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The President:

Prof. Dr. Bernhard Ehrenzeller

To Martel and Partel

Summary

When it comes to investing, humans not always behave as rational as one might think. My work tackles questions related to seemingly irrational investment behavior by using the active fund management industry as a quasi-laboratory. To answer these questions, I have collected an extensive fund and fund manager dataset. This dissertation contains three studies.

In the paper "In Military We Trust: The Effect of Managers' Military Background on Mutual Fund Flows", we take a mutual fund investor's point of view. We address the question why investors continue to pay such high fees to fund managers and advisers, although actively managed funds have long been shown to underperform passive investments. The paper reveals that trust-building characteristics of fund managers affect purchase decisions of mutual fund investors. We exploit variation in fund managers' prior affiliations with the U.S. military, a well-trusted institution, and relate it to fund flows. We find that funds with ex-military managers have significantly higher flows relative to other funds. Additionally, we show that investor inclination toward ex-military managers strengthens with managers' military involvement and its salience and with nationwide confidence in the military.

The second paper, "Back to the Roots: Ancestral Origin and Mutual Fund Manager Portfolio Choice", aims to understand how ancestry impacts investment decisions. The paper focuses on ancestry-induced biases that fund managers exhibit in their portfolios. We exploit variation in the ancestries of U.S. mutual fund managers and find that, compared with their peers, managers overweight stocks from their ancestral home countries. Similarly, they overweight industries that are comparatively large in their ancestral home countries. These effects are more pronounced for managers whose connection to the home country is more recent. Managers who overweight their ancestral home countries or industries do not exhibit superior performance for these holdings, which supports a familiarity bias, rather than informational advantage, based on ancestral ties.

Lastly, the third paper entitled "Jumping on the ESG Bandwagon: The Effect of ESG-Related Fund Name Changes on Fund Flows" examines whether fund firms take advantage of the environmental, social, and governance (ESG) topic to market their funds. I analyze the recent phenomenon that fund firms rebrand their conventional funds toward ESG or "sustainable investing". I find that funds earn abnormal flows after they rename to include ESG buzzwords in their name. ESG score improvements in their portfolios suggest that, on average, rebranded funds deliver on their new label's promise. However, I show that retail investors direct abnormal flows to rebranded funds irrespective of ESG score improvements. This indicates that retail investors rely on a fund's name when assessing its ESG-orientation and may thus be susceptible to greenwashing.

Zusammenfassung

Beim Tätigen von Investitionen handeln Menschen nicht immer rational. Vorliegendes Werk befasst sich mit Fragen im Zusammenhang dieser offenbaren Irrationalität und nutzt dafür die Fondsmanagementbranche gleichsam als "Labor". Ein umfangreicher Datensatz über Fonds und Fondsmanager bildet die Basis für diese Dissertation, welche drei Studien umfasst.

In der Studie "In Military We Trust: The Effect of Managers' Military Background on Mutual Fund Flows" nehmen wir die Sichtweise eines Fondsanlegers ein. Wir gehen der Frage nach, warum Anleger weiterhin hohe Gebühren an Fondsmanager und Berater zahlen, obwohl aktiv verwaltete Fonds seit langem nachweislich schlechter abschneiden als passive Anlagen. Die Studie zeigt, dass vertrauensbildende Eigenschaften von Fondsmanagern die Kaufentscheidungen der Fondsanleger beeinflussen. Wir setzen die frühere Zugehörigkeit mancher Fondsmanager zum US-Militär, einer der vertrauenswürdigsten Institutionen, mit Fondsströmen in Beziehung. Wir finden, dass Fonds mit Ex-Militärs als Manager im Vergleich zu anderen Fonds deutlich höhere Fondsströme aufweisen. Dieser Effekt ist umso stärker, je grösser das Engagement des Fondsmanagers im Militär war, je deutlicher das Engagement hervorgehoben wird und je besser es um das landesweite Vertrauen ins Militär steht.

Die zweite Studie, "Back to the Roots: Ancestral Origin and Mutual Fund Manager Portfolio Choice", untersucht, wie sich die Abstammung auf Investitionsentscheidungen auswirkt. Die Studie konzentriert sich dabei auf mögliche Verzerrungen in den Portfolios von Fondsmanagern, die durch deren Abstammung hervorgerufen werden. Wir nutzen Variation in der Abstammung von US-Fondsmanagern und stellen fest, dass die Manager Aktien aus ihren Ursprungsländern im Vergleich zu ihrer Referenzgruppe übergewichten. Ebenso übergewichten sie Branchen, die in ihren Ursprungsländern besonders stark vertreten sind. Beide Effekte sind umso ausgeprägter, je aktueller der Bezug des Managers zum Ursprungsland ist. Wenn Manager in ihre Ursprungsländer oder deren Branchen investieren, weisen sie dabei keine überdurchschnittliche Performance auf. Die Übergewichtungen lassen sich daher eher durch Vertrautheitsvorurteile aufgrund der Abstammung erklären als durch Informationsvorteile.

Die dritte Studie, "Jumping on the ESG Bandwagon: The Effect of ESG-Related Fund Name Changes on Fund Flows", analysiert, ob Fondsgesellschaften das Thema Umwelt, Soziales und Unternehmensführung (ESG) für die Vermarktung ihrer Fonds nutzen. Ich untersuche dazu die neuere Tendenz, dass Fondsgesellschaften ihre konventionellen Fonds in Richtung ESG umbenennen. Es zeigt sich, dass Fonds abnormale Fondsströme erhalten, sobald ihr Name mit ESG-Schlagwörtern versehen wird. Verbesserungen der ESG-Werte in den Portfolios deuten darauf hin, dass die umbenannten Fonds im Durchschnitt ihrem neuen Namen gerecht werden. Kleinanleger investieren in diese Fonds jedoch weitgehend unabhängig von Verbesserungen der ESG-Werte, was nahelegt, dass sie sich bei der Beurteilung der ESG-Orientierung eines Fonds auf dessen Namen verlassen und somit anfällig für "Greenwashing" sein können.

In Military We Trust: The Effect of Managers' Military Background on Mutual Fund Flows*

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ABSTRACT

This paper shows that trust-building characteristics of fund managers affect purchase decisions of mutual fund investors. We exploit variation in fund managers' prior affiliations with the U.S. military, a well-trusted institution, and relate it to fund flows. Funds with ex-military managers receive significantly higher flows and have a 6.5% faster annual growth rate relative to other funds. Investor inclination toward these managers strengthens with their military involvement and its salience and with nationwide confidence in the military. Military managers' superiority in competition for investor funds is not due to variation in fund or managerial attributes and is robust to alternative explanations.

JEL classification: G11, G23.

Keywords: Trust, Mutual Funds, Investment Decision, Fund Managers, Military

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What determines the decision to invest in one mutual fund over another? On average, mutual funds are known to persistently underperform passive investment strategies net of fees (Jensen (1968); Carhart (1997)). Nonetheless, investors continue to pay billions of dollars in fees to managers and advisers absent proof that they provide sufficient performance to compensate for their fees (Bergstresser, Chalmers, and Tufano (2009); Fama and French (2010); Hoechle, Ruenzi, Schaub, and Schmid (2018)). That is, either the market for asset management is inefficient (investors pay fees without being compensated) or fund and manager-specific factors beyond returns alone guide the decision to invest in a mutual fund (Hortaçsu and Syverson (2004)). In this paper, we provide support for the view that distinct trust-building attributes of fund managers affect the purchase decisions of mutual fund investors.

Trust plays a pivotal role in the various decisions we make, from facilitation of personal relationships to participation in economic activities (Knack and Keefer (1997)). Investment decisions are no exception. As suggested by Guiso, Sapienza, and Zingales (2004), trust reflects a general reliance on the integrity and fairness of the financial system and may serve as an explanation to the limited stock market participation puzzle. With regard to asset management, Mullainathan, Schwartzstein, and Shleifer (2008) indicate that the majority of advertisement campaigns by investment advisers and mutual funds draw on trust and less on past performance. Kostovetsky (2015) shows that investors attach value to their relationship with the asset management company, which affects their capital allocation decisions when ownership changes. In the model of Gennaioli, Shleifer, and Vishny (2015), managerial qualities, personal connections, familiarity and persuasive advertising underlie trust in a manager, which helps reduce the investor's perception of the riskiness of investments and correspondingly justifies manager fees and influences investment decisions. Following this line of reasoning, we investigate whether potentially trust-related biographical characteristics of mutual fund managers, specifically their prior engagement in the military, affect the investment choices of mutual fund investors.

A manager's prior military affiliation may promote investor trust for several reasons. We argue that such a background may serve as a signal that alleviates the investor's uncertainty regarding the manager's motives and prospective actions. First, military service demands a high degree of personal commitment and dedication that may translate to more compliant and ethical behavior in later civilian employment. Koch-Bayram and Wernicke (2018) find that ex-military CEOs are less inclined to engage in financial misconduct. In this regard, trust functions as an implicit contract, which serves as a substitute for costly monitoring, and investors likely prefer managers who require less monitoring. In addition, evidence from peer-to-peer lending suggests that lenders discriminate in favor of individuals that display signs of military involvement (Pope and Sydnor (2011)). Further, serving in the military may indicate a high level of patriotism, which has been found to provide important guidance for social behavior (Huddy and Khatib

(2007)). Military service may also signify social identity. In particular, individuals tend to follow the actions of others seen as members of their own social group (Cialdini and Goldstein (2004)) and likely increase cooperation with them (Blader and Tyler (2009)). Thus, a shared social identity between investor and manager may induce trust. Finally, ex-military personnel may be perceived as being better able to fulfill the investor's expectations. The possibility of such perceptions is supported by research showing that the perceived qualities of ex-military individuals cast candidates in a positive light during electoral campaigns (Teigen (2013)), serve as a productivity screening device in a civilian labor market (De Tray (1982)), and enhance success in corporate executive positions (Duffy (2006)).

In this paper, we posit that mutual fund managers with prior military background have an advantage when competing for investor funds because they are perceived as having certain military-associated characteristics that foster trust. Consequently, investors are more likely to allocate capital to funds managed by military-experienced individuals, even in the absence of evidence suggesting that they have superior investment skills relative to their nonmilitary peers. In addition, we posit that such trust-mediated allocation of assets is likely to be more pronounced during episodes of extreme performance realization and heightened confidence in the military and when background information is presented saliently.

To investigate our hypothesis, we use a novel data set of U.S. equity mutual funds that contains biographical information of fund managers. The U.S. mutual fund setting entails unique opportunities for studying the effects of fund manager's military background on investor capital allocation decisions for two reasons. First, it allows disentangling effects related to a military background from differences in other fund or managerial attributes, including performance. Second, the U.S. military is the most trusted of all institutions in American society and is historically perceived to be an effective and well-run establishment.[1] Likewise, U.S. military personnel are associated with the highest levels of honesty and ethical standards.

Our main empirical findings indicate that public information about a manager's prior military experience affects fund flows. Mutual funds managed by individuals with a military background have on average 10.6 percentage points higher annualized net flows relative to comparable funds with managers who have a nonmilitary background. Further, all else being equal, a mutual fund managed by an individual with a military background has an annualized growth rate that is up to 6.5% higher relative to other funds. The observed economically sizable effect of managers' military background on fund flows is not subsumed by variation in commonly used flow-related fund or manager-specific attributes. Further, it is robust to several alternative explanations and remains unchanged even when we restrict the analysis to funds

[1]Historical data from Gallup's Confidence in Institutions survey suggests that U.S. citizens — independent of their party affiliation — gave the highest confidence rating to the military, out of all institutions in society, including the church, academia, the congress, the presidency, newspapers (media), the police, the criminal justice and medical systems and so forth, in every year over the 1975–2017 period.

that are almost identical in terms of main observable characteristics.

The results from several additional tests indicate that the content and salience of information disclosures of a military background influence mutual fund investor decisions. We find that fund managers whose military service is disclosed as being prolonged and including heroic achievements and meritorious service in a combat zone attract additional annual flows of 6.5% compared with managers who only disclose that they served in the military. The fund flow effect is more pronounced when investors are exposed to salient, eye-catching information and when they obtain this information with little effort on their part. Moreover, the effect of managers' military background only occurs in the sample of single-managed funds; it is suppressed in team-managed funds. In addition, confirming the presumption that military background may serve as a substitute for costly monitoring and reduce investors' perception of investment riskiness, we find that ex-military managers are less likely to engage in window dressing activities and overall exhibit more ethical behavior relative to their nonmilitary peers.

We perform several tests to investigate the relation between the managers' military experience and fund flows more closely. Our findings shed light on the role that trust may play in investor decisions. An association exists between investors' buying and selling behavior toward military-managed mutual funds and the nationwide confidence in the U.S. military and perception of security. We find that periods with a high level of trust in public institutions, and the military in particular, are associated with distinct partisan attitudes of investors toward military-managed funds. In contrast, during periods of relatively low confidence in the military and low perceived security, investors tend to allocate less capital to funds managed by ex-military individuals. Moreover, we observe that ex-military managers' fund flows plunge following the exogenous events of military-related scandals that may have adversely affected trust in the military.

To further support the trust-related asset allocation conjecture, we conduct a difference-in-differences analysis around the dates of managerial turnover. In the absence of any other fundamental events and all else being equal, managers with a military background receive net fund inflows that are 5.7 percentage points higher during the first month of active management relative to other managers. The difference in fund flows following the induction of military-experienced managers is persistent, while the two groups exhibit parallel movements in fund flow outcomes in the absence of a manager change. We also show that flow differences between military- and nonmilitary-managed funds are particularly large for extreme performance realizations. Military managers have higher fund flows relative to their nonmilitary counterparts following both extremely good and extremely poor fund performance. Collectively, the results of these tests support the conjecture that trust induced by a manager's military background influences mutual fund investors' decisions.

In addition, we determine that a substantial fraction of investors are likely to consider fund manager background information when making their investment decisions. First, we perform an online survey of mutual fund investors. The survey results indicate that the majority of mutual fund investors know their fund managers and are aware of the manager's profile when they are investing. Second, we conduct an online fund investment experiment to gather additional evidence on the relation between a manager's military background and fund flows. In the experiment, we ask participants (U.S. mutual fund investors) to allocate money between two funds. We keep the fund and basic manager information constant, but we randomly assign a military background to managers. Results indicate that participants invest significantly more money into a fund when it has an ex-military manager. In contrast, when we specify no prior military affiliation for managers of both funds, we find no significant difference in asset allocation.

Our finding of ex-military managers' relative superiority in attracting fund flows raises an intriguing equilibrium question: Why would not all mutual funds employ military-experienced individuals? A potential answer is that the supply of qualified individuals with military experience may be too limited to meet the increasing demand for mutual fund managers over the sample period of our study. This limitation may consequently prevent fund management companies from appointing more ex-military individuals to their funds, even though such appointments would be advantageous. In the same vein, Benmelech and Frydman (2015) suggest that firms are constrained in hiring corporate executives with a military background because the supply of such individuals is insufficient. In addition, we consider several alternative answers to our question; for example, fund management companies may simply be unaware of the flow effect we uncover, or ex-military managers may perform worse. However, we do not find these explanations to be consistent with our data. Finally, we acknowledge other potential costs of hiring ex-military managers (e.g., the possibility of higher compensation), which we are not able to address within our setting and leave for future research.

Our empirical findings are consistent with the broad implications of portfolio management delegation models, which emphasize the role of trust (Gennaioli et al. (2015)). In particular, our findings support the view that trust in the manager that is induced by salient background information may reduce investors' perception of investment riskiness. Investors who seek to reduce anxiety around risky investment choices hire a money manager and base the hiring on manager characteristics. Thus, military-experienced managers are likely to be perceived as money guardians having military-associated qualities. While our study does not directly test the Gennaioli et al. (2015) theory, our key results can be interpreted naturally under the description of trust-mediated fund allocation that this theory offers. Our findings that trust induces fund flows also support the key premises of theoretical models of coarse thinking (Mullainathan et al. (2008)) and strategic persuasion (Glazer and Rubinstein (2004)).

The empirical findings in our study further contribute to the vast literature on the determinants of mutual fund flows. Previous studies relate fund flows to various fund and managerial characteristics, including past fund performance (Berk and Green (2004), among others), advertisement (Jain and Wu (2000)), fund name changes (Cooper, Gulen, and Rau (2005)), fund ratings (Del Guercio and Tkac (2008)), manager gender (Niessen-Ruenzi and Ruenzi (2019)), and manager name (Kumar, Niessen-Ruenzi, and Spalt (2015)), among others. On a general level, our study relates to that of Cici, Gehde-Trapp, Göricke, and Kempf (2018), who show that both fund managers and fund families can benefit from a manager's experience outside the fund management industry.

More broadly, our study adds to the literature that emphasizes how the unique attributes of military-experienced managers affect economic outcomes (Malmendier, Tate, and Yan (2011); Benmelech and Frydman (2015)). Evidence from our study also complements earlier literature on how an individual's military experience influences later life socioeconomic achievements (Sampson and Laub (1996); MacLean and Elder Jr (2007)) and aids the development of qualities that can be beneficial in the labor market (Jackson, Thoemmes, Jonkmann, Lüdtke, and Trautwein (2012)). To the best of our knowledge, our study is the first to relate prior military experience to asset management and to analyze customer-based perception of ex-military individuals.

The remainder of the paper proceeds as follows. Section I describes the data set and the data collection process and provides basic statistics. Section II focuses on the relationship at the center of the study and examines the effect of a manager's military background on fund flows. Section III presents evidence that the observed relationship can be attributed to military-associated partisanship. Section IV presents the supplementary analysis, followed by Section V, which concludes the paper.

I. Data and Sample Design

We rely on multiple data sources to identify our sample and obtain information for the empirical analysis. In this section, we describe these data sources, outline the process of identifying managers with a military background, and provide the sample descriptive statistics. Appendix A provides supplementary details on the construction of all main variables used in the empirical part of the study.

A. Data on Mutual Funds

Data on mutual funds come from CRSP Survivor-Bias-Free U.S. Mutual Fund Database (CRSP MF) and Morningstar Direct Mutual Fund Database (MS Direct). First, we obtain data on fund share class characteristics for the set of actively managed domestic equity-only U.S. mutual funds from the CRSP MF. The data are then aggregated at the fund level by weighting the respective fund share classes with the corresponding total net assets. The main variable of interest in the empirical analysis is net fund flows. We do not observe flows directly, so we infer flows from fund returns and total net assets. Following standard practice in the literature (e.g., Sapp and Tiwari (2004); Frazzini and Lamont (2008)), we compute flows F_t^i for fund i in month t as

$$F_t^i = \frac{TNA_t^i - TNA_{t-1}^i}{TNA_{t-1}^i} - r_t^i \tag{1}$$

where TNA_t^i is fund i's total net assets in month t and r_t^i stands for fund i's net return in month t. To ensure that the results are not unduly influenced by outliers, we follow Kumar et al. (2015) and drop fund flow observations below the 1st percentile and those above the 99th percentile.[2]

Second, we establish a match between MS Direct and CRSP MF fund classes by carefully following the data appendix provided by Pástor, Stambaugh, and Taylor (2015), who identify matches relying on CUSIPs as well as the funds' tickers. Further, we restrict the sample to include only the funds that were managed by a single manager for at least one month over their entire lifespan.[3] Following the rationale of Agarwal, Ma, and Mullally (2015), we exclude cases in which single managers run more than four funds at the same time because these managers are likely to be team managers. We also remove funds reportedly managed by anonymous managers.

To obtain the data on fund holdings, we match CRSP MF with Thomson Reuters Mutual Fund Holdings Database (MF Holdings) using the MFLINKS tables. Only holdings of common stocks (share codes 10 and 11) are considered, and information on stocks is obtained from CRSP and Compustat databases.

B. *Identifying Managers with a Military Background*

We obtain the fund manager names as well as the start and end dates of their management period at the respective fund via MS Direct. The choice of this database 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 CRSP MF. We extract the fund managers' short profiles and, if available, information on academic degrees, certifications, and affiliations from MS Direct. We restrict the sample to all fund-month observations for which a single manager was managing the fund for at least one month. In total, after the Morningstar-CRSP match,

[2]Additionally, we check that the main results persist when we use raw fund flows, winsorize the observations, drop observations below the 5th percentile and above the 95th percentile, or exclude funds with total net assets lower than $1 million.

[3]Although we also consider a sample of team-managed funds in Table VI, our focus in this study is on single-managed mutual funds.

we identify 2,903 funds over the sample years from 1991 to 2017.

To establish a complete profile for each manager, we perform a comprehensive cross-database search and obtain additional information from Morningstar, Bloomberg, Marquis Who's Who, Financial Industry Regulatory Authority (FINRA), LinkedIn, SEC filings, Intelius database, GI Search engine, Ancestry.com, Legacy.com, fund company websites, and articles in U.S. newspapers from LexisNexis and Newspapers.com. To guard against the possibility of wrong matches, we drop observations from the sample whenever we get multiple matching profiles or conflicting information from various sources. We restrict our sample to fund managers for whom we observe Morningstar and/or Bloomberg profiles and identify the date of birth. As a result, we are able to collect information on the personal characteristics and complete biographical information, including the prior military background of the fund managers. If a military affiliation exists for a manager, we can usually extract an extensive military profile, including information about training, dates of service, involvement in military conflicts, military rank, and military awards.[4] Figure B1, Figure B2, and Figure B3 in Appendix B provide military profile examples from Morningstar, Bloomberg, and fund firm advertising materials.

Importantly, we define a fund manager as having military experience prior to joining the fund management industry only if this information was available to investors during the manager's corresponding active management period. For example, the manager's Morningstar, Bloomberg, LinkedIn or fund company website profile at the time of active management may clearly state the prior military experience. If the manager was active in the past, we make sure that such information was freely circulating and available to investors at some point during the manager's active period. Specifically, for each fund manager in our sample we review whether information on military affiliation was disclosed in SEC filings, prospectuses, U.S. newspapers, or any of the manager and fund family-related internet resources during the manager's active period. We further enrich this data by combining it with legacy web content from fund firms' historical websites that we access through the Internet Archive's Wayback Machine available at archive.org.[5]

In total, our final sample consists of 1,858 (73.92% of total) individuals single-managing 2,448 funds (84.33% of funds that were single-managed for at least one month). Within this set, 229 of the funds (9.35% of the sample) are single-managed by 123 (6.62% of the sample)

[4]However, in some cases we have to rely only on vague background description, e.g., "…was a decorated officer in the U.S. Marine Corps…"

[5]For every domain of a fund firm's website, we request the full history of all snapshots recorded by the Internet Archive. We download the entire content linked to the last available snapshot of a given month by querying the Wayback Machine's API. Fund firms from our sample start registering domains in 1993. First websites are launched in 1995 and often commented or advertised in newspapers. The earliest snapshots of our fund firms' websites stored in the archive date back to 1996, the same year the Internet Archive started to crawl the web. We retrieve domains of fund firms that have closed down or changed their domain name through advertisements and articles in historical newspapers via newspapers.com. In addition, we are able to retrieve historical domain names through Usenet newsgroups and finance-related magazines (e.g., Money or Kiplinger's Personal Finance).

managers with a military background (served in the military).[6] Additionally, we identify 159 funds that were managed by teams that included at least one manager with military experience.

C. Sample Characteristics

Table I separately reports statistics for funds managed by individuals with and without prior military experience. Comparing the sample means for the two groups of funds, we find a significant difference in the net fund flow measure but not in other characteristics. Mutual funds run by managers with a military background have annualized fund flows that are 10.6 percentage points higher relative to funds managed by nonmilitary individuals (t-statistic of 5.06). In contrast, we observe no economically or statistically significant variation across the groups in any other fund characteristic, including return, risk, size, age, expenses, and turnover. There are no differences in the distribution channels, the Morningstar ratings, or the share of expenses set aside for marketing purposes. Importantly, we observe virtually no heterogeneity in portfolio holdings between military and nonmilitary managers. For example, managers with military experience do not invest more in defense stocks relative to other managers.

Manager characteristics show no statistically significant variation across the two groups in most cases. In particular, we find no difference between military and nonmilitary managers' marital status, educational background, mutual fund industry experience, fund tenure, name-specific attributes, or media coverage. The only exception is that managers with prior military experience tend to be older. Later in this paper, we show that the main result on the relation between military background and fund flows remains unaltered after controlling for the managers' biological age.

D. A First Look at the Military Trust – Fund Flow Relationship

To preliminarily explore whether military-related attitudes affect the decisions of U.S. mutual fund investors, we plot the average annual fund flow difference between managers with and without military background against Gallup's survey-based military confidence index.

As an illustrative example for this link, Figure 1 depicts the evolution of the two indicators over time. The dynamics of the fund flow difference coincide reasonably well with the evolution of the military confidence index. Managers with military experience enjoy higher relative fund inflows during periods of high confidence in the U.S. military institution, while episodes of relative fund outflows occur around periods of low confidence in the military. The correlation

[6] This number compares favorably to the share of military-experienced managers documented in the corporate finance literature. Benmelech and Frydman (2015) show that the share of ex-military corporate executives is approximately 6% in recent years. Moreover, the overall share of individuals who served in the military is 6.3% of the total U.S. population according to the Department of Veterans Affairs Veteran Population Projection Model 2016.

coefficient is 0.41. Further, the extreme values of Gallup's measure of satisfaction with the nation's military strength and preparedness (for the periods when available) also correspond to the episodes of relatively large inflows (outflows) into (from) the funds managed by military-experienced individuals. This simple relationship suggests a potential role of military-related partisanship in the asset allocation process of mutual fund investors.

II. Military Background of Mutual Fund Managers and Fund Flows

This section presents empirical results on the relation between military experience of mutual fund managers and fund flows.

A. Baseline results

Given that the U.S. military has the highest confidence (trust) rating among all institutions in American society throughout the sample years, we conjecture that social affection and military-associated partisanship may affect asset allocation decisions of mutual fund investors. Therefore, prior military experience of mutual fund managers, other traits being equal, could draw capital flows into funds managed by such individuals. To test this conjecture, we examine aggregate investor behavior at the fund level and investigate whether military-managed funds attract higher inflows than nonmilitary-managed funds. In particular, we estimate regressions with monthly net fund flows as the dependent variable.

In the regression analysis, we relate net fund flows to a *Military* dummy variable that equals one if the fund is single-managed in a given month by an individual with prior military experience, and zero if a manager does not have a military background. Importantly, the *Military* indicator variable covers only fund managers whose background information is publicly available to the investors during the managers' active management period. The set of controls is composed of fund characteristics, including *Fund return*, *Fund performance rank*, *Fund size*, *Fund age*, *Fund risk*, *Expense ratio*, *Turnover ratio*, *Family flows* and *Lagged fund flows*, and manager-specific attributes, such as *Fund tenure* and mutual fund *Industry tenure. Fund performance rank* is computed as the performance relative to all other funds in the same market segment in a given month. *Fund risk* is the time series standard deviation of the fund return using the rolling past 12-month return observations. Segment is based on the Morningstar fund style indicator, and controls are lagged by one month. We double-cluster standard errors by year and fund to allow for correlation between repeated observations from the same fund, and we show that our results are unlikely to be induced by some unobservable factors or any heterogeneous trends by including period, segment, family, fund, and interaction fixed effects.

Estimation results are presented in Table II.

Results of the flow regressions are consistent with the conjecture that military-experienced mutual fund managers, all else being equal, attract higher fund flows. Flows into military-managed funds are significantly higher than those into nonmilitary-managed funds. The coefficients on the main variable of interest, the *Military* dummy, are positive and statistically significant in all specifications of the model. In column (1), we present the estimates after including time-varying control variables but no fixed effects. The impact of the *Military* dummy is positive and significant at the 1% level (coefficient = 0.005, t-stat. = 3.80). In columns (2) through (6), we add various fixed effects as well as alternative controls for fund performance and lagged fund flows.

Specifically, in columns (2) through (4), we present estimates of the specifications with segment, year, and segment-by-month-year fixed effects. The coefficient estimates on the *Military* dummy are positive and significant at the 1% level, ranging from 0.003 to 0.005. Further, a possibility exists that fund families that are better at attracting client flows are also better at attracting managers with potentially beneficial characteristics such as military experience. In addition, families that are better at marketing may also provide more information about their managers. Thus, in column (5) we include family-by-month-year fixed effects. In this setting we are able to compare flows to funds with and without an ex-military manager in the same family at the same time. Comparing within family-month-year, we observe a similar magnitude of the military effect with the point estimate on the *Military* dummy being once again positive and statistically significant (coefficient = 0.003, t-stat. = 2.16). In column (6), we include fund fixed effects, which allows us to identify the military manager effect from managerial turnover within funds and to control for unobservable factors at the fund level that can potentially influence fund flows. The estimate on the *Military* indicator is positive (coefficient = 0.003) and statistically significant (t-stat. = 1.93). This outcome suggests that neither time-invariant unobserved heterogeneity at the segment, family, or fund level, nor time-varying heterogeneous trends drive our results.[7] Overall, this section indicates that fund managers' military experience is positively related to fund flows.

The effect is also economically significant: the coefficient estimates imply that a fund managed by an individual with a military background, depending on the model specification, grows by about 3.2 to 6.5 annualized percentage points more than a comparable fund run by a manager with no military experience. The magnitude compares favorably to the mean annual net fund flows of 22.4% in Table I.

[7] In addition, we check that the observed military effect remains unchanged when we double-cluster standard errors on fund family and month-year (coefficient = 0.003, t-stat. = 2.79) instead of fund level and month-year as in the baseline specification (3) of Table II.

B. Robustness of the Results

In this section, we closely consider several alternative explanations for our baseline findings. Results are presented in Table III.

First, we ensure that our results are robust to several conventional alterations of our main setup. Kronlund, Pool, Sialm, and Stefanescu (2020) show that saliently presented information about long-term mutual fund performance, particularly one-year returns, affects investor capital allocation decisions. Therefore, in tests (1) through (3) we augment the baseline flow regression (column 3 of Table II) with controls for past performance, namely three-month, one-year, and five-year returns. Although past performance appears to be an important determinant of flows, results of these tests indicate that the observed military effect is not attenuated. We find that the estimates are significant and remarkably similar in economic magnitude to the baseline results, even in a more limited sample of test (3).

Demographic attributes of mutual fund managers may influence fund flows. Niessen-Ruenzi and Ruenzi (2019) show that gender-related discrimination affects fund flows, such that female-managed funds receive significantly lower inflows than similar male-managed funds. Roussanov and Savor (2014) show that single men, including mutual fund managers, are substantially different in managerial behavior relative to married men, while research in psychology suggests that people tend to trust married individuals more than single individuals (Rahn and Transue (1998)). Inclusion of demographic controls in test (5) shows that inferences remain unchanged, suggesting that our results are not simply a by-product of demographic attributes.[8]

Alternatively, our main variable of interest may indirectly proxy for manager's educational background because military service can pave the way to a better and less expensive education through various military tuition assistance programs. Indeed, in Table I, we show that military managers on average are slightly better educated, being more likely to have a graduate degree. However, the results reported in test (6) indicate that our inferences do not change when we account for the educational effects on fund flows.

