overweighting is more pronounced for SP500 stocks (16.20% vs. 5.79%), stocks with higher sales (14.02% vs. 7.60%), stocks with higher analyst coverage (12.72% vs. 4.89%), and stocks with higher SG&A (23.03% vs. 1.16%).

III. Do Funds Outperform in Their Managers' Ancestral Home Countries and Industries?

The previous section shows that fund managers significantly overweight stocks whose firms are headquartered in their ancestral home countries and whose industries are most representative of their ancestral home countries. Our evidence suggests that this overweighting may be due to familiarity. We now formally test the information and familiarity hypotheses by analyzing security-level performance. If ancestry provides managers with an informational advantage, we would expect to observe an outperformance of their ancestry-linked securities. In contrast, if familiarity drives the choice to invest in ancestry-linked stocks, performance implications will depend on whether managers have any skill in general. In case managers have skill, familiarity will negatively affect the performance of ancestry-linked stocks because informed investment choices are substituted by behavioral ones. Alternatively, familiarity should have no impact on performance.

A. *Performance of Ancestral Home Country Securities*

First, we study the performance of stocks headquartered in the fund manager's ancestral home country. We closely follow Jagannathan et al. (2022) and construct value-weighted portfolios of these stocks. The benchmark portfolio consists of stock holdings associated with the fund manager's ancestral home country but held by managers with different ancestries in the same Morningstar category. For example, for a small-cap value fund run by a manager with Italian ancestry, at the beginning of each month, we take a long position in all Italian stocks held by the fund and take a short position in all Italian stocks held by small-cap value funds whose managers are of non-Italian ancestry. We then hold the positions until we rebalance the portfolio based on updated holdings of both sets of funds.

Using a standard calendar-time portfolio approach, we study the performance by first constructing an ancestry-linked portfolio of ancestral home country stocks for each fund and time period. We then form an unlinked portfolio by selecting stocks in managers' ancestral home countries held by managers in the same Morningstar category and in the same time period but with different ancestry. We keep the stocks in the subportfolios until the next holding report date to reflect changes in holdings. Within each fund portfolio, stocks are weighted by their dollar market value at the beginning of the holding period. We then compute value-weighted, calendar-time portfolios by averaging across funds weighting individual fund portfolio returns by the fund's TNA value at the beginning of the holding period.

Table XVI presents key statistics of the long-short portfolio and the portfolio's long-only leg, which is calculated net of the U.S. Treasury bill yield. Both are reported for the full sample of managers; for first- to third-generation immigrant managers; and for higher-generation immigrant managers. We present raw returns and the Fama-French 4-factor alphas along with the respective 4-factor loadings. The model employed is based on Global ex U.S. factors.[18]

Columns 1 to 3 present raw returns, alphas, and loadings of only the long positions. For the full sample, mean returns are 120 bps per month, and alpha is positive but insignificant at 10 bps. Loadings on *MOM* are negative and significantly different from zero, indicating a preference against momentum stocks when investing in the ancestral home country. Results remain similar when restricting the sample to managers of lower (column 2) and higher (column 3) immigrant generations, except that more recent immigrant managers prefer growth stocks, as suggested by the negative loadings on *HML*.

Columns 4 to 6 present results for the long-short portfolios relative to unlinked managers. For the full sample, raw returns average an insignificant -1 bps, and the 4-factor alpha is indistinguishable from zero. Factor loadings are statistically insignificant, implying no noteworthy portfolio tilts. Importantly, we do not find a significant alpha when restricting the sample to first- to third-generation immigrant managers, whom we find to place comparably large weights on home country stocks. These non-positive performance results suggest that managers do not possess a superior ability to pick ancestry-linked stocks. Instead, they likely choose based on familiarity, which appears to produce outcomes no worse than the stock selection methods employed by other managers.

B. *Performance of Ancestral Home Industry Securities*

To investigate the performance of managers' ancestral home industry stocks, we slightly adjust the approach followed in the prior subsection. We construct value-weighted portfolios of funds' U.S. stock holdings in the industries that are most prevalent in their managers' ancestral home country. The benchmark portfolio consists of stock holdings in these industries held by managers in the same Morningstar category but with different ancestries. For example, if a large-cap value fund run by a manager with German ancestry holds stocks in the "Automobiles and Parts" sector, at the beginning of each month, we take a long position in

[18]In unreported results, we also analyze Global ex U.S. 6-factor alphas. The alphas from these regressions remain indistinguishable from zero.

all "Automobiles and Parts" stocks held by the fund and take a short position in all "Automobiles and Parts" stocks held by large-cap value funds with non-German managers during the same period. Analogous to the prior subsection, we follow a standard calendar-time portfolio approach to study performance.

Table XVII shows the key performance statistics of the ancestral home industry long-short portfolio and its long-only leg (net of the U.S. Treasury bill yield). We again present raw returns and the Fama-French 4-factor alphas along with the respective 4-factor loadings. The model employed is based on U.S. factors.[19]

For the full sample in column 1, the long-only leg mean returns are 100 bps per month, and alpha is statistically not different from zero. Loadings on *SMB* and *HML* are significantly positive, indicating a preference for small stocks and value stocks when investing in ancestral home industries. Results are similar for managers of lower and higher immigrant generations in columns 2 and 3, respectively. The insignificant raw returns and alphas of the long-short portfolio in columns 4 to 6 indicate that managers are not better at picking stocks in industries that are most prevalent in their ancestral home countries. Importantly, this finding also applies to first- to third-generation immigrant managers who significantly overweight their top ancestral home industries.

IV. Robustness

A. *Subsample Analysis*

Testing whether ancestry plays a role in portfolio decisions relies on the presumption that fund managers are aware of their ancestry and attach value to it. The 2010 ACS suggests that around 10% of respondents self-report their ancestral descent as "American", rather than the officially recognized racial and ethnic groups, and only about 11% do not report

[19]In unreported results, we also analyze U.S. 6-factor alphas. The alphas from these regressions remain indistinguishable from zero.

any ancestry. These numbers imply that most Americans know from which countries their families immigrated to the U.S.[20] As a measure of ancestral home country tie strength in Table XI and Table XII, *MgrGeneration* is likely to be negatively correlated with a fund manager's awareness of his or her ancestral origin. However, we develop two alternative measures that more directly capture the importance fund managers place on their ancestry: connectedness with relatives from the ancestral home country and involvement in genealogical research. We define *MgrFBRelatives* as a dummy equal to one if a fund manager has Facebook.com connections with relatives living in the ancestral home country.[21] We further define *MgrAncestryProfile* as a dummy equal to one if a fund manager has an account on Ancestry.com.[22]

In Panel A and B of Table XVIII, we re-estimate our baseline regressions from Table IV and Table IV, respectively, and form subsamples including only observations where *MgrFBRelatives* (columns 1 and 2) or *MgrAncestryProfile* (columns 3 and 4) are equal to one. In columns 5 and 6, we augment the regressions of Table XI and Table XII column 4 with interaction terms between our two alternative measures of ancestry awareness and *MgrHmCountry* and *Rank1HmIndustry*, respectively. This approach allows us to control for a manager's immigrant generation, which may be associated with *MgrFBRelatives* and *MgrAncestryProfile*.

The coefficients in Panel A columns 1 and 2 of Table XVIII reveal that managers with connections to relatives in their ancestral home countries overweight these countries by 64.60%, compared to our baseline results of 20.34% in Table IV. Similarly, managers who are or have been involved in genealogical research overweight their home countries by 40.03%. When we control for managers' immigrant generation and fund-country fixed effects in columns 5 and

[20]A 2019 survey conducted by OnePoll and commissioned by Ancestry.com finds that 75% of Americans know their ancestral home countries and that 60% know the country origin of their last name.

[21]We identify 271 Facebook profiles with open friend lists among the 1,349 fund managers with ancestry information. Of those, 39 have connections to relatives from the ancestral home countries.

[22]We locate a fund manager's Ancestry.com account by searching for both of the fund manager's parents in family trees that users submitted to Ancestry.com. Among these users, we identify fund manager accounts by account name or by the relation indicated in the user profile. We thus verify Ancestry.com accounts for 101 fund managers.

6, the positive and significant coefficients on the interaction terms between $MgrHmCountry$ and $MgrFBRelatives$, as well as $MgrAncestryProfile$, suggest that managers who attach more importance to their ancestry exhibit more ancestral home country bias than other managers. Results in Panel B columns 1 to 4 point in a similar direction: managers with connections to their ancestral home country and managers active in genealogy overweight their home country's top industry by 12.1% and 10.5%, respectively, compared to 3.78% in Table VI. However, results are not robust to the inclusion of additional controls in columns 5 and 6.

B. *Alternative Classifications of Ancestry*

In unreported analyses, we estimate the model from column 3 of Table IV using three broader classifications of ancestry:[23] We group countries by continent and region according to the United Nations Statistics Division and by the official languages spoken according to the CIA World Factbook. We define the variables $MgrHmContinent$, $MgrHmRegion$, and $MgrHmLanguage$ analogously to $MgrHmCountry$ using continents, regions, and official languages spoken, respectively, instead of countries. Observations remain monthly fund-country observations, so that we can analyze whether funds overweight countries in their manager's ancestral home continent, region, or language area while controlling for the ancestral home country itself.

When adding $MgrHmContinent$, $MgrHmRegion$, and $MgrHmLanguage$ individually or collectively to the model from column 3 of Table IV, their coefficients are statistically insignificant, whereas the coefficient on $MgrHmCountry$ remains almost unaltered. This result indicates that funds do not exhibit a bias toward countries from their managers' ancestral home region, continent, or language area other than the home country itself. The insignificant coefficient on $MgrHmLanguage$ also suggests that ancestral home country overweighting is not due to an informational advantage, which corroborates our findings

[23]Unfortunately, more granular classifications of ancestry, such as states within a country, are not available in the 1940 federal census.

regarding the lack of outperformance in ancestry-linked securities.