Network may be another factor that affects fund flows. Agarwal, Lu, and Ray (2021) show that money managers use opportunities to network and attract fund flows even when attending charitable events. Cohen, Frazzini, and Malloy (2008) report that mutual fund managers benefit from shared educational networks with corporate board members, and the benefit is particularly pronounced for graduates of highly recognized institutions. In test (7), we check whether the higher networking potential of Ivy League graduates affects our results. We also recognize that the wealth and income of mutual fund managers' parents affect future fund performance (Chuprinin and Sosyura (2018)). Correspondingly, we propose that the parental professional

[8]Even though previous research consistently finds no significant impact of manager's biological age on fund flows, we also control for age because it is the only managerial attribute that shows statistically significant variation across the two groups in Table I, Panel B.

network may help managers to build connections and facilitate fund inflows. With this in mind, we use specification (10) to check if the parental involvement in fund management can explain our results. Results of both tests indicate that our findings are robust to alternative explanations related to educational and parental networks.

Another explanation for our baseline results is that investors pay more attention to salient managerial characteristics such as names, and military managers may simply have names that sound familiar to U.S. investors. Such familiarity can in turn explain the observed heterogeneity in fund flows. Kumar et al. (2015) document significantly lower inflows into funds managed by individuals with foreign-sounding names than into other funds. We implement a machine-learning algorithm from Ye, Han, Hu, Coskun, Liu, Qin, and Skiena (2017) to define foreignness of a manager's name. The results reported in test (9) indicate that both magnitude and significance of the main coefficient estimate remain when we control for foreignness of managers' names.

Recent evidence shows that experience outside the fund management industry gives managers an information advantage, which results in a higher propensity to hold more and to pick better stocks from the area of their expertise (Cici et al. (2018)). Therefore, we check that investors' preference for military-managed funds is neither due to a potentially higher share of defense stocks in total holdings (test (4)) nor affected by the manager's expertise in other industries (test (8)).

Mutual fund investors may be attracted to funds that reinforce their market position and acquire customers by conducting a marketing campaign. Barber, Odean, and Zheng (2005) show that investors tend to purchase funds that draw their attention through marketing or advertising. We therefore control for marketing expenses, which we define as the share of a fund's expenses for marketing (from NSAR-B filings) in total expenses. Indeed, funds with a higher share of marketing expenses seem to attract higher fund flows, but importantly the effect of military experience of mutual fund managers on fund flows remains unchanged in the joint regression specification (11). Additionally, we control for media coverage of fund managers (test (13)), which is important for two reasons: (i) media coverage has been shown to affect net investor flows (Kaniel, Starks, and Vasudevan (2007)), and (ii) military managers may generally have a higher profile in U.S. society. We find that the effect of military background is not attenuated by including the managers' media coverage control.

Next, we exclude index funds from the sample test (14) and control for distribution channels (12). Results for each of these alterations indicate that the coefficient estimate on the *Military* indicator variable is still statistically significant and economically meaningful. Finally, another concern is that the fund flow effect we uncover in Table II may simply be driven by investor preference for military individuals that is unrelated to presumed managerial qualities. If that is the case, we should observe similar military-related flow patterns for index funds. However, results reported in test (15) indicate that the military background effect is not present in the sample of index funds, which renders a simple preference explanation unlikely.

C. Degree of Involvement in the Military and Fund Flows

Previous sections suggest a robust link between the military experience of mutual fund managers and fund flows. This suggestion implies that information disclosures about the military background of an active manager influence mutual fund investor decisions. However, both the amount of information revealed and the details about the military experience vary considerably across managers. Some managers in the sample are medal-decorated war veterans, while others only communicate that they served in the military. In this regard, if there is information that draws attention to prolonged military service, heroic achievements, and meritorious service in a combat zone, it may amplify the effect on flows into funds managed by an individual with a military background. To investigate this possibility, we differentiate managers by their degree of involvement in the military and estimate flow regressions.

Table IV provides evidence of heterogeneity in fund flow effects across managers with various degrees of military involvement and recognition. The *Conflict/Medal* indicator variable is coded as one for funds managed by an individual who served a tour of duty in a conflict zone. In total, we identified 66 such funds, with 20% having managers who received United States Armed Forces awards and decorations, including the Bronze Star Medal, Purple Heart, Combat Action Ribbon, service stars, and so forth. Further, to cover the other extreme of military involvement, we additionally identified 43 funds that are managed by managers who have undergone military training but have never served in the military. In particular, the *Military training* dummy takes the value of one if a manager graduated from any of the U.S. military schools and academies or voluntarily participated in any type of military training, but never served a period of active duty. The regression setup is similar to that applied in the previous section.

Consistent with the view that partisan investors allocate funds, among other things, based on a fund manager's military background, we find that in both univariate sorting (Panel A) and regression analysis (Panel B) the *Conflict/Medal* variable is significantly and positively related to fund flows. Comparing the sample means for funds managed by individuals who served a tour of duty and for peer funds with managers who do not have such background, we find a remarkable difference of 21.9 annualized percentage points (t-statistic of 3.39) in net fund flow between the two groups. The coefficient on the interaction term *Military*$\times$*Conflict/Medal* is positive and significant (coefficient = 0.005, t-stat. = 2.06). The magnitude compares favorably to the estimates of the *Military* dummy, indicating that managers who present themselves as war veterans attract more flows in comparison to those who just disclose that they served in the military. In contrast, *Military training* produces negative and not statistically significant estimates across all specifications. By construction, this variable largely captures military-related education of fund managers. In this, our results are consistent with prior research that documents no fund flow effects of managers' education (Niessen-Ruenzi and Ruenzi (2019)).

D. Salience of Information and Fund Flows

Previous research suggests that cosmetic effects irrationally influence investor decisions. Hirshleifer (2001) suggests that even irrelevant, redundant, or outdated news affects security prices if presented saliently. Cooper, Dimitrov, and Rau (2001) document stock price reactions to timely firm name changes. Similarly, asset allocation decisions of mutual fund investors are influenced by cosmetic features of funds and fund managers, for instance, by style-related fund name changes (Cooper et al. (2005)), fund manager name disclosures (Kumar et al. (2015)), or other salient attention-grabbing information (Barber et al. (2005)). In this section, we explore if the observed relation between military experience and fund flows differs with respect to the salience of information investors are exposed to.

The investor's level of effort to obtain information on the managers' military background varies by manager. Therefore, we differentiate managers by the source that discloses the relevant information. Table V provides evidence on the fund flow effect for different means of information disclosure. The first group, *Investment media*, includes cases in which information on prior military experience is disclosed through investment media sources, namely, Morningstar and Bloomberg. The second group, *Personal disclosures*, covers cases in which this information is not available in investment outlets but can be found on fund company websites or professional networks, such as LinkedIn. The third group, *Other sources*, includes cases in which military background information is only disclosed via major or regional newspapers and other alternative media outlets. This categorization differentiates the investor's effort to obtain information. Correspondingly, we suggest that the probability of the investor becoming aware of the manager's biographical facts is higher for the first two groups relative to the third group.

Additionally, we identify 37 funds with ex-military managers that are not included in our main sample since information on their military service was not publicly available during the period of active fund management. In these cases, the information only becomes available in managers' obituaries. The *Post-mortem placebo* group in Table V covers managers for whom military affiliation is disclosed only in obituary notices after their death and not prior to it. As such, this last group serves as a placebo test.

The average flow differences between military and nonmilitary managers indicate a sharp distinction between the groups. Mutual funds with a manager whose prior involvement in the military is disclosed via investment media have 17.2% higher annualized fund flows (t-statistic of 3.52). Managers with slightly more salient disclosures attract 22.1% p.a. higher fund flows per annum (t-statistic of 6.27). In contrast, revealing this information through other sources that are less prominent has no effect on fund flows. The magnitudes of the monthly flow regression coefficient estimates favorably support the notion that the fund flow effect is more pronounced when investors are exposed to salient, attention-grabbing information. As expected, results from the placebo group of funds reveal no fund flow effect, which further supports this notion.

Thus far, the analysis has focused only on single-managed funds and excluded all team-managed funds. Next, we examine whether funds managed by teams that include individuals with prior military experience are able to attract more fund flows relative to funds that do not have such managers in their teams. For this purpose, we additionally identify 159 funds with at least one military manager who is part of the team and re-estimate the baseline regressions using the sample of team-managed funds. The regression setup is otherwise similar.

The fund flow effect of a manager's military background is suppressed in team-managed funds. Table VI relates monthly net fund flows to a *Military team* dummy variable that equals one if the fund is managed in a given month by a team that includes a manager with a military background and zero otherwise. In columns (1) and (2), we present the estimates of regressions after including various controls along with segment and time fixed effects. The coefficient on the main variable of interest is positive but not statistically or economically significant (in the specification with lagged fund flows). Adding the share of military managers in a management team and several interaction terms with sources of information disclosure neither changes the baseline evidence nor reveals new results. The table's main message is that no significant flow effect is present between funds with military managers in teams and funds managed by nonmilitary teams. This finding is consistent with the supposition that a manager's personal background information is much less salient and eye-catching in team-managed funds relative to single-managed funds.

III. Evidence of Military-Based Partisanship

This section presents evidence that the observed relationship between a manager's military background and fund flows can be attributed to the military-associated partisanship that affects asset allocation decisions of mutual fund investors.

A. Fund Flows and Social Attitudes toward the Military

Figure 1 provides illustrative evidence on how social attitudes toward the military institution and military-related partisanship affect the decisions of U.S. mutual fund investors. This example suggests that investors' buying and selling behavior toward mutual funds managed by individuals with a military background positively correlates with the level of confidence and satisfaction with the U.S. military. In other words, investors tend to allocate more capital to military-managed funds when confidence in the military is high, while the difference in fund flows between military- and nonmilitary-managed funds is less pronounced in times of low confidence.

To provide formal statistical evidence on the link between partisan mutual fund investor decisions and a manager's military experience, we conduct three additional tests. First, we repeat regressions of monthly net fund flows on the military indicator for periods of high and low levels of confidence in the military, classified based on the median level of the Gallup's confidence in the military index from Figure 1. Second, we collect National Instant Criminal Background Check System (NICS) data on purchases of firearms, provided by the Federal Bureau of Investigation, and consider the information as an alternative proxy for nationwide confidence in the military institution.

Table VII first reports evidence on the fund flow effect for periods of low and high confidence in the military. The results reported in columns (1) and (2) show that in both cases the *Military* dummy is significantly positively related to fund flows, with estimates of 0.002 (t-statistic of 1.83) and 0.003 (t-statistic of 3.07) for low and high confidence periods, respectively. The magnitudes of the coefficients favorably support the notion that the fund flow effect is more pronounced when confidence in the military is relatively high.

Next, Table VII relates an alternative measure of confidence in the military (i.e., the change in purchases of firearms) to monthly net fund flows. Studies in psychology and political science document a strong link between the perception of insecurity and associated trust in public institutions. Blanco and Ruiz (2013) show that an individual's perception of insecurity is negatively related to satisfaction with the political regime and confidence (trust) in public institutions, including the military.[9] In the context of Figure 1, when the confidence in the military institution is low, the aggregate level of perceived insecurity is likely to be high and vice versa. Alongside, Diener and Kerber (1979), Cao, Cullen, and Link (1997), and Carlson (2012), among others, show that U.S. citizens perceive firearm purchases as a potential complex response to distrust in public institutions and anxieties regarding insecurity.[10] Therefore, we consider purchases of firearms as an alternative measure of the confidence in the military.[11] The results reported in column (3) show that the coefficient on the interaction term between *Firearm checks (NICS)* and the *Military* dummy is negative and significant (coefficient = -0.003, t-stat. = -2.70). This outcome indicates that fund flows are lower for military-managed funds when the nationwide perceived insecurity is high and, correspondingly, the confidence in the military institution is low.

[9] Other studies in political science suggest that trust in public (political) institutions is positively related to partisan strength (Hooghe and Oser (2017)), while an apparent distrust in politics can result in unwillingness to publicly declare a partisan identity despite attitudes to the contrary (Petrocik (2009)).

[10] Notably, the aforementioned papers do not explicitly state which public institution failures (the police or the military) trigger gun purchases the most; however, in all these papers, the need for protection and the perception of insecurity are found to be the main psychological reasons for firearm purchases.

[11] Importantly, according to Gallup's Confidence in Institutions survey data, 34% to 51% of U.S. households had a gun in possession over the sample period of our study.

In specifications (4) and (5), we split the sample into periods of relatively high and low levels of insecurity, respectively. Results in column (4) suggest that during periods of positive change in firearm purchases, when the aggregate level of perceived insecurity is likely to be high, funds managed by military-experienced individuals tend to draw less pronounced investor interest and have difficulties in attracting fund flows. In contrast, results for the periods of negative changes in firearm purchases, in column (5), show that the estimate on the *Military* dummy is positive (coefficient = 0.004), statistically significant at the 1% level, and much higher in magnitude relative to its counterpart in column (4). This outcome suggests that periods of relatively low perceived insecurity and high level of trust in public institutions are associated with distinct investors' partisan attitudes toward military-managed mutual funds.

Overall, this evidence is consistent with the view that military-associated partisanship exists among mutual fund investors, and it provides additional support for the conjecture of trust-based investor asset allocation behavior toward military-managed mutual funds.

B. Fund Flows and Managerial Turnover

Mutual fund managers come and go. It has long been recognized that a fund manager change is one of the most informative occurrences in a mutual fund's lifetime. Khorana (1996) shows that on average the replacement of a mutual fund manager leads to subsequent underperformance. Chevalier and Ellison (1999) build on this evidence and, among other findings, indicate the potential inflow-related benefits of replacing a poor-performing manager. In a theoretical model, Dangl, Wu, and Zechner (2006) suggest that management replacements may be accompanied by capital inflows, depending on the tenure of the manager that is being replaced. Importantly, regardless of the reason why the change occurred, such an event draws the investors' attention and puts an incoming manager in the spotlight, providing a perfect setting for exploring the existence of military-based partisanship among mutual fund investors.

Therefore, we investigate the fund flow dynamics around the dates of managerial turnover. In particular, we examine whether funds that shift to managers with a military background subsequently exhibit different fund flows relative to funds that employ nonmilitary fund managers. We only consider instances when the incoming manager single-handedly manages the fund, and overlapping periods of management are excluded.

Figure 2 illustrates an increase in average monthly net inflows into both types of funds after the management change. Noteworthy, flows into funds managed by individuals with a military background are substantially higher than the ones into funds with nonmilitary managers. For both groups, fund inflows reach their maximum in the month of the manager change. In the subset of military-managed funds, inflows remain high for all the subsequent months, while funds managed by nonmilitary individuals experience an inflow decline to around the pre-turnover level. The differences in net inflows between the two groups over the 10 months following the managerial turnover are economically significant. Funds managed by individuals with military experience receive between 6.6% and 38.4% higher annualized fund flows.

Figure 3 provides additional evidence by presenting average flows for the two groups around the dates when a single manager leaves the fund. By contrast, we observe an outflow from funds previously managed by individuals with a military background during the month of managerial turnover, while flows into nonmilitary funds are essentially unaffected. The month in which the manager change occurs is the only period in the 20 months surrounding it that has an actual outflow. The difference amounts to a sizable -12.0 annualized percentage points.

While the above descriptive tests present some evidence of heterogeneity in fund flows between the two groups around the dates of managerial turnover, one can argue that the observed inflows are induced by the change in management itself rather than investor military-related partisanship affecting the asset allocation decision. That is, a fund company can choose to heavily advertise that it has replaced a manager, drawing attention to the superiority of an incoming manager relative to the manager that is being replaced. Jain and Wu (2000) show that advertised funds are indeed able to attract significantly higher inflows.

To alleviate this concern and address possible endogeneity between the two groups, we implement a difference-in-differences approach by comparing changes in fund flows around the dates of managerial turnover of funds with military management (treatment funds) to changes in fund flows of funds with nonmilitary managers (control funds). In this test, we restrict the sample to funds that only had one change from team to solo management over the sample period of our study, and we use the following specification:

$$F_t^i = \alpha_0 + \beta_1 Treat_i + \beta_2 (Treat_i \times Post_t) + \gamma X + \eta_j + \tau_t + \epsilon_{i,t} \tag{2}$$

where F_t^i is the net fund inflow of fund i, as specified in equation (1); $Treat_i$ is an indicator for funds that were ever managed by individuals with a military background and affected by the managerial turnover; $Post_t$ is an indicator variable that equals one for months of solo management period and zero otherwise; X is a vector of control variables; and, η_j and τ_t are segment and period fixed effects, respectively. In the above model, the treatment occurs at different times and the full set of period dummies is included. Our main results are unaffected if we standardize the treatment periods. The primary coefficient of interest in the above specification is the coefficient β_2 on the difference-in-differences estimator, $Treat_i \times Post_t$, which indicates if the average change in fund flows from before the change to solo management to afterward was different in the two groups.

Table VIII reports the results for a difference-in-differences estimation according to equation (2). The coefficients on the interaction, $Treat_i \times Post_t$, are uniformly statistically significant regardless of the model specification. Coefficients equal 0.006 (t-stat. = 7.24) and 0.002 (t-stat. = 2.48) in columns (1) and (2), respectively. In column (1), we report the estimates after including just the segment and period fixed effects and no control variables, and in column (2), we introduce a set of control variables detailed in Section II. These findings are also economically meaningful; all else being equal, the coefficient estimates imply that individuals with a military background receive up to 6.7 annualized percentage points higher net fund inflows than others. Importantly, we find that in both specifications, $Treat_i$ indicator reports small and insignificant coefficients, suggesting that the treatment and control funds exhibit parallel movements in their fund flow outcomes in the absence of the treatment shock. The pre-change parallel trend in fund flows between the two groups is further confirmed in columns (3) and (5), where we augment the difference-in-differences design with interaction terms of the $Treat_i$ variable with periods preceding the managerial change. Findings indicate that no statistical difference in the outcome variable exists prior to the management rotation. In contrast, the coefficients on the interaction terms of the $Treat_i$ variable with post-change periods in column (4) and (5) suggest that the net fund inflows increase following the induction of military-experienced managers. The fund flow effect is the most pronounced in the first month of active management ($Treat_i \times Post0$), indicating that managers with a military background receive 5.7% higher inflows during the first month of active management relative to other managers. The difference in fund flows between the two groups is persistent, however, it slightly weakens over time.

The evidence of this section is hard to reconcile with an alternative fundamental-based explanation and supports the notion that military-induced trust in the manager affects investors' buying and selling behavior toward mutual funds.

C. A Closer Look at the Flow-Performance Relationship of Military-Managed Funds

Investors are ultimately concerned about performance outcomes. Thus, in this section we investigate if the observed flow patterns are also reflected in the distribution of performance realizations of mutual funds. Specifically, we explore whether an investor's willingness to allocate more capital to military-managed funds than to other funds persists after both extreme positive and negative performance months.[12] Given our previous results, we expect that managers with a military background attract relatively more flows regardless of the extremity of performance outcomes.

Table IX relates monthly net fund flows to the performance of mutual funds. Column (1) shows that the coefficients on the main variable of interest, the interaction term *Military* $\times$ *Performance rank*, is positive and statistically significant (coefficient = 0.010, t-statistic of 6.10). This outcome suggests that fund flows are higher for those military-managed funds that

[12] We rely on scaled performance ranks to gauge the performance outcomes. Performance rank represents the position of the fund's monthly return relative to all other funds in the same market segment (based on Morningstar style boxes).

are at the top of the performance ranking. In other words, the observed differences in fund flows between the two groups can be attributed to significantly higher capital inflows into mutual funds with military-experienced managers following the months of outperformance.

Barber et al. (2005) show that the fund flow-performance relationship is in fact nonlinear. Therefore, the remaining specifications in Table IX estimate a quadratic performance-flow relationship. The coefficient estimates in columns (3) and (4) reveal that the interaction term of the dummy for military managers with squared past performance is uniformly statistically significant and positive, while the interactions with linear past performance are negative, emphasizing the non-linearity of the flow-performance relationship. This outcome indicates that the difference between military and nonmilitary-managed funds is especially large for extreme performance realizations. In particular, the results suggest that military-managed mutual funds not only have higher fund flows following extremely good performance, but also following months of very poor return realizations relative to their nonmilitary-managed counterparts. These findings are largely unaffected by the inclusion of various fixed effects in the regressions.

D. Microlevel evidence from an online experiment

The key assumption of this paper is that the majority of investors are likely to be sensitive to fund manager background information when making investment decisions. To verify this assumption, we perform an online survey among U.S. mutual fund investors via Amazon Mechanical Turk (AMT). Specifically, we ask 200 mutual fund investors whether they knew and considered the fund manager's profile at the time of investing. Sixty-seven percent of the respondents reply in the affirmative.

Results of Section IIC and Section IID suggest that investors are likely to base their purchase decisions partially on a manager's personal background information and that military-associated partisanship exists among mutual fund investors. However empirically controlling for all other potential drivers of fund flows in our setting is not possible. Thus, we conduct an online experiment via AMT to further investigate the relation between managers' military affiliation and fund flows. The procedure allows us (i) to control for fund characteristics, so we can rule out statistical discrimination-related explanations of our results, and (ii) to examine the impact of investor characteristics on investment decisions, in contrast to the previous empirical analysis focusing on aggregate investor behavior at the fund level. As in Kumar et al. (2015), we recruit individuals at AMT to complete a hypothetical fund investment task in which they are required to split an investment of 100 dollars between two funds, which are labeled "fund A" and "fund B".[13]

Our investment experiment is conducted with 804 individuals who self-report that they are located in the United States and own mutual funds. We provide subjects with information about

[13]We thank Alexandra Niessen-Ruenzi for providing us with the experimental setup.

each fund A and B, including fund segment, size, inception date, expense ratio, annual turnover, the top five holdings, past performance, a short description of the investment objective, and a short profile describing the fund manager.[14] The experiment lasts four rounds. In each round, participants split 100 dollars between two funds. To avoid subjects learning that the experiment is about military affiliation and to ensure that our experimental results are robust, one of the two funds is managed by an ex-military manager only in rounds 2 and 4, while neither fund is managed by such individual in rounds 1 and 3. In round 2 both funds have very similar fund attributes, but in round 4 we assign negative past returns to fund A.

Next, subjects are randomly assigned to one of two groups. The key feature of the experiment is that in rounds 2 and 4 half of the individuals observe that fund A is managed by an ex-military fund manager, whereas fund B is managed by a nonmilitary manager. In rounds 1 and 3, individuals of both groups observe only nonmilitary-managed funds. Hence, any difference in investment behavior between the two groups can solely be attributed to the fund manager's military background.

Table X presents the results of this experiment. Table X, Panel A shows that AMT participants invest 3.36 dollars more in the fund A when it has a manager with military experience. Results of both rounds 2 and 4 uniformly suggest that subjects allocate more money to the fund with an ex-military manager. Moreover, the inclination toward military-experienced managers persists when subjects are confronted with negative past returns of the military-managed fund (round 4), corroborating the evidence in Section IIIC. In contrast, when we specify no prior military affiliation to managers of both funds (untabulated placebo rounds 1 and 3), we find no significant difference in asset allocation.

Results reported in Table X, Panel B provide further evidence on the relation between fund manager military background and fund flows, while focusing on specific investor characteristics.[15] In columns (2) and (3), we investigate subsamples of subjects by party affiliation (i.e., Democrats and Republicans). The participants self-report party identification. We find the military background effect on investment allocation decisions in both subsamples, with the coefficients of 4.32 (t-stat of 1.72) for the Democrats and 4.53 (t-stat of 1.89) for the Republicans. This outcome is consistent with Gallup's survey evidence that U.S. citizens, independent of their party affiliation, perceive military-affiliated individuals as trustworthy. In column (4), we use several additional interaction terms and show that our results are more pronounced among older investors.

We find that the effect of a fund manager's military background on the amount invested

[14]Each of the fund profiles represents a hypothetical diversified equity mutual fund singlehandedly run by a male manager with an American-sounding name, e.g., "Charles Miller."

[15]Additionally, when we exclude AMT participants who spent less than two minutes on the experiment from our sample, we find that the observed effect strengthens with participation time, indicating that our results are not induced by AMT workers who did not take the task seriously.

in a fund is economically sizable, but lower in magnitude than the effect that we document in our CRSP/Morningstar sample.[16] This result makes intuitive sense because participants are likely to pay less attention to a manager's profile when they do not have their own money at stake. Further, in our experimental setting, the military background effect is lower in magnitude compared to the relatively more salient effects related to gender and manager name documented in Kumar et al. (2015) and Niessen-Ruenzi and Ruenzi (2019).

Overall, the results of this section further confirm the previously observed relation between managerial military background and fund flows and suggest that the majority of investors consider manager background information when making their investment decisions.

IV. Additional Tests

A. Military Background and Window Dressing

Previous research suggests that investors likely prefer managers that require less monitoring (Gennaioli et al. (2015)). In the context of our paper, investors may view managers' military background as an indicator of potentially more compliant and ethical behavior that reduces perceived investment risk. Consequently, an intriguing question is whether ex-military managers live up to investors' expectations and actually act more ethically relative to other managers.

To answer this question, we examine whether managers with military experience are less likely to engage in window dressing activities relative to nonmilitary managers. Solomon, Soltes, and Sosyura (2014) argue that investors pay attention to portfolio holdings reports and, among other things, evaluate managers based on their particular stock picks. Consequently, some fund managers window dress their portfolios (remove poorly performing holdings) before filing dates in an attempt to deceive investors. These practices are generally viewed as unethical at best and may even be illegal (Lakonishok, Shleifer, Thaler, and Vishny (1991); Patel and Sarkissian (2013)). Following Agarwal, Gay, and Ling (2014), we rely on two measures of window dressing, namely Rank Gap and Backward Holding Return Gap (BHRG). Rank Gap is a relative window dressing measure that captures inconsistency between a fund's performance rank and the two ranks based on winner and loser stocks proportions in the reported holdings. BHRG is the difference between the net return of a hypothetical portfolio that is based on the fund's reported holdings and the fund's actual return. The time period is from 2003 — the year from which funds were required to file holdings information on a quarterly basis — to 2017.

Table XI relates a manager's military background to the two window dressing measures. The coefficients on the military dummy variable are uniformly negative and statistically significant. This result suggests that managers with a military background engage in significantly less

[16]To the best of our knowledge, no major military-related events occured around the dates of the experiment (August 2019) that could negatively affect our results.

window dressing relative to their nonmilitary peers. In other words, they are less likely to remove poorly performing holdings before filing dates. Moreover, we observe this pattern regardless of whether the fund is in the top or bottom quintile of performance within its segment prior to the holdings report. While acknowledging the existence of other potential explanations, we suggest that these findings point to the conclusion that ex-military managers demonstrate more compliant and ethical behavior relative to others. Additional cross-database screening for evidence of managerial misconduct of various kinds revealed no instances of ex-military managers in our sample being involved in any illegal activity.[17]

B. *Matched Sample Analysis*

To guard against the possibility of a spurious relationship between military background and fund flows caused by sample-specific unobserved characteristics of funds or managers, we perform two different matching procedures. In doing so, we attempt to bring the sample properties of the control (nonmilitary) funds as close as possible to the military-managed funds. Thus, we assume that if the observed characteristics of the two groups of funds are identical, then the unobserved attributes are likely to be similar as well.

Table XII presents results from a matched sample analysis. We use two approaches to match funds. First, for each observation with a military-experienced manager, we search for nonmilitary-managed twin funds with similar fund or managerial characteristics. In doing so, we require values of the non-categorical variables for nonmilitary fund in a given month to be within 5% of those of a military-managed fund. The set of characteristics includes fund's segment, family, size, age, share of marketing expenses, performance, and manager's gender, biological age, industry tenure, and foreignness of a name. In all cases, we require the matching attributes to be from the same month and drop all other nonmilitary funds' observations that do not have a matching military counterpart in a given month. Second, we perform the propensity score nearest neighborhood matching procedure on the set of fund characteristics, including fund performance, fund size, expense ratio, turnover, fund age, and lagged fund flows. Then we re-estimate the baseline flow regression (column 3 of Table II) based on the resulting matched samples.

Results of the matched sample analysis show a uniformly positive and statistically significant impact of the *Military* dummy on fund flows. The magnitudes of the coefficients in specifications (2) to (16) compare favorably to the estimate in (1), suggesting that in 13 out of 15 cases confining the sample to better matches in terms of observable characteristics results in a similar or more pronounced effect of manager's military background on fund flows. Moreover, when we

[17] Similar to Egan, Matvos, and Seru (2019), we collect data from FINRA BrokerCheck. The data include all disciplinary events, including civil, criminal, and regulatory events, as well as disclosed investigations for all registered brokers and the set of investment advisers who are also registered as brokers.

match funds based on fund segment and manager gender, and additionally require the matching funds to be in the same fund family (in (5)) or to have very similar returns (in (10)), and when we perform propensity score matching (in (12) to (16)), the sample size shrinks significantly, but statistical significance remains. This evidence indicates that restricting the analysis to more similar funds does not alter the baseline results on the military background effect, which means that an unobservable variable explanation of our results is unlikely.

C. Alternative Measures of Fund Flows

Thus far, the main dependent variable of this paper has been relative net fund flows, that is, the percentage change in total assets under management, net of internal growth. However, recent studies question the reliability of the relative fund flow measure due to apparent violations of additive constraint. Spiegel and Zhang (2013), for instance, suggest using a fund's market share instead. Therefore, in this section, we test two alternative specifications of the fund flow measure, namely, the absolute dollar flows and the change of a fund's market (segment) share as dependent variables.

Table XIII reports results for the two alternatively specified fund flow measures. Our findings confirm the existence of a positive impact of the managerial military experience on fund flows for both measures. In columns (1) and (2), coefficient estimates of the *Military* dummy in all-inclusive flow regressions with the absolute dollar flows as the dependent variable are still positive and significant. Results are also economically meaningful, with military managers receiving \$3.3 million higher monthly fund flows on average relative to their nonmilitary counterparts. Further, results of the quantile regression with the change of a fund's segment share as the dependent variable also reveal that the coefficient estimate of the main variable of interest, the *Military* dummy, is positive and significant at the 1% level (t-statistic of 5.15). Thus, the inference that a military background of mutual fund managers affects fund flows remains unchanged.

D. Fund Performance and Persistence

Next, we examine whether the observed relationship between military background and fund flows arises from the possibility that investors rationally prefer managers with a military background due to their potential superiority in generating risk-adjusted performance or higher performance persistence. Table XIV, Panel A, reports the risk-adjusted alpha estimates of a hypothetical long-short portfolio that assumes a long position in all military-managed funds and a short position in all nonmilitary-managed funds in our sample. Regardless of the factor model, the difference portfolio does not deliver any economically or statistically significant risk-adjusted alphas. All alpha estimates, based on either net or gross performance, are close to zero and far from being statistically significant (t-statistics ranging from 0.38 to 1.50). This suggests that significant performance differences between military and nonmilitary managers are unlikely. As an additional test, we compare fund performance persistence of military and nonmilitary managers. Performance persistence is computed as the average time-series standard deviation of monthly performance ranks. The results of Table XIV, Panel B reveal no statistically significant difference between the two groups, indicating that military managers do not deliver more stable performance relative to other managers.

The evidence of this section suggests that investor inclination toward military-managed funds is unlikely to be associated with rational performance-chasing investor behavior. Rather, it provides additional support to the notion that trust in the manager induced by that individual's military background affects investors' buying and selling behavior toward mutual funds.

E. Potential Equilibrium Outcomes of Hiring Ex-Military Managers

Our findings suggest that fund management companies are likely to benefit from hiring managers with a military background because they are associated with relatively higher fund flows. However, taking into account the advantages of hiring ex-military individuals, an important question remains: Why then are most mutual funds not managed by individuals with military experience?

A potential answer to this question is that the supply of qualified military-experienced individuals may be too low to meet the increasing demand for mutual fund managers over the sample period of our study. Figure 4A plots the share of ex-military fund managers and education level of veterans by birth cohort, illustrating the shift in educational attainment of military personnel. This evidence suggests that in the first part of the twentieth century, the likelihood of highly educated individuals serving in the military was higher relative to all other men in the population. Perhaps, among other things, this finding may be related to the fact that prior to 1951 potential military inductees were not permitted to postpone service to attend college.[18] Following the change in the selection process, the proportion of men with college degrees in the military substantially decreased. Consequently, the share of ex-military personnel among mutual fund managers followed a similar path and remained low from the mid-1950s cohorts onward. Thus, the decreased supply of highly educated military-experienced individuals is likely to be inadequate to meet the demand for fund managers, illustrated in Figure 4B by the steadily declining share of fund managers with a military background among all managers over the sample period.

Several other potential reasons exit for why fund management companies do not widely em-

[18] See Bound and Turner (2002) for more information on other potential reasons for the observed differences in educational attainment of military personnel across various cohorts.

ploy military-experienced fund managers. One possibility is that they may simply be unaware of the flow effect that we uncover in this paper. However, we observe that within our data set, the vast majority of fund companies reveal general background about their active managers through easily accessible media sources. In addition, the results of Section IID indicate that fund companies have fund flow benefits associated with disclosing information through such information outlets, suggesting that most of the fund management companies are likely to act strategically in revealing information about a manager's military background. Another possibility is that fund companies are reluctant to employ ex-military managers because these managers perform worse than others. However, we find that managers with a military background do not exhibit significantly different skills or managerial traits relative to other managers, and if anything, they tend to be more ethical. Overall, we find no supportive evidence for these alternative mechanisms. We acknowledge that other equilibrium mechanisms that we are not able to address in our setting are possible (e.g., higher compensation paid to managers with military experience).

V. Conclusions

In this paper, we investigate whether biographical characteristics of mutual fund managers, specifically prior engagement in the military, influence investor asset allocation decisions. We suggest that distinct trust-building attributes of fund managers with prior military experience result in investors perceiving them as money guardians with military-associated qualities. Thus, investors are more likely to allocate capital to funds managed by military-experienced individuals, even when these managers do not exhibit superior investment skill compared with their nonmilitary peers. We find that mutual funds with military-experienced managers have annualized net fund flows that are 10.6 percentage points higher and grow by up to 6.5% faster per annum relative to comparable funds run by managers who do not have such a background. Military managers' superiority in competing for investor funds is robust to several alternative explanations, and cannot be explained by fund or managerial attributes, including performance. Additionally, we find that the content and salience of disclosures about the military background also influence investor decisions; that is, the fund flow effect is more pronounced when investors are exposed to salient, accentuated information.

Although we observe no evidence of rational statistical reasons for such investor decisions, results from several tests provide support for trust-mediated allocation of assets. We find that investors' buying and selling behavior toward military-managed funds is related to nationwide confidence in the military, ratified by distinct investors' partisan attitudes toward these funds during the episodes of heightened trust. Consistent with this finding, we observe that ex-military managers experience significantly lower fund flows following the exogenous events of military-related scandals that have adversely affected nationwide trust in the military. Further, we find that military managers have higher fund inflows relative to their nonmilitary counterparts following both extremely good and poor performance. The difference-in-differences analysis around the dates of managerial turnover reveals that, even without any other fundamental events and all else being equal, incoming managers with a military background receive significantly higher net fund flows relative to other managers. In an experimental setting in which we randomly assign military background to managers and eliminate the possibility for rational choice explanations, we find that subjects invest significantly more money in a fund when it is managed by an ex-military manager. Last, using investor-level information, we observe that military-induced asset allocation is unaffected by investor political party identification but is more pronounced among older investors.

Taken together, the findings of this paper suggest that military-associated trust-building attributes of fund managers influence mutual fund investor decisions. The empirical findings of this paper provide support to portfolio management delegation theories, particularly those emphasizing the role of trust, and can be interpreted under the description of trust-mediated fund allocation offered in them. Future research could further investigate the causes and effects of trust in the asset management industry. One direction for future research would be an exploration of the potential for trust-induced investor decision-making related to other economic agents (e.g., corporate executives, financial analysts, and hedge fund managers). Finally, it might be useful to explore other managerial characteristics that could potentially foster investor trust and affect investor purchase decisions.

Appendix A. Variable Description

Table AI. Descriptions of Main Variables and Sources.
This table provides descriptions and sources of variables used in our study. The following abbreviations are used: CRSP - CRSP Survivorship Bias Free Mutual Fund Database; MS - Morningstar Direct Database; BL - Bloomberg; MQ - Marquis Who's Who database; FINRA - BrokerCheck; LI - LinkedIn, SEC - SEC filings, NSAR-B filings; INT - Intelius database; GI - GI Search engine; ANC - Ancestry.com; LEG - Legacy.com; FW - Fund company websites; LN - LexisNexis; NP - Newspapers.com; Gallup - Gallup's Confidence in Institutions survey; FBI - Federal Bureau of Investigation NICS database; AE - Authors' estimations; MC - Manually collected.

Variables	**Description**	**Source**
Panel A: Dependent Variables		
Fund flows	Monthly net percentage fund flows, computed as $(TNA_t^i - TNA_{t-1}^i(1+r_t^i))/TNA_{t-1}^i$, where TNA_t^i is the fund i's total net assets in month t and r_t^i stands for the net return in month t.	CRSP, AE
Absolute dollar flows	Monthly absolute dollar value of fund flows, computed as $TNA_t^i - TNA_{t-1}^i(1+r_t^i)$, where TNA_t^i is the fund i's total net assets in month t and r_t^i stands for the net return in month t.	CRSP, AE
Change of a fund's market (segment) share	A fund's market (segment) share in a given month divided by the fund's market (segment) share in the previous month, where the segment share is a fraction of a fund's TNA in the average segment TNA.	CRSP, AE
Panel B: Main Independent Variables		
Military	Dummy variable equal to one if a fund is single-managed by an individual with a military background in a given month, and zero otherwise.	MS, BL, MQ, FW, LI, SEC, GI, LN, NP, AE, MC
Military team	Dummy variable equal to one if a fund management team includes a manager with prior military background in a given month, and zero otherwise.	MS, BL, MQ, FW, LI, SEC, GI, LN, NP, AE, MC
Conflict/Medal	Dummy variable equal to one if a fund is single-managed by an individual who served a tour of duty in a conflict zone and, 0 otherwise.	MS, BL, MQ, FW, LI, SEC, GI, LN, NP, AE, MC
Military training	Dummy variable equal to one if a manager has never served in the military but has graduated from any of the U.S. military schools and academies or voluntary participated in any type of military training, and zero otherwise. Based on additionally collected data.	MS, BL, MQ, FW, LI, SEC, GI, LN, NP, AE, MC
Panel C: Fund Variables		

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Table AI – continued from previous page.

Variables	Description	Source
Military team share	Share of military-experienced managers in a fund management team.	MS, BL, MQ, FW, LI, SEC, GI, LN, NP, AE, MC
Returns (raw)	A fund's monthly raw net return.	CRSP
Performance rank	Performance rank based on a fund's monthly return relative to all other funds in the same market segment (based on the Morningstar style boxes) in a given month normalized to be between 0 and 1.	CRSP, AE
Performance rank^2	Squared value of performance rank.	CRSP, AE
Three-months returns	A fund's net return over the past three months.	CRSP, AE
One-year returns	A fund's net return over the past 12 months.	CRSP, AE
Five-year returns	A fund's net return over the past 60 months.	CRSP, AE
Fund risk	Time series standard deviation of a fund's returns using the rolling twelve-months window of past returns.	CRSP, AE
Fund age	Logarithm of a fund's age in full years from the date the fund was first offered, as defined in CRSP.	CRSP, AE
Fund size	Logarithm of a fund's total net assets in million USD.	CRSP, AE
Turnover ratio	A fund's turnover ratio.	CRSP
Expense ratio	A fund's expense ratio in %.	CRSP
Marketing expenses	Share of a fund's marketing expenses in its total expenses.	SEC, AE, MC
Family flow	Average of fund flows over all funds belonging to the same fund family as a given fund in a given month, net of flows in a fund itself.	CRSP, AE
No load fund	Dummy variable equal to one if a fund does not charge a front-end load fee in a given month, and zero otherwise.	CRSP
Retail fund	Dummy variable equal to one if a fund is a retail fund in a given month and 0 otherwise.	CRSP
Institutional fund	Dummy variable equal to one if a fund is an institutional fund in a given month, and zero otherwise.	CRSP
Defense holdings	Share of defense stocks in total fund's portfolio in a given month.	TR
Lagged fund flow	One month lagged flows of a given fund.	CRSP, AE
Investment media	Dummy variable equal to one for funds that disclose information on manager's prior military experience through investment media sources, and zero otherwise.	MC, MS, BL

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Table AI – continued from previous page.

Variables	Description	Source
Personal disclosures	Dummy variable equal to one if information on manager's prior military experience is not available in investment outlets, but on fund company websites or professional networks, and zero otherwise.	MC, FW, LI
Other sources	Dummy variable equal to one if military background information is only disclosed via major or regional newspapers or other alternative media outlets, and zero otherwise.	MC, NP
Post-mortem placebo	Dummy variable equal to one if military background information is only disclosed in obituary notices after manager passing, but not prior to that. Based on additionally collected data.	MC, LEG
Panel D: Manager-Specific and Other Variables		
Age	Biological age of a manager in years in a given month.	MS, BL, INT, FW, NP, MC
Married (Marital status)	Dummy variable equal to one if a fund manager is married in a given month, and zero otherwise.	MS, INT, FW, NP, MC
Fund tenure	Tenure of a manager in years in a given month, computed as difference between a current date and the date when the manager has started managing the fund.	MS, FINRA, AE
Industry tenure	Tenure of a manager in years in a given month, computed as difference between a current date and the date when the manager joined the fund management industry.	MS, FINRA, AE
Bachelors only	Dummy variable equal to one if a manager has a bachelor's degree as the highest degree earned, and zero otherwise.	MS, BL, LI, MQ, MC
MBA and above	Dummy variable equal to one if a manager has a MBA/PhD/JD/MD degree as the highest degree earned, and zero otherwise.	MS, BL, LI, MQ, MC
Ivy league	Dummy variable equal to one if a manager has any degree from an Ivy league school, and zero otherwise.	MS, BL, LI, MQ, MC
Foreign name	Dummy variable equal to one if a manager's name is perceived as non-English sounding (but rather as African, Asian, Arabic, Hispanic, etc.), and zero otherwise. Estimations are based on Ye et al. (2017)'s machine-learning algorithm.	AE
Non-financial industry experience	Dummy variable equal to one if a manager has prior non-financial industry experience, and zero otherwise.	MS, BL, LI, MC
Media coverage	Number of articles in the LexisNexis "U.S. newspapers" universe referencing the manager in the headline or story body in a given month.	LN, MC

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Table AI – continued from previous page.

Variables	Description	Source
Father manager	Dummy variable equal to one if a manager's father has worked in the asset management industry, and zero otherwise.	MS, MQ, ANC, LEG, NP, MC
Confidence in the military index	Normalized confidence in the military index in a given year, computed as ratio of "great deal confidence" to "very little/none confidence" respondents in a given year. Survey data is based on a random sample of approximately 1,000 adults, aged 18 and older, from all 50 U.S. states.	Gallup, AE
Satisfaction with the military	Normalized satisfaction with the nation's military strength and preparedness index in a given year.	Gallup, AE
Firearm checks (NICS)	The percentage change in the number of background checks on purchases of firearms conducted through the National Instant Criminal Background Check System.	FBI, AE

Appendix B. Military Background Information

MORNINGSTAR®

Fuller & Thaler Behavioral Small-Cap Equity Fund Investor Shares FTHNX

★★★★★

Manager(s) FTHNX

Russell J. Fuller

09/08/2011 —

Dr. Fuller is founder and president of the firm and oversees its research and investment activities. He founded the firm in 1993 and has over 48 years of investment experience. His four-decade long experience spans academic research to investment management. Prior to establishing Fuller & Thaler, he worked at two investment management firms, and began his investment career as a security analyst with a brokerage firm that later merged with Paine Webber. In the academic field, his last position was Chairman of the Finance Department at Washington State University. He has also held positions at the University of British Columbia, Canada, and the University of Auckland, New Zealand. Dr. Fuller has published an investment textbook and numerous journal articles. He has served on the editorial board for the Financial Analysts Journal and is currently on the advisory board for the Journal of Portfolio Management. Dr. Fuller received the Graham & Dodd award from the Association for Investment Management and Research for his paper entitled "Predictability Bias." He has served on the Board of Directors of the CFA Society of San Francisco and in 2006 was presented with their Distinguished Member Award in appreciation of his leadership and dedication to the financial community. He also served as an officer in the United States Army from 1967 to 1970 where he was awarded the US Bronze Star and the Cross of Gallantry. Dr. Fuller received a BA, MBA and PhD (in finance) from the University of Nebraska, and he holds the Chartered Financial Analyst designation. He is an owner of the firm and Chairman of the Board of Directors.

Certification	CFA
Education	B.A. University of Nebraska, 1976
	M.B.A. University of Nebraska, 1971
	Ph.D. University of Nebraska, 1976

Other Assets Managed ▶

Figure B1. Morningstar sample profile of a fund manager with military background. This figure shows an exemplary manager profile retrieved from Morningstar Direct. The information regarding the manager's military background is highlighted in blue.

Bloomberg

Executive Profile

Anthony Eugene Sutton

Portfolio Manager & Analyst, Redwood Investments, LLC

Age	Total Calculated Compensation	
55	--	This person is connected to **0** Board Member in **0** organization across **3** different industries.

Background

Mr. Anthony Eugene Sutton, also known as Tony, is a Portfolio Manager and Analyst since 2012 at Redwood Investments, LLC. Mr. Sutton joined the firm in 2010 and serves as Portfolio Manager for SMID growth and Analyst for the large cap core and large cap growth strategies. His primary research coverage includes biotechnology, medical equipment, software, and services. Prior to joining this, Mr. Sutton was a Managing Director and Portfolio Manager at Putnam Investment Management, LLC. He joined the firm in 2001. Prior to this, he was a Specialty Growth Analyst at Putnam Investment Management covering health care, biotechnology, defense, and technology. Mr. Sutton was an Associate Analyst at Fidelity Management and Research from 1989 to 1993 and Portfolio Manager at Cabot Money Management from 1995 to 1998. He also served as the Chief Investment Officer at McDonald-Sutton Asset Management, LLC from 1998 to 2001. Mr. Sutton is a combat-decorated former US Marine, specializing in intelligence with extended tours served in the Middle East and Central America from 1982 to 1988. He began his investment career at Fidelity Investments and following graduate school, he managed growth portfolios for private clients. Mr. Sutton received M.B.A from MIT Sloan School of Management in 1993 and B.A. from Monmouth University in 1989.

Figure B2. Bloomberg sample profile of a fund manager with military background. This figure shows an exemplary manager profile retrieved from Bloomberg Executive Profiles. The information regarding the manager's military background is highlighted in blue.

Princeton Global Asset Management LLC

Investment Professionals

RONALD K. STRIBLEY, Managing Director, has implemented an investment philosophy focused on the "Value Style" for over 30 years. During this period he developed and refined a systematic and disciplined investment process that seeks to find equities which have low Price to Earnings Ratios with tangible evidence of improving corporate fundamentals. He is the founder of Stribley Capital Management. Ron was a partner in The Ayco Company L.P., a wholly owned subsidiary of Goldman Sachs, where he created, implemented, and managed a Value Style Portfolio. Prior to joining Ayco, Ron was First Vice President for The Glenmede Trust Company, where he managed in excess of $2.5 Billion including the large capitalization US equity Pew Charitable Trust portfolio. Ron is a CFA® Charterholder since 1975 and has passed the NASD Series 7 and 66 examinations. He received his BSBA degrees from Babson College and then served a tour of duty in Viet Nam with the 11th Armored Calvary Regiment and was awarded the Bronze Star. Following his honorable discharge as a 1st Lieutenant, he completed his Masters at Babson College.

Figure B3. A fund firm's sample profile of a fund manager with military background. This figure shows an exemplary manager profile retrieved from a fund firm's advertising materials. The information regarding the manager's military background is highlighted in blue.

REFERENCES

Agarwal, Vikas, Gerald D Gay, and Leng Ling, 2014, Window dressing in mutual funds, *Review of Financial Studies* 27, 3133–3170.

Agarwal, Vikas, Yan Lu, and Sugata Ray, 2021, Are hedge funds' charitable donations strategic?, *Journal of Corporate Finance* 66, 101842.

Agarwal, Vikas, Linlin Ma, and Kevin Mullally, 2015, Managerial multitasking in the mutual fund industry, CFR Working Papers 13-10 [rev.], University of Cologne, Centre for Financial Research (CFR).

Barber, Brad M, Terrance Odean, and Lu Zheng, 2005, Out of sight, out of mind: The effects of expenses on mutual fund flows, *Journal of Business* 78, 2095–2120.

Benmelech, Efraim, and Carola Frydman, 2015, Military CEOs, *Journal of Financial Economics* 117, 43–59.

Bergstresser, Daniel, John M R Chalmers, and Peter Tufano, 2009, Assessing the costs and benefits of brokers in the mutual fund industry, *Review of Financial Studies* 22, 4129–4156.

Berk, Jonathan B, and Richard C Green, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269–1295.

Blader, Steven L, and Tom R Tyler, 2009, Testing and extending the group engagement model: Linkages between social identity, procedural justice, economic outcomes, and extrarole behavior, *Journal of Applied Psychology* 94, 445.

Blanco, Luisa, and Isabel Ruiz, 2013, The impact of crime and insecurity on trust in democracy and institutions, *American Economic Review* 103, 284–88.

Bound, John, and Sarah Turner, 2002, Going to war and going to college: Did World War II and the GI Bill increase educational attainment for returning veterans?, *Journal of Labor Economics* 20, 784–815.

Cao, Liqun, Francis T Cullen, and Bruce G Link, 1997, The social determinants of gun ownership: Self-protection in an urban environment, *Criminology* 35, 629–658.

Carhart, Mark M, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Carlson, Jennifer D, 2012, 'I don't dial 911': American gun politics and the problem of policing, *British Journal of Criminology* 52, 1113–1132.

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

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.

Cialdini, Robert B, and Noah J Goldstein, 2004, Social influence: Compliance and conformity, *Annual Review of Psychology* 55, 591–621.

Cici, Gjergji, Monika Gehde-Trapp, Marc-André Göricke, and Alexander Kempf, 2018, The investment value of fund managers' experience outside the financial sector, *Review of Financial Studies* 31, 3821–3853.

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.

Cooper, Michael J, Orlin Dimitrov, and P Raghavendra Rau, 2001, A rose.com by any other name, *Journal of Finance* 56, 2371–2388.

Cooper, Michael J, Huseyin Gulen, and P Raghavendra Rau, 2005, Changing names with style: Mutual fund name changes and their effects on fund flows, *Journal of Finance* 60, 2825–2858.

Dangl, Thomas, Youchang Wu, and Josef Zechner, 2006, Market discipline and internal governance in the mutual fund industry, *Review of Financial Studies* 21, 2307–2343.

De Tray, Dennis, 1982, Veteran status as a screening device, *American Economic Review* 72, 133–42.

Del Guercio, Diane, and Paula A Tkac, 2008, Star power: The effect of Morningstar ratings on mutual fund flow, *Journal of Financial and Quantitative Analysis* 43, 907–936.

Diener, Edward, and Kenneth W Kerber, 1979, Personality characteristics of American gun-owners, *Journal of Social Psychology* 107, 227–238.

Duffy, Tim, 2006, Military experience & CEOs: Is there a link?, Korn/Ferry International Report.

Egan, Mark, Gregor Matvos, and Amit Seru, 2019, The market for financial adviser misconduct, *Journal of Political Economy* 127, 233–295.

Fama, Eugene F, and Kenneth R French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F, and Kenneth R French, 2010, Luck versus skill in the cross-section of mutual fund returns, *Journal of Finance* 65, 1915–1947.

Frazzini, Andrea, and Owen Lamont, 2008, Dumb money: Mutual fund flows and the cross-section of stock returns, *Journal of Financial Economics* 88, 299–322.

Gennaioli, Nicola, Andrei Shleifer, and Robert Vishny, 2015, Money doctors, *Journal of Finance* 70, 91–114.

Glazer, Jacob, and Ariel Rubinstein, 2004, On optimal rules of persuasion, *Econometrica* 72, 1715–1736.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2004, The role of social capital in financial development, *American Economic Review* 94, 526–556.

Hirshleifer, David, 2001, Investor psychology and asset pricing, *Journal of Finance* 56, 1533–1597.

Hoechle, Daniel, Stefan Ruenzi, Nic Schaub, and Markus Schmid, 2018, Financial advice and bank profits, *Review of Financial Studies* 31, 4447–4492.

Hooghe, Marc, and Jennifer Oser, 2017, Partisan strength, political trust and generalized trust in the United States: An analysis of the general social survey, 1972–2014, *Social Science Research* 68, 132–146.

Hortaçsu, Ali, and Chad Syverson, 2004, Product differentiation, search costs, and competition in the mutual fund industry: A case study of S&P 500 index funds, *Quarterly Journal of Economics* 119, 403–456.

Huddy, Leonie, and Nadia Khatib, 2007, American patriotism, national identity, and political involvement, *American Journal of Political Science* 51, 63–77.

Jackson, Joshua J, Felix Thoemmes, Kathrin Jonkmann, Oliver Lüdtke, and Ulrich Trautwein, 2012, Military training and personality trait development: Does the military make the man, or does the man make the military?, *Psychological Science* 23, 270–277.

Jain, Prem C, and Joanna Shuang Wu, 2000, Truth in mutual fund advertising: Evidence on future performance and fund flows, *Journal of Finance* 55, 937–958.

Jensen, Michael C, 1968, The performance of mutual funds in the period 1945–1964, *Journal of Finance* 23, 389–416.

Kaniel, Ron, Laura T Starks, and Vasudha Vasudevan, 2007, Headlines and bottom lines: Attention and learning effects from media coverage of mutual funds, Working Paper, University of Texas.

Khorana, Ajay, 1996, Top management turnover an empirical investigation of mutual fund managers, *Journal of Financial Economics* 40, 403–427.

Knack, Stephen, and Philip Keefer, 1997, Does social capital have an economic payoff? A cross-country investigation, *Quarterly Journal of Economics* 112, 1251–1288.

Koch-Bayram, Irmela F, and Georg Wernicke, 2018, Drilled to obey? Ex-military CEOs and financial misconduct, *Strategic Management Journal* 39, 2943–2964.

Kostovetsky, Leonard, 2015, Whom Do You Trust?: Investor-Advisor Relationships and Mutual Fund Flows, *Review of Financial Studies* 29, 898–936.

Kronlund, Mathias, Veronika Krepely Pool, Clemens Sialm, and Irina Stefanescu, 2020, Out of sight no more? The effect of fee disclosures on 401(k) investment allocations, NBER Working Paper No. 27573.

Kumar, Alok, Alexandra Niessen-Ruenzi, and Oliver G Spalt, 2015, What's in a name? Mutual fund flows when managers have foreign-sounding names, *Review of Financial Studies* 28, 2281–2321.

Lakonishok, Josef, Andrei Shleifer, Richard H Thaler, and Robert W Vishny, 1991, Window dressing by pension fund managers, *American Economic Review* 81, 227–231.

MacLean, Alair, and Glen H Elder Jr, 2007, Military service in the life course, *Annual Review of Sociology* 33, 175–196.

Malmendier, Ulrike, Geoffrey Tate, and Jon Yan, 2011, Overconfidence and early-life experiences: The effect of managerial traits on corporate financial policies, *Journal of Finance* 66, 1687–1733.

Mullainathan, Sendhil, Joshua Schwartzstein, and Andrei Shleifer, 2008, Coarse thinking and persuasion, *Quarterly Journal of Economics* 123, 577–619.

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

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, 2013, Deception and managerial structure: A joint study of portfolio pumping and window dressing practices, Working Paper, University of Western Ontario.

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.

Petrocik, John Richard, 2009, Measuring party support: Leaners are not independents, *Electoral Studies* 28, 562–572.

Pope, Devin G, and Justin R Sydnor, 2011, What's in a picture? Evidence of discrimination from prosper.com, *Journal of Human Resources* 46, 53–92.

Rahn, Wendy M, and John E Transue, 1998, Social trust and value change: The decline of social capital in American youth, 1976–1995, *Political Psychology* 19, 545–565.

Roussanov, Nikolai, and Pavel Savor, 2014, Marriage and managers' attitudes to risk, *Management Science* 60, 2496–2508.

Sampson, Robert J, and John H Laub, 1996, Socioeconomic achievement in the life course of disadvantaged men: Military service as a turning point, circa 1940-1965, *American Sociological Review* 347–367.

Sapp, Travis, and Ashish Tiwari, 2004, Does stock return momentum explain the "smart money" effect?, *Journal of Finance* 59, 2605–2622.

Solomon, David H, Eugene Soltes, and Denis Sosyura, 2014, Winners in the spotlight: Media coverage of fund holdings as a driver of flows, *Journal of Financial Economics* 113, 53–72.

Spiegel, Matthew, and Hong Zhang, 2013, Mutual fund risk and market share-adjusted fund flows, *Journal of Financial Economics* 108, 506–528.

Teigen, Jeremy M, 2013, Military experience in elections and perceptions of issue competence: An experimental study with television ads, *Armed Forces & Society* 39, 415–433.

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*, CIKM '17, 1897–1906 (ACM, New York, NY, USA).

Table I. Fund and Manager Characteristics

This table reports fund and manager characteristics for our sample of funds managed by individuals with prior military experience and for the peer managers who do not have such experience. Both groups of funds are restricted to fund managers who single-managed U.S. domestic equity funds at some point between 1991 and 2017. The differences between the group means and the corresponding t-statistics, clustered by fund for fund attributes and clustered by manager for manager attributes, are reported in columns (3) and (4), respectively. Panel A reports fund characteristics. Fund flows are the net percentage flows of the fund in a given month (annualized), as specified in equation (1). Other fund characteristics include: raw returns (annualized); performance rank of the fund in a given month relative to all other funds in the same market segment; fund risk (time series standard deviation of the fund returns using the rolling past twelve month return observations); fund age as the natural logarithm of fund age in years in a given month; fund size as natural logarithm of the fund's size in million USD; turnover ratio; expense ratio; marketing expenses as the share of marketing expenses (NSAR-B filings) in total expenses; Morningstar rating; family flows as the monthly growth rate of fund's family; defense holdings as the share of defense stocks in total fund's portfolio in a given month; and indicator variables for no load, retail, and institutional funds. Panel B reports specific manager characteristics, including biological age, fund and industry tenure, and share of managers with foreign name. The panel also reports the fractions of managers by their top degree and Ivy league school attainment. Manager's media coverage is the number of times a fund manager is mentioned in a given month in the headline or story body of all U.S. newspapers.

Panel A: Fund Characteristics				
Variable	Military managers (1)	Other managers (2)	Difference (3)	t-statistic (4)
Fund flows	0.224	0.118	0.106	5.06
Returns (raw)	0.096	0.091	0.005	0.79
Performance rank	0.556	0.552	0.004	1.13
Performance rank^2	0.394	0.390	0.004	0.95
Fund risk	0.045	0.047	-0.001	-1.27
Fund age	1.882	2.056	-0.174	-1.38
Fund size	4.887	5.078	-0.190	-0.94
Turnover	0.863	0.827	0.036	0.31
Morningstar rating	3.175	3.098	0.077	0.62
Expense ratio	0.012	0.012	-0.001	-1.47
Marketing expenses	0.341	0.332	0.009	0.35
Family flows	0.010	0.006	0.007	1.65
No load fund	0.219	0.197	0.022	0.49
Retail fund	0.719	0.873	-0.154	-0.88
Institutional fund	0.489	0.476	0.012	0.27
Defense holdings	1.379	1.485	-0.106	-0.78
Panel B: Manager Characteristics				
Age	53.003	46.773	6.230	3.96
Married	0.851	0.856	-0.005	-1.17
Fund tenure	8.038	6.513	1.524	1.19
Industry tenure	11.144	9.155	1.989	1.80
Bachelors only	0.237	0.288	-0.051	-0.80
MBA top	0.682	0.587	0.095	1.22
PhD/JD/MD top	0.054	0.059	-0.004	-0.11
Ivy league bachelors	0.215	0.149	0.066	0.87
Ivy league MBA	0.230	0.227	0.003	0.04
Ivy league	0.406	0.305	0.101	1.04
Foreign name	0.229	0.298	-0.069	-0.87
Media coverage	2.405	2.192	0.214	0.56

Table II. Military Background of Mutual Fund Managers and Fund Flows
This table relates managers' military background to fund flows. The dependent variable is monthly net percentage fund flows. The main independent variable is the military dummy that equals one if a fund is single-managed by an individual with military background in a given month, and zero if the manager does not have a military background. The set of control variables is comprised of variables described in Table I and in Appendix A. All control variables, except family flows, are lagged by one month. Segment is defined by the Morningstar fund style indicator. Specification (1) reports results of percentage fund flow regression without fixed effects. Regression specifications (2) to (6) include period, segment, family, fund, and/or interaction fixed effects. Period FE stands for month-year fixed effects. Standard errors are double-clustered by fund and month-year. The corresponding t-statistics are reported in parentheses.