C. Portfolio Distance

An alternative to investigating ancestral home country overweighting is to test whether fund managers overinvest in stocks whose headquarters are geographically close to their ancestral home countries. Similar to Pool et al. (2012), we determine the center of a country using a population-weighted method based on Hall, Bustos, Olén, and Niedomysl (2019) rather than the geographic centroid. The resulting point minimizes the expected distance to a randomly selected person in that country. Stock locations are determined via exact headquarter contact information obtained from Thomson Datastream. For each stock in a fund's portfolio, we then calculate the distance between the center of the fund manager's ancestral home country and the stock's headquarter location.

Figure 2 relates excess portfolio weights, calculated as stock weights minus the equally weighted average stock weight of all funds in the same nine-box Morningstar category and month, to the geographical distance between stock location and the fund manager's ancestral home country. Average excess portfolio weights in bps are presented for seven distance categories (the 95% confidence intervals are shown with shading). The excess weight in stocks headquartered within 100 miles of a fund manager's ancestral home country is 17 bps on average. The average stock weight of 59 bps implies an overweighting of 29.0%, which is comparable to our estimates reported in Table XIV. Excess weights decrease for stocks located further away.

D. Alternative Explanations

Consistent with the familiarity hypothesis, we find fund managers overweight stocks from their ancestral home countries and industries but do not achieve superior performance. However, two alternative explanations could lead to similar results.

First, fund firms may select managers originating from certain countries when they intent to build up exposure to these countries or their associated industries. The small absolute exposure of U.S. equity funds toward foreign stocks, as well as the persistence of the ancestral home biases across multiple generations, cast doubt on this explanation. Also, our holding analysis around turnover events shows that funds only slowly start to build up positions in the managers' ancestral home countries or industries after their arrival, which further contradicts a selection story.

Second, funds may simply cater to the preferences of their investors when building up positions in certain countries and industries. This alternative explanation is based on the fact that ancestry among Americans is not distributed evenly across the U.S. For example, German-Americans are most prevalent in the Midwest, and English-Americans are predominantly found in the Northwest and West. If we now assume that labor markets for fund managers are geographically segmented, funds should be more likely to hire managers from the nearby area. At the same time, a fund's investor base may be more concentrated in this area. Hence, the ancestries of the fund manager and the investor base may be positively correlated, making it difficult to determine whether manager or investor preferences drive our results. Related to this alternative explanation, the ancestral home industry bias also could be due to the local equity preference, as documented in Coval and Moskowitz (1999), if one assumes that ancestry shapes the local industry structure. When mutual funds overinvest in stocks that are headquartered nearby, they would thereby overweight the industries that are prevalent in the area's predominant ancestral home country.[24]

The results from our regressions including fund-country and fund-industry fixed effects in Table IV and Table VI provide evidence against the local catering story, as fund firm locations rarely change. Also, this explanation would suggest that smaller funds cater more strongly to preferences of the local investor base. In Table IX, we instead find that larger funds exhibit more pronounced ancestral home country bias.

[24]For example, a fund located in the Midwest may be more likely to hire a manager with German ancestry (if the fund manager labor market is geographically segmented) and to invest in the automotive industry (if the fund has a local equity preference).

To formally test whether funds cater to local investor preferences based on ancestry, we re-estimate the models from Table IV and Table VI, controlling for populations of ancestries across the U.S. We collect state- and county-level ancestry data from the 2010 U.S. census and the 2010 ACS. Exact fund headquarter locations within the U.S. are obtained from CRSP and assigned to a state and county. We include $StateAncestry_{i,c,t}$ or $CountyAncestry_{i,c,t}$ in column 2 of Table IV, representing the percentage of people in fund i's headquarter state or county, respectively, who originate from country c. The coefficients of $StateAncestry$ and $CountyAncestry$ are both indistinguishable from zero, indicating that funds do not cater to local ancestries when investing in foreign equity. Similarly, we augment Table VI column 2 with $Rank1HmIndustryCnty_{i,s,t}$, $Rank2HmIndustryCnty_{i,s,t}$, and so on, or $Rank1HmIndustrySt_{i,s,t}$, $Rank2HmIndustrySt_{i,s,t}$, and so on. These dummy variables equal one if industry s in time t is ranked first, second, and so on, respectively, according to equation (3), in the dominant ancestral home country of the population in fund i's headquarter state or county. The coefficients of these variables are not significantly different from zero, suggesting that our industry bias results are not driven by a local catering story.

V. Conclusion

This paper examines the relationship between investors' ancestry and their portfolio allocation decisions. To distinguish the impact of ancestry from other institutional and economic factors, we investigate the investment behavior of U.S. mutual fund managers who are descendants of immigrants. Our paper provides several contributions to the academic literature on culture affecting preferences and belief formation.

We document that fund managers' ancestry shapes their investments. In their non-U.S. portfolios, funds overweight stocks from their managers' ancestral home countries by 132 bps, or 20.34%, compared with their peers. Similarly, they overweight the industries that are comparatively large in their managers' ancestral home countries, especially the countries' signature industries. The ancestral biases we uncover are pervasive across fund styles, ancestral countries of origin, and immigrant generations. They are more pronounced for less resource-constrained funds and for managers whose connection to their ancestral home country is more recent. We also show that managers who overweight their ancestral home countries or industries do not exhibit superior performance for these holdings. This finding supports a familiarity bias rather than an informational advantage based on ancestral ties.

Taken together, our work is consistent with the hypothesis that investors' origins can bias their decision-making and have a slowly diminishing but pervasive effect. We document previously unexplored real effects of ancestry on portfolio choice that have important implications for future research on culture and finance. Our results also have asset pricing implications. Prior research shows that investors require a premium to trade unfamiliar stocks and that familiarity-based investing is present even among professional investors (Pool et al. (2012); Cao, Han, Hirshleifer, and Zhang (2011)). We provide evidence that ancestry induces familiarity and hence plays an important role in the price formation of assets.

Appendix A. Variable Description

Table A.I. Descriptions of Main Variables and Sources.
This table provides descriptions and sources of variables used in our study. The following abbreviations are used: MS Direct - Morningstar Direct Mutual Fund Database; CRSP - The Center for Research in Security Prices; TDS - Thomson Datastream; ANC - Ancestry.com; FB - Facebook.com; LEG - Legacy.com; NP - Newspapers.com; MQ - Marquis Who's Who database; INT - Intelius database; BL - Bloomberg; LI - LinkedIn.com; LN - LexisNexis; FW - Fund company websites; FINRA - BrokerCheck; UN - United Nations Statistics Division; CIA - CIA World Factbook; CS - Compustat.

Variables	**Description**	**Source**
Panel A: Dependent Variables		
Country Weight $w_{i,c,t}$	Fund i's net assets invested in stocks headquartered in country c divided by the total net assets of fund i's non-U.S. equity portfolio during month t.	MS Direct
Industry Weight $w_{i,s,t}$	Fund i's net assets invested in stocks assigned to industry c (based on the Datastream Industry Classification Benchmark) divided by the total net assets of fund i's U.S. equity portfolio during month t.	MS Direct, TDS
Panel B: Main Independent Variables		

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Table A.I – continued from previous page.

Variables	Description	Source
$\text{MgrHmCountry}_{i,c,t}$	A dummy that equals one if the fund manager of fund i and month t originates from country c and zero otherwise. Country of origin is based on the birth country of the youngest direct paternal ancestor.	MS Direct, ANC, FB, LEG, NP, MQ, INT, BL, LI, LN, FW
$\text{MgrHmCountryAlgo}_{i,c,t}$	A dummy that equals one if the fund manager of fund i and month t originates from country c according to the name-based nationality classification algorithm by Ye et al. (2017).	MS Direct, BL, FINRA
$\text{MgrHmContinent}_{i,k,t}$	A dummy that equals one if the fund manager of fund i and month t originates from continent k and zero otherwise. Country of origin is based on the birth country of the youngest direct paternal ancestor. Countries are assigned to continents according to the United Nations Statistics Division.	MS Direct, ANC, FB, LEG, NP, MQ, INT, BL, LI, LN, FW, UN

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Table A.I – continued from previous page.

Variables	Description	Source
$\text{MgrHmRegion}_{i,r,t}$	A dummy that equals one if the fund manager of fund i and month t originates from region r and zero otherwise. Country of origin is based on the birth country of the youngest direct paternal ancestor. Countries are assigned to regions according to the United Nations Statistics Division.	MS Direct, ANC, FB, LEG, NP, MQ, INT, BL, LI, LN, FW, UN
$\text{MgrHmLanguage}_{i,l,t}$	A dummy that equals one if the fund manager of fund i and month t originates from language area l and zero otherwise. Country of origin is based on the birth country of the youngest direct paternal ancestor. Countries are assigned to language areas according to the official languages spoken according to the CIA World Factbook.	MS Direct, ANC, FB, LEG, NP, MQ, INT, BL, LI, LN, FW, CIA

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Table A.I – continued from previous page.

Variables	Description	Source
$\text{Rank1HmIndustry}_{i,s,t}$ $\text{Rank2HmIndustry}_{i,s,t}$, etc.	Dummies that equal one if industry s in time t is ranked first, second, etc., according to equation (3) in fund i's fund manager ancestral home country. Equation (3) describes the $Excess\ Home\ Industry\ Market\ Share_{c,s,t}$, which is the difference between the market share of industry s in country c and time t, and the global market share of the same industry s in time t. The global g market share is based on market values in the world market portfolio excluding country c.	MS Direct, ANC, TDS, FB, LEG, NP, MQ, INT, BL, LI, LN, FW
$\text{MorningstarBMWt}_{i,c,t}$, $\text{MorningstarBMWt}_{i,s,t}$, etc.	The average country c or industry s etc. weight (depending on the specification) of all funds within the same Morningstar category as fund i during month t.	MS Direct, TDS
Panel C: Fund Variables		
$\text{MFHQCountry}_{i,c,t}$	A dummy that is one if the fund firm of fund i is headquartered in country c during month t.	MS Direct
Total net assets (TNA)	A fund's total assets minus total liabilities as of month-end. Reported in millions of dollars.	CRSP

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Table A.I – continued from previous page.