	Dependent Variable: Fund Flows					
	(1)	(2)	(3)	(4)	(5)	(6)
Military	0.005	0.005	0.003	0.003	0.003	0.003
	(3.80)	(3.42)	(3.20)	(3.27)	(2.16)	(1.93)
Fund returns	0.071	0.168				
	(9.37)	(9.74)				
Performance rank			0.012	0.013	0.008	0.011
			(15.78)	(16.38)	(11.55)	(14.43)
Lagged fund flow			0.415	0.412	0.268	0.340
			(43.48)	(43.54)	(28.26)	(35.04)
Fund risk	-0.181	-0.291	-0.143	-0.302	-0.083	-0.116
	(-11.68)	(-12.23)	(-9.33)	(-9.88)	(-5.90)	(-6.94)
Fund size	-0.002	-0.002	-0.001	-0.001	-0.001	-0.006
	(-9.97)	(-8.28)	(-10.43)	(-10.46)	(-7.92)	(-15.49)
Fund age	-0.007	-0.007	-0.004	-0.004	-0.003	-0.000
	(-16.75)	(-16.53)	(-15.61)	(-15.60)	(-10.68)	(-0.10)
Turnover	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001
	(-1.00)	(-0.76)	(-0.91)	(-0.90)	(-2.49)	(-1.79)
Expense ratio	0.079	0.096	0.041	0.043	0.181	0.032
	(2.92)	(3.23)	(2.00)	(2.05)	(2.94)	(0.82)
Family flows	0.462	0.397	0.278	0.274	0.360	0.257
	(24.01)	(19.85)	(19.07)	(18.95)	(34.29)	(16.25)
Industry tenure	-0.000	0.000	0.000	0.000	0.000	-0.000
	(-0.23)	(1.42)	(1.34)	(1.31)	(0.22)	(-1.72)
Fund tenure	-0.000	-0.000	-0.000	-0.000	0.000	-0.000
	(-2.79)	(-3.36)	(-2.85)	(-2.76)	(0.75)	(-0.14)
Segment FE	No	Yes	Yes	No	No	No
Period FE	No	Yes	Yes	No	No	Yes
Segment × Period FE	No	No	No	Yes	No	No
Family × Period FE	No	No	No	No	Yes	No
Fund FE	No	No	No	No	No	Yes
Adj. R-squared	0.087	0.099	0.266	0.270	0.610	0.300
N of funds	2,412	2,412	2,412	2,412	2,064	2,380
Observations	170,371	170,371	170,371	170,371	136,799	170,338

Table III. Alternative Explanations and Robustness of the Results

This table reports results of robustness tests. Specifically, this table shows the estimates of net percentage fund flows regressed on the military dummy, but, depending on the robustness test, flow regressions include additional control variables or are estimated with an adjusted sample of funds. Additional control variables for managerial attributes include manager's gender, biological age, marital status, education, prior experience, foreignness of a name, father background, and media coverage. Additional control variables for fund attributes include long-term performance; retail, institutional and no load fund indicators; the share of defense stocks in the fund portfolio; and the share of fund marketing expenses in a given month. All of the variables are described in Appendix A. The setup also includes the standard set of control variables and is otherwise identical to the specification (3) of Table II. Standard errors are double-clustered by fund and month-year.

Alternative explanations		Dependent Variable: Fund Flows			
		Coefficient	t-statistic	N of funds	Observations
(1)	Return 3-months control	0.002	2.97	2,403	168,901
(2)	Return 1-year control	0.002	2.20	2,297	155,467
(3)	Return 5-year control	0.002	2.18	1,612	96,689
(4)	Defense holdings share control	0.002	2.22	2,167	76,967
(5)	Coefficient estimates (military) when controlling for demographics				
	Gender	0.003	3.16	2,412	170,371
	Gender and age	0.003	3.93	2,399	169,123
	Gender, age and marital status	0.004	4.05	2,242	153,147
(6)	Coefficient estimates (military) when controlling for degree				
	Bachelors only	0.003	3.13	2,406	169,843
	MBA and above	0.003	3.25		
(7)	Controlling for the level of recognition of education				
	Military	0.003	3.11	2,402	169,556
	Ivy league	0.001	3.45		
(8)	Non-Financial industry experience				
	Military	0.003	3.17	2,406	169,887
	Non-financial industry experience	0.000	0.21		
(9)	Foreign name				
	Military	0.003	3.32	2,412	170,371
	Foreign name	-0.001	-2.79		
(10)	Manager's family background				
	Military	0.004	2.98	1,014	56,656
	Father fund manager	0.002	1.41		
(11)	Marketing expenses				
	Military	0.004	3.18	1,665	101,465
	Marketing expenses	0.000	3.98		
(12)	Coefficient estimates (military) by distribution channels				
	Retail fund	0.003	3.24	2,404	170,264
	Institutional fund	0.003	3.09	2,404	170,264
	No load fund	0.003	3.21	2,412	170,371
(13)	Manager's media coverage control				
	Military	0.002	2.38	1,391	134,293
	Media coverage	0.000	0.14		
(14)	Excluding index funds	0.005	2.83	2,154	153,447
(15)	Placebo: Subsample of index funds	0.002	0.45	258	16,899

Table IV. Fund Flows and the Degree of Military Involvement

This table relates percentage fund flows to the managers' degree of involvement in the military. Panel A presents results of a univariate sorting by the Conflict/Medal dummy and the Military training indicator variable. The Conflict/Medal dummy equals one if a fund is managed by an individual who served a tour of duty in a conflict zone, and zero otherwise. The Military training dummy covers another extreme of military involvement and takes the value of one if a manager has never served in the military but has graduated from any of the U.S. military schools and academies or participated in any type of military training and zero otherwise. The Conflict/Medal indicator variable represents a subset of military managers, while the Military training dummy covers additionally collected data on managers who have just undergone military training. Panel B shows the estimates of net percentage fund flows regressed on the aforementioned variables and on the interaction term with the military dummy. The setup of the regressions includes the standard set of control variables and is otherwise identical to the baseline specification (3) of Table II. Standard errors are double-clustered by fund and month-year and t-statistics are reported in parentheses.

Panel A: Univariate sorting	Fund Flows			
	Military managers	Other managers	Difference	t-statistic
Conflict/Medal	0.029	0.010	0.018	3.39
Military training	0.010	0.010	-0.001	-0.16

Panel B: Regression analysis	Dependent Variable: Fund flows			
	(1)	(2)	(3)	(4)
Military	0.002	0.002		
	(2.70)	(2.55)		
Military $\times$ Conflict/Medal	0.005	0.006	0.007	
	(2.06)	(2.15)	(2.70)	
Military training	-0.003			-0.001
	(-1.42)			(-0.66)
Controls	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.266	0.266	0.266	0.266
N of funds	2,412	2,412	2,412	2,412
Observations	170,371	170,371	170,371	170,371

Table V. Information Distribution Channels and Fund Flows

This table presents mean fund flows estimates from univariate sorting (Panel A) and coefficient estimates of net percentage fund flows from the regressions (Panel B) by four distinct distribution channels for military background information disclosure. The Investment media indicator variable equals one for funds that disclose information on the manager's prior military experience through investment media sources, namely, Morningstar and Bloomberg, and zero otherwise. The Personal disclosures dummy is coded as one if this information is not available in investment outlets, but on fund company websites or professional networks, and zero otherwise. The Other sources variable takes the value of one if military background information is only disclosed via major or regional newspapers or other alternative media outlets, and zero otherwise. The Post-mortem placebo variable is one for cases in which military affiliation is disclosed in obituary notices after manager passing, but not prior to that. The first three variables represent subsets of military managers, while the Post-mortem placebo dummy covers additionally collected data. Panel B shows the estimates of net percentage fund flows regressed on the aforementioned variables. We use the same regression setup, including the standard set of control variables, as in the baseline specification (3) of Table II. Standard errors are double-clustered by fund and month-year and t-statistics are reported in parentheses.

Panel A: Univariate sorting	Fund flows			
	Military managers	Other managers	Difference	t-statistic
Investment media	0.025	0.010	0.014	3.52
Personal disclosures	0.028	0.010	0.018	6.27
Other sources	0.011	0.010	0.000	0.11
Post-mortem placebo	0.011	0.010	0.000	0.11

Panel B: Regression analysis	Dependent Variable: Fund flows			
	(1)	(2)	(3)	(4)
Investment media	0.006			
	(3.14)			
Personal disclosures		0.007		
		(4.39)		
Other sources			-0.001	
			(-1.00)	
Post-mortem placebo				-0.002
				(-1.39)
Controls	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.266	0.267	0.266	0.266
N of funds	2,412	2,412	2,412	2,412
Observations	170,371	170,371	170,371	170,371

Table VI. Managers' Military Background and Fund Flows: Team-Managed Funds
This table reports the estimates of the regressions with monthly net percentage fund flows as the dependent variable and military team indicator as the explanatory variable. The military team dummy takes the value of one if a fund management team includes a manager with prior military background in a given month and equals zero if there are no military-experienced individuals in a management team that manages a fund. The setup of the regressions includes the standard set of control variables (apart from manager-specific industry experience and fund tenure controls) and is otherwise identical to regression specifications of Table II. Specifications (3) and (4) additionally include interaction terms with the share of military-experienced managers in a management team and with three distinct information distribution channels (specified in Table V), respectively. Standard errors are double-clustered by fund and month-year and t-statistics are reported in parentheses.

	Dependent Variable: Fund Flows			
	(1)	(2)	(3)	(4)
Military team	0.000	0.000	-0.001	0.001
	(0.11)	(0.15)	(-0.39)	(0.25)
Military team share			0.003	
			(0.43)	
Military team × Investment media				0.001
				(0.35)
Military team × Personal disclosures				-0.001
				(-0.55)
Military team × Other sources				-0.001
				(-0.20)
Lagged fund flow		0.397	0.397	0.397
		(34.68)	(34.68)	(34.69)
Performance rank	0.012	0.009	0.009	0.009
	(12.91)	(14.34)	(14.33)	(14.33)
Fund risk	-0.284	-0.159	-0.159	-0.159
	(-10.63)	(-8.73)	(-8.73)	(-8.74)
Fund size	-0.000	-0.000	-0.000	-0.000
	(-1.03)	(-0.17)	(-0.16)	(-0.11)
Fund age	-0.008	-0.004	-0.004	-0.004
	(-18.63)	(-17.53)	(-17.52)	(-17.49)
Turnover ratio	0.001	0.001	0.001	0.001
	(3.48)	(3.29)	(3.28)	(2.28)
Expense ratio	0.048	0.022	0.022	0.019
	(0.63)	(0.47)	(0.47)	(0.40)
Family flow	0.294	0.211	0.211	0.211
	(15.76)	(14.66)	(14.67)	(14.64)
Segment FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.080	0.232	0.232	0.232
N of funds	2,019	2,019	2,019	2,019
Observations	184,183	184,183	184,183	184,183

Table VII. Fund Flows, Confidence in the Military, and Perceived Insecurity
This table relates fund flows to the nationwide confidence in the military and perceived insecurity. The table reports estimates of the regressions of monthly net fund flows on the military dummy for periods of high and low levels of confidence in the military, as classified based on the median level of Gallup's normalized confidence in the military index. Second, it shows the estimates of monthly net percentage fund flows regressed on the military dummy interacted with lagged firearm checks (NICS). The setup of the regressions is otherwise identical to the baseline specification (3) of Table II. Standard errors are double-clustered by fund and month-year, t-statistics are reported in parentheses.

	Dependent variable: Fund flows				
	Confidence in Military index		NICS FBI Checks		
	Periods (years) of low confidence	Periods (years) of high confidence	NICS FBI checks on purchases (1998/12-2017/12)	NICS FBI checks on purchases: Periods of pos. change	NICS FBI checks on purchases: Periods of neg. change
	(1)	(2)	(3)	(4)	(5)
Military	0.002	0.003	0.003	0.002	0.004
	(1.83)	(3.07)	(3.16)	(2.45)	(3.29)
Military × NICS			-0.003		
			(-2.70)		
NICS			-0.006		
			(-1.26)		
Controls	Yes	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.272	0.262	0.246	0.243	0.248
N of funds	2,104	2,059	2,267	2,252	2,206
Observations	89,966	79,746	136,025	81,432	53,826

Table VIII. Fund Flows and Managerial Changes

This table presents evidence on ordinary least squares estimates of the difference-in-differences design of equation (2). The dependent variable is monthly net fund inflows. The sample is restricted to funds with only one episode of change to single management over the period between 1991 and 2017. Treat is an indicator for funds that were ever managed by individuals with military background. Post indicator takes the value of one if a fund is solo-managed, and zero if a fund is team-managed in a given month. Columns (3) to (5) present evidence on the timing of the effect of managerial turnover on fund flows by presenting estimates from a modified version of equation (2). Pre1 and Pre2 are indicator variables for observations one and two months prior to the managerial turnover, respectively. Post1, Post2, and Post3 are indicator variables for observations one, two, and three months, respectively, after the managerial turnover. Post0 is an indicator variable for observations that occur during the months of managerial turnover. Controls include: performance rank; fund size; fund risk; fund age; turnover ratio; expense ratio; and family flows. All control variables, except family flows, are lagged by one month and are defined in Table I and in Appendix A. Segment is defined by the Morningstar fund style indicator. Period FE stands for month-year fixed effects. Standard errors are double-clustered by fund and month-year and t-statistics are reported in parentheses.

	Dependent Variable: Fund Flows				
	(1)	(2)	(3)	(4)	(5)
Treat_i	0.001	0.002			
	(0.76)	(1.24)			
$\text{Treat}_i \times \text{Post}_t$	0.006	0.002			
	(7.24)	(2.48)			
$\text{Treat}_i \times$ Pre2			0.004		0.004
			(0.34)		(0.34)
$\text{Treat}_i \times$ Pre1			0.005		0.005
			(0.33)		(0.33)
$\text{Treat}_i \times$ Post0			0.057		0.057
			(3.66)		(3.66)
$\text{Treat}_i \times$ Post1				0.034	0.046
				(3.16)	(3.16)
$\text{Treat}_i \times$ Post2				0.029	0.029
				(2.89)	(2.90)
$\text{Treat}_i \times$ Post3				0.027	0.027
				(2.18)	(2.18)
Controls	No	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.033	0.088	0.078	0.078	0.078
N of funds	1,684	1,619	1,619	1,619	1,619
Observations	210,749	197,484	197,484	197,484	197,484

Table IX. Flow-Performance Relationship

The dependent variable is monthly net percentage fund flows. The independent variables include the military dummy and its interaction terms with lagged performance variables. The setup of the regressions is otherwise identical to the baseline specification (3) of Table II and includes the standard set of control variables. Standard errors are double-clustered by fund and month-year, t-statistics are reported in parentheses.

	Dependent Variable: Fund Flows			
	(1)	(2)	(3)	(4)
Military	0.004	0.010	0.012	0.011
	(3.44)	(2.30)	(2.75)	(2.48)
Military × Performance rank	0.010	-0.024	-0.031	-0.025
	(6.10)	(-1.94)	(-2.50)	(-2.05)
Military × Performance rank^2		0.016	0.020	0.016
		(2.04)	(2.57)	(2.10)
Performance rank^2		0.011	0.010	0.012
		(5.34)	(4.98)	(5.66)
Performance rank	0.012	-0.005	-0.004	-0.006
	(15.68)	(-1.62)	(-1.36)	(-1.84)
Controls	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	No
Segment FE	Yes	Yes	Yes	No
Family FE	No	No	Yes	No
Segment×Period FE	No	No	No	Yes
Adj. R-squared	0.266	0.267	0.276	0.271
N of funds	2,412	2,412	2,406	2,064
Observations	170,371	170,371	170,363	169,857

Table X. Microlevel Evidence From an Online Experiment

This table presents results of the Amazon Mechanical Turk online investment experiment. Panel A shows the fraction of money invested in fund A if it is managed by a military-experienced manager or by a manager without such experience, the difference between the amounts invested, and the respective t-statistic. All participants have identified themselves as U.S. mutual fund investors. Panel B shows the estimates of money invested in fund A regressed on a Military fund dummy variable and participant demographic characteristics. The Military fund indicator takes the value of one for funds which are randomly assigned to be military-managed and zero otherwise. Controls include a gender dummy and a dummy for old investors (above median biological age). Columns (1) and (4) present results for the full sample of subjects. Columns (2) and (3) present results for the two subsamples by self-reported participant party affiliation, namely Democrats and Republicans. t-statistics are reported in parentheses.

Panel A. Average distributions (Rounds including military managers)

	% of funds allocated to fund A if		Difference	
	military manager	nonmilitary manager	(mil. - nonmil.)	t-statistic
Round 2	63.04	59.50	3.54	1.96
Round 4	13.36	10.18	3.17	5.55
Round 2 + Round 4	38.20	34.84	3.36	2.20

Panel B. Regressions (Rounds including military managers)

	All subjects	Democrats	Republicans	Interactions
	(1)	(2)	(3)	(4)
Military fund	3.36	4.32	4.53	0.68
	(2.20)	(1.72)	(1.89)	(0.27)
Female × Military fund				0.08
				(0.98)
Old × Military fund				5.42
				(1.77)
Adj. R-squared	0.01	0.01	0.01	0.01
Observations	1,608	610	658	1,608

Table XI. Ex-Military Managers and Window Dressing

This table relates manager's military background to window dressing activities. The dependent variable is either Rank Gap or Backward Holding Return Gap (BHRG). The main independent variable is the military dummy that equals one if a fund is single-managed by an individual with a military background in a given month, and zero if the manager does not have a military background. Rank Gap is the difference between a fund's performance rank and the two ranks based on winner and loser stock proportions in the reported holdings. BHRG is calculated as the difference between the net return of a hypothetical portfolio (based on the fund's holdings in the previous quarter) and the fund's actual return. The set of control variables is comprised of variables described in Table I and in Appendix A. All of the regression specifications include period and segment fixed effects. Period FE stands for quarter-year time fixed effects. Standard errors are based on clustering at the fund level. The corresponding t-statistics are reported in parentheses.

	Full Sample		Bottom 20% perf.		Top 20% perf.	
	Rank Gap	BHRG	Rank Gap	BHRG	Rank Gap	BHRG
Military	-0.024	-0.006	-0.018	-0.009	-0.020	-0.010
	(-2.96)	(-1.68)	(-1.82)	(-2.63)	(-1.83)	(-2.90)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.198	0.059	0.216	0.088	0.191	0.119
N of funds	924	924	695	695	678	678
Observations	10,388	10,388	2,134	2,134	2,319	2,319

Table XII. Matching Funds

This table reports results of the matched sample analysis. In specification (1), we report the baseline regression results. In the following specifications, we keep the regression setup, but estimate regressions on various samples of matched funds. To identify a match for a military-managed fund, we find a nonmilitary-managed counterpart fund based on the similarities of the set of matching criteria in a given month. We use the following matching criteria: manager's gender, foreignness of a name, biological age, industry experience, and fund's segment, family, size, age, performance, expense ratio, turnover, and the share of marketing expenses (NSAR-B filings) in total expenses. The first matching procedure identifies nonmilitary funds as a match if values of the non-categorical variables are in the range of five percent from the military-managed counterpart fund values in a given month. In these regressions, the set of control variables is identical to the baseline specification and standard errors are double-clustered by fund and month-year. The table also reports the estimates of the propensity score nearest neighbourhood matching (the second matching procedure) on the set of fund characteristics and t-statistics based on the bootstraped standard errors.

		Dep. Variable: Fund Flows		
		Coefficient	t-stat.	Obs.
(1)	No Matching (Table II, Specification 3)	0.003	3.20	170,371
Matching fund and manager characteristics:				
(2)	Time and gender	0.003	3.20	155,767
(3)	Time, gender, and foreign name	0.002	2.63	110,348
(4)	Time, gender, and segment	0.003	3.21	155,109
(5)	Time, gender, segment, and fund family	0.004	2.73	25,612
(6)	Time, gender, segment, and fund size	0.004	3.12	140,866
(7)	Time, gender, segment, and fund age	0.003	3.25	143,179
(8)	Time, gender, segment, and manager age	0.003	3.62	135,813
(9)	Time, gender, segment, and manager tenure	0.002	2.81	139,729
(10)	Time, gender, segment, and performance	0.003	2.26	20,934
(11)	Time, gender, segment, and marketing exp.	0.004	3.22	83,833
Propensity score matching on the following fund characteristics:				
(12)	Perf., and size	0.007	9.78	47,225
(13)	Perf., size, and expense ratio	0.006	6.85	26,103
(14)	Perf., size, expense ratio, and turnover	0.006	7.15	26,030
(15)	Perf., size, expense ratio, turnover, and age	0.005	6.49	25,962
(16)	Perf., size, expense ratio, turnover, age, and lagged flows	0.003	3.13	25,891

Table XIII. Alternative Dependent Variable Definition

This table reports results for the alternative measures of fund flows as dependent variables. We use absolute dollar flows and the change of a fund's market share as in Spiegel and Zhang (2013) instead of relative flows as dependent variable. Specifications (1) and (2) report the regression estimates of monthly absolute dollar flows on the military dummy. These specifications differ in fixed effects applied, but the regression setup is otherwise identical to the baseline specification of Table II and includes the standard set of control variables. Specification (3) reports regression estimates of the change of a fund's market (i.e., segment) share on the military dummy. We use quantile regressions to estimate the coefficient and also include the standard set of controls and fixed effects. For presentation purposes, we report the coefficient of change in a fund's market share as multiplied by 100. Standard errors are double-clustered by fund and month-year, t-statistics are reported in parentheses.

	Modified Dependent Variable		
	Absolute fund flows		Change in fund's market share
	(1)	(2)	(3)
Military	3.294	3.472	0.003
	(1.88)	(2.02)	(5.15)
Controls	Yes	Yes	Yes
Segment FE	Yes	No	Yes
Period FE	Yes	No	Yes
Segment × Period FE	No	Yes	Yes
R-squared (Pseudo R^2)	0.067	0.070	0.200
N of funds	2,412	2,412	2,412
Observations	170,371	170,371	170,371

Table XIV. Fund Performance and Persistence

This table shows additional results for fund performance and performance persistence of military managers vs. nonmilitary managers. Panel A reports results from a regression with the equal-weighted return of a difference portfolio that is long in all funds that are single-managed by an individual with military background and short in all funds with nonmilitary managers as the dependent variable. The portfolio is rebalanced on a monthly basis. Estimates of fund performance are measured using the capital asset pricing model (column (1)), the Fama and French (1993) three-factor model (column (2)) and the four-factor model of Carhart (1997) in column (3). Results for both net and gross (before expenses) performance are reported. Panel B shows results for the average time-series standard deviation of monthly performance ranks of military and nonmilitary managers along with the differences between the group means. The corresponding t-statistics are in parentheses and are based on robust standard errors.

Panel A: Fund Performance: Military – Nonmilitary				
		CAPM_t^{m-n}	$\text{Three-Factor}_t^{m-n}$	$\text{Four-Factor}_t^{m-n}$
		(1)	(2)	(3)
Net performance				
	Alpha_t	0.000	0.000	0.000
		(0.38)	(1.50)	(1.49)
	R-squared	0.012	0.202	0.202
Gross performance				
	Alpha_t	0.001	0.001	0.001
		(1.03)	(1.24)	(1.22)
	R-squared	0.009	0.208	0.208

Panel B: Performance Persistence			
	Military managers	Nonmilitary managers	Difference
Persistence^{net}	0.279	0.281	-0.002
$\text{Persistence}^{gross}$	0.269	0.275	-0.006

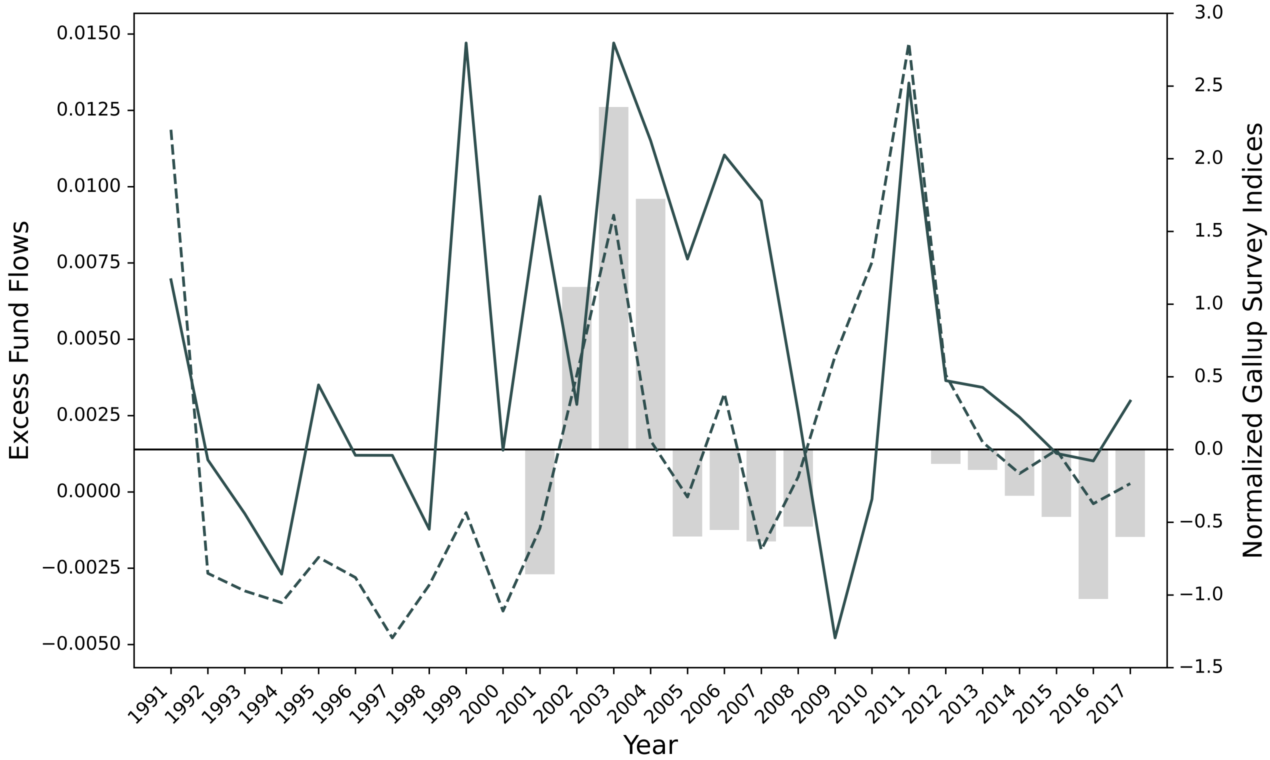

Figure 1. Difference in fund flows and confidence in military. Graph plots the time series of difference in fund flows between the funds that are single-managed by military managers and nonmilitary managers (solid line) and the dynamics of Gallup's normalized confidence in the military index (dashed line). Bars indicate the values of normalized satisfaction with the nation's military strength and preparedness (Gallup's Survey).

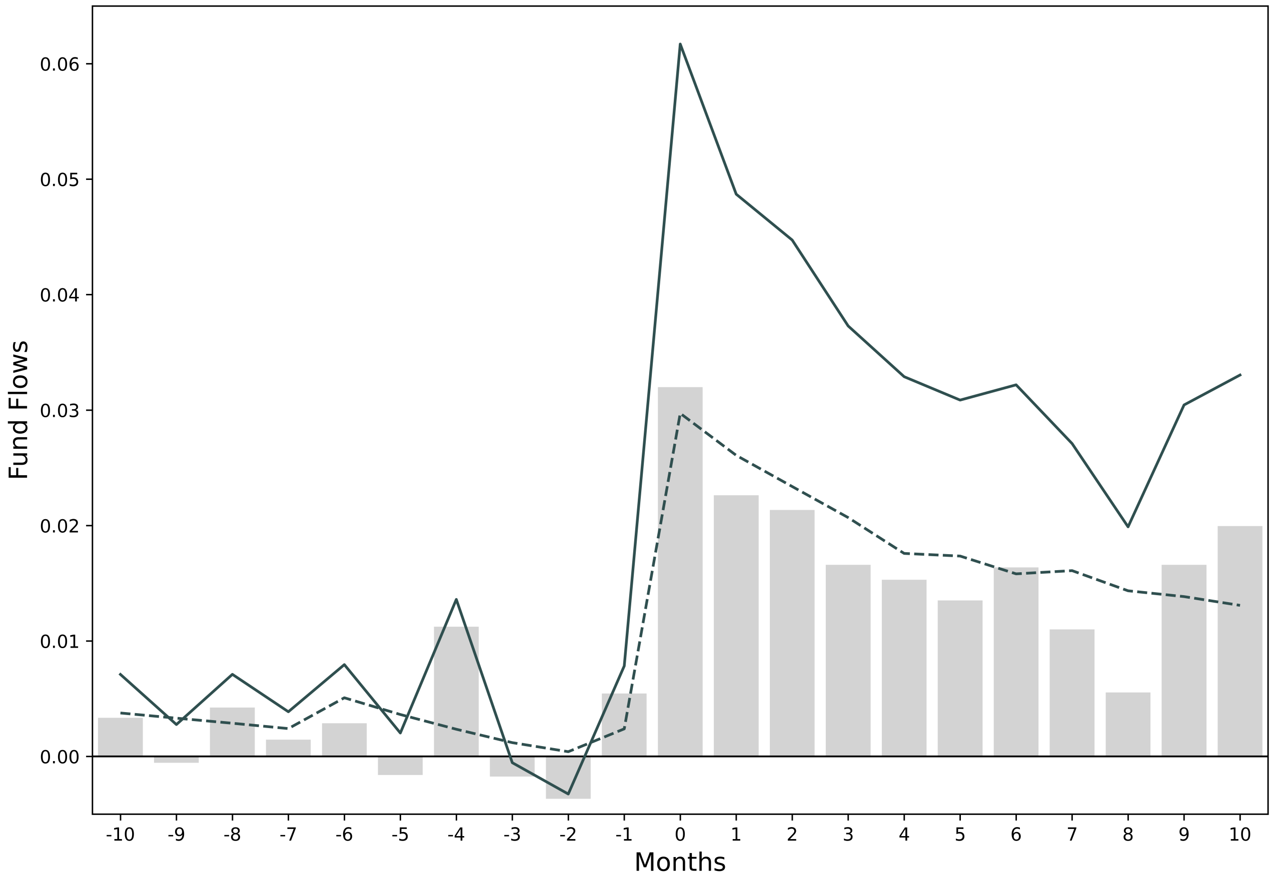

Figure 2. Dynamics of average monthly net inflows into military-managed funds vs. nonmilitary-managed funds. Graph plots the dynamics of net fund flows of funds that become single-managed by military managers (solid line) and the dynamics of net fund flows of funds that shift to single-management by nonmilitary managers (dashed line). Bars indicate the difference in net inflows between the two groups. Date zero is the month of manager change.