Variables	Description	Source
FundTNAQuin	A fund's TNA quintile minus one, where one is the largest quintile based on the fund's TNA each month.	CRSP
FamTNAQuin	A fund's fund family TNA quintile minus one, where one is the largest quintile based on fund family TNA each month.	CRSP
Fund age	Number of years from the date the fund was first offered.	CRSP
Value	A dummy equal to one if the fund is categorized as a value fund according to MS Direct.	MS Direct
Growth	A dummy equal to one if the fund is categorized as a growth fund according to MS Direct.	MS Direct
SmallCap	A dummy equal to one if the fund is categorized as a small-cap fund according to MS Direct.	MS Direct
LargeCap	A dummy equal to one if the fund is categorized as a large-cap fund according to MS Direct.	MS Direct
Panel D: Manager-Specific Variables		

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Table A.I – continued from previous page.

Variables	Description	Source
MgerGeneration	A manager's immigrant generation minus one. A manager's immigrant generation is one, two, three, etc., if he or she was born outside the U.S, if the fund manager's father was born outside the U.S., if the fund manager's grandfather was born outside the U.S., etc.	MS Direct, ANC, FB, LEG, NP, MQ, INT, BL, LI, LN, FW
MgrAge	A dummy that equals one if the manager's biological age is greater than the sample's median manager age in a given month.	MS Direct, ANC, FB, LEG, NP, MQ, INT, BL, LI, LN, FW
MgrExperience	A dummy that equals one if the manager's fund management experience is greater than the sample's median manager fund management experience in a given month. Fund management experience is measured the number of years between the manager's first appearance on a fund in the MS Direct universe and a given month.	MS Direct

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Table A.I – continued from previous page.

Variables	Description	Source
Manager fund tenure	Number of years a manager has been active on a fund. Computed as the difference between a given month and the date when the manager has started managing the fund.	MS Direct
MgrCollCountry	A dummy that equals one if the fund manager's undergraduate degree is from a college in country *c*.	MS Direct, ANC, FB, NP, MQ, BL, LI, LN, FW
MgrIvy	A dummy that equals one if the fund manager has a degree from an Ivy League school.	MS Direct, FB, NP, MQ, BL, LI, LN, FW
MgrMBA	A dummy that equals one if the fund manager holds an MBA.	MS Direct, FB, NP, MQ, BL, LI, LN, FW
MgrFBRelatives	A dummy equal to one if the fund manager has Facebook.com connections with relatives living in his or her ancestral home country.	FB, ANC, INT, LEG, NP, MQ, LN
MgrAncestryProfile	A dummy equal to one if a fund manager has an account on Ancestry.com.	ANC

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Table A.I – continued from previous page.

Variables	Description	Source
Panel E: Stock Variables		
U.S. Exchange	An indicator whether a security is traded on an U.S. exchange.	MS Direct
Index Stocks	An indicator whether a security is included in the main national stock market index.	TDS, CS
Patriot Stocks	An indicator whether a security's name contains references to certain countries or variations thereof (e.g., "United Kingdom", "British", "Great Britain", "Royal").	MS Direct
Heritage Stocks	An indicator whether the issuer of a security was incorporated before the sample's median year of incorporation in a given month.	MS Direct, TDS, CS
S&P500 Stocks	An indicator whether a security is included in the S&P500 index.	CRSP
High Sales	An indicator whether the security issuer's sales are greater than than the sample's median sales in a given month.	TDS

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Table A.I – continued from previous page.

Variables	Description	Source
High Analyst Coverage	An indicator whether the security issuer's analyst coverage is greater than than the sample's median sales in a given month. Analyst coverage is the number of analysts who are covering the security issuer.	TDS
High SG&A	An indicator whether the security issuer's selling, general and administrative expenses are greater than than the sample's median SG&A in a given month.	TDS

REFERENCES

Agarwal, Vikas, Linlin Ma, and Kevin Mullally, 2018, Managerial multitasking in the mutual fund industry, Working paper.

Bekaert, Geert, Campbell R. Harvey, Christian T. Lundblad, and Stephan Siegel, 2007, Global growth opportunities and market integration, *Journal of Finance* 62, 1081–1137.

Bekaert, Geert, Campbell R. Harvey, Christian T. Lundblad, and Stephan Siegel, 2011, What segments equity markets?, *Review of Financial Studies* 24, 3841–3890.

Berk, Jonathan B., and Jules H. Van Binsbergen, 2015, Measuring skill in the mutual fund industry, *Journal of Financial Economics* 118, 1–20.

Cao, H. Henry, Bing Han, David Hirshleifer, and Harold H. Zhang, 2011, Fear of the unknown: Familiarity and economic decisions, *Review of Finance* 15, 173–206.

Chevalier, Judith, and Glenn Ellison, 1999, Career concerns of mutual fund managers, *Quarterly Journal of Economics* 114, 389–432.

Christelis, Dimitris, Michael Ehrmann, and Dimitris Georgarakos, 2017, Exploring differences in household debt across the united states and euro area countries, *Journal of Money, Credit and Banking* .

Chuprinin, Oleg, and Denis Sosyura, 2018, Family descent as a signal of managerial quality: Evidence from mutual funds, *Review of Financial Studies* 31, 3756–3820.

Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2008, The small world of investing: Board connections and mutual fund returns, *Journal of Political Economy* 116, 951–979.

Coval, Joshua D., and Tobias J. Moskowitz, 1999, Home bias at home: Equity preference in domestic portfolios, *Journal of Finance* 54, 2045–2073.

Coval, Joshua D., and Tobias J. Moskowitz, 2001, The geography of investment: Informed trading and asset prices, *Journal of Political Economy* 109, 811–841.

Du, Qianqian, Frank Yu, and Xiaoyun Yu, 2017, Cultural proximity and the processing of financial information, *Journal of Financial and Quantitative Analysis* 52, 2703–2726.

Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake, 2011, Holdings data, security returns, and the selection of superior mutual funds, *Journal of Financial and Quantitative Analysis* 46, 341–367.

Eun, Cheol S., Wei Huang, and Sandy Lai, 2008, International diversification with large-and small-cap stocks, *Journal of Financial and Quantitative Analysis* 489–523.

Fernandez, Raquel, and Alessandra Fogli, 2009, Culture: An empirical investigation of beliefs, work, and fertility, *American Economic Journal: Macroeconomics* 1, 146–77.

French, Kenneth, and James Poterba, 1991, Investor diversification and international equity markets, *American Economic Review* 81, 222–26.

Giavazzi, Francesco, Ivan Petkov, and Fabio Schiantarelli, 2019, Culture: Persistence and evolution, *Journal of Economic Growth* 24, 117–154.

Giuliano, Paola, 2007, Living arrangements in western europe: Does cultural origin matter?, *Journal of the European Economic Association* 5, 927–952.

Goetzmann, William N., and Alok Kumar, 2008, Equity portfolio diversification, *Review of Finance* 12, 433–463.

Greenwood, Robin, and Stefan Nagel, 2009, Inexperienced investors and bubbles, *Journal of Financial Economics* 93, 239–258.

Grinblatt, Mark, and Matti Keloharju, 2001, What makes investors trade?, *Journal of Finance* 56, 589–616.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2006, Does culture affect economic outcomes?, *Journal of Economic Perspectives* 20, 23–48.

Haliassos, Michael, Thomas Jansson, and Yigitcan Karabulut, 2017, Incompatible European partners? Cultural predispositions and household financial behavior, *Management Science* 63, 3780–3808.

Hall, Ola, Maria Francisca Archila Bustos, Niklas Boke Olén, and Thomas Niedomysl, 2019, Population centroids of the world administrative units from nighttime lights 1992-2013, *Scientific Data* 6, 1–8.

Hong, Harrison, and Leonard Kostovetsky, 2012, Red and blue investing: Values and finance, *Journal of Financial Economics* 103, 1–19.

Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein, 2004, Social interaction and stock-market participation, *Journal of Finance* 59, 137–163.

Ince, Ozgur S., and R. Burt Porter, 2006, Individual equity return data from Thomson Datastream: Handle with care!, *Journal of Financial Research* 29, 463–479.

Ivković, Zoran, and Scott Weisbenner, 2005, Local does as local is: Information content of the geography of individual investors' common stock investments, *Journal of Finance* 60, 267–306.

Jagannathan, Murali, Wei Jiao, and Andrew Karolyi, 2022, Is there a home field advantage in global markets?, *Journal of Financial Economics* 143, 742–770.

Jin, Li, and Anna Scherbina, 2011, Inheriting losers, *Review of Financial Studies* 24, 786–820.

Kalmijn, Matthijs, 1999, Father involvement in childrearing and the perceived stability of marriage, *Journal of Marriage and the Family* 409–421.

Kang, Jun-Koo, and René Stulz, 1997, Why is there a home bias? An analysis of foreign portfolio equity ownership in Japan, *Journal of Financial Economics* 46, 3–28.

Korniotis, George M., and Alok Kumar, 2011, Do older investors make better investment decisions?, *Review of Economics and Statistics* 93, 244–265.

Lazarsfeld, Paul F., and Robert K. Merton, 1954, Friendship as a social process: A substantive and methodological analysis, *Freedom and Control in Modern Society* 18, 18–66.

Malmendier, Ulrike, and Stefan Nagel, 2011, Depression babies: Do macroeconomic experiences affect risk taking?, *Quarterly Journal of Economics* 126, 373–416.