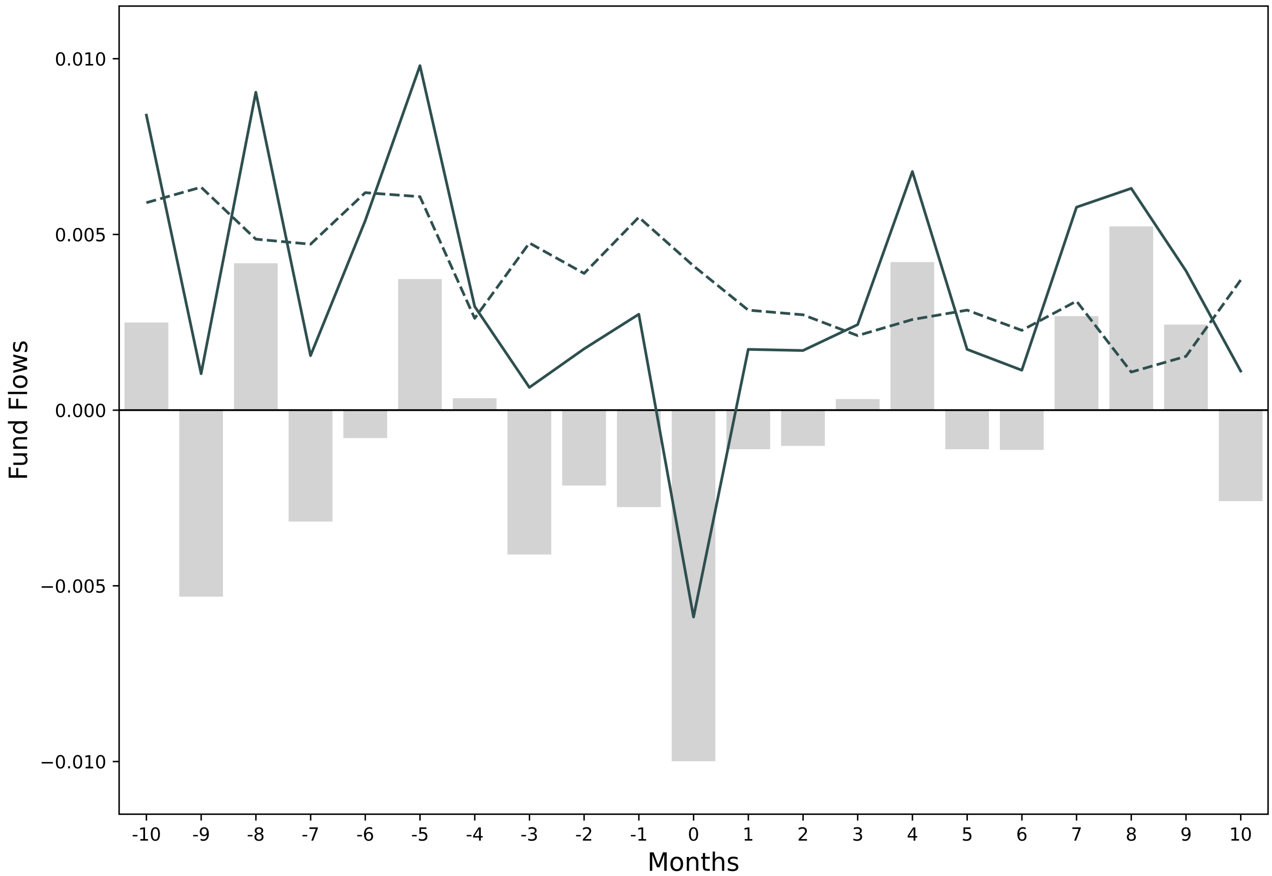

Figure 3. Dynamics of average monthly net inflows into military-managed funds vs. nonmilitary-managed funds around the dates of management change. Graph plots the dynamics of net fund flows of funds with leaving military managers (solid line) and nonmilitary managers (dashed line). Bars indicate the difference in net inflows between the two groups. Date zero is the month of manager change.

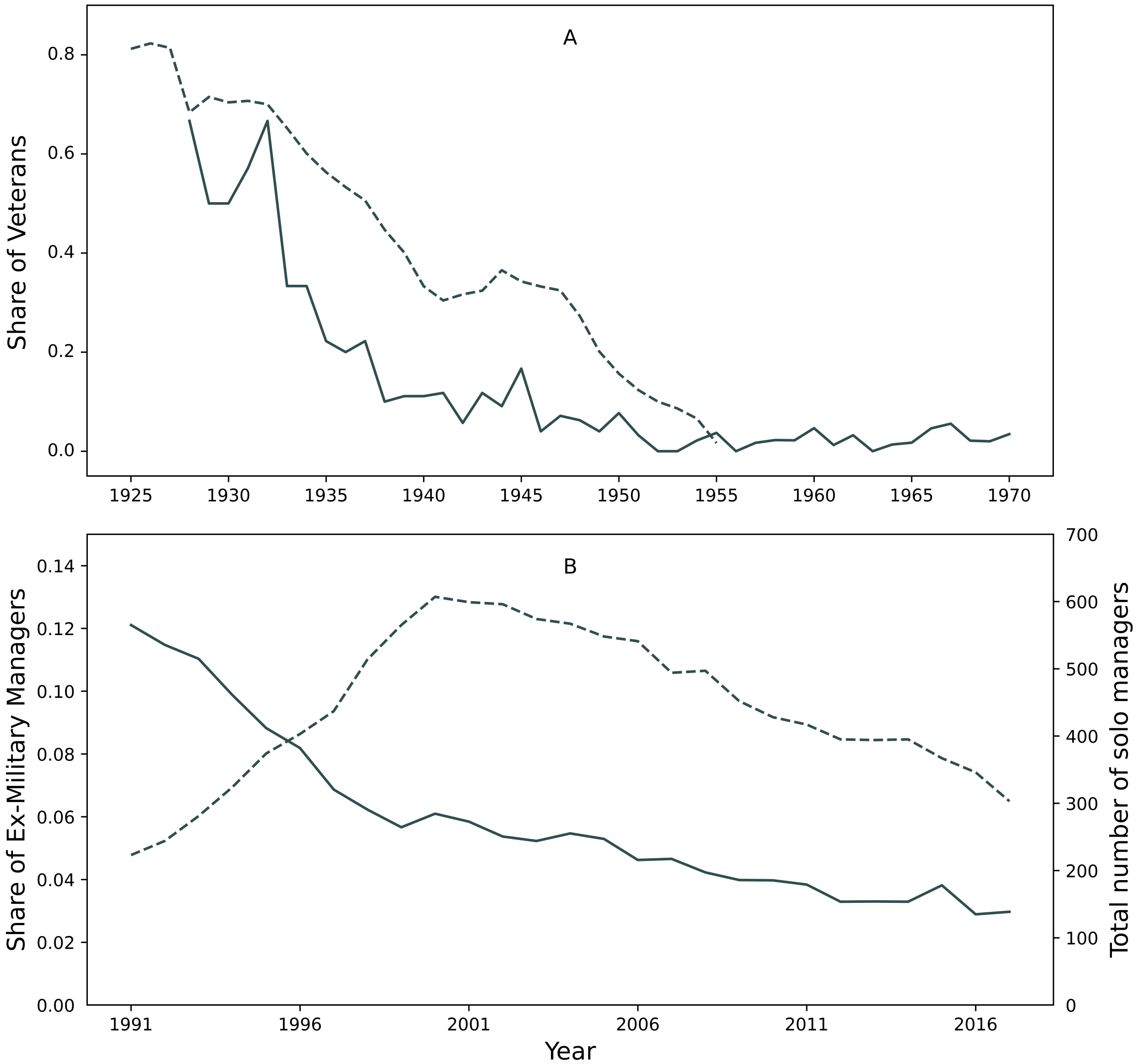

Figure 4. Share of veterans. A, among fund managers by birth cohort, 1925-1970. B, among fund managers by year, 1991–2017. Graph A depicts the share of veterans among all of the solo mutual fund managers in our sample by birth cohort (solid line) and the share of educational attainment (college level) of the veteran population using data from 3% of the 1980 decennial census, restricted to white males. Graph B plots the share of military managers who single-managed at least one U.S. equity mutual fund for at least one full month (solid line) in a given year and the total number of solo managers (dashed line) by year.

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 and 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. The documented ancestral biases are pervasive across fund styles and across different manager ancestries. The effect is more pronounced for funds that are less resource-constrained and for managers whose connection to their ancestral home country is more recent. Stocks linked to managers' ancestry do not outperform stocks in the same countries and industries but held by managers of other ancestry, confirming that ancestry-linked investments are not informed.

JEL classification: G11, G41.

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

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The home bias phenomenon is well-documented in equity holdings around the world (French and Poterba (1991); Tesar and Werner (1995); Kang and Stulz (1997)). Similarly, local bias in domestic portfolios tends to favor nearby firms (Coval and Moskowitz (1999); Grinblatt and Keloharju (2001); Ivković and Weisbenner (2005); Seasholes and Zhu (2010)). In the literature, it has long been subject to debate 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. Yet, Pool, Stoffman, and Yonker (2012) show that US mutual fund managers exhibit a familiarity bias in their portfolio allocation decisions toward their home states. In this article, our unique sample allows to specify familiarity bias more precisely and to analyze the persistence of familiarity bias in portfolio choice.

In testing whether familiarity plays a role in the portfolio choices of professional managers, we face the same challenge as Pool et al. (2012), 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. Extending the line of reasoning in Pool et al. (2012) and exploiting the fact that the U.S. is a nation of immigrants, we argue that firms headquartered in a fund manager's ancestral home country satisfy these criteria. Specifically, we argue that a manager who is socialized in the U.S. [1] but 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. 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. 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 a variety of backgrounds that differ from the fund manager's ancestry.

To investigate the role of this ancestry-induced familiarity bias in portfolio decisions, we proceed in two steps. 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

[1] We consider managers to be socialized in the U.S. if they are U.S. born or received at least one college degree from a U.S. institution.

"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 to be 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 that are headquartered in their ancestral home countries compared to 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 "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 "ancestral industry bias". Our findings are robust to the inclusion of fund fixed effects, which enables us to identify the effect using within-fund variation only.

In the cross-section, we find further support for an ancestry-induced familiarity bias in portfolio decisions. 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, though, our results suggest a strongly persistent familiarity bias, as even managers with centuries-old connections to their ancestral home country exhibit this overweighting. We also find that the bias is pervasive across different ancestries.

When investigating the types of 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 larger for stocks that resemble national identity and have a longer 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 (2020) 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, lending support to 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. The concept of culture is broad, however, 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 unique 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 provides novel evidence of cultural preferences and their persistence.

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 that specialize in foreign equity are likely to be managed by managers who were not socialized in the U.S. In line with Jagannathan et al. (2020), 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. (2020) 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.[2] 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.[3]

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 (2015), 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 aforementioned filters, 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. To

[2]Jagannathan et al. (2020) define a manager's home country according to the country where the manager earned his or her bachelor's degree.

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

properly evaluate investment decisions, we restrict our sample to managers with at least 12 consecutive fund-month observations. 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.[4] 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 Thomson Reuters, which includes only holdings identified by CUSIP, MS Direct data also include positions without CUSIP (i.e., mostly 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. For the 2,357 fund managers who pass these criteria and whose funds were successfully matched, we initiate the following data collection process.

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 at 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

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

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.[5] 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 in which 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 surnames following marriage, which makes it difficult to apply our search algorithm to identify the fund manager's maternal ancestry.[6] 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, 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

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

[6]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.

using investment advisor and broker registration records from the Financial Industry Regulatory Authority (FINRA). These records include currently and previously registered investment advisers, as well as 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 by using the full name and exact date of birth. As birth records are issued by each state's health department, 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 names of the bride's and groom's parents. We establish a unique match by checking the bride's and groom's name and birth date. 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, who are 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 number of funds and aggregate TNA, is Large Growth, with an average of 54 funds each month and 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 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 fairly dispersed across the globe. Yet, most fund managers can trace back 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.[7] 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 at all 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 toward 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.

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 indicates that our results do not merely reflect the standard home bias. Later in this paper, we show that the result on the relation between fund managers' ancestry and their country weightings remains unaltered after controlling for several other factors, such

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

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;[8] $MorningstarBMWt_{i,c,t}$ 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. 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 manager overweights stocks from his or her ancestral home country by 132 bps compared with other solo

[8]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.

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.[9] 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

[9]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. (2020), we find an even more pronounced ancestral home country bias of nearly 30%.

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.[10] 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.

B. Ancestral Industry Bias

Although the ancestral home country overweighting we find has high relative and statistical significance, its absolute economic magnitude is arguably low. 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. By limiting the sample to U.S. equity holdings, we ensure 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).[11] 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

[10]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.

[11]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.

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 the largest, three largest, and five largest industries in terms of market share when compared to the global average.[12] 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.[13] 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 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

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

[13] 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.

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; $Rank1Hm$ $Industry_{i,s,t}$, $Rank2HmIndustry_{i,s,t}$, 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).[14]

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

[14]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.[15] 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 differ-

[15] 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.

ence 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 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.[16] 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 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 ances-

[16] 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.

tral 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.[17] 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.

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

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

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

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").[18] 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 ("heritage stocks") may be more likely to be associated with a certain country. Results indicate

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

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?

Results in the previous section show 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, then performance implications will depend on whether managers have any skill in general. In case managers have skill, familiarity will negatively affect 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 that are headquartered in the fund manager's ancestral home country. We closely follow Jagannathan et al. (2020) 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.[19]

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

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

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 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.[20]

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 any ancestry. These numbers imply that most Americans know from which countries their families immigrated to the U.S.[21] 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

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

[21] 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.

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.[22] We further define $MgrAncestryProfile$ as a dummy equal to one if a fund manager has an account on Ancestry.com.[23]

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 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:[24] 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

[22]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.

[23]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.

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

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 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.[25]

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.

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

[25] 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).

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 advances and tests new hypotheses linking investors' ancestry to investment 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. Recent literature suggests that culture affects preferences and belief formation. Our paper offers novel evidence on whether ancestry influences portfolio choice.

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 funds that are less resource-constrained 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, which supports a familiarity bias, rather than 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 pricing 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		
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
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
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
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

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Table A.I – continued from previous page.

Variables	Description	Source
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
Rank1HmIndustry$_{i,s,t}$ 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
MorningstarBMWt$_{i,c,t}$, 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		
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
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
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
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

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Table A.I – continued from previous page.

Variables	Description	Source
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
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, 2015, Managerial multitasking in the mutual fund industry, CFR Working Papers 13-10 [rev.], University of Cologne, Centre for Financial Research (CFR).

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, 2020, Is there a home field advantage in global markets?, Working Paper, Binghamton University and Cornell University.

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*, CIKM '17, 1897–1906 (ACM, New York, NY, USA).

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

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

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

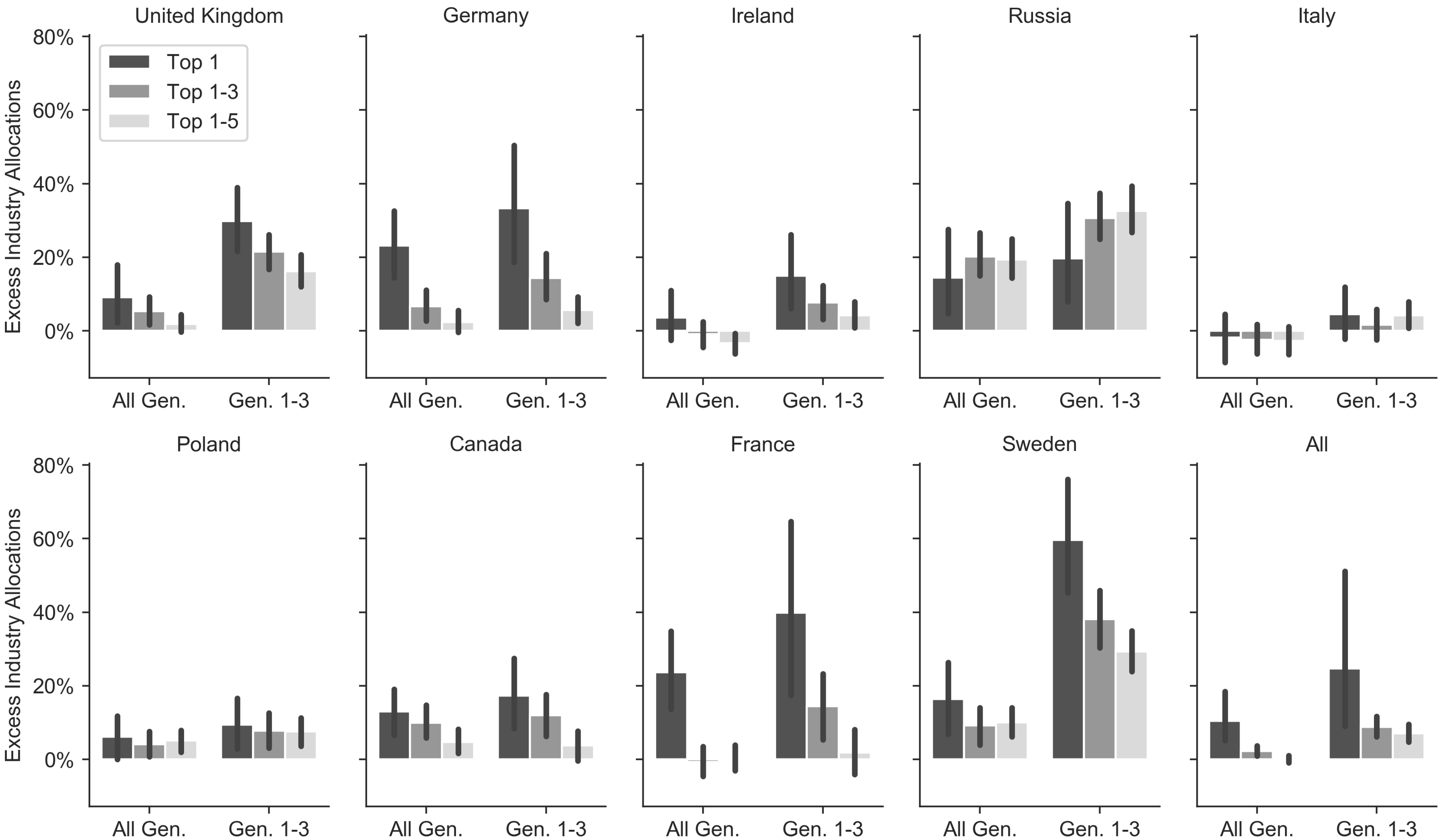

Figure 1. Excess allocations to U.S. industries that are among the top industries in the ancestral home country, across managers' ancestral origin and immigrant generation. This figure displays funds' average excess portfolio allocations to U.S. industries that are among the largest (Top 1), three largest (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.

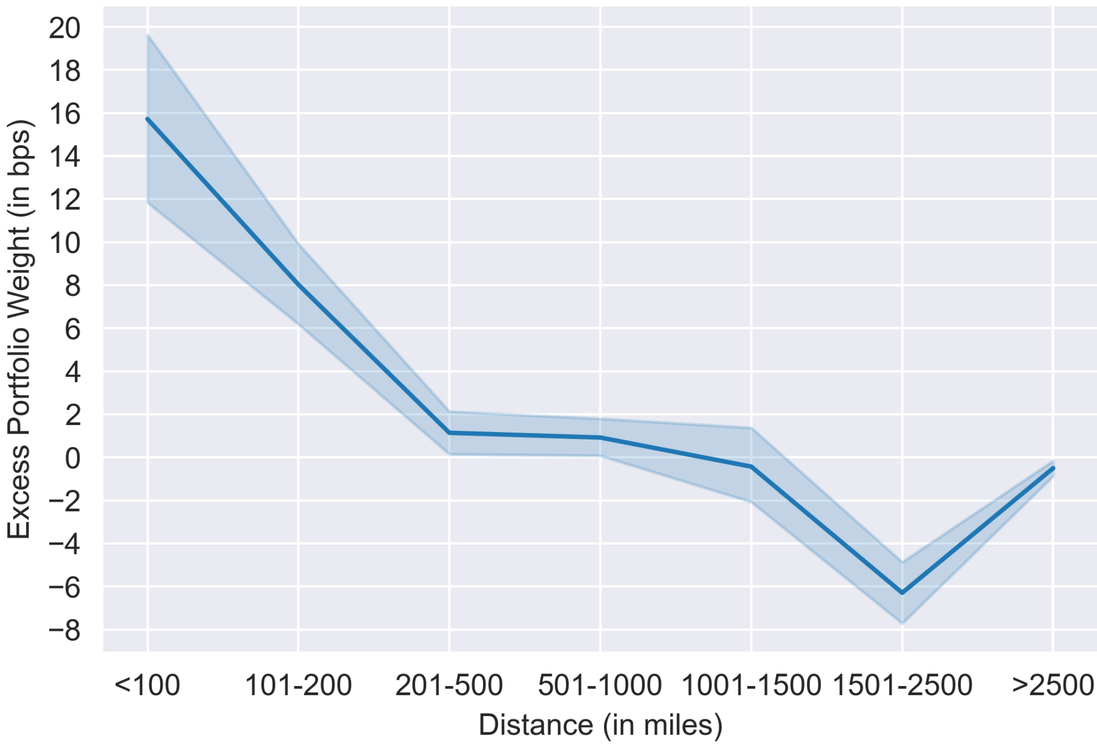

Figure 2. Excess portfolio weights by distance from managers' ancestral home country. This figure relates average excess weights in stocks to the geographical distance between stock issuer location and fund managers' ancestral home countries. Observations are at the fund-month-stock level. Stock issuer 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.

Jumping on the ESG Bandwagon: The Effect of ESG-Related Fund Name Changes on Fund Flows*

ALEXANDER COCHARDT†

ABSTRACT

This paper exploits variation in mutual fund names and examines whether fund firms take advantage of the environmental, social, and governance (ESG) topic to market their funds. I analyze 2,292 ESG-related fund name changes between 2005 and 2021 and their effect on fund flows, portfolio holdings, and subsequent fund returns. I find that one year after changing their name to include ESG terms, funds experience an average cumulative abnormal flow of 13.87%, while performance is not improved. On average, funds' asset-weighted ESG scores increase, which provides evidence that funds deliver on the promise implied by their name change. However, flow increase in retail fund share classes is similar across name-change funds irrespective of ESG score improvement, suggesting retail investor irrationality and greenwashing risk.

JEL classification: G11, G41.

Keywords: ESG, Greenwashing, Mutual Funds, Fund Flows, Investor Irrationality

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Environmental, social, and governance (ESG) investing, i.e., investment strategies that incorporate ESG criteria when investing in firms, grew substantially in the last decade. About one in three dollars under professional management in the U.S. – approximately $12 trillion – is invested according to sustainable investment strategies (US SIF Foundation (2020)). Recent market surveys suggest that the upward trend in the sustainable investment sector is likely to continue, as 85% of investors express interest in sustainable investments.[1] This makes ESG a variable of growing importance within investors' decision-making process.

As a response to investor demand, fund firms are increasingly offering ESG or "sustainable investing" funds.[2] In doing so, with ESG-investing lacking a clear and agreed upon definition (Chen and Mussalli (2020)), fund firms may face a temptation to seem ESG-conscious while their investment strategy does not justify an ESG label.[3] In this paper, I study one of the most natural ways for fund firms to engage in such greenwashing:[4] by including ESG buzzwords in their funds' names. Specifically, I analyze fund name changes in the mutual fund industry if a fund's new name is different from the old name by a certain identifier, e.g., "social" or "sustainable".[5]

In the past, fund firms have been shown to cosmetically change fund names in an effort to attract higher investor flows. Cooper, Gulen, and Rau (2005) find that fund firms take advantage of current hot investment styles, such as "value" or "growth", by renaming their funds to reflect an according orientation without changing the portfolio managed by the fund. Even after the U.S. Securities and Exchange Commission (SEC) introduced Rule 35d-1 (or "Names Rule") in 2001 to regulate misleading mutual fund names, Espenlaub, ul Haq, and Khurshed (2017) find that cosmetic name changes remain widespread. In the context of ESG, the applicability of the Names Rule, which requires a fund to invest at least 80% of its assets in the type of investment suggested by its name, remains unclear.[6] Acknowledging this problem, in March 2020, the SEC issued a request for public comment on potential changes to the Names

[1] The study can be found in Morgan Stanley's 2020 edition of the Sustainable Signals series, "Individual Investor Interest Driven by Impact, Conviction and Choice".

[2] As of Q4 2020, Morningstar's "Sustainable Landscape Global Funds" list counts 5'061 fund share classes, compared to just 2'446 in 2014.

[3] Interestingly, Reiser and Tucker (2019) document a large variation in investment strategies, portfolios, and voting records across ESG funds.

[4] Greenwashing generally describes when companies mislead their clients about the ESG-related benefits of their products and services. See Delmas and Burbano (2011) for a discussion on the drivers of greenwashing and its increased incidence.

[5] To cater to the increased attention paid to ESG, fund firms generally may either launch new funds or rebrand their conventional funds. As suggested in a report by Morningstar (Hale (2021)), a sizable fraction of the newly offered ESG funds stem from the transformation of already existing funds.

[6] The period for public comment ended in May 2020. At the time of writing, the SEC has not taken follow-up actions to its initial request. As of today, there is no indication that the Names Rule will be expanded to ESG investing in the foreseeable future. In the EU and the U.K. there are no current plans to implement a names rule addressing ESG. However, effective March 10, 2021, the EU requires financial firms that have investors in the EU to disclose how ESG issues could affect the value of their portfolios and what impact their investments have on the wider world, e.g., carbon emissions of companies held by the fund.

Rule. Hence, analyzing ESG-related fund names may prove useful for future debate.

How prevalent are such ESG-related name changes? Since most growth in ESG-investing, especially in the U.S., occured over the past few years, prior reports on name changes are limited to anecdotal evidence (e.g., Robins (2018); Stuart (2020)). I am able to identify a sample of 299 U.S.-domiciled and 1,993 non-U.S. domiciled equity mutual fund share classes that undergo an ESG-related name change over the period from January 2005 to February 2021.

To investigate fund firms' renaming practices with respect to ESG, I proceed in three steps. First, I analyze which funds are involved in ESG-related name changes and what effect such name changes have on flows in and out of the funds. Second, I examine whether the new name reflects fund portfolio holdings using common ESG scores. Third, I assess whether flows following the name change are sensitive to changes in ESG scores.

I posit that investors at least partly rely on a fund's name when determining whether funds are committed to ESG topics. Due to its difficult-to-grasp character, ESG likely increases the already high complexity of purchase decisions in the mutual fund marketplace. As shown in Del Guercio and Tkac (2008) and Evans and Fahlenbrach (2012), mutual fund investors, especially retail investors, resort to clearly displayed information when making purchases. Naturally, a fund's name is among the most prominently visible fund characteristics available to investors. Other ways to assess a fund's ESG-orientation have long been associated with costly search, since ESG information was only available at the portfolio company level. With its introduction in March 2016, Morningstar's Sustainability Rating represents the first freely accessible fund-level information on ESG next to a fund's name (Ammann, Bauer, Fischer, and Müller (2019)).

If investors infer a fund's ESG orientation from its name, ESG-related name changes should have an impact on fund flows. As investors marketwide are documented to value sustainability (Hartzmark and Sussman (2019)), I expect a positive flow effect when funds rename to include ESG terms. Using a panel regression framework and an event study with a control sample of propensity-score matched funds, I find that funds earn significantly positive abnormal flows of over 13% in the year after incorporating ESG terms in their names. Funds that replace an existing ESG term in their names with a new ESG term also garner abnormal flows, whereas funds that are no longer labeled with ESG terms exhibit negative but insignificant abnormal flows. In the cross-section, I find that both retail and institutional investors react favorably to the inclusion of ESG terms in fund names.

I provide additional evidence that investors are likely to pay attention to ESG terms in fund names when choosing among funds. First, results from an online survey conducted among mutual fund investors suggest that the majority of investors generally take into account information in fund names when they are investing. Second, I ask participants (U.S. mutual fund investors) in an online fund investment experiment to allocate money between two funds.

While keeping all other fund information constant, I randomly assign an ESG-term to a fund's name. Results indicate that participants invest significantly more money into a fund when its name is ESG-related.

Do funds deliver on the promise implied by their name change? Repurposing funds toward ESG-investing is likely associated with costs, for example, developing expertise to assess the compliance of a particular portfolio investment (e.g., Kempf and Osthoff (2008); Van Duuren, Plantinga, and Scholtens (2016)). On the other hand, greenwashing may entail risks of civil lawsuits and criminal charges (e.g., Delmas and Burbano (2011)). I find that funds exhibit a surge in turnover ratios by between 8 and 11 percentage points in the year after being branded as ESG. At the same time, asset-weighted ESG metrics significantly improve, which provides evidence that, on average, these name changes are not cosmetic but involve ESG-oriented portfolio rebalancing. However, funds that merely switch from one ESG-related name to another show no signs of significant portfolio adjustments.

To test whether fund investors are able to differentiate between cosmetic and noncosmetic name changes, I sort funds whose new name includes an ESG term by their post-name-change ESG score improvement. Flow reactions of retail investors to the name changes do not significantly differ between below- (cosmetic) and above-median (noncosmetic) funds. In contrast, institutional investors seem to effectively screen for funds that are committed to ESG and direct their flows to these funds.

Taken together, my results are consistent with a simple story. Fund firms reposition their conventional and less attractive funds with an ESG-label to benefit from increased fund flows. ESG score improvements suggest that, on average, funds deliver on their label's promise, while it seems difficult for retail investors to determine funds' ESG commitment, leaving room for greenwashing.

This paper is most closely related to the literature on the effect of fund names on fund flows. Next to names that reflect currently hot investment styles (Cooper et al. (2005)), other fund name characteristics have been found to attract fund flows. Investors allocate more capital to fluently named funds and to funds whose names are positioned at the beginning of alphabetical listings (Green and Jame (2013); Jacobs and Hillert (2016)). Consistent with these papers, I show that investors pay attention to ESG-related fund name changes resulting in increased fund flows. Also, funds receiving abnormal flows irrespective of ESG score improvements corroborates prior evidence that investors are irrationally influenced by cosmetic effects.

The paper further contributes to the growing strand of literature on sustainable investing. Most of this literature studies the link between stock or fund performance and ESG criteria (e.g., Filbeck, Gorman, and Zhao (2009); Capelle-Blancard and Monjon (2014)). More recent research focuses on the effect of sustainability on fund flows and on the use of sustainability information in investment decisions. Ammann et al. (2019) provide empirical evidence for increasing investor attention paid to sustainable investments. Investors seem to positively react to the introduction of Morningstar's fund sustainability ratings. Riedl and Smeets (2017) find that both social preferences and social signaling explain why investors hold socially responsible mutual funds and are willing to forgo financial performance. Experimental evidence in Hartzmark and Sussman (2019) suggests that investors view sustainability as a predictor of future performance. I provide another piece of evidence that investors attach value to ESG. Addressing the relationship between ESG-names and investment demand is uncharted territory. Studies on ESG labels in other industries have shown that such labels generally lead to increased demand for labeled products and services (e.g., Bjørner, Hansen, and Russell (2004)).

More broadly, my study adds to the literature on agency problems in the mutual fund industry. Funds have been shown to engage in attempts to deceive investors about their performance (e.g., Brown and Goetzmann (1997)), effective portfolio holdings (e.g., Agarwal, Gay, and Ling (2014), and activeness (e.g., Cremers and Petajisto (2009)). To test whether funds mislead their investors regarding ESG-orientation, prior literature relies on the comparison between ESG and conventional funds (e.g., Kempf and Osthoff (2008). Focusing on name-change events allows to analyze within-fund variation of ESG-relevant metrics.

The remainder of the paper proceeds as follows. Section I describes the data set, the data collection process, and provides basic statistics. Section II focuses on the determinants of ESG-related fund name changes and their effect on fund flows. Section III investigates turnover and ESG score patterns around ESG-related name-change events. Section IV presents supplementary analyses, followed by Section V that concludes the paper.