Morse, Adair, and Sophie Shive, 2011, Patriotism in your portfolio, *Journal of Financial Markets* 14, 411–440.

Nguyen, Duc Duy, Jens Hagendorff, and Arman Eshraghi, 2018, Does a CEO's cultural heritage affect performance under competitive pressure?, *Review of Financial Studies* 31, 97–141.

Niessen-Ruenzi, Alexandra, and Stefan Ruenzi, 2019, Sex matters: Gender bias in the mutual fund industry, *Management Science* 65, 3001–3025.

Pagnini, Deanna L., and S. Philip Morgan, 1990, Intermarriage and social distance among US immigrants at the turn of the century, *American Journal of Sociology* 96, 405–432.

Pan, Yihui, Stephan Siegel, and Tracy Yue Wang, 2017, Corporate risk culture, *Journal of Financial and Quantitative Analysis* 52, 2327–2367.

Pástor, Luboš, Robert F. Stambaugh, and Lucian A. Taylor, 2015, Scale and skill in active management, *Journal of Financial Economics* 116, 23–45.

Patel, Saurin, and Sergei Sarkissian, 2017, To group or not to group? Evidence from mutual fund databases, *Journal of Financial and Quantitative Analysis* 52, 1989–2021.

Pool, Veronika K., Noah Stoffman, and Scott E. Yonker, 2012, No place like home: Familiarity in mutual fund manager portfolio choice, *Review of Financial Studies* 25, 2563–2599.

Pool, Veronika K, Noah Stoffman, and Scott E. Yonker, 2015, The people in your neighborhood: Social interactions and mutual fund portfolios, *Journal of Finance* 70, 2679–2732.

Pool, Veronika K., Noah Stoffman, Scott E Yonker, and Hanjiang Zhang, 2019, Do shocks to personal wealth affect risk-taking in delegated portfolios?, *Review of Financial Studies* 32, 1457–1493.

Richerson, Peter, and Robert Boyd, 2005, *Not by genes alone: How culture transformed human evolution* (University of Chicago Press).

Schumacher, David, 2018, Home bias abroad: Domestic industries and foreign portfolio choice, *Review of Financial Studies* 31, 1654–1706.

Seasholes, Mark S., and Ning Zhu, 2010, Individual investors and local bias, *Journal of Finance* 65, 1987–2010.

Seru, Amit, Tyler Shumway, and Noah Stoffman, 2010, Learning by trading, *Review of Financial Studies* 23, 705–739.

Shive, Sophie, 2010, An epidemic model of investor behavior, *Journal of Financial and Quantitative Analysis* 45, 169–198.

Tesar, Linda L., and Ingrid M. Werner, 1995, Home bias and high turnover, *Journal of International Money and Finance* 14, 467–492.

Tversky, Amos, and Daniel Kahneman, 1973, Availability: A heuristic for judging frequency and probability, *Cognitive Psychology* 5, 207–232.

Ye, Junting, Shuchu Han, Yifan Hu, Baris Coskun, Meizhu Liu, Hong Qin, and Steven Skiena, 2017, Nationality classification using name embeddings, in *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, 1897–1906.

Table I. Sample Composition, Fund and Manager Characteristics
This table reports fund and manager characteristics for our sample of funds managed by solo managers whose ancestral origin we were able to identify. Panel A reports the average fund's total net assets (TNA), the average number of funds, the average percentage of aggregate TNA of all solo-managed funds in the Morningstar-CRSP intersection, and the percentage of those funds covered per month and by Morningstar category for 75,571 monthly observations. Panel B reports summary statistics for fund and manager characteristics. For both fund-specific variables and manager-specific variables, the unit of observation is fund-month or, equivalently, fund-manager-month, as our sample includes solo-managed fund-month observations only.

Panel A: Sample Composition

Morningstar Category	Sample avg. aggr. TNA per month ($ millions)	Sample avg. fund TNA per month ($ millions)	Sample avg. funds per month	Avg. % of benchmark TNA covered per month	Avg. % of benchmark funds covered per month
U.S. Large Blend	43,047	1,069	35	80.76	69.87
U.S. Large Growth	138,151	1,956	54	77.47	73.21
U.S. Large Value	34,792	1,064	30	82.81	72.87
U.S. Mid-Cap Blend	5,633	385	12	74.45	76.95
U.S. Mid-Cap Growth	19,278	655	24	76.43	72.58
U.S. Mid-Cap Value	12,241	1,328	8	82.99	80.02
U.S. Small Blend	8,543	467	16	80.55	74.09
U.S. Small Growth	7,775	294	20	69.46	71.89
U.S. Small Value	2,235	235	8	80.07	79.45
Total	260,359	1,131	189	80.09	70.84

Panel B: Summary Statistics

Variable	Mean	Median	SD	N
Fund TNA ($ bn.)	1.26	0.17	4.9	75,571
Fund age (years)	12.90	9.17	12.94	75,571
Manager age	49.06	47.92	10.30	75,571
Manager fund tenure	4.81	3.72	5.01	75,571
Manager industry exp.	8.76	6.98	7.09	75,571
Manager generation	4.87	4.00	3.00	75,571
Ivy League school	0.36	0.00	0.48	75,571

Table II. Manager Ancestral Home Countries

This table reports the fund managers' average immigrant generation and the percentage of fund managers per ancestral home country in our sample. We compare fund managers' ancestral origins as identified in the U.S. census with self-reported ancestry information of U.S. households from the 2010 American Community Survey (ACS). We do not report ancestral home countries for which only one fund manager is identified (i.e., Bosnia and Herzegovina, Belarus, Armenia, Cape Verde, Brazil, Jordan, Georgia, Israel, Latvia, Morocco, Philippines, Saudi Arabia, Singapore, South Korea, Sri Lanka, Syria, and Albania.)

	Our Sample		ACS 2010
Ancestral Home Country	Avg. generation	% of managers	% of respondents
United Kingdom	8.11	21.37	13.69
Germany	4.88	20.04	16.40
Ireland	5.41	10.64	11.78
Russia	3.27	7.59	1.12
Italy	3.01	5.96	5.78
Poland	3.05	4.39	3.24
Austria	3.26	2.90	0.25
Canada	3.29	2.61	0.10
India	1.20	2.53	0.09
France	5.56	2.08	3.07
Sweden	3.57	2.01	1.48
Netherlands	7.65	1.71	1.63
Norway	4.28	1.34	1.58
Switzerland	5.25	1.19	0.33
Greece	2.56	1.19	0.44
Czech Republic	3.85	1.19	0.58
Hungary	3.63	1.19	0.51
Denmark	3.44	0.74	0.48
China	2.00	0.74	1.08
Romania	2.55	0.52	0.15
Turkey	2.00	0.52	0.06
Belgium	4.17	0.45	0.13
Ukraine	3.17	0.45	0.31
Mexico	2.80	0.37	10.11
Japan	3.00	0.30	0.27
Egypt	1.25	0.30	0.06
Spain	4.75	0.30	–
Iran	1.50	0.30	0.14
South Africa	1.33	0.22	0.02
Taiwan	1.67	0.22	–
Lebanon	2.67	0.22	0.16
Portugal	2.33	0.22	0.47
Slovakia	3.00	0.15	0.26
Slovenia	2.50	0.15	0.06
Argentina	2.00	0.15	–
Cuba	1.50	0.15	0.56
Croatia	2.50	0.15	0.14

Table III. Weights on Stocks from Managers' Ancestral Home Countries.
This table compares average allocations at the country level based on all non-U.S. holdings of all funds in our sample. Every cell displays average allocations (in percentage of non-U.S. holdings) to a certain country, conditional on whether the respective fund managers have ancestors from that country (*Home*) or not (*Foreign*). Additional columns show these average allocations across fund managers' immigrant generations. Empty cells indicate fewer than ten identified managers of the respective ancestry. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

Country	All Generations			Generation 1-3		Generation 4-6		Generation 7-9		Generation > 9	
	Home	Foreign	Diff.	Home	Diff.	Home	Diff.	Home	Diff.	Home	Diff.
United Kingdom	17.79	13.91	3.88***	22.63	9.15***	19.81	6.33***	19.60	5.69***	15.88	1.97***
Germany	2.14	1.53	0.61***	3.03	1.50***	1.88	0.35***	2.82	1.29***	–	–
Ireland	5.07	3.21	1.86***	6.32	3.11***	4.47	1.27***	6.89	3.68***	–	–
Russia	0.61	0.36	0.26**	0.81	0.45***	0.41	0.05	–	–	–	–
Italy	1.30	0.41	0.89***	1.65	1.24***	0.57	0.16*	–	–	–	–
Poland	0.12	0.14	-0.02	0.09	-0.05	0.17	0.03	–	–	–	–
Austria	0.09	0.04	0.05*	0.16	0.13**	–	–	–	–	–	–
Canada	25.53	21.07	4.46***	26.16	5.09***	24.58	3.51***	–	–	–	–
India	2.49	0.85	1.63***	2.49	1.63***	–	–	–	–	–	–
France	4.54	2.43	2.11***	6.46	4.04***	6.40	3.97***	–	–	–	–
Sweden	2.86	0.85	2.00***	3.89	3.04***	2.04	1.19***	–	–	–	–
Netherlands	11.33	6.81	4.52***	–	–	–	–	–	–	12.03	5.22***
Norway	1.15	0.51	0.63*	2.25	1.74**	–	–	–	–	–	–
Switzerland	8.81	6.37	2.43***	–	–	–	–	–	–	–	–
Greece	0.97	0.38	0.59**	0.97	0.59**	–	–	–	–	–	–
Czech Republic	0.02	0.01	0.01	–	–	–	–	–	–	–	–
Hungary	0.18	0.03	0.16	–	–	–	–	–	–	–	–
Denmark	1.23	0.31	0.92***	–	–	–	–	–	–	–	–
China	8.45	3.53	4.92***	–	–	–	–	–	–	–	–