I. Data and Sample Construction

A. Mutual Fund Data

My initial sample contains the whole universe of equity mutual funds covered by the Morningstar Direct Mutual Fund Database (MS Direct). I restrict the sample to the time period between January 2005 and February 2021, as the term ESG investing was first coined in 2005 (UN Global Compact (2004)). I include defunct and active fund share classes to overcome a potential survivorship bias. The sample is limited to actively managed equity funds (i.e., I exclude index funds and funds that focus on bonds, commodities, and alternative assets). I restrict the sample to equity funds because I later calculate ESG portfolio metrics based on company-level ESG data that are rarely available for other asset classes (see Section IC).

The main variable of interest in the empirical analysis is net fund flows. One does not observe flows directly, so I infer flows from fund returns and total net assets (TNA). Following standard practice in the literature (e.g., Sirri and Tufano (1998); Sapp and Tiwari (2004);

Frazzini and Lamont (2008)), I compute flows $F_{i,t}$ for fund i in month t as

$$F_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}}{TNA_{i,t-1}} - r_{i,t}, \tag{1}$$

where $TNA_{i,t}$ is fund i's TNA in month t and $r_{i,t}$ stands for fund i's net return in month t. This measure reflects the percentage growth of a fund's TNA in excess of the growth that would have occurred if no new funds had flowed in and all dividends had been reinvested. I winsorize $F_{i,t}$ at the 1% and 99% level to mitigate the influence of extreme outliers.

I also obtain information on fund holdings from MS Direct that was found to be much more complete and available in higher frequency compared to holding data from Thomson Reuters (Elton, Gruber, and Blake (2011)). Further, MS Direct provides fund holding data not only for U.S.-domiciled funds, which offers the opportunity to expand the sample to international funds. This is important since the U.S. market for ESG investing continues to lag behind the European market in terms of number of investable funds and funds' TNA. According to MS Direct's "Sustainable Landscape Global Funds Q4 2020" list, there are only 363 ESG-Funds domiciled in the U.S., compared to 4,018 in Europe.

For the U.S.-domiciled funds, I obtain additional information on fund share class characteristics from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database (CRSP). To establish a match between fund share classes in CRSP and MS Direct, I 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. Applying the aforementioned criteria leaves me with 140,960 non-U.S. domiciled fund share classes and 32,568 U.S.-domiciled fund share classes that were successfully matched with CRSP. Depending on the fund domicile, I initiate the following data collection process.

B. Identifying ESG-Related Name Changes

B.1. U.S.-Domiciled Equity Funds

For the U.S.-domiciled equity fund sample, I sort all funds on CRSP fund number, and follow any name changes in the fund_name field for the same CRSP fund number. CRSP fund numbers are unique fund share class identifiers that allow to track name changes for a given fund. In total, I find 28,783 name changes in the sample. Next, I screen for funds whose name change is related to ESG as indicated in the fund's old or new name. The term ESG can vary broadly in how it is defined and what it implies in an investment context. In the fund literature, several key words are associated with the term ESG (e.g., Nofsinger and Varma (2014)). I define funds as having an ESG-related name change if the new name is different from the old name by one of the following identifiers:[7] “clean”, “clima-”, “env-” (e.g., environment), “ESG”, “ethic-”, “gov-” (e.g., governance), “green”, “impact”, “renew-”, “resp-” (e.g., responsible), “soc-” (e.g., socially), “SRI”, “sus-” (e.g., sustainable).

If the new fund name includes any of these identifiers while the old name does not, the name change is classified as a “To ESG” name-change event. Conversely, if any of these identifiers is included in the old name but removed from the new name, the name change is classified as a “From ESG” name-change event. If any of these identifiers is included in the old name but replaced with another one in the new name, the name change is classified as a “Hold ESG” name-change event. The respective name-change date is the effective date, as provided by CRSP, when the fund name begins or ceases (in the case of “From ESG” events) to include any of these ESG terms. I only retain changes in the sample whose respective change dates are available in CRSP. Due to the ambiguity of some of the ESG identifiers, I manually review each name change to ensure correct identification. I exclude 428 wrongly identified name changes (e.g., “Evergreen Fund”) from the sample. 299 (or roughly 1%) of fund name changes in the sample of U.S. domiciled equity funds are ESG-related.

Name changes usually involve all of a fund’s share classes. To avoid double counting when conducting portfolio-based analyses in Section IIIA, I follow Chen, Hong, Huang, and Kubik (2004) and Carhart, Carpenter, Lynch, and Musto (2002) and keep only the primary share class of each fund, as indicated in MS Direct. For these analyses, the U.S.-domiciled fund sample thus includes 114 ESG-related name changes of 110 funds. 76 name changes are “To ESG” events, 25 “Hold ESG” events, and 13 “From ESG” events.

B.2. Equity Funds Domiciled Outside the U.S.

For funds domiciled outside the U.S., collecting data on name changes is less straightforward. First, there exists no comprehensive database on legal fund name history. Second, legal fund names are usually indicated in the official language of the respective fund domicile. I start by matching fund share classes with Thomson Datastream (TDS) based on ISINs obtained from MS Direct. MS Direct’s ISIN coverage of non-U.S. domiciled fund share classes in my sample is about 84%. 89% of ISINs are successfully matched with TDS, leaving me with 104,417 fund share classes. TDS offers data on a fund’s current name (NAME), previous name (PNAME), and the date of the last name change (DNMC). 56,933 fund share classes have a previous name in TDS, which implies at least that many name changes. Name-change dates are available for 22,641 fund share classes.

Similar to the process described for U.S.-domiciled funds, I define funds as having an ESG-related name change if the current name is different from the previous name by a specific

[7] Results in the following analyses are not sensitive to the addition or removal of specific keywords. When applying the same identifiers as in Nofsinger and Varma (2014), sample size decreases but results remain very similar.

identifier. In addition to the keywords mentioned above, I collect ESG keywords that reflect country-specific official languages by manually screening the TDS names of funds included in MS Direct's "Sustainable Landscape Global Funds Q4 2020" list. Table A.I in the Appendix provides the complete list of keywords found. Applying these keywords to all matched fund share classes in TDS yields 3,752 candidate ESG-related name changes, out of which 1,296 have a name-change date. To verify TDS change dates and to find dates of name changes that have no TDS date, I manually screen sales prospectuses (available in MS Direct), fund websites, and Fondsweb.com. I am able to identify dates of 2,945 potential ESG-related fund name changes. As with the U.S.-domiciled funds, I categorize name changes in "To ESG", "From ESG", and "Hold ESG" events. Again, I manually review each potential ESG name change due to the ambiguity of the keywords and exclude wrongly identified name changes. 1'933 (or around 3.5%) of name changes in the sample of non-U.S. domiciled equity funds are ESG-related.

After restricting the sample to funds' primary share classes, as indicated in MS Direct, the non-U.S. domiciled fund sample includes 264 ESG-related name changes of 264 equity funds.[8] 142 name changes are "To ESG" events, 96 "Hold ESG" events, and 26 "From ESG" events.

B.3. Identified ESG-Related Name Changes

Table I describes the sample collection process and reports the resulting ESG-related name changes by type and most common identifiers. In total, I screen 85,716 equity fund name changes over the period from January 2005 to February 2021 and find that 2,292 (or around 2.7%) of these name changes are ESG-related as defined in the prior subsections. Restricting the sample to primary share classes leaves me with 378 name changes of 374 unique funds. 218 and 121 of the name changes are "To ESG" and "Hold ESG" events, respectively, whereas there are only 39 "From ESG" name changes. This indicates that most ESG-related name changes involve fund rebrandings from conventional categories toward the ESG category. The most common ESG identifier in a fund's old or new name is the word "Sustainable" with 149 occurrences in my sample. The words "ESG" and "Responsible" follow second and third with 60 and 45 occurrences, respectively. As already noted in the prior literature (e.g., Townsend (2020)), the term "SRI" was largely replaced by "ESG" after the mid-2000s.

Table A.II in the Appendix lists a random sample of 25 identified ESG-related name changes of U.S.-domiciled funds, including funds' old names, new names, and the corresponding name-change types. For example, the "American Century Fundamental Equity Fund" changed its name to "American Century Sustainable Equity Fund", adding "Sustainable" to its name, and is hence categorized as "To ESG".

Figure 1 plots the number of ESG-related name changes of U.S.-domiciled (Panel A) and

[8]Due to the data collection process of the non-U.S. sample, I cannot identify multiple ESG-related name changes per fund.

non-U.S. domiciled (Panel B) equity mutual funds by year and name-change type. Both panels show that the majority of "To ESG" name changes take place in the most recent years of the sample period, indicating that rebranding funds toward ESG is a relatively new phenomenon and likely to persist.[9] The surge in ESG-related name changes is not driven by a general upward movement of fund name changes. The secondary axis in Panel A shows the fraction of ESG-related name changes in the U.S.-domiciled fund sample as the percentage of total name changes in the CRSP-Morningstar equity mutual fund intersection. In 2020, almost 5% of all fund name changes involved ESG terms. In contrast to Cooper et al. (2005), who document that style-related name changes tend to occur in waves, I observe that – at least over the 16 years covered in my sample – ESG-related name changes are experiencing a continued upward trend.

C. ESG Metrics

To measure whether ESG-related name changes are associated with the investment objective implied by the new name, I rely on two sources of ESG metrics to mitigate data availability issues, i.e., MS Direct and Sustainalytics.

Morningstar introduced a sustainability rating in March 2016, which provides an aggregated ESG metric for mutual funds. The rating is based on fund holdings and is calculated from companies' ESG and controversy scores as provided by Sustainalytics. Morningstar evaluates funds only if at least 50% of assets are covered by a company ESG and controversy score. The rating indicates a fund's level of sustainability relative to funds in the same Morningstar Category on a scale from one (worst) to five (best).[10] The advantage of using Morningstar's sustainability rating is twofold. First, it is available on a monthly basis and covers the most recent months of my sample, i.e., when most of the ESG-related name changes take place. Second, the rating is freely accessible and clearly visible to investors (Ammann et al. (2019)).

However, due to the short time series of Morningstar's rating, I also obtain stock-level ESG metrics directly from Sustainalytics. For most of the companies, ESG ratings by Sustainalytics start as early as 2009. The extensive scope of Sustainalytics ensures a high coverage for portfolio holdings of U.S.-domiciled and non-U.S. domiciled funds (Joliet and Titova (2018)).[11] In addition, calculating fund-level ESG metrics based on data from Sustainalytics allows for a more granular analysis compared to the five-category rating scale of Morningstar's sustainability

[9]Hale (2021) notes that name changes toward ESG are expected to further increase in the following years.

[10]Funds with the 10% highest and 10% lowest portfolio sustainability scores in their Morningstar Category receive a rating of five and one, respectively. The following top and bottom 22.5% are assigned a rating of four and two, respectively. The middle 35% receive a rating of three. Steen, Moussawi, and Gjolberg (2020) provide a detailed description of the rating construction.

[11]Sustainalytics is a leading ESG rating agency with a worldwide coverage (its rating universe includes more than 12,000 companies). In contrast, other ESG databases, e.g., MSCI KLD, mainly cover companies listed on U.S. exchanges.

rating.

To aggregate stock-level ESG data from Sustainalytics to the fund level, I follow the same methodology that Morningstar uses to derive its rating: first, I obtain companies' total ESG scores from Sustainalytics. A company's total ESG score measures the degree to which a company's economic value may be at risk due to ESG factors relative to their respective industry peers on a 0 to 100 scale.[12] Since peer groups have varying ESG score ranges and means, I normalize the scores of each peer group via z-score transformation:

$$z_{c,t} = \frac{ESG_{c,t} - \mu_{peer,t}}{\sigma_{peer,t}}, \tag{2}$$

where $ESG_{c,t}$ is company c's ESG score at time t, $\mu_{peer,t}$ is the mean ESG score in company c's peer group at time t, and $\sigma_{peer,t}$ is the standard deviation of ESG scores in company c's peer group at time t. I then create normalized ESG scores on a 0 to 100 scale and with a mean of 50 to make them comparable across peer groups, which is important when analyzing diversified fund portfolios:

$$NormESG_{c,t} = 50 + 10z_{c,t} \tag{3}$$

Next, I aggregate the normalized company ESG scores to a fund ESG score by calculating the asset-weighted average of all covered securities within a fund's portfolio. I establish a match between fund holdings retrieved from MS Direct and Sustainalytics based on ISINs. I require at least 50% of a fund portfolio's assets to have a company ESG score. Over the period from 2009 to 2020, ESG score coverage of portfolio holdings reaches 79% on average.

$$ESG_{f,t} = \sum_{c=1}^{n} w_{c,t} NormESG_{c,t}, \tag{4}$$

where $ESG_{f,t}$ is fund f's portfolio ESG score at time t, n is the number of companies in fund f's portfolio at time t, and $w_{c,t}$ is company c's rescaled asset weight in fund f's portfolio of covered companies (s.t. $\sum_{c=1}^{n} w_{c,t} = 1$).

Lastly, I assign a percentile rank to each fund based on $ESG_{f,t}$ relative to other funds in the same Morningstar category, resulting in $RankESG_{f,t}$. A higher $RankESG_{f,t}$ indicates better ESG scores. This way, I ensure comparability between different fund investment objectives, e.g., small-cap and large-cap. Dolvin, Fulkerson, and Krukover (2019) report a significant difference in sustainability scores between small-cap and large-cap funds, with large-cap funds having better scores.

[12]ESG scores are based on a set of more than 800 indicators, grouped into three categories: environmental (e.g., environmental policy and disclosure, carbon intensity, and waste intensity), social (e.g., working conditions and diversity programs) and governance (e.g., bribery and corruption policy, board independence, and board diversity). Sustainalytics assigns sector-specific weights to each indicator, resulting in environmental, social, governance and total ESG scores.

D. Sample Characteristics

Table II reports the mean and median characteristics for the U.S.-domiciled (Panel A) and non-U.S. domiciled (Panel B) name-change fund sample and compares them with other equity mutual funds in the respective MS Direct universe. Fund characteristics are matched on the name-change date and grouped by name-change type.

Prior to the ESG-related name change, both mean and median levels indicate that name-change funds appear to be smaller (in terms of TNA) than corresponding equity funds in the mutual fund universe. Differences are especially pronounced for "To ESG" funds; one month prior to the name change, median U.S.-domiciled and non-U.S domiciled "To ESG" funds have only \$29.86 million and \$17.49 million in TNA, compared to \$747.51 million and \$71.12 million for the median equity fund, respectively. At the same time, median U.S. and non-U.S. "To ESG" funds are 1.49 and 1.08 years older, respectively.

No clear picture emerges regarding name-change funds' expense ratios and past performance measures. Net returns of "To ESG" and "Hold ESG" funds one month prior to the name change are comparable to the rest of the fund universe. Medium- to long-term performance measures, i.e., the 12-month Carhart (1997) four-factor alpha and the Morningstar Star Rating,[13] indicate a slight underperformance of "To ESG" and "Hold ESG" funds prior to the name change. Underperformance seems more pronounced for "From ESG" funds.

Most importantly, U.S. funds experience negative fund flows one month prior to an ESG-related name change, whereas average flows are positive for other U.S. equity funds at the same time. Similarly, non-U.S. funds exhibit positive but lower average flows than other funds. The same holds true for both fund samples when looking at fund flows over a 6-month period before the ESG-related name change. These results are in line with Cooper et al. (2005), who document low fund flows prior to style-based fund name changes. Together with the comparably small size and advanced age of name-change funds, a long decline in fund flows may be a motive for ESG-related name changes.

To preliminarily explore whether ESG-related name changes coincide with fund portfolio adjustments and affect a funds' ESG-orientation, Table II includes fund turnover ratio, Morningstar Sustainability Rating (Globe Rating), and *RankESG* (as defined in Section IC) at the time of the name change. While turnover ratios of "Hold ESG" and "From ESG" funds are comparable to or lower than the average equity fund in the universe, "To ESG" funds appear to engage in more frequent trading when changing their name. U.S. and non-U.S. "To ESG" funds have an average turnover ratio of 79.63% and 79.35%, in comparison to 62.84% and 66.79% for other funds, respectively. As one might expect, "Hold ESG" and "From ESG" funds have a better ESG performance at the time of the name change, as indicated by the Globe Rating

[13] I calculate 12-month alphas using monthly international (Global incl. U.S.) Fama and French (1993) as well as momentum risk factors from Kenneth R. French's website.

and *RankESG*. The median U.S. "Hold ESG" fund has a Globe Rating of four and ranks in the 88th percentile based on its portfolio ESG score. Interestingly, "To ESG" funds in both samples appear to already exhibit a comparably high ESG performance when changing their name to include an ESG-term.

II. Determinants and Flow Effects of ESG-Related Fund Name Changes

Results in the prior subsection suggest that a decline in fund attractiveness may drive funds' ESG-related name changes. In this section, I first carry out more formal tests on the characteristics of funds that change their names and the point in their lifecycle at which they choose to do so. Second, I analyze how investors respond to funds' ESG-related name changes.

A. Which Funds Change Their Names, and When?

To gain a better understanding of which funds change their names and when, I follow Cooper et al. (2005) and Espenlaub et al. (2017) and employ a cross-sectional as well as time-series logistic regression.

Panel A of Table III reports results of the cross-sectional logistic regression that investigates what kinds of funds engage in ESG-related name changes. I restrict the whole fund sample to months of ESG-related name changes and assign funds that have an ESG-related name change a dummy of one, and other funds zero. Thus, the sample for Panel A includes 96 cross-sections pooled together, one for each change month in the sample. I regress the name-change dummy on one-month lagged returns, log of one-month lagged TNA, one-month lagged fund flows, six-month returns and average fund flows prior to the name change, 12-month alpha from a Carhart (1997) model, 12-month standard deviation of returns, and log of age (in years). In columns 1 and 2, I split the sample by fund domicile. Consistent with the results in Table II, fund size and six-month average fund flows prior to the name change are significantly and negatively related to a fund's name-change likelihood in both subsamples. Similarly, fund age is positively related to the name-change likelihood. Taken together, these results confirm that older and smaller funds with declining flows change their names. Results also align with the determinants of name changes that indicate traditional investment styles (e.g., "value" and "growth"), as documented in Cooper et al. (2005) and Espenlaub et al. (2017), except that negative past performance does not seem to drive ESG-related name changes.

The time-series logistic regression in Panel B of Table III examines at what point in their life cycle funds choose to change their name. I restrict the whole fund sample to name-change funds only and assign them dummies of one in the name-change month and zero in all other months. I use all the time-series data available for each name-change fund and regress the name-change month dummy on the lagged explanatory variables from Panel A. Results are broken down into "To ESG","Hold ESG", and "From ESG" name changes. Corroborating my earlier results, I find that fund size and six-month average fund flows prior to the name change are significant determinants for all types of ESG-related name changes. In addition, "From ESG" name changes appear to be driven by poor past performance, as indicated by the significantly negative coefficient of 12-month alpha.

B. How Do Investors React to ESG-Related Fund Name Changes?

Results from the logistic regressions in Section IIA tell a simple story: small, old, and less attractive funds choose to change their name in an effort to regain attraction to investors. In this subsection, I employ two methods to investigate how investors react to ESG-related fund name changes. In particular, I focus on the impact of these name changes on fund flows, which serve as a proxy for investor reaction. If investors attach value to ESG, as shown in Ammann et al. (2019) and Hartzmark and Sussman (2019), and if investors irrationally consider fund names when investing in mutual funds, as suggested by Cooper et al. (2005), I should observe that "To ESG" funds receive abnormally high inflows after changing their name to ESG. The same may hold true for "Hold ESG" funds, if they switch from dated ESG terms to more contemporary ones (e.g., Townsend (2020)). In case investors rationally choose among funds, I would also observe abnormal inflows as long as the name change is associated with a more ESG-focused investment style of the respective fund. The fact that name changes usually involve all of the funds' share classes allows to separately examine flow reactions of both institutional and retail investors to the name change. Consequently, for the following analyses, I keep multiple share classes (i.e., those aimed at institutional investors and those aimed at retail investors) per fund in the sample.

The main challenge in assessing fund flow effects of ESG-related name changes is to disentangle the name-change effect from other fund characteristics that potentially influence fund flows. Previous studies have found that investors base their fund purchase decisions on various fund characteristics, including past fund performance (e.g., Berk and Green (2004)), advertisement (Jain and Wu (2000)), and fund ratings (Del Guercio and Tkac (2008)), among others. To control for these fund flow determinants, I use a panel regression framework and a propensity score matching approach.

B.1. Panel Regression

In the panel regression, I restrict the sample to funds that engage in ESG-related name changes and use an interval of 24 months around the name-change event.[14] I construct a dummy, *ESGNameChange*, that is equal to zero for periods leading up to the name change, and one for periods thereafter. I regress monthly net fund flows $F_{i,t}$ on this dummy along with other control variables:

$$F_{i,t} = \alpha + \beta ESGNameChange_{i,t} + \delta Controls_{i,t} + \epsilon_{i,t} \tag{5}$$

where $Controls_{i,t}$ is a vector of control variables that have been found to influence mutual fund flows, in particular one-month lagged returns, 12-month alpha from a Carhart (1997) model, and Morningstar's Star Rating that proxy for short-, mid-, and long-term fund performance, respectively. I also control for one-month lagged fund flows, 12-month return volatility as a measure of risk, log of lagged fund TNA as a proxy for fund size, fund expenses estimated by funds' lagged net expense ratio and turnover ratio, and fund age. Additionally, I include a flow benchmark to control for time-varying overall flows into and out of the mutual fund industry and for flows between different investment styles. The flow benchmark is calculated as the average fund flow in a fund's Morningstar global category in a given time period.

Table IV reports separate regressions for "To ESG", "Hold ESG", and "From ESG" name changes. To investigate distinct flow reactions of retail and institutional investors, regressions in columns 2, 4, and 6 include an interaction term between *ESGNameChange* and *Retail*, which is a dummy variable equal to one for fund share classes that MS Direct classifies as non-institutional.[15] The results of the flow regressions are consistent with the conjecture that ESG-labeled mutual funds, all else being equal, attract higher fund flows. Flows into "To ESG" (columns 1 and 2) and "Hold ESG" (column 3 and 4) funds significantly increase after the ESG-related name change, whereas flows into "From ESG" funds stagnate or even decrease (columns 5 and 6).

For "To ESG" and "Hold ESG" funds, the impact of the *ESGNameChange* dummy is positive and significant at the 1% level with coefficients of 0.011 and 0.014, respectively. These findings are also economically meaningful; all else being equal, the coefficient estimates imply that funds that change their name toward ESG or hold on to an ESG name receive 14 or 18 annualized percentage points higher net fund inflows after the change. Interestingly, for neither type of ESG-related name changes, flow effects are more pronounced in retail share classes (columns 2 and 4), indicating that retail as well as institutional investors react favorably to

[14]Results are qualitatively similar when extending the interval to 36 and 48 months surrounding the name-change event, respectively.

[15]Institutional share classes are primarily aimed at institutional investors. According to Morningstar, these include "I" share classes, classes with a minimum initial purchase of more than $100,000, and institutional share classes as defined by the provider of the fund.

"To ESG" and "Hold ESG" name changes. Institutional mutual fund investors are shown to pay attention to more sophisticated measures (e.g., Del Guercio and Tkac (2008)) and likely have access to detailed information on a fund's sustainability, as suggested by Ammann et al. (2019). The flow effects of ESG-related name changes on institutional share classes point in the direction that these name changes may be accompanied by significant ESG-oriented portfolio adjustments.

Funds that remove ESG terms from their name experience no significant flow effects after the name change. However, the name change has a negative flow effect on retail fund share classes, as indicated by the negative and statistically significant coefficient of the interaction term *ESGNameChange* $\times$ *Retail*.

B.2. Propensity Score Matching

To study investor reactions to ESG-related name changes, one would prefer to compare funds that changed their names to otherwise identical funds. Since name changes usually involve all fund share classes, I cannot observe such otherwise identical funds. I therefore rely on a propensity score matching algorithm to construct a suitable fund control group. In contrast to the panel regressions in the prior subsection, propensity score matching allows to account for differences in fund characteristics that might not be adequately captured through a linear (or log-linear) relationship. For example, Chevalier and Ellison (1997) and Sirri and Tufano (1998) document a convex relationship between past performance and fund flows.

I follow Cooper et al. (2005) and estimate a propensity score for each fund by running a logistic regression for each event date. I assign each name-changing fund a dummy of one, and all other funds zero, and regress this dummy on the following independent variables: one-month lagged returns, log of one-month lagged TNA, six-month returns and average fund flows prior to the name change, Morningstar's Star Rating, 12-month alpha from a Carhart (1997) model, 12-month standard deviation of returns, and log of age (in years). Funds' propensity scores, i.e., the fitted values from this regression, can be interpreted as the probability of being a fund in my treatment group. For each fund with an ESG-related name change, I identify one matching no-name-change fund with the closest propensity score to the name-change fund. I then compute abnormal fund flows for each name-change fund as the monthly difference in flows with respect to the matching fund. Finally, I calculate cumulative abnormal fund flows (CAFs) as the sum of abnormal fund flows over specified event periods.

Table V reports average CAFs to all, "To ESG", "Hold ESG", and "From ESG" name changes for various time intervals around the respective name-change month. Panel A presents results for all share classes, whereas the sample is restricted to retail and institutional share classes in Panel B and C, respectively. As reported in the first row of Table V, in the 12 months leading up to the name change (column 1), funds do not experience statistically significant abnormal flows. This result helps confirm that the propensity score matching algorithm does an adequate job in finding matching funds. In contrast, in the 12 months following the name change (column 6), there is a significant increase in abnormal flows. Name-changing funds earn CAFs of 12.95% in excess of those earned by the matching funds. As expected, I find that the increase in fund flows is concentrated in funds that change their names toward ESG or hold on to an ESG name. These funds earn significant CAFs of 5.29% and 5.26%, respectively, in the three months following the name change. Over one year, they earn CAFs of 13.87% and 14.14%, compared to an insignificant -1.53% for "From ESG" funds. These results corroborate my findings from the panel regression in the prior subsection.

How does this fund flow effect compare with other name-based flow effects in the literature? Before the SEC introduced Rule 35d-1 in 2001 to regulate misleading mutual fund names, Cooper et al. (2005) find that funds with style-related name changes benefit from CAFs of 20.17% in the year after the name change. This effect is even more pronounced if funds change their names to reflect currently hot investment styles (i.e., when the corresponding style premium is high). After the introduction of Rule 35d-1, Espenlaub et al. (2017) document abnormal flows of around 13% in the year after the name change, which aligns well with the effect I discover for ESG-related name changes.

Similar to the panel regression results, Panels B and C indicate that both retail and institutional investors react favorably to "To ESG" and "Hold ESG" name changes. However, I do not find that "From ESG" name changes have a negative flow effect on retail fund share classes, as in colum 6 of Table IV.

III. Do Name Changing Funds Make ESG-Oriented Portfolio Adjustments?

A. *Turnover Ratio and ESG Metrics Around Name Changes*

Results in Section II indicate that investors react positively to funds changing their names toward ESG or holding on to an ESG name. As this effect is not limited to retail investors, ESG-related name changes may coincide with portfolio adjustments that also attract institutional investors. In this section, I test whether funds deliver on their promise implied by their new name. Similar to Section IIB, I employ a panel regression framework and a propensity score matching approach to analyze portfolio adjustments surrounding name-change events. Specifically, I examine the dynamics of fund turnover and ESG metrics. If fund name changes involve portfolio adjustments, one should observe that turnover significantly increases for all types of name changes around the change months. ESG metrics of "To ESG" funds should improve, whereas "From ESG" funds should experience a drop in ESG metrics. For "Hold ESG" funds the situation is less clear, as such name changes may reflect a stronger commitment toward ESG-oriented investing or just a switch from dated ESG terms to more contemporary ones (e.g., Townsend (2020)). Importantly, for this section's analysis, I follow Chen et al. (2004) and Carhart et al. (2002) and keep only the primary share class of each fund, as share classes refer to the same fund portfolio.

A.1. Panel Regression

I again restrict the sample to funds that engage in ESG-related name changes and use an interval of 24 months around the name-change event. I regress *ESGNameChange* (as defined in Section II) on *TurnoverRatio*, *GlobeRating*, and *RankESG*, respectively, along with other control variables from Table IV:

$$TurnoverRatio_{i,t} = \alpha + \beta ESGNameChange_{i,t} + \delta Controls_{i,t} + \epsilon_{i,t}, \tag{6}$$

$$GlobeRating_{i,t} = \alpha + \beta ESGNameChange_{i,t} + \delta Controls_{i,t} + \epsilon_{i,t}, \tag{7}$$

$$RankESG_{i,t} = \alpha + \beta ESGNameChange_{i,t} + \delta Controls_{i,t} + \epsilon_{i,t} \tag{8}$$

Table VI reports the results of these panel regressions in Panel A, B, and C, respectively. Results are broken down into "To ESG" (columns 1 to 3), "Hold ESG" (columns 4 to 6), and "From ESG" (columns 7 to 9) name changes. To control for time-invariant fund characteristics, I additionally include fund fixed effects in columns 3, 6 and 9.

The positive and statistically significant coefficients of *ESGNameChange* for "To ESG" funds in Panel A indicate that such funds increase their turnover after they change the name toward ESG. In the 12 months following the name change, "To ESG" funds exhibit a surge in turnover ratio by between 8 and 11 percentage points, depending on the specification. Even when controlling for fund fixed effects, the coefficient of *ESGNameChange* remains significant at the 10% level. This effect is also economically sizeable, as the average turnover ratio of "To ESG" funds is 69% in the 12 months before the name change, as suggested by the constant in column 1. "Hold ESG" and "To ESG" funds, on the other hand, do not appear to engage in significant portfolio adjustments following the name change. Coefficients of *ESGNameChange* are statistically indistinguishable from zero across all specifications.

Panel B displays results for changes in funds' Globe Rating and provides a similar picture. For "To ESG" funds, the impact of *ESGNameChange* is positive and significant at the 1% level with coefficients ranging between 0.27 and 0.43, respectively. This indicates that funds that change their name toward ESG deliver on their promise and appear to significantly strengthen their ESG-focus, as proxied by the Globe Rating. Globe Ratings of "Hold ESG" and "From ESG" funds neither significantly improve nor deteriorate. Using *RankESG* as a more granular ESG measure in Panel C confirms these results. "To ESG" funds increase their ESG percentage

Rank by 14 to 15 percentage points in the 12 months after the name change (significant at the 1% level). The ESG percentage rank of "Hold ESG" funds slightly drops by 4 percentage points when including fund fixed effects in column 6 (significant at the 10% level).

A.2. Propensity Score Matching

To investigate the dynamics of fund turnover and ESG metrics around name changes more closely, I compare name-changing funds with the propensity-score matched funds from Section IIB. Specifically, I compute excess $TurnoverRatio$, $GlobeRating$, and $RankESG$ for each name-change fund. Excess values are calculated as the difference with respect to the fund's matching fund.

Figure 2 shows funds' excess $TurnoverRatio$, $GlobeRating$, and $RankESG$ in the 24 months surrounding an ESG-related name change. Each row of subplots represents one of the three variables of interest, whereas columns represent "To ESG", "Hold ESG", and "From ESG" name changes, respectively. The shaded area marks the 90% confidence interval. In line with the panel regression results, "To ESG" funds significantly increase their turnover ratio and ESG scores after the name change. Excess turnover ratio dynamics suggest that funds start to adjust their portfolios shortly before the name change. Portfolio activity peaks two to three quarters after the name change. ESG scores start to surge with the month of the name change and continue to increase in subsequent periods. "Hold ESG" and "From ESG" funds do not exhibit significant portfolio adjustments.

B. Cosmetic and Noncosmetic Name Changes

In the previous sections, I find that both funds changing their names toward ESG and funds holding on to an ESG name benefit from increased flows. At the same time, only "To ESG" name changes appear to be accompanied by significant improvements in portfolio ESG metrics. These results raise the question whether fund investors are able to differentiate between cosmetic and noncosmetic ESG-related name changes. In an efficient market, cosmetic name changes should not be rewarded with an increase in fund flows. However, cosmetic effects have been found to irrationally influence investor decisions. Hirshleifer (2001) suggests that even irrelevant, redundant, or outdated news affects security prices if presented saliently. Cooper, Dimitrov, and Rau (2001) document stock price reactions to timely firm name changes. Similarly, asset allocation decisions of mutual fund investors are influenced by cosmetic style-related fund name changes (Cooper et al. (2005)).

In this section, I test whether there is a difference in fund flows when the ESG-related name change is cosmetic as opposed to noncosmetic. I define cosmetic and noncostmetic name changes based on funds' post-name-change portfolio adjustments. Specifically, I sort "To ESG" and "Hold ESG" funds by their excess *RankESG* 12 months after the name change and create below- (cosmetic) and above-median (noncosmetic) fund groups.

Table VII reports the event study CAFs for the cosmetic and noncosmetic fund group broken down into "To ESG" and "Hold ESG" name changes. Results are reported separately for retail (Panel A) and institutional (Panel B) fund share classes. For retail share classes, I cannot reject the hypothesis that cosmetic name changes earn the same amount of abnormal flows than noncosmetic name changes. Flow reactions to both "To ESG" and "Hold ESG" name changes do not significantly differ between the cosmetic and noncosmetic fund group. Cosmetic "To ESG" name changes garner 13.24% abnormal fund flows in the 12 months after the name change, whereas noncosmetic name changes lead to insignificantly higher abnormal flows of 14.53%. In the sample of institutional fund share classes, however, I find statistically significant differences between flow reactions to cosmetic and noncosmetic name changes. Cosmetic "To ESG" and "Hold ESG" funds attract insignificant abnormal flows of 5.11% and 4.01% in the 12 months after the name change, whereas noncosmetic funds earn 17.44% and 18.52%, respectively.

These results suggest that retail investors are not able to adequately distinguish between cosmetic and noncosmetic fund name changes. Institutional investors, on the other hand, seem to effectively screen for funds that are committed to ESG and direct their flows to these funds.

IV. Additional Tests

A. *Alternative Fund Benchmarks*

To check if the observed patterns around ESG-related name changes are driven by the propensity matching methodology, I first examine raw flows instead of abnormal flows. Results remain qualitatively unchanged. Name-change funds garner cumulative flows of 20.42% in the 12 months following the name change. "To ESG" and "Hold ESG" funds earn significant flows of 21.64% and 23.84%, respectively, whereas "From ESG" funds earn insignificant flows of 4.36%. The flow difference between cosmetic and noncosmetic name changes remains insignificant (significant) in the sample of "To ESG" and "Hold ESG" retail (institutional) fund share classes across all periods after the name change.

Second, I calculate abnormal fund flows relative to median flows of all equity mutual funds in the Morningstar universe for each month. Again, results remain qualitatively unchanged, with "To ESG" and "Hold ESG" funds earning significant abnormal flows of 14.68% and 14.95% in the 12 months after the name change, respectively.

In addition, I recalculate funds' excess *TurnoverRatio*, *GlobeRating*, and *RankESG* as the difference with respect to median values in the Morningstar fund universe instead of matched fund values. I observe the same pattern as in Figure 2, i.e., that excess turnover ratios and

ESG scores of "To ESG" funds become significantly positive after the name change, whereas "Hold ESG" and "From ESG" funds do not appear to adjust their portfolios on average.

B. Microlevel Evidence from an Online Experiment

A major assumption of this paper is that investors consider a mutual fund's name when making investment decisions. Results in Cooper et al. (2005) and Niessen-Ruenzi and Ruenzi (2019) suggest that fund investors are not only sensitive to the name of a fund but also to the name of the responsible manager. To check whether investors pay attention to fund names, I perform an online survey among mutual fund investors via Amazon Mechanical Turk (AMT).[16] I ask 200 mutual fund investors whether they are aware of the fund's name at the time of investing and whether they rely on information in a fund's name when making an investment decision. 93% and 86% of the respondents reply in the affirmative, respectively.

Results in Section II and Section IIIB indicate that mutual fund investors are likely to base their purchase decisions at least partially on information conveyed in a fund's name and that investors value ESG-focused investment strategies. Even though the event-study design allows to analyze the flow effect around name changes, one cannot rule out the possibility that other potential fund flow drivers change at the same time. Therefore, I conduct an online experiment via AMT to further investigate the link between ESG-related names and fund flows.[17] The experiment also permits to exploit variation in investor characteristics, in contrast to the previous analyses that only focus on aggregate retail and institutional investor behavior. Similar to Kumar, Niessen-Ruenzi, and Spalt (2015), I ask individuals via AMT to complete a hypothetical investment allocation task in which they are required to split an investment of 100 dollars between two funds A and B each round.[18]

The investment task is successfully completed by 592 individuals who self-report that they reside in the U.S. and are invested in mutual funds.[19] Participants receive a summary sheet about each of the two funds, including fund name, past performance, fund size, expense ratio, annual turnover, the top ten holdings, inception date, and a short fund manager description.[20] The experiment lasts four rounds. In each round, participants split 100 dollars between the two funds that are base-labeled "Europe Select Equity 100" (A) and "Worldwide Strategic Equity 200" (B) in round 1, "Global Choice Equity 100" (A) and "Worldwide Investors Equity 100" (B) in round 2, "Global Portfolio Equity 200" (A) and "US Investments Equity 100" (B) in

[16] AMT offers the possibility to choose survey participants based on the qualification "Financial Asset Owned - Mutual Funds".

[17] Hartzmark and Sussman (2019) also employ an AMT experimental design in an ESG mutual fund context.

[18] I thank Alexandra Niessen-Ruenzi for providing me with the experimental setup.

[19] In line with average hourly wages and Amazon's recommendations, workers were paid $12 per hour. Average time of task completion was close to 7 minutes. I exclude those AMT participants from my sample who spent less than two minutes on the experiment to ensure that the task was taken seriously.

[20] The fund profiles represent diversified equity mutual funds.

round 3, and "US Selector Equity 50" (A) and "Asia Choice Equity 100" (B) in round 4.

Participants are randomly assigned to one of two groups. The experiment's key feature is that in rounds 2 and 4, the term "Sustainable" is inserted into fund A's name for one group but not for the other.[21] Everything else remains unchanged. To avoid that participants learn about the experiment's purpose, participants of both groups observe only non-ESG funds in round 1 and 3. The main interest lies in the different investment allocations of the two groups in round 2 and 4, which are solely due to the ESG-related fund names. In round 2, both funds are very similar in terms of the remaining fund attributes, but in round 4 I assign negative past returns to fund A to ensure that my experimental results are robust.

Table VIII presents the experimental evidence. Panel A shows that participants invest 4.01 dollars more in fund A when its name includes "Sustainable". As suggested by Hartzmark and Sussman (2019), investors view sustainability as a positive fund characteristic. Both rounds 2 and 4 indicate that participants draw information from a fund's name and allocate more money to the fund whose name implies an ESG-focus. The comparably large fraction allocated to fund A with negative past returns in round 4 provides evidence that ESG-focused funds attract relatively more flows regardless of the extremity of performance outcomes. In the unreported placebo rounds 1 and 3, where no fund name additions were made, I find no significant difference in asset allocation.

Panel B of Table VIII shows coefficient estimates when regressing money invested in fund A on *ESG-Name*, while controlling for investor characteristics. *ESG-Name* is a dummy equal to one if "Sustainable" is included in the fund's name and zero otherwise. Columns 2 and 3 present results of subsamples split by participants' self-reported party affiliation (Democrats and Republicans). The coefficient on *ESG-Name* is positive and statistically signifant in both subsamples, indicating that ESG-related fund names have an effect on allocation decisions independent of investor party affiliation. The coefficient is comparably larger for Democrats, corroborating findings in Hong and Kostovetsky (2012) who show that even professional Democratic investors underinvest in companies deemed socially irresponsible. In column 4, I interact *ESG-Name* with other investor characteristics, namely gender and age. Results show that younger investors react significantly more positive to the ESG-related fund name.

Compared to the empirical results in the CRSP-MS Direct sample, effects in the experimental setting are lower in magnitude. This is not surprising, as the experiment is designed to capture the raw fund name effect, while evidence in the prior sections suggest that "To ESG" name changes tend to involve strategic changes. Also, participants likely pay less attention to the information shown in the summary sheets when no real money is at stake.[22] The experi-

[21] "Global Choice Sustainable Equity 100" in round 2 and "US Selector Sustainable Equity 50" in round 4, respectively. The term "Sustainable" and its position within the fund name is chosen because it is most frequently observed in my ESG-related name-change sample.

[22] To the author's best knowledge, no major ESG-related events occured around the dates of the experiment

ment's results are comparable in magnitude with the experimental effects related to gender and manager name documented in Kumar et al. (2015) and Niessen-Ruenzi and Ruenzi (2019).

Overall, results in this section confirm the previously observed relation between ESG-related fund names and fund flows, and suggest that investors consider information conveyed in fund names when making their investment decisions.

C. Alternative Measures of Funds' ESG Orientation

Another way to test whether name-change funds adjust their portfolios, especially with respect to ESG, is to analyze factor loadings around the name change. A major advantage of this approach is that fund returns are available on a daily basis, as compared to the monthly frequency of ESG metrics. For each name change, I employ the Carhart (1997) model and run a regression over a 12 month period before and after the name change using daily returns. I obtain daily international (Global incl. U.S.) Fama and French (1993) as well as momentum risk factors from Kenneth R. French's website. To examine differences in funds' ESG investment style, I slightly adjust the standard Carhart (1997) model and replace the market return by returns of the MSCI World ESG Leaders index. This index aims to include companies worldwide that have the best ESG ratings in each sector.

Panel A of Table IX reports average *Alpha* and loadings on the market (*Mkt-RF*), size (*SMB*), value (*HML*), and momentum (*MOM*) factors. Comparing funds' pre-name-change with post-name-change loadings confirms the results from Section IIIA. "Hold ESG" and "From ESG" funds do not significantly adjust their investment style following the name change, whereas "To ESG" funds significantly increase their market exposure. Interestingly, "To ESG" funds significantly increase their exposure toward large stocks. It is well documented that firms' sustainability performance is positively related to firm size due to increased pressure by shareholders, the general public and media (e.g., Artiach, Lee, Nelson, and Walker (2010)).

Panel B of Table IX reports average *Alpha* and loadings from the adjusted Carhart (1997) model. *Mkt-RF* is replaced by *ESG-RF*, which is the return of the MSCI World ESG Leaders index net of the U.S. Treasury bill yield. For "To ESG" funds, the difference between post-name-change and pre-name-change *ESG-RF* is positive and significant at the 1% level, indicating that these funds increase their exposure to companies with high ESG performance relative to sector peers. Again, "Hold ESG" and "From ESG" exhibit no significant changes in investment styles following the name change.

(December 2020) that could unduly affect the results.

D. Alternative Explanation

Fund mergers have been found to significantly affect fund flows of the acquiring and target funds (e.g., Park (2013); Jayaraman, Khorana, and Nelling (2002)). As fund name changes may be part of a merger between funds, previous results could be biased. Potentially, merging funds may also exhibit a mechanical increase in fund flows if their TNA is aggregated. Even though the identifiers used in this paper (Morningstar's security ID and CRSP's fund number) uniquely determine a fund share class and I require the identifier to stay the same over the full event period, I mitigate the merger concern in two ways.[23] First, I follow Cooper et al. (2005) and repeat the flow analyses dropping month zero (i.e., the month of the name change) from the sample. Results are robust to this removal, with "To ESG" and "Hold ESG" funds earning abnormal flows of 12.78% and 12.97% from months 1 to 12 after the name change. Second, I manually collect the prospectuses, fund fact sheets and supplements of name-changing funds via MS Direct that were published one reporting period before and one period after the name change. If these documents state that the respective fund was involved in a fund merger, I remove it from the sample. I find and exclude only eight such funds, leaving the results nearly unchanged.

V. Conclusion

ESG refers to a wide spectrum of environmental, social, and corporate governance considerations. As demand for ESG investing grew substantially in recent years, fund firms have an incentive to rebrand conventional funds toward ESG or "sustainable investing" in competing for investor funds – a development that created potential ground for misrepresentation. This paper studies funds' ESG-related rebrandings and their impact on fund flows, turnover, and ESG metrics. I identify a sample of 110 U.S.-domiciled and 264 non-U.S. domiciled equity mutual funds that undergo ESG-related name changes over the period from January 2005 to February 2021. The majority of these name changes involve the switch from non-ESG to ESG names and take place in the more recent years of the sample period, indicating that ESG-related fund rebranding is likely to persist.

Results in this paper tell a simple story: small, old, and less attractive funds try to regain attraction to investors by changing their names to include ESG terms. I estimate that ESG-seeking investors reward funds with significant abnormal flows of over 13% in the 12-month period following the name change toward ESG. Post-name-change increases in funds' turnover and improvements in ESG metrics suggest that, on average, name-change funds deliver on their new label's promise. However, I find that retail investors direct abnormal flows to ESG-rebranded funds irrespective of ESG score improvements. My paper underlines the importance

[23] Next to using winsorized fund flows throughout the paper.

of fund names to investors, indicating that they rely on a fund's name when assessing its ESG-orientation. Such reliance makes them susceptible to potential greenwashing.

As cosmetic name changes in the fund management industry remain widespread even after the advent of SEC's Rule 35d-1 (Espenlaub et al. (2017)), the understanding of investor reactions to ESG terms in fund names is of great importance. When asked "Are you aware of the fund's name at the time of investing?" and "Do you rely on information in a fund's name when making an investment decision?", ninety-three and eighty-six percent of respondents answer in the affirmative. However, confusion and uncertainty surrounding both the ESG definition and the meaning of sustainable investing likely amplify the risk of misleading or deceptive fund names. In this context, my findings may prove useful for future debate.

Appendix A.

Table A.I. ESG Keywords for Non-U.S. Domiciled Mutual Funds.
This table reports the ESG keywords collected by manually screening current and previous names of funds in TDS that are included in MS Direct's "Sustainable Landscape Global Funds Q4 2020" list.

ESG Keywords					
acqua	engmt.	hållbar	oekovision	sclyrspbl	verte
act4	entwicklung	hållbarhet	oekoworld	SDG	vesi
action	env	hållbart	öko	security	vlr.
alternative energy	env.	hidrogeno	ökotrend	sicherheit	warming
aqua	envir	hllbar	ökovision	smart energy	waste
bæredygtig	environ	Humain	okoworld	smart food	water
bewegen	environ.	humaines	onc.	soc	well-being
bien-être	environment	human	oncology	socially	werte
biosphere	environmental	humanfond	opptys	socialmente	women
carbon	environnement	idéel	peace	socly	WWF
cbn	envm.	Ideell	people	solidaire	zukunft
change	ESG	imp	planet	solution	
chg	ethi	imp.	planete	sostenibilidad	
circulair	ethi.	impact	planète	sostenible	
circular	ethica	innovationen	positive	sostenibles	
clean	ethical	innovative	prevención	sozial	
clima	ethik	ipct.	prevention	SRI	
climate	ethique	ISR	problem	sus	
cn.en.	etico	karbon	protection	sust	
cncc	etisk	klima	puhdas	sust.	
cncc.	etiska	klimaschutz	rcyc	sustain	
cnsmr	evolución	klimatrends	rcyc.	sustain.	
conscious	evolution	lavkarbon	recreation	sustainability	
development	fair	low carbon	recycling	sustainable	
développement	fairinvest	low cbn.	renewable	sustby	
diversität	food	medioambiente	renouvelables	sustby.	
diversité	footprint	mensch	renováveis	sustnbl	
diversity	förnybar	miljö	resp	terra	
durable	fos free	miljø	resp.	transition	
durables	fossil free	nachhaltig	responsable	treibhaus	
duurzaam	fossilfri	nachhaltige	responsável	udvikling	
dvppt.	fuel scrd	nachhaltigkeit	responsibility	umw	
e.t.h.i.c.a.	fuel screened	nat res	responsible	umw.	
eco	future cities	natural resource	rspby	umwelt	
education	gender	natural resources	rspby.	umweltfonds	
eficiencia	gouvernance	new energy	rspnsble	umweltinvest	
energética	gov	nutrition	santé	valeurs	
engage	governance	ocean	scly	values	
engagement	green	oeko	scly.	verde	

Table A.II. Examples of ESG-Related Mutual Fund Name Changes.
This table reports a random sample of 25 ESG-related name changes of U.S. mutual funds between January 2005 and February 2021. Name-change type "To ESG" indicates that the fund's new name includes an ESG-term while its old name does not. "Hold ESG" indicates that the new and old fund name include different ESG terms. "From ESG" indicates that the fund's old name includes an ESG-Term while the new name does not. ESG terms are displayed in bold.

Old Fund Name	New Fund Name	Name-Change Type
AB International Growth Fund	AB **Sustainable** International Thematic Fund	To ESG
Aberdeen Select International Equity Fund	Aberdeen International **Sustainable** Leaders Fund	To ESG
American Century Fundamental Equity Fund	American Century **Sustainable** Equity Fund	To ESG
Boston Common US Equity Fund	Boston Common **ESG Impact** US Equity Fund	To ESG
Quaker Strategic Growth Fund	Quaker **Impact** Growth Fund	To ESG
Epiphany FFV Fund	Dana Epiphany **ESG** Equity Fund	To ESG
DWS European Equity Fund	DWS **ESG** International Core Equity Fund	To ESG
Goldman Sachs Blue Chip Fund	Goldman Sachs US Equity **ESG** Fund	To ESG
JPMorgan Intrepid Advantage Fund	JPMorgan Intrepid **Sustainable** Leaders Fund	To ESG
Pax Growth Fund	Pax **ESG** Beta Quality Fund; Individual Investor Class Shares	To ESG
Putnam Multi-Cap Growth Fund	Putnam **Sustainable** Leaders Fund	To ESG
Russell US Defensive Equity Fund	Russell **Sustainable** Equity Fund	To ESG
Touchstone Large Cap Growth Fund	Touchstone **Sustainability** and **Impact** Equity Fund	To ESG
Touchstone Premium Yield Equity Fund	Touchstone International **ESG** Equity Fund	To ESG
Transamerica Dividend Focused	Transamerica **Sustainable** Equity Income Fund	To ESG
UBS International Equity Fund	UBS Global **Sustainable** Equity Fund	To ESG
USAA World Growth Fund	USAA **Sustainable** World Fund	To ESG
Alger **Green** Fund	Alger **Responsible** Investing Fund	Hold ESG
BlackRock **Impact** US Equity Fund	BlackRock Advantage **ESG** US Equity Fund	Hold ESG
Calvert VP **SRI** Mid Cap Growth Portfolio	Calvert VP **Social** Mid Cap Growth Portfolio	Hold ESG
Dreyfus **Socially Responsible** Growth Fund	Dreyfus **Sustainable** US Equity Portfolio	Hold ESG
Gabelli **SRI Green** Fund	Gabelli **ESG** Fund	Hold ESG
EntrepreneurShares All Cap **Impact** Fund	EntrepreneurShares US All Cap Fund	From ESG
Virtus Small-Cap **Sustainable** Growth Fund	Virtus KAR Small-Cap Growth Fund	From ESG
Walden **Social** Equity Fund	Walden Equity Fund	From ESG

Table A.III. Descriptions of Main Variables and Sources.
This table provides descriptions and sources of variables used in my study. The following abbreviations are used: MS - Morningstar Direct Database; CRSP - CRSP Survivorship Bias Free Mutual Fund Database; TDS - Thomson Datastream; FFW - Fund Firm Websites; FW - Fondsweb.com; SUS - Sustainalytics; SEC - SEC filings; AE - Author's estimations; MC - Manually collected.

Variables	Description	Source
Panel A: Dependent Variables		
Fund flows $F_{i,t}$	Monthly net percentage mutual fund flows, computed as $[TNA_{i,t} - TNA_{i,t-1}(1 + r_{i,t})]/TNA_{i,t-1}$, where $TNA_{i,t}$ is the fund i's total net assets in month t and $r_{i,t}$ stands for the net return in month t.	MS
Turnover ratio	A fund's turnover ratio. Obtained directly from MS, computed by taking the lesser of purchases or sales and dividing by average monthly net assets.	MS, AE
Globe rating	An aggregated measure based on a fund's sustainability rating, which indicates a fund's exposure toward ESG risks. Morningstar ranks all funds within a Morningstar global category by their historical sustainability scores and divides them into five groups by percent rank (higher percent ranks indicate better ESG performance): Top 10% = "High" (five globes), Next 22.5% = "Above Average" (four globes), Next 35% = "Average" (three globes), Next 22.5% = "Below Average" (two globes), Bottom 10% = "Low" (one globe).	MS, SUS
RankESG	A fund's percentile rank based on $ESG_{f,t}$ relative to other funds in the same Morningstar global category. Higher RankESG indicates better ESG performance. $ESG_{f,t}$ is calculated for each fund and month by asset-weighting the normalized ESG scores of the companies held within the fund portfolio. Company ESG scores come from Sustainalytics and are normalized as described in Section IC.	MS, SUS, AE
Panel B: Main Independent Variables		
ESGNameChange	A dummy variable equal to zero for periods leading up to an ESG-related name change and one for periods thereafter.	MS, CRSP, TDS, FFW, FW, SEC, AE, MC
Retail	A dummy variable equal to one for fund share classes that MS Direct classifies as non-institutional.	MS
To ESG	A dummy variable equal to one if the fund's new name includes any of the ESG identifiers described in Section IB while the old name does not.	MS, CRSP, TDS, FFW, FW, SEC, MC

Continued on next page...

Table A.III – continued from previous page.

Variables	Description	Source
Hold ESG	A dummy variable equal to one if any of the ESG identifiers described in Section IB is included in the old name and replaced with another one in the new name.	MS, CRSP, TDS, FFW, FW, SEC, MC
From ESG	A dummy variable equal to one if the fund's old name includes any of the ESG identifiers described in Section IB while the new name does not.	MS, CRSP, TDS, FFW, FW, SEC, MC
Panel C: Fund Variables		
1-M lagged return	A fund's monthly raw net return lagged by one month.	MS, AE
1-M lagged TNA	A fund's monthly total net asset value lagged by one month.	MS, AE
1-M lagged flow	A fund's monthly flows $F_{i,t}$ lagged by one month.	MS, AE
Expense ratio	A fund's expense ratio.	MS, CRSP
Turnover ratio	A fund's turnover ratio.	MS, CRSP
Return over past 6M	Compounded one-month fund returns over the past 6 months.	MS, AE
Mean flow over past 6M	A fund's average net flows over the past 6 months.	MS, AE
Star rating	A fund's one (lowest) to five (highest) Morningstar Performance Rating as obtained from MS Direct.	MS
12-M alpha	A fund's four-factor alpha form a Carhart (1997) model using monthly fund returns over the past 12 months. If the fund does not have 12 months of data, all available data is used as long as there is at least 9 months of data	MS, AE
Fund age	A fund's age in years that the fund has been active at the current time time period. Calculated using the Inception Date variable from MS Direct.	MS, AE
Flow benchmark	Average fund flows in a fund's Morningstar global category per month.	MS, AE

REFERENCES

Agarwal, Vikas, Gerald D Gay, and Leng Ling, 2014, Window dressing in mutual funds, *Review of Financial Studies* 27, 3133–3170.

Ammann, Manuel, Christopher Bauer, Sebastian Fischer, and Philipp Müller, 2019, The impact of the Morningstar Sustainability Rating on mutual fund flows, *European Financial Management* 25, 520–553.

Artiach, Tracy, Darren Lee, David Nelson, and Julie Walker, 2010, The determinants of corporate sustainability performance, *Accounting & Finance* 50, 31–51.

Berk, Jonathan B, and Richard C Green, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269–1295.

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

Bjørner, Thomas Bue, Lars Gårn Hansen, and Clifford S Russell, 2004, Environmental labeling and consumers' choice—an empirical analysis of the effect of the Nordic Swan, *Journal of Environmental Economics and Management* 47, 411–434.

Brown, Stephen J, and William N Goetzmann, 1997, Mutual fund styles, *Journal of Financial Economics* 43, 373–399.

Capelle-Blancard, Gunther, and Stéphanie Monjon, 2014, The performance of socially responsible funds: Does the screening process matter?, *European Financial Management* 20, 494–520.

Carhart, Mark M, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Carhart, Mark M, Jennifer N Carpenter, Anthony W Lynch, and David K Musto, 2002, Mutual fund survivorship, *Review of Financial Studies* 15, 1439–1463.

Chen, Joseph, Harrison Hong, Ming Huang, and Jeffrey D Kubik, 2004, Does fund size erode mutual fund performance? The role of liquidity and organization, *American Economic Review* 94, 1276–1302.

Chen, Mike, and George Mussalli, 2020, An integrated approach to quantitative ESG investing, *Journal of Portfolio Management* 46, 65–74.

Chevalier, Judith, and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167–1200.

Cooper, Michael J, Orlin Dimitrov, and P Raghavendra Rau, 2001, A rose.com by any other name, *Journal of Finance* 56, 2371–2388.

Cooper, Michael J, Huseyin Gulen, and P Raghavendra Rau, 2005, Changing names with style: Mutual fund name changes and their effects on fund flows, *Journal of Finance* 60, 2825–2858.

Cremers, KJ Martijn, and Antti Petajisto, 2009, How active is your fund manager? A new measure that predicts performance, *Review of Financial Studies* 22, 3329–3365.

Del Guercio, Diane, and Paula A Tkac, 2008, Star power: The effect of Morningstar ratings on mutual fund flow, *Journal of Financial and Quantitative Analysis* 43, 907–936.

Delmas, Magali A, and Vanessa Cuerel Burbano, 2011, The drivers of greenwashing, *California Management Review* 54, 64–87.

Dolvin, Steven, Jon Fulkerson, and Anna Krukover, 2019, Do "good guys" finish last? The relationship between Morningstar sustainability ratings and mutual fund performance, *Journal of Investing* 28, 77–91.

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.

Espenlaub, Susanne, Imtiaz ul Haq, and Arif Khurshed, 2017, It's all in the name: Mutual fund name changes after SEC Rule 35d-1, *Journal of Banking & Finance* 84, 123–134.

Evans, Richard B, and Rüdiger Fahlenbrach, 2012, Institutional investors and mutual fund governance: Evidence from retail–institutional fund twins, *Review of Financial Studies* 25, 3530–3571.

Fama, Eugene F, and Kenneth R French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Filbeck, Greg, Raymond Gorman, and Xin Zhao, 2009, The "best corporate citizens": Are they good for their shareholders?, *Financial Review* 44, 239–262.

Frazzini, Andrea, and Owen Lamont, 2008, Dumb money: Mutual fund flows and the cross-section of stock returns, *Journal of Financial Economics* 88, 299–322.

Green, T Clifton, and Russell Jame, 2013, Company name fluency, investor recognition, and firm value, *Journal of Financial Economics* 109, 813–834.

Hale, Jon, 2021, Sustainable funds U.S. landscape report, Available at Morningstar: https://www.morningstar.com/lp/sustainable-funds-landscape-report.

Hartzmark, Samuel M, and Abigail B Sussman, 2019, Do investors value sustainability? A natural experiment examining ranking and fund flows, *Journal of Finance* 74, 2789–2837.

Hirshleifer, David, 2001, Investor psychology and asset pricing, *Journal of Finance* 56, 1533–1597.

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

Jacobs, Heiko, and Alexander Hillert, 2016, Alphabetic bias, investor recognition, and trading behavior, *Review of Finance* 20, 693–723.

Jain, Prem C, and Joanna Shuang Wu, 2000, Truth in mutual fund advertising: Evidence on future performance and fund flows, *Journal of Finance* 55, 937–958.

Jayaraman, Narayanan, Ajay Khorana, and Edward Nelling, 2002, An analysis of the determinants and shareholder wealth effects of mutual fund mergers, *Journal of Finance* 57, 1521–1551.

Joliet, Robert, and Yulia Titova, 2018, Equity SRI funds vacillate between ethics and money: An analysis of the funds' stock holding decisions, *Journal of Banking & Finance* 97, 70–86.

Kempf, Alexander, and Peer Osthoff, 2008, SRI funds: Nomen est omen, *Journal of Business Finance & Accounting* 35, 1276–1294.

Kumar, Alok, Alexandra Niessen-Ruenzi, and Oliver G Spalt, 2015, What's in a name? Mutual fund flows when managers have foreign-sounding names, *Review of Financial Studies* 28, 2281–2321.

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

Nofsinger, John, and Abhishek Varma, 2014, Socially responsible funds and market crises, *Journal of Banking & Finance* 48, 180–193.

Park, Minjung, 2013, Understanding merger incentives and outcomes in the US mutual fund industry, *Journal of Banking & Finance* 37, 4368–4380.

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

Reiser, Dana Brakman, and Anne Tucker, 2019, Buyer beware: Variation and opacity in ESG and ESG index funds, *Cardozo Law Review* 41, 1921.

Riedl, Arno, and Paul Smeets, 2017, Why do investors hold socially responsible mutual funds?, *Journal of Finance* 72, 2505–2550.

Robins, William, 2018, Funds rename to include 'sustainability' or 'ESG' in title, Available at Citywire: https://citywire.co.uk/new-model-adviser/news/funds-rename-to-include-sustainability-or-esg-in-title/a1154199.

Sapp, Travis, and Ashish Tiwari, 2004, Does stock return momentum explain the "smart money" effect?, *Journal of Finance* 59, 2605–2622.

Sirri, Erik R, and Peter Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance* 53, 1589–1622.

Steen, Marie, Julian Taghawi Moussawi, and Ole Gjolberg, 2020, Is there a relationship between Morningstar's ESG ratings and mutual fund performance?, *Journal of Sustainable Finance & Investment* 10, 349–370.

Stuart, Elizabeth, 2020, Surge in funds rebranding as sustainable, Available at Morningstar: https://www.morningstar.co.uk/uk/news/201590/surge-in-funds-rebranding-as-sustainable.aspx.