Table IV. Weights on Stocks from Managers' Ancestral Home Countries. This table reports results from an OLS estimation of various forms of the regression

$$w_{i,c,t} = \beta MgrHmCountry_{i,c,t} + \delta MorningstarBMWt_{i,c,t} + \Gamma' Controls_{i,c,t} + \epsilon_{i,c,t},$$

where $w_{i,c,t}$ is the weight in fund i's non-U.S. portfolio of firms headquartered in country c during month t; $MgrHmCountry_{i,c,t}$ is a dummy that equals one if the fund manager of fund i in month t has ancestors from country c; $MorningstarBMWt_{i,c,t}$ is the average non-U.S. portfolio weight in country c of all funds within the same Morningstar category as fund i during month t; and $Controls_{i,c,t}$ is a vector of control variables. The sample includes 2,421,400 solo-managed monthly fund-country observations and covers 1,677 unique funds. $MFHQCountry_{i,c,t}$ is a dummy variable that is one if the fund firm of fund i is headquartered in country c during month t and zero otherwise. Standard errors in parentheses are clustered at the fund level. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

	Dependent Variable: Country Weight $w_{i,c,t}$				
	(1)	(2)	(3)	(4)	(5)
MgrHmCountry	5.44***	1.32***	1.31***	1.32***	0.86**
	(0.46)	(0.30)	(0.30)	(0.30)	(0.39)
MFHQCountry			4.04		
			(4.35)		
MorningstarBMWt		1.00***	1.00***	1.00***	0.87***
		(0.01)	(0.01)	(0.01)	(0.02)
Intercept	2.37***	-0.02	-0.02	-0.02	0.30***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.39)
Fixed Effects	No	No	No	Fund	Fund-Country
Adj. R-squared	0.01	0.33	0.33	0.33	0.33
N of funds	1,677	1,677	1,677	1,677	1,677
Observations	2,421,400	2,421,400	2,421,400	2,421,400	2,421,400

Table V. Weights on Stocks from Managers' Name-Based Ancestral Home Countries

This table reports results from an OLS estimation of various forms of the regression

$$w_{i,c,t} = \beta MgrHmCountryAlgo_{i,c,t} + \delta MorningstarBMWt_{i,c,t} + \Gamma' Controls_{i,c,t} + \epsilon_{i,c,t},$$

where $w_{i,c,t}$ is the weight in fund i's non-U.S. portfolio of firms headquartered in country c during month t; $MgrHmCountryAlgo_{i,c,t}$ is a dummy that equals one if the fund manager of fund i in month t originates from country c according to the nationality classification algorithm by Ye et al. (2017); $MorningstarBMWt_{i,c,t}$ is the average non-U.S. portfolio weight in country c of all funds within the same Morningstar category as fund i during month t; and $Controls_{i,c,t}$ is a vector of control variables. $MFHQCountry_{i,c,t}$ is a dummy variable that is one if the fund firm of fund i is headquartered in country c during month t and zero otherwise. The sample includes 2,421,400 solo-managed monthly fund-country observations and covers 1,677 unique funds. Standard errors in parentheses are clustered at the fund level. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

	Dependent Variable: Country Weight $w_{i,c,t}$				
	(1)	(2)	(3)	(4)	(5)
MgrHmCountryAlgo	12.71***	0.51	0.50	0.51	1.09
	(0.59)	(0.48)	(0.48)	(0.48)	(0.68)
MFHQCountry			4.17		
			(4.30)		
MorningstarBMWt		1.00***	1.00***	1.00***	0.87***
		(0.01)	(0.01)	(0.01)	(0.02)
Intercept	2.20***	-0.00	-0.00	-0.00	0.30
	(0.01)	(0.02)	(0.02)	(0.02)	(0.05)
Fixed Effects	No	No	No	Fund	Fund-Country
Adj. R-squared	0.03	0.33	0.33	0.33	0.33
N of funds	1,677	1,677	1,677	1,677	1,677
Observations	2,421,400	2,421,400	2,421,400	2,421,400	2,421,400

Table VI. Weights on Industries Most Prevalent in Managers' Ancestral Home Countries.
This table reports results from an OLS estimation of various forms of the regression

$$w_{i,s,t} = \alpha + \beta_1 Rank1HmIndustry_{i,s,t} + \beta_2 Rank2HmIndustry_{i,s,t} + \beta_3 Rank3HmIndustry_{i,s,t} + \beta_4 Rank4HmIndustry_{i,s,t} \\ + \beta_5 Rank5HmIndustry_{i,s,t} + \delta MorningstarBMW_{i,s,t} + \Gamma' Controls_{i,s,t} + \epsilon_{i,s,t},$$

where $w_{i,s,t}$ is the weight in fund i's U.S. portfolio of firms in industry s at time t; $Rank1HmIndustry_{i,s,t}$, $Rank2HmIndustry_{i,s,t}$, and so on, are dummies that equal one if industry s in time t is ranked first, second, and so on, according to equation (3), in fund i's fund manager ancestral home country; $MorningstarBMWt_{i,s,t}$ is the average U.S. portfolio weight in industry s of all funds within the same Morningstar category as fund i during month t; and $Controls_{i,s,t}$ is a vector of control variables. The overall sample includes 3,665,160 solo-managed monthly fund-country observations and covers 1,749 unique funds. Standard errors in parentheses are clustered at the fund level. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

	Dependent Variable: Industry Weight $w_{i,s,t}$							
	(1)		(2)		(3)		(4)	
	All	Gen. 1-3	All	Gen. 1-3	All	Gen. 1-3	All	Gen. 1-3
Rank1HmIndustry	2.55***	2.93***	0.17**	0.46***	0.16*	0.45***	0.04	0.28***
	(0.11)	(0.19)	(0.07)	(0.13)	(0.07)	(0.13)	(0.06)	(0.11)
Rank2HmIndustry	1.07***	1.43***	0.03	0.25*	0.03	0.26*	0.01	0.14**
	(0.09)	(0.18)	(0.07)	(0.15)	(0.07)	(0.15)	(0.04)	(0.07)
Rank3HmIndustry	0.51***	0.62***	0.06	0.19*	0.05	0.19*	0.03	0.06
	(0.06)	(0.12)	(0.05)	(0.09)	(0.04)	(0.10)	(0.03)	(0.06)
Rank4HmIndustry	0.45***	0.29***	-0.01	0.07	-0.01	0.07	0.03	0.07
	(0.05)	(0.09)	(0.04)	(0.06)	(0.04)	(0.06)	(0.02)	(0.04)
Rank5HmIndustry	0.20***	0.01	-0.04	0.01	-0.03	0.01	-0.02	0.03
	(0.05)	(0.08)	(0.03)	(0.06)	(0.03)	(0.06)	(0.02)	(0.03)
MorningstarBMWt			1.00***	1.00***	1.00***	1.00***	0.86***	0.86***
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Intercept	2.12***	2.10***	-0.00	-0.03	-0.01	-0.03	0.31***	0.30***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.03)	(0.05)
Fixed Effects	No	No	No	No	Fund	Fund	Fund-Industry	Fund-Industry
Adj. R-squared	0.01	0.02	0.45	0.44	0.45	0.46	0.44	0.43
N of funds	1,749	859	1,749	859	1,749	859	1,749	859
Observations	3,665,160	1,259,370	3,665,160	1,259,370	3,665,160	1,259,370	3,665,160	1,259,370

Table VII. Ancestral Home Country Overweighting Around Manager Turnover The table reports the funds' average excess weights in their former and new managers' ancestral home countries one year prior to and one year following manager turnover, as well as the difference in excess weights. Excess weights are calculated as a fund's non-U.S. portfolio weight in the manager's ancestral home country minus the average Morningstar benchmark non-U.S. portfolio weight in that country. The analysis uses 262 fund manager turnover events from 1985 to 2016 when the former and new manager come from different ancestral home countries. We focus on cases where a solo manager is replaced by another solo manager. Standard errors are reported in parentheses. Significance levels of a t-test testing whether the estimate is significantly different from zero are denoted by *, **, and ***, which correspond to the 10%, 5%, and 1% levels, respectively.

	Prior to Turnover	Following Turnover	Difference
Excess weight in former manager's home country	1.54*	-0.24	-1.78**
	(0.93)	(0.62)	(0.84)
Excess weight in new manager's home country	0.05	0.20	0.15
	(0.55)	(0.47)	(0.53)

Table VIII. Ancestral Home Industry Overweighting Around Manager Turnover
The table reports the funds' average excess weights in the industry that is largest (top 1) in the ancestral home country of their former and new manager at one year prior to and one year following manager turnover, as well as the difference in excess weights. Excess weights are calculated as a fund's U.S. portfolio weight in the manager's top 1 ancestral home industry minus the average Morningstar benchmark U.S. portfolio weight in that industry. The analysis uses 262 fund manager turnover events from 1985 to 2016 when the former and new manager come from different ancestral home countries. We focus on cases where a solo manager is replaced by another solo manager. Standard errors are reported in parentheses. Significance levels of a t-test testing whether the estimate is significantly different from zero are denoted by *, **, and ***, which correspond to the 10%, 5%, and 1% levels, respectively.

	Prior to Turnover	Following Turnover	Difference
Excess weight in former manager's top 1 ancestral industry	0.12	0.00	-0.12
	(0.21)	(0.18)	(0.12)
Excess weight in new manager's top 1 ancestral industry	0.07	0.13	0.05
	(0.18)	(0.17)	(0.16)

Table IX. Fund Characteristics and Ancestral Home Country Overweighting
This table reports the coefficient estimates and standard errors from the OLS regression equation estimated in column 3 of Table III, including interaction terms with various fund characteristics. The sample includes 2,421,400 solo-managed monthly fund-country observations and covers 1,677 unique funds. *Value* is a dummy that equals one if the fund is categorized as a value fund according to Morningstar. *Growth* is a dummy that equals one if the fund is categorized as a growth fund according to Morningstar. *SmallCap* is a dummy that equals one if the fund is categorized as a small-cap fund according to Morningstar. *LargeCap* is a dummy that equals one if the fund is categorized as a large-cap fund according to Morningstar. *FamTNAQuin* is equal to the fund's fund family total net assets (TNA) quintile minus one, where one is the largest quintile based on fund family TNA each month. *FundTNAQuin* is equal to the fund's TNA quintile minus one, where one is the largest quintile based on fund TNA each month. All specifications include the main effect for the interaction variables but coefficient estimates are unreported for the sake of brevity. Standard errors in parentheses are clustered at the fund level. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

	Dependent Variable: Country Weight $w_{i,c,t}$				
	(1)	(2)	(3)	(4)	(5)
MgrHmCountry	1.68***	0.51*	1.51***	2.13***	1.82**
	(0.54)	(0.30)	(0.34)	(0.50)	(0.93)
MgrHmCountry×Value	0.44				0.42
	(0.93)				(0.91)
MgrHmCountry×Growth	-0.93				-0.86
	(0.66)				(0.68)
MgrHmCountry×SmallCap		-0.02			-0.05
		(0.65)			(0.67)
MgrHmCountry×LargeCap		1.20*			0.85
		(0.67)			(0.69)
MgrHmCountry×FamTNAQuin			-0.21*		-0.06
			(0.13)		(0.27)
MgrHmCountry×FundTNAQuin				-0.41**	-0.41**
				(0.20)	(0.21)
MFHQCountry	3.99	3.95	4.13	4.00	3.95
	(4.36)	(4.08)	(4.35)	(4.34)	(4.38)
MorningstarBMWt	1.00***	1.00***	1.00***	1.00***	1.00***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Intercept	-0.03	-0.00	-0.03	-0.04	-0.04
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Adj. R-squared	0.33	0.33	0.33	0.33	0.33
N of funds	1,677	1,677	1,677	1,677	1,677
Observations	2,421,400	2,421,400	2,421,400	2,421,400	2,421,400

Table X. Fund Characteristics and Ancestral Home Industry Overweighting
This table reports the coefficient estimates and standard errors from the OLS regression equation estimated in specification (2) Gen. 1-3 of Table VI, including interaction terms with various fund characteristics. The sample includes 1,259,370 solo-managed monthly fund-industry observations and covers 859 unique funds. *Value* is a dummy that equals one if the fund is categorized as a value fund according to Morningstar. *Growth* is a dummy that equals one if the fund is categorized as a growth fund according to Morningstar. *SmallCap* is a dummy that equals one if the fund is categorized as a small-cap fund according to Morningstar. *LargeCap* is a dummy that equals one if the fund is categorized as a large-cap fund according to Morningstar. *FamTNAQuin* is equal to the fund's fund family total net assets (TNA) quintile minus one, where one is the largest month based on fund family TNA each quarter. *FundTNAQuin* is equal to the fund's TNA quintile minus one, where one is the largest quintile based on fund TNA each month. All specifications include the main effect for the interaction variables but coefficient estimates are unreported for the sake of brevity. Standard errors in parentheses are clustered at the fund level. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

	Dependent Variable: Industry Weight $w_{i,s,t}$				
	(1)	(2)	(3)	(4)	(5)
Rank1HmIndustry	0.50***	0.45*	0.42***	0.42**	0.48*
	(0.19)	(0.25)	(0.13)	(0.19)	(0.28)
Rank1HmIndustry×Value	0.29				0.28
	(0.41)				(0.41)
Rank1HmIndustry×Growth	-0.25				-0.24
	(0.24)				(0.26)
Rank1HmIndustry×SmallCap		-0.33			-0.35
		(0.31)			(0.31)
Rank1HmIndustry×LargeCap		0.08			0.06
		(0.31)			(0.32)
Rank1HmIndustry×FamTNAQuin			0.02		0.01
			(0.11)		(0.12)
Rank1HmIndustry×FundTNAQuin				0.01	0.02
				(0.08)	(0.09)
MorningstarBMWt	1.00***	1.01***	1.01***	1.01***	1.00***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Intercept	-0.02	-0.02	-0.02	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Adj. R-squared	0.44	0.44	0.44	0.44	0.44
N of funds	859	859	859	859	859
Observations	1,259,370	1,259,370	1,259,370	1,259,370	1,259,370

Table XI. Manager Characteristics and Ancestral Home Country Overweighting.
This table reports the coefficient estimates and standard errors from the OLS regression equation estimated in column 5 of Table IV, including interaction terms with various fund manager characteristics. The sample includes 2,421,400 solo-managed monthly fund-country observations and covers 1,820 unique funds. $MgrAge$ is a dummy that equals one if the manager's age is greater than the sample's median manager age in month t. $MgrExperience$ is a dummy that equals one if the manager's managing experience is greater than the sample's median manager experience in month t. $MgerGeneration$ equals the manager's immigrant generation, as defined in Section 1, minus one. $MgrCollCountry$ is a dummy that equals one if the manager's undergraduate degree is from a college in country c. $MgrIvy$ is a dummy that equals one if the manager has a degree from an Ivy League school. $MgrMBA$ is a dummy that equals one if the manager holds an MBA. All specifications include a constant and the main effect for the interaction variables, but coefficient estimates are unreported for the sake of brevity. Standard errors in parentheses are clustered at the fund level. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

	Dependent Variable: Country Weight $w_{i,c,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MgrHmCountry	0.86**	1.15***	1.30***	2.63***	0.71*	0.48	0.80	3.01***
	(0.39)	(0.44)	(0.46)	(0.59)	(0.41)	(0.48)	(0.74)	(0.62)
MgrHmCountry×MgrAge		-0.82						
		(0.62)						
MgrHmCountry×MgrExperience			-1.06*					-0.97*
			(0.55)					(0.55)
MgrHmCountry×MgrGeneration				-0.46***				-0.46***
				(0.16)				(0.16)
MgrHmCountry×MgrCollCountry					14.17			
					(11.36)			
MgrHmCountry×MgrIvy						1.03	1.20	
						(0.87)	(0.93)	
MgrHmCountry×MgrMBA							-0.61	
							(0.92)	
MorningstarBMWt	0.87***	0.87***	0.87***	0.87***	0.87***	0.87***	0.87***	0.87***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Fixed Effects	Fund-Country	Fund-Country	Fund-Country	Fund-Country	Fund-Country	Fund-Country	Fund-Country	Fund-Country
Adj. R-squared	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33
Observations	2,421,400	2,421,400	2,421,400	2,420,600	2,421,400	2,421,400	2,420,600	2,421,400

Table XII. Manager Characteristics and Ancestral Home Industry Overweighting

This table reports the coefficient estimates and standard errors from the OLS regression equation estimated in specification (4) Gen. 1-3 of Table VI, including interaction terms with various fund manager characteristics. The sample includes 1,259,370 solo-managed monthly fund-industry observations and covers 859 unique funds. *MgrAge* is a dummy that equals one if the manager's age is greater than the sample's median manager age in month t. *MgrExperience* is a dummy that equals one if the manager's managing experience is greater than the sample's median manager experience in month t. *MgerGeneration* equals the manager's immigrant generation, as defined in Section 1, minus one. *Ivy* is a dummy that equals one if the manager has a degree from an Ivy League school. All specifications include a constant and the main effect for the interaction variables but coefficient estimates are unreported for the sake of brevity. Standard errors in parentheses are clustered at the fund level. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

	Dependent Variable: Industry Weight $w_{i,s,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rank1HmIndustry	0.21**	0.18*	0.19*	0.39**	0.15	0.11	0.37**
	(0.09)	(0.10)	(0.10)	(0.17)	(0.27)	(0.13)	(0.17)
Rank1HmIndustry×MgrAge		0.05					
		(0.16)					
Rank1HmIndustry×MgrExperience			0.04				0.06
			(0.15)				(0.16)
Rank1HmIndustry×MgrGeneration				-0.13*			-0.14*
				(0.08)			(0.08)
Rank1HmIndustry×MgrIvy					0.17	0.15	
					(0.17)	(0.20)	
Rank1HmIndustry×MgrMBA						0.09	
						(0.20)	
MorningstarBMWt	0.86***	0.86***	0.86***	0.86***	0.86***	0.86***	0.86***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Fixed Effects	Fund-Industry	Fund-Industry	Fund-Industry	Fund-Industry	Fund-Industry	Fund-Industry	Fund-Industry
Adj. R-squared	0.43	0.43	0.43	0.43	0.43	0.43	0.43
Observations	1,259,370	1,259,370	1,259,370	1,259,370	1,259,370	1,259,370	1,259,370

Table XIII. Manager Origin and Ancestral Home Country Overweighting.
This table reports the coefficient estimates and standard errors from the OLS regression equation estimated in column 5 of Table IV, including interaction terms with the fund managers' ancestral home country. The sample includes 2,421,400 solo-managed monthly fund-country observations and covers 1,677 unique funds. *UK*, *Germany*, *Ireland*, *Russia*, *Italy* are dummy variables that respectively equal one if the managers' ancestry links to the United Kingdom, Germany, Ireland, Russia, or Italy. *Rest* is a dummy that equals one if the manager has ancestors from a country not listed above. All specifications include a constant and the main effect for the interaction variables, but coefficient estimates are unreported for the sake of brevity. Standard errors in parentheses are clustered at the fund level. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

	Dependent Variable: Country Weight $w_{i,c,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
MgrHmCountry	0.69**	0.97**	0.80**	0.95**	0.85**	0.92*
	(0.28)	(0.48)	(0.40)	(0.43)	(0.46)	(0.53)
MgrHmCountry×UK	0.95					
	(1.62)					
MgrHmCountry×Germany		-0.57				
		(0.63)				
MgrHmCountry×Ireland			0.41			
			(1.02)			
MgrHmCountry×Russia				-1.05**		
				(0.45)		
MgrHmCountry×Italy					0.17	
					(0.81)	
MgrHmCountry×Rest						-0.18
						(0.73)
MorningstarBMWt	0.87***	0.87***	0.87***	0.87***	0.87***	0.87***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Fixed Effects	Fund-Country	Fund-Country	Fund-Country	Fund-Country	Fund-Country	Fund-Country
Adj. R-squared	0.33	0.33	0.33	0.33	0.33	0.33
Observations	2,421,400	2,421,400	2,421,400	2,421,400	2,421,400	2,421,400

Table XIV. Stock Characteristics and Ancestral Home Country Overweighting.
This table reports results from an OLS estimation of various forms of the regression

$$w_{i,k,t} = \alpha + \beta MgrHmCountry_{i,k,t} + \delta MorningstarBMWt_{i,k,t} + \Gamma' Controls_{i,k,t} + \epsilon_{i,k,t},$$

where $w_{i,k,t}$ is the weight in fund i's non-U.S. portfolio of stock k during month t; $MgrHmCountry_{i,k,t}$ is a dummy that equals one if the manager of fund i in month t has ancestors from the country where stock k is headquartered; $MorningstarBMWt_{i,k,t}$ is the average non-U.S. portfolio weight in stock k of all funds within the same Morningstar category as fund i during month t; and $Controls_{i,c,t}$ is a vector of control variables. The sample includes 9,999,081 solo-managed monthly fund-stock observations. For each fund-month, we include stocks held by at least one fund in the same nine-box Morningstar category. $MFHQCountry_{i,s,t}$ is a dummy that is one if the fund firm of fund i is headquartered in the same country as stock s during month t. Column 1 shows the regression results for the full sample. In columns 2 and 3, securities traded and not traded on U.S. exchanges are included in the samples, respectively. Columns 4 and 5 split the sample into securities included in and excluded from national stock market indices, respectively. In columns 6 and 7, the sample consists of stocks whose names contain and do not contain references to certain countries (patriot vs. non-patriot stocks), respectively. In columns 8 and 9, the sample is split into stocks incorporated before and after the median year of incorporation (heritage vs. non-heritage stocks), respectively. Standard errors in parentheses are clustered at the fund level. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively. The mean stock weight and the percentage of home-country overweighting are reported at the bottom of each column.

	Dependent Variable: Stock Weight $w_{i,k,t}$								
	All	U.S. Exchange	Non-U.S. Exchange	Index Stocks	Non-Index Stocks	Patriot Stocks	Non-Patriot Stocks	Heritage Stocks	Non-Heritage Stocks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MgrHmCountry	0.14***	0.26***	0.06**	0.18***	0.12***	0.42***	0.12***	0.16***	0.15***
	(0.03)	(0.07)	(0.03)	(0.05)	(0.04)	(0.15)	(0.03)	(0.06)	(0.05)
MFHQCountry	0.20	0.27	0.17	0.03	0.05	0.02	0.27	0.28	0.01
	(0.21)	(0.45)	(0.25)	(0.20)	(0.23)	(0.13)	(0.23)	(0.31)	(0.31)
MorningstarBMWt	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***
	(0.02)	(0.02)	(0.02)	(0.04)	(0.02)	(0.06)	(0.02)	(0.03)	(0.03)
Intercept	-0.00	-0.01	-0.00	-0.01	-0.00	-0.02	-0.00	-0.00	-0.00
	(0.00)	(0.02)	(0.00)	(0.02)	(0.01)	(0.03)	(0.00)	(0.01)	(0.01)
Adj. R-squared	0.10	0.10	0.10	0.09	0.09	0.15	0.10	0.11	0.10
Obs. (thousands)	9,999	3,905	6,094	2,816	6,280	838	9,161	3,953	4,131
Mean Stock Weight	0.59	0.90	0.38	0.54	0.56	0.59	0.59	0.54	0.65
% Home-Country Overweight	24.10	28.38	16.38	32.36	21.71	71.16	20.27	29.77	23.00

Table XV. Stock Characteristics and Ancestral Home Industry Overweighting.
This table reports results from an OLS estimation of various forms of the regression

$$w_{i,k,t} = \alpha + \beta Rank1HmIndustry_{i,k,t} + \delta MorningstarBMWt_{i,k,t} + \Gamma' Controls_{i,k,t} + \epsilon_{i,k,t},$$

where $w_{i,k,t}$ is the weight in fund i's U.S. portfolio of stock k during month t; $Rank1HmIndustry_{i,k,t}$ is a dummy that equals one if industry s in time t is ranked first, according to equation (3), in fund i's fund manager ancestral home country; $MorningstarBMWt_{i,k,t}$ is the average U.S. portfolio weight in stock k of all funds within the same Morningstar category as fund i during month t; and $Controls_{i,c,t}$ is a vector of control variables. The sample includes 37,554,379 solo-managed monthly fund-stock observations and is restricted to first- to third-generation immigrant managers. For each fund-month, we include stocks held by at least one fund in the same nine-box Morningstar category. Column 1 shows regression results for the full sample. Columns 2 and 3 split the sample into securities included in and excluded from the SP500, respectively. In columns 4 to 9, the sample is split into stocks by the median level of sales, analyst coverage, and SG&A, respectively. Standard errors in parentheses are clustered at the fund level. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively. The mean stock weight and the percentage of home-industry overweighting are reported at the bottom of each column.

	Dependent Variable: Stock Weight $w_{i,k,t}$								
	All	S&P500 Stocks	Non-S&P500 Stocks	High Sales	Low Sales	High Analyst Coverage	Low Analyst Coverage	High SG&A	Low SG&A
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rank1HmIndustry	0.01***	0.03***	0.00*	0.02***	0.00**	0.02***	0.00	0.03***	0.00
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
MorningstarBMWt	1.00***	0.99***	1.04***	0.99***	1.04***	0.99***	1.04***	0.99***	1.04***
	(0.02)	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.05)
Intercept	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	(0.00)
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Adj. R-squared	0.17	0.20	0.08	0.18	0.11	0.18	0.10	0.18	0.10
Obs. (thousands)	37,554	9,349	27,118	17,730	17,730	16,169	16,118	15,944	15,944
Mean Stock Weight	0.08	0.16	0.04	0.12	0.03	0.12	0.04	0.11	0.04
% Home-Industry Overweight	10.55	16.20	5.79	14.02	7.60	12.72	4.89	23.03	1.16

Table XVI. Performance in Ancestral Home Country Securities.
This table reports the performance from 1991 to 2017 of active U.S. equity funds' stock holdings that are headquartered in the manager's ancestral country of origin. In column 1, we report the performance of a portfolio that buys these ancestral home country stocks and compute returns net of U.S. Treasury bill yield. In column 2 and 3, we report corresponding results when restricting the sample to first- to third- or higher-generation managers, respectively. Column 4 reports the performance of a long-short portfolio (rebalanced every holding reporting date) that buys ancestral home country stocks and sells short stocks from the same country held by managers in the same Morningstar category but with different ancestry. For example, consider a small-cap value fund holding Italian stocks at the beginning of a holding period whose manager has Italian ancestry. In this case, the long side consists of all Italian stocks held by the fund, and the short side consists of all Italian stocks held during the same period by small-cap value funds but whose managers do not have Italian ancestry. In columns 5 and 6, we report corresponding results when restricting the sample to first- to third- or higher-generation immigrant managers, respectively. For ancestral home country stock performance, we report the mean returns, *Alpha*, and loadings on the Fama-French International (Global ex U.S.) market (*Mkt-RF*), size (*SMB*), value (*HML*), and momentum (*MOM*) factors. Robust standard errors are reported in parentheses. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

	Long holdings of ancestral home country stocks only			Long holdings of ancestral home country stocks, Short same-country holdings held by managers of other origin		
	All	Gen. 1-3	Gen. > 3	All	Gen. 1-3	Gen. > 3
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Returns	0.012***	0.013***	0.011***	-0.001	-0.002	-0.000
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.001)
Alpha	0.001	0.001	0.000	0.000	-0.000	-0.000
	(0.002)	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)
Mkt-RF	0.929***	0.974***	0.915***	0.011	0.073	-0.014
	(0.046)	(0.074)	(0.046)	(0.030)	(0.053)	(0.034)
SMB	0.010	0.062	-0.014	-0.005	0.064	-0.035
	(0.094)	(0.155)	(0.094)	(0.064)	(0.129)	(0.068)
HML	-0.122	-0.293**	-0.052	0.029	-0.045	0.055
	(0.075)	(0.125)	(0.081)	(0.076)	(0.114)	(0.085)
MOM	-0.113**	-0.170**	-0.084	-0.055	-0.060	-0.043
	(0.052)	(0.074)	(0.055)	(0.035)	(0.059)	(0.040)
Adj. R-squared	0.73	0.61	0.68	0.00	0.00	0.00
Obs.	320	320	320	319	319	319

Table XVII. Performance in Ancestral Home Industry Securities.
This table reports the performance from 1983 to 2017 of active U.S. equity funds' U.S. stock holdings in industries that are most prevalent in their managers' ancestral home country. In column 1, we report the performance of a portfolio that buys these ancestral home industry stocks and compute returns net of U.S. Treasury bill yield. Columns 2 and 3 report corresponding results when restricting the sample to first- to third- or higher-generation managers, respectively. Column 4 reports the performance of a long-short portfolio (rebalanced every holding reporting date) that buys ancestral home industry stocks and sells short stocks from the same industry held by managers in the same Morningstar category but with different ancestry. For example, consider a large-cap value fund holding stocks in the "Automobiles and Parts" sector at the beginning of a holding period whose manager has German ancestry. In this case, the long side consists of all "Automobiles and Parts" stocks held by the fund, and the short side consists of all "Automobiles and Parts" stocks held during the same period by large-cap value funds but whose managers do not have German ancestry. In columns 5 and 6, we again restrict the sample to first- to third- or higher-generation managers, respectively. For ancestral home industry stock performance, we report mean returns, *Alpha* and loadings on the Fama-French U.S. market (*Mkt-RF*), size (*SMB*), value (*HML*), and momentum (*MOM*) factors. Robust standard errors are reported in parentheses. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

	Long holdings of ancestral home industry stocks only			Long holdings of ancestral home industry stocks, Short same-industry holdings held by managers of other origin		
	All	Gen. 1-3	Gen. > 3	All	Gen. 1-3	Gen. > 3
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Returns	0.010***	0.009***	0.011***	-0.001	-0.001	-0.000
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Alpha	0.002	0.001	0.002	0.000	-0.002	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Mkt-RF	1.076***	1.108***	1.070***	-0.020	0.024	-0.025
	(0.033)	(0.036)	(0.041)	(0.013)	(0.022)	(0.018)
SMB	0.123**	-0.021	0.174**	0.064***	0.010	0.086***
	(0.058)	(0.052)	(0.068)	(0.018)	(0.031)	(0.024)
HML	0.300***	0.156***	0.377***	0.047*	0.015	0.033
	(0.049)	(0.051)	(0.072)	(0.024)	(0.032)	(0.030)
MOM	-0.033	-0.040	0.010	0.010	0.033	-0.004
	(0.030)	(0.049)	(0.049)	(0.013)	(0.018)	(0.018)
Adj. R-squared	0.75	0.80	0.72	0.03	0.00	0.02
Obs.	409	403	409	403	403	403

Table XVIII. Ancestral Biases and Awareness of Ancestral Origin.
This table reports the coefficient estimates and standard errors from regressions including *MgrFBRelatives* and *MgrAncestryProfile*, and their interactions with *MgrHmCountry* (Panel A) and Rank1HmIndustry (Panel B), respectively. *MgrFBRelatives* is equal to one if the manager has relatives in his Facebook.com friend list who live in his ancestral home country. *MgrAncestryProfile* is one if the manager has an ancestry.com account. Columns 1 to 4 are subsample re-estimations of Table IV and Table IV, and columns 5 and 6 augment the regressions from Table XI and Table XII column 4. Standard errors are clustered at the fund level. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

Panel A: Country Bias	Dependent Variable: Country Weight $w_{i,c,t}$					
	MgrFBRelatives=1		MgrAncestryProfile=1		All	
	(1)	(2)	(3)	(4)	(5)	(6)
MgrHmCountry (MHC)	11.37***	5.34**	6.00***	2.34***	2.43***	2.45***
	(3.55)	(2.38)	(1.47)	(1.10)	(0.60)	(0.56)
MHC×MgrFBRelatives					6.23**	
					(2.83)	
MHC×MgrAncestryProfile						2.94**
						(1.42)
MHC×MgerGeneration					-0.44***	-0.48***
					(0.16)	(0.16)
MorningstarBMWt		1.02***		0.97***	0.87***	0.87***
		(0.05)		(0.03)	(0.02)	(0.02)
Intercept	2.23***	-0.18	2.35***	0.01	0.25***	0.25***
	(0.09)	(0.12)	(0.04)	(0.06)	(0.05)	(0.05)
Fixed Effects	No	No	No	No	Fund-Country	Fund-Country
Adj. R-squared	0.03	0.36	0.01	0.35	0.33	0.33
Observations	80,040	80,040	236,040	236,040	2,421,400	2,421,400

Panel B: Industry Bias	Dependent Variable: Industry Weight $w_{i,c,t}$					
	MgrFBRelatives=1		MgrAncestryProfile=1		Gen. 1-3	
	(1)	(2)	(3)	(4)	(5)	(6)
Rank1HmIndustry (R1HI)	3.32***	0.59**	2.95***	0.49**	0.34**	0.36**
	(0.55)	(0.28)	(0.43)	(0.25)	(0.17)	(0.17)
R1HI×MgrFBRelatives					0.23	
					(0.18)	
R1HI×MgrAncestryProfile						0.12
						(0.12)
R1HI×MgerGeneration					-0.11*	-0.12*
					(0.07)	(0.07)
MorningstarBMWt		1.01***		0.99***	0.86***	0.86***
		(0.02)		(0.02)	(0.02)	(0.02)
Intercept	2.14***	-0.01	2.18***	0.03	0.30***	0.30***
	(0.01)	(0.01)	(0.01)	(0.05)	(0.05)	(0.05)
Fixed Effects	No	No	No	No	Fund-Industry	Fund-Industry
Adj. R-squared	0.02	0.45	0.01	0.42	0.43	0.43
Observations	106,200	106,200	322,920	322,920	1,259,370	1,259,370

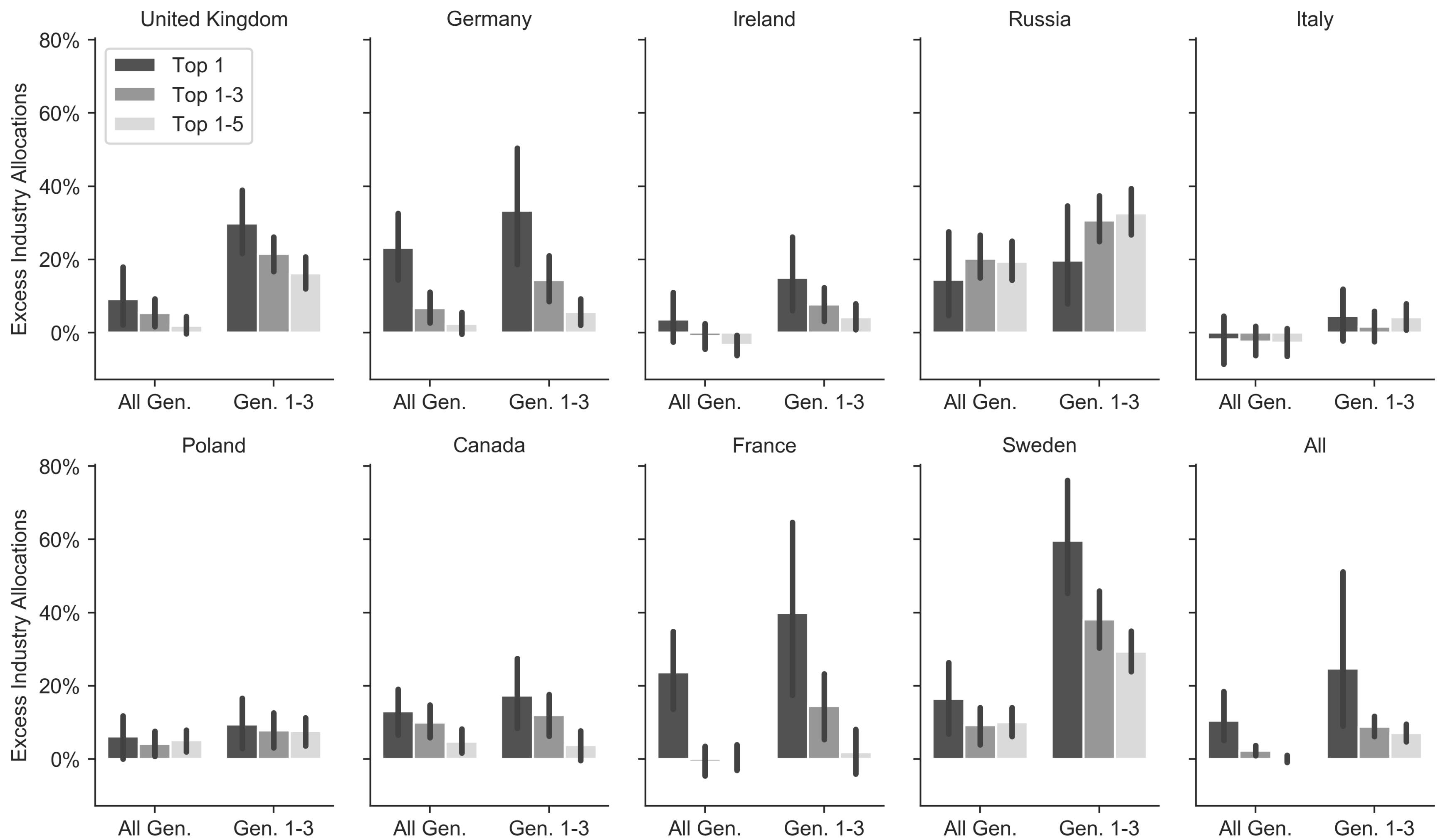

Figure 1. Excess allocations to U.S. industries that are among the top industries in the ancestral home country, across managers' ancestral origin and immigrant generation. This figure displays funds' average excess portfolio allocations to U.S. industries that are among the largest (Top 1), three largest (Top 1-3), or five largest industries (Top 1-5) in the ancestral home country stock markets, across fund manager' ancestral origin and immigrant generation. Ancestral home countries with at least ten associated fund managers of generations 1-3 and later generations are included. Countries are ordered from largest to smallest sample contribution. The final subfigure presents averages across all countries. The black lines indicate the 95% confidence interval around the estimate.

Figure 2. Excess portfolio weights by distance from managers' ancestral home country. This figure relates average excess weights in stocks to the geographical distance between stock issuer location and fund managers' ancestral home countries. Observations are at the fund-month-stock level. Stock issuer location is determined via exact corporate headquarter contact information from Thomson Datastream. For managers' ancestral home country location, we calculate population centroids per country based on data from Hall et al. (2019). Excess portfolio weights are calculated as stock weights minus the equally weighted average stock weight of all funds in the same nine-box Morningstar category and month. The shaded area marks the 95% confidence interval. The average stock weight is 59 bps.