Townsend, Blaine, 2020, From SRI to ESG: The origins of socially responsible and sustainable investing, *Journal of Impact and ESG Investing* 1, 10–25.

UN Global Compact, 2004, Who cares wins: Connecting financial markets to a changing world.

US SIF Foundation, 2020, US SIF report on US sustainable and impact investing trends.

Van Duuren, Emiel, Auke Plantinga, and Bert Scholtens, 2016, ESG integration and the investment management process: Fundamental investing reinvented, *Journal of Business Ethics* 138, 525–533.

Table I. Mutual Fund Name-Change Sample Description

This table describes the sample collection process and the identified ESG-related name changes over the January 2005 to February 2021 period. Columns 1 and 2 present the name-change sample of U.S.-domiciled and non-U.S. domiciled equity funds, respectively. For U.S.-domiciled funds (according to MS Direct), I use CRSP to identify ESG-related name changes. I sort all funds on their CRSP fund number and keep track of any name change in the fund_name field for the same CRSP fund number. Funds are defined as having an ESG-related name change if their new name differs from the old name by one of the following identifiers: “clean”, “clima-”, “env-”, “ESG”, “ethic-”, “gov-”, “green”, “impact”, “renew-”, “resp-”, “soc-”, “SRI”, “sus-”. For non-U.S. domiciled funds, I screen current and previous fund names in TDS and identify ESG-related name changes using the identifiers shown in Table A.I in the Appendix. Name changes are categorized as ”To ESG” if the fund’s new name includes an ESG-term while its old name does not, ”Hold ESG” if the new and old name include different ESG terms, ”From ESG” if the old name includes an ESG-Term while the new name does not. The table also reports the most common ESG identifiers included in a fund’s old or new name. Fund names may include multiple ESG identifiers.

	Number		
	In U.S.-Domiciled Fund Sample	In Non-U.S. Domiciled Fund Sample	Total
	(1)	(2)	(3)
Total equity mutual fund name changes	28,783	56,933	85,716
ESG-related name changes	299	1,993	2,292
ESG-related name changes in primary share class	114	264	378
Unique funds	110	264	374
Name-Change Type:			
To ESG	76	142	218
Hold ESG	25	96	121
From ESG	13	26	39
Most common ESG identifiers:			
Sustainable	37	112	149
ESG	26	34	60
Responsible	12	33	45
Social	25	7	32
Impact	13	16	29
SRI	8	20	28
Green	6	12	18

Table II. Characteristics of Name-Change Funds and Other Mutual Funds

This table compares the mean and median characteristics for the U.S.-domiciled (Panel A) and non-U.S. domiciled (Panel B) name-change fund sample with other equity mutual funds in the respective MS Direct universe, matched on the name-change date and grouped by name-change type. Lagged variables represent fund characteristics N months (M) before the name change. Monthly returns and total net assets (TNA) are obtained from MS Direct. Lagged returns are computed by compounding one-month returns over N months. Flows are calculated as $[TNA_{i,t} - TNA_{i,t-1}(1 + r_{i,t})]/TNA_{i,t-1}$, as in Sirri and Tufano (1998). Expense ratio and turnover ratio come from CRSP for the U.S.-domiciled fund sample and from MS Direct for the non-U.S. domiciled fund sample. Star Rating is the one (lowest) to five (highest) Morningstar Performance Rating obtained from MS Direct. 12-M alpha is calculated as Carhart (1997) four-factor alpha using monthly returns over the 12 months prior to the date of the name change. If the fund does not have 12 months of data prior to the name-change, all available data is used as long as there is at least 9 months of data. 12-M volatility is the standard deviation of monthly net returns over the previous 12 months. Globe Rating is the one (lowest) to five (highest) Morningstar Sustainability Rating. Rank ESG is a fund's percentile rank based on $ESG_{f,t}$, as specified in equation (4), relative to other funds in the same Morningstar global category. Fund age is the number of years that the fund has been active at the time of the name-change month and is calculated using the Inception Date variable from MS Direct.

Panel A: U.S.-Domiciled Fund Sample

	To ESG		Other Funds		Hold ESG		Other Funds		From ESG		Other Funds	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1-M lagged return (%)	1.95	1.52	1.99	1.24	1.39	1.21	0.48	1.25	1.27	1.32	1.55	3.01
1-M lagged TNA ($ mn.)	81.49	29.86	746.35	747.51	137.87	36.22	614.77	621.89	183.91	121.42	480.63	448.17
1-M lagged flow (%)	-1.81	-1.04	1.06	0.89	-0.01	-0.01	1.37	1.23	-1.06	-0.00	2.85	2.79
Expense ratio (% p.a.)	1.32	1.23	1.19	1.16	1.17	1.17	1.26	1.26	1.29	1.19	1.38	1.45
Turnover ratio (% p.a.)	79.63	72.00	62.84	61.90	49.33	26.42	66.91	65.24	76.87	91.50	77.87	82.39
Return over past 6M (%)	7.70	6.86	8.37	5.67	2.51	4.50	1.80	3.23	8.90	1.77	5.25	5.67
Mean flow over past 6M (%)	-0.89	-0.95	1.19	1.05	0.70	-0.51	1.51	1.58	1.07	0.66	2.68	2.90
Star Rating	2.87	3.00	3.05	3.00	3.00	3.00	3.02	3.00	2.60	3.00	2.97	3.00
12-M alpha (%)	-0.21	-0.08	0.11	0.10	0.14	0.08	0.00	-0.09	-0.27	-0.15	0.05	0.06
12-M volatility (%)	4.41	4.01	4.84	4.47	4.03	3.85	4.33	4.12	5.77	6.06	4.28	2.99
Globe Rating	3.15	3.00	3.00	3.00	3.63	4.00	3.01	3.00	–	–	–	–
Rank ESG (percentile)	63	74	50	50	75	88	50	50	56	57	51	50
Fund age (years)	13.38	12.75	11.48	11.26	10.56	10.91	10.23	10.09	9.76	10.92	8.68	8.28

Table II. Continued

Panel B: Non-U.S. Domiciled Fund Sample

	To ESG		Other Funds		Hold ESG		Other Funds		From ESG		Other Funds	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1-M lagged return (%)	2.26	2.35	2.07	1.89	3.34	3.73	3.15	2.20	0.80	1.04	1.44	1.37
1-M lagged TNA ($ mn.)	63.24	17.49	71.78	71.12	44.07	23.88	71.57	71.18	31.67	14.17	72.60	69.75
1-M lagged flow (%)	0.69	-0.01	2.82	2.36	0.42	0.03	2.80	2.53	0.03	-0.00	2.85	2.79
Expense ratio (% p.a.)	1.45	1.30	1.48	1.46	1.42	1.34	1.52	1.46	1.73	1.66	1.55	1.48
Turnover ratio (% p.a.)	79.35	70.34	66.79	66.48	54.29	26.59	68.10	66.48	60.57	55.75	67.17	67.17
Return over past 6M (%)	6.89	6.48	7.82	6.96	8.29	5.13	7.57	3.14	5.13	5.21	5.27	5.07
Mean flow over past 6M (%)	0.09	-0.18	2.93	2.60	1.40	0.37	2.86	2.73	-0.19	-0.46	3.06	2.97
Star Rating	3.09	3.00	3.13	3.00	3.05	3.00	3.12	3.00	2.71	3.00	3.13	3.00
12-M alpha (%)	0.05	0.03	0.20	0.20	0.16	0.02	0.21	0.13	-0.35	-0.43	-0.08	-0.08
12M-volatility (%)	5.41	5.25	6.08	6.19	5.50	5.29	5.99	5.32	4.24	4.12	4.68	4.39
Globe Rating	3.43	3.00	3.04	3.00	3.64	4.00	3.04	3.00	3.50	3.00	3.02	3.00
Rank ESG (percentile)	63	71	50	50	70	84	50	50	64	70	50	50
Fund age (years)	9.00	8.59	7.43	7.51	7.55	7.47	7.30	7.27	7.97	7.83	7.17	7.13

Table III. Determinants of ESG-Related Fund Name Changes
This table reports results of a cross-sectional (Panel A) and time-series (Panel B) logistic regression. The logistic regression in Panel A is estimated as follows: I restrict the sample to months of ESG-related name changes and assign funds that have an ESG-related name change a dummy of one, and other funds zero. I regress this dummy on variables that indicate fund performance, size, and flows, as defined in Table II. For the time-series logistic regression in Panel B, I restrict the sample to name-change funds and assign them dummies of one in the name-change month and zero in all other months. Results are broken down into "To ESG", "Hold ESG", and "From ESG" name changes. p-Values are in parentheses.

Panel A: Cross-Sectional Logistic Regression

	U.S.-Domiciled Fund Sample	Non-U.S. Domiciled Fund Sample	All Funds
	(1)	(2)	(3)
Constant	-6.77	-7.92	-7.73
	(0.00)	(0.00)	(0.00)
1-M lagged return	0.03	0.02	0.02
	(0.34)	(0.19)	(0.22)
Log of 1-M lagged TNA ($ mn.)	-0.16	-0.03	-0.05
	(0.00)	(0.00)	(0.00)
1-M lagged flow	-0.02	-0.01	-0.01
	(0.05)	(0.11)	(0.11)
Return over past 6M	0.01	0.02	0.02
	(0.60)	(0.49)	(0.51)
Mean flow over past 6M	-0.07	-0.18	-0.12
	(0.04)	(0.02)	(0.03)
12-M alpha	-0.12	-0.26	-0.85
	(0.21)	(0.86)	(0.57)
12-M volatility	-0.00	-0.03	-0.03
	(0.33)	(0.23)	(0.25)
Log of fund age (years)	0.56	0.08	0.14
	(0.00)	(0.01)	(0.00)
N	1,145,061	5,188,330	6,333,391

Table III. Continued

Panel B: Time-Series Logistic Regression			
	To ESG	Hold ESG	From ESG
	(1)	(2)	(3)
Constant	-3.83	-3.78	-2.83
	(0.00)	(0.00)	(0.00)
1-M lagged return	0.43	1.74	-1.14
	(0.39)	(0.21)	(0.60)
Log of 1-M lagged TNA ($ mn.)	-0.09	-0.06	-0.07
	(0.00)	(0.00)	(0.01)
1-M lagged flow	-0.33	-0.13	-0.08
	(0.24)	(0.62)	(0.92)
Return over past 6M	0.59	0.03	-1.80
	(0.43)	(0.99)	(0.21)
Mean flow over past 6M	-1.76	-0.67	-3.36
	(0.00)	(0.09)	(0.04)
12-M alpha	0.94	1.15	-1.99
	(0.52)	(0.27)	(0.06)
12-M volatility	3.19	3.74	-3.59
	(0.14)	(0.07)	(0.20)
N	102,575	36,182	10,943

Table IV. ESG-Related Name Changes and Fund Flows - Panel Regression

This table reports the results of panel OLS regressions of monthly fund flows on *ESGNameChange* and other fund characteristics. *ESGNameChange* is a dummy equal to zero for periods leading up to an ESG-related name change and one for periods thereafter. *Retail* is a dummy equal to one for fund share classes that MS Direct classifies as non-institutional. *Flow benchmark* is calculated as the average fund flow for each month and Morningstar global category. Remaining controls are defined in Table II. The sample is restricted to funds that engage in ESG-related name changes and to an interval of 24 months around the name-change date. I split the sample into subsamples for "To ESG", "Hold ESG", and "From ESG" name-change events. The main effect of *Retail* is included but unreported. Standard errors in parantheses are clustered on the fund share class level. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

	Dependent Variable: Fund Flows $F_{i,t}$					
	To ESG		Hold ESG		From ESG	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.019	0.018	0.026	0.027	-0.026	-0.031
	(0.013)	(0.014)	(0.021)	(0.023)	(0.032)	(0.035)
ESGNameChange	0.011***	0.012***	0.014***	0.015***	-0.003	0.004
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.05)
ESGNameChange × Retail		-0.001		-0.002		-0.008**
		(0.008)		(0.009)		(0.003)
1-M lagged return	0.042*	0.041*	0.038	0.040	0.064	0.064
	(0.025)	(0.024)	(0.042)	(0.042)	(0.047)	(0.047)
Log of 1-M lagged TNA ($ mn.)	-0.005***	-0.005***	-0.004**	-0.004**	-0.004*	-0.004*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
1-M lagged flow	0.095***	0.094***	0.106***	0.106***	0.137*	0.137*
	(0.025)	(0.025)	(0.033)	(0.031)	(0.077)	(0.075)
Expense ratio	-0.001	-0.001	0.008	0.008	0.002	0.002
	(0.002)	(0.002)	(0.005)	(0.005)	(0.004)	(0.005)
Turnover ratio	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
1-M lagged Star Rating	0.011***	0.011***	0.011***	0.011***	0.019***	0.019***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.005)
12-M alpha	0.004	0.002	0.168	0.157	0.005	0.028
	(0.151)	(0.152)	(0.362)	(0.361)	(0.369)	(0.363)
12-M volatility	0.106	0.103	0.157	0.156	-0.186	-0.188
	(0.087)	(0.086)	(0.176)	(0.175)	(0.227)	(0.223)
Log of fund age (years)	-0.002	-0.002	-0.014**	-0.013**	-0.007	-0.008
	(0.003)	(0.003)	(0.006)	(0.006)	(0.005)	(0.006)
Flow benchmark	0.365***	0.361***	0.254*	0.247*	0.177*	0.173*
	(0.102)	(0.102)	(0.144)	(0.141)	(0.104)	(0.101)
Adj. R-squared	0.045	0.045	0.062	0.063	0.042	0.043
N	12,632	12,632	3,291	3,291	1,319	1,319

Table V. Cumulative Abnormal Fund Flows Around ESG-Related Name Changes This table presents average cumulative abnormal flows (CAFs) earned by funds in the year before to the year after their ESG-related name change. Flows are calculated as $[TNA_{i,t} - TNA_{i,t-1}(1 + r_{i,t})]/TNA_{i,t-1}$, as in Sirri and Tufano (1998). For each name-change fund, abnormal fund flows are calculated as the monthly difference in flows with respect to a propensity-score matched fund. I follow Cooper et al. (2005) and estimate a propensity score for each fund by running a logistic regression for each name-change month. I assign each name-change fund a dummy of one, and all other funds zero, and regress this dummy on the following independent variables, as described in Table II: one-month lagged returns, log of one-month lagged TNA, six-month returns and average fund flows prior to the name change, Morningstar's Star Rating, 12-month alpha from a Carhart (1997) model, 12-month standard deviation of returns, and log of age (in years). CAFs are calculated as the sum of the monthly abnormal fund flows during the respective time periods. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

		Months					
	N	−12 to 0	−6 to 0	−3 to 0	0 to 3	0 to 6	0 to 12
		(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Cumulative Abnormal Flows for All Fund Share Classes (%)							
ESG Name Changes	1,002	-2.31	-1.27	-1.08	4.83***	8.79***	12.95***
		(2.65)	(1.64)	(1.15)	(1.48)	(1.93)	(2.48)
To ESG	654	-3.11	-1.84	-1.44	5.29***	9.37***	13.87***
		(3.23)	(1.87)	(1.44)	(1.94)	(2.48)	(3.13)
Hold ESG	283	-0.60	-0.12	-0.91	5.26**	9.64***	14.14***
		(2.33)	(2.73)	(2.23)	(2.57)	(3.50)	(4.65)
From ESG	65	-1.78	-0.49	1.80	-1.60	-0.70	-1.53
		(2.36)	(1.80)	(2.22)	(2.24)	(1.58)	(1.78)
Panel B. Cumulative Abnormal Flows for Retail Fund Share Classes (%)							
ESG Name Changes	764	-2.26	-1.57	-1.44	4.03***	8.75***	13.07***
		(2.91)	(1.90)	(1.34)	(1.50)	(2.54)	(3.72)
To ESG	494	-3.34	-2.83	-2.11	4.48**	9.35***	13.98***
		(3.60)	(2.18)	(1.67)	(2.16)	(2.84)	(4.41)
Hold ESG	217	0.28	1.20	-0.67	4.62**	9.83**	14.79**
		(1.80)	(1.28)	(1.62)	(2.32)	(3.98)	(6.20)
From ESG	53	-2.54	-1.16	1.62	-2.60	-1.21	-2.41
		(2.16)	(1.24)	(1.81)	(2.70)	(1.46)	(2.89)
Panel C. Cumulative Abnormal Flows for Institutional Fund Share Classes (%)							
ESG Name Changes	238	-2.52	-0.31	0.07	7.42**	8.91***	12.56***
		(3.08)	(1.23)	(1.22)	(3.34)	(3.46)	(4.72)
To ESG	160	-2.42	1.20	0.61	7.79***	9.42***	13.55***
		(3.10)	(1.54)	(1.79)	(3.06)	(3.53)	(5.20)
Hold ESG	66	-3.51	-4.47	-1.69	7.35**	9.03**	12.01***
		(4.59)	(5.63)	(2.17)	(3.30)	(3.95)	(4.63)
From ESG	12	1.59	2.46	2.59	2.81	1.54	2.37
		(2.15)	(3.81)	(4.24)	(4.69)	(2.12)	(3.35)

Table VI. ESG Name Changes, Turnover and ESG Metrics - Panel Regression
This table reports the results of panel OLS regressions of fund turnover ratio (Panel A), Globe Rating (Panel B), and RankESG (Panel C), respectively, on $ESGNameChange$ (as defined in Section IIB) and other fund controls of Table IV. The three dependent variables are specified in Table II. The sample is split into subsamples for "To ESG" (columns 1 to 3), "Hold ESG" (columns 4 to 6), and "From ESG" (columns 7 to 9) name-change events (as defined in Table I). The sample is restricted to the primary share class of each fund, as indicated in MS Direct. Standard errors are clustered on the fund share class level and are reported in parentheses. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

	To ESG			Hold ESG			From ESG		
Panel A. Dependent Variable: $TurnoverRatio_{i,t}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.69***	1.71***	4.85	0.55***	1.42*	3.87***	0.79***	-0.12	0.89
	(0.08)	(0.53)	(3.07)	(0.09)	(0.84)	(0.95)	(0.16)	(0.91)	(0.61)
ESGNameChange	0.08**	0.11**	0.09*	-0.01	-0.01	0.04	0.03	-0.01	-0.03
	(0.03)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)	(0.10)	(0.05)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Fixed effects	No	No	Fund	No	No	Fund	No	No	Fund
Adj. R-squared	0.01	0.05	0.08	0.00	0.08	0.18	0.00	0.12	0.14
N	2,144	1,781	1,781	725	639	639	390	264	264
Panel B. Dependent Variable: $GlobeRating_{i,t}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	3.22***	2.75***	3.24	3.92***	3.87***	2.98	3.13***	-1.95	-10.47
	(0.10)	(0.76)	(2.95)	(0.11)	(0.79)	(2.68)	(0.42)	(1.81)	(23.34)
ESGNameChange	0.35***	0.43***	0.27***	0.03	0.15	-0.04	-0.08	-0.04	-0.17
	(0.09)	(0.10)	(0.07)	(0.11)	(0.15)	(0.15)	(0.49)	(0.57)	(0.55)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Fixed effects	No	No	Fund	No	No	Fund	No	No	Fund
Adj. R-squared	0.02	0.09	0.09	0.00	0.11	0.11	0.00	0.13	0.14
N	2,622	2,310	2,310	1,205	901	901	156	146	146
Panel C. Dependent Variable: $RankESG_{i,t}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.61***	0.62***	0.17	0.74***	0.74***	-0.07	0.54***	-1.62	-4.54
	(0.03)	(0.21)	(1.14)	(0.03)	(0.26)	(0.57)	(0.09)	(1.77)	(3.75)
ESGNameChange	0.14***	0.15***	0.14***	0.03	-0.01	-0.04*	-0.03	-0.04	-0.04
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.11)	(0.07)	(0.03)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Fixed effects	No	No	Fund	No	No	Fund	No	No	Fund
Adj. R-squared	0.06	0.12	0.15	0.00	0.17	0.18	0.04	0.13	0.13
N	1,838	1,673	1,673	1,210	970	970	162	138	138

Table VII. Cumulative Abnormal Fund Flows and ESG Score Improvements
This table presents average cumulative abnormal flows (CAFs) earned by funds in the year before to the year after cosmetic and noncosmetic ESG-related name changes. CAFs are calculated as in Table V. I define cosmetic and noncosmetic name changes based on whether a fund's excess *RankESG* (as described in Section IIIA) in 12 months after the name change is below (cosmetic) or above (noncosmetic) the median excess *RankESG* of funds of the same name-change type. The table also reports t-statistics from testing the null hypothesis that mean CAFs across cosmetic and noncosmetic name changes are equal. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

		Months					
	N	−12 to 0	−6 to 0	−3 to 0	0 to 3	0 to 6	0 to 12
		(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Cumulative Abnormal Flows for Retail Fund Share Classes (%)							
To ESG							
Cosmetic	179	-2.93	-2.16	-1.80	3.85**	9.01**	13.24***
		(3.18)	(2.83)	(2.10)	(1.94)	(4.60)	(5.01)
Noncosmetic	177	-3.53	-1.66	-0.77	4.86**	10.06***	14.53***
		(3.84)	(1.99)	(1.00)	(2.44)	(3.56)	(4.21)
T-test for differences		0.12	-0.14	-0.44	-0.32	-0.19	-0.20
Hold ESG							
Cosmetic	91	-1.43	-1.17	-1.32	3.82*	8.78**	12.36**
		(2.91)	(2.51)	(2.53)	(2.27)	(4.22)	(5.98)
Noncosmetic	90	1.74	2.36	0.83	5.01***	11.14***	15.88***
		(4.22)	(3.15)	(1.76)	(2.10)	(4.01)	(6.19)
T-test for differences		-0.62	-0.87	-0.70	-0.38	-0.41	-0.41
Panel B. Cumulative Abnormal Flows for Institutional Fund Share Classes (%)							
To ESG							
Cosmetic	64	0.74	1.98	0.07	3.92*	4.36	5.11
		(3.87)	(3.08)	(2.26)	(2.30)	(3.83)	(3.85)
Noncosmetic	63	-2.83	0.02	1.63	10.71***	13.71***	17.44***
		(3.55)	(2.29)	(2.01)	(3.32)	(4.15)	(5.04)
T-test for differences		0.68	0.51	-0.52	-1.69	-1.66	-1.98
Hold ESG							
Cosmetic	27	-2.89	-4.50	-2.55	2.73	3.62	4.01
		(4.14)	(3.42)	(2.57)	(2.26)	(3.02)	(3.60)
Noncosmetic	26	-4.35	-4.25	0.58	11.02***	14.10***	18.52***
		(5.22)	(4.81)	(3.36)	(3.51)	(5.10)	(7.01)
T-test for differences		0.22	-0.04	-0.74	-2.00	-1.77	-1.84

Table VIII. Microlevel Evidence From an Online Experiment

This table presents results of the Amazon Mechanical Turk online investment allocation experiment. Panel A compares the fraction of money invested in fund A if the fund's name does and does not contain the term "Sustainable" in addition to the base label, the mean difference between the amounts invested, and the respective t-statistic. The 592 Participants are residents in the U.S. and invested in mutual funds (self-reported). Panel B shows coefficient estimates when regressing money invested in fund A on an *ESG-Name* dummy variable and participant characteristics. *ESG-Name* is equal to one for funds that are randomly assigned to include the term "Sustainable" and zero otherwise. Participant characteristics include a *Female* dummy and a *Young* dummy that indicates below median biological age. Columns 1 and 4 display results for the full sample, while columns 2 and 3 show results for subsamples split by participants' self-reported party affiliation (Democrats and Republicans). t-statistics are reported in parentheses. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

Panel A. Average distributions (Rounds including ESG-related Fund Names)

	% of funds allocated to fund A if:			
	ESG-Name	No ESG-Name	Difference	t-statistic
	(1)	(2)	(3)	(4)
Round 2	55.01	50.64	4.37**	1.99
Round 4	27.38	23.73	3.64***	3.12
Round 2 + Round 4	41.19	37.19	4.01***	2.71

Panel B. Regressions (Rounds including ESG-related Fund Names)

	All subjects	Democrats	Republicans	Interactions
	(1)	(2)	(3)	(4)
ESG-Name	4.01***	4.81***	2.52*	2.50*
	(2.71)	(2.92)	(1.74)	(1.73)
Female×ESG-Name				1.76
				(1.25)
Young×ESG-Name				3.39*
				(1.94)
Adj. R-squared	0.02	0.02	0.02	0.02
N	1,184	481	483	1,184

Table IX. ESG-Related Fund Name Changes and Factor Loadings
This table reports average *Alpha* and factor loadings from a Carhart (1997) four-factor model using daily fund returns over a 12 month period before and after an ESG-related name change. Results are broken down into "To ESG", "Hold ESG", and "From ESG" name changes. Daily international (Global incl. U.S.) Fama and French (1993) as well as momentum risk factors are obtained from Kenneth R. French's website. Panel A reports average *Alpha* and loadings on the market (*Mkt-RF*), size (*SMB*), value (*HML*), and momentum (*MOM*) factors. In Panel B, the market factor is replaced by *ESG-RF*, which is the daily return of the MSCI World ESG Leaders index net of the U.S. Treasury bill yield.

Panel A. Standard Carhart (1997) Model

	To ESG			Hold ESG			From ESG		
	-12 to 0	0 to 12	Paired *t*	-12 to 0	0 to 12	Paired *t*	-12 to 0	0 to 12	Paired *t*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Alpha (%)	-0.00	-0.00	0.86	-0.00	-0.00	1.16	-0.01	-0.01	0.23
Mkt-RF	0.85	0.89	2.87	0.89	0.89	-0.18	0.98	0.98	0.27
SMB	0.16	0.09	-1.91	0.25	0.22	-1.05	-0.04	-0.01	0.95
HML	0.06	-0.00	-1.60	0.08	0.05	-0.73	0.05	0.01	-1.18
MOM	0.04	0.02	-0.55	0.03	-0.01	-0.27	0.08	0.04	-1.09

Panel B. Carhart (1997) Model with MSCI ESG Index as Market Return

	To ESG			Hold ESG			From ESG		
	-12 to 0	0 to 12	Paired *t*	-12 to 0	0 to 12	Paired *t*	-12 to 0	0 to 12	Paired *t*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Alpha (%)	-0.00	-0.00	1.13	-0.00	-0.00	0.79	-0.01	-0.01	1.06
ESG-RF	0.83	0.91	3.71	0.91	0.91	-0.35	1.01	0.98	-1.36
SMB	0.28	0.20	-1.84	0.41	0.39	-0.48	0.16	0.19	1.09
HML	0.06	-0.01	-1.49	0.08	0.04	-0.80	0.09	0.06	-0.62
MOM	0.03	-0.01	-1.29	0.02	-0.03	-1.31	-0.01	0.03	1.48

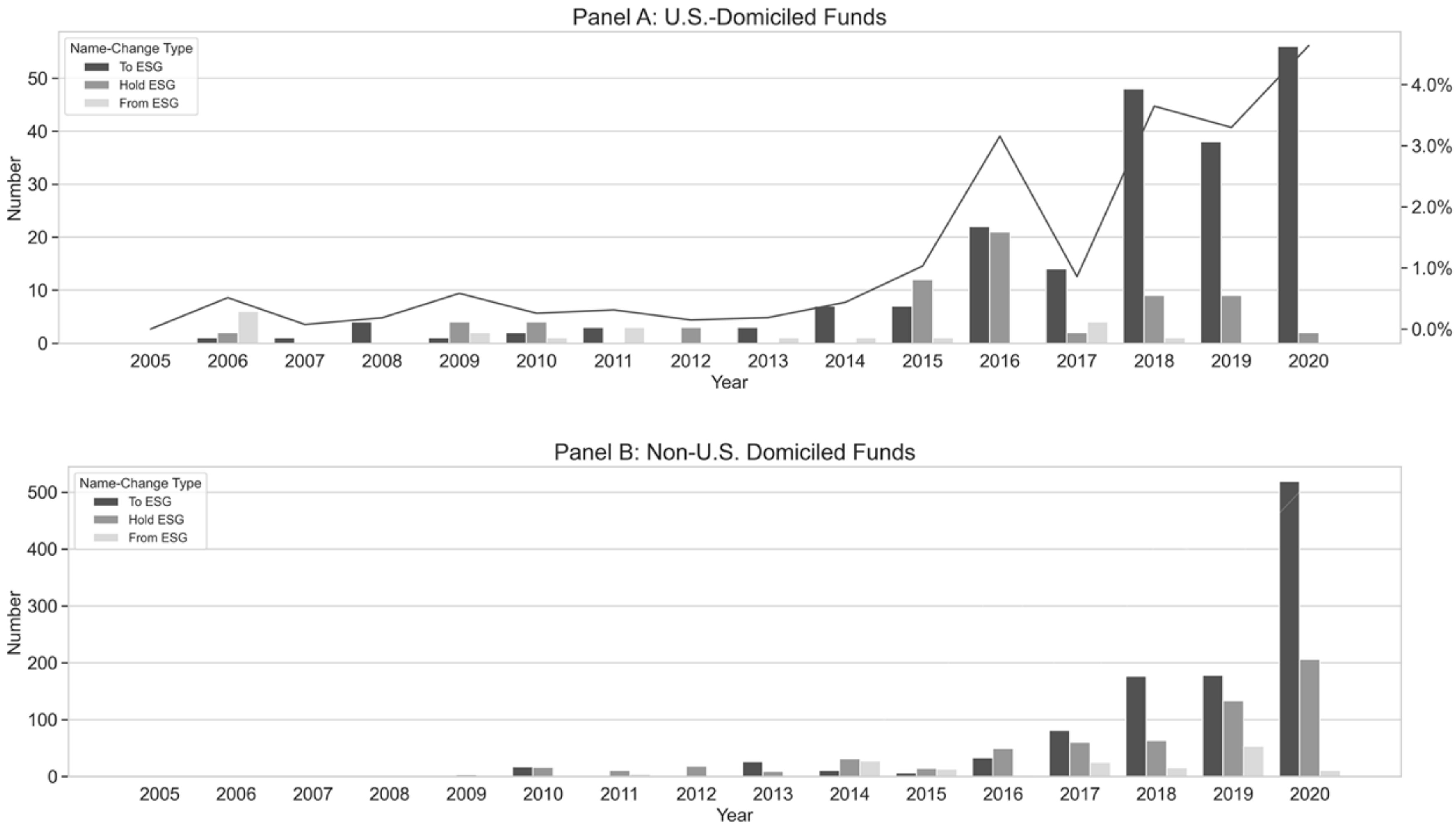

Figure 1. ESG-Related Equity Mutual Fund Name Changes per Year and Type. This figure shows the number of ESG-related name changes of U.S.-domiciled (Panel A) and non-U.S. domiciled (Panel B) equity mutual fund share classes across the sample years and name-change types. The secondary axis in Panel A shows the fraction of ESG-related name changes in the U.S.-domiciled fund sample as the percentage of total name changes in the CRSP-Morningstar equity mutual fund intersection..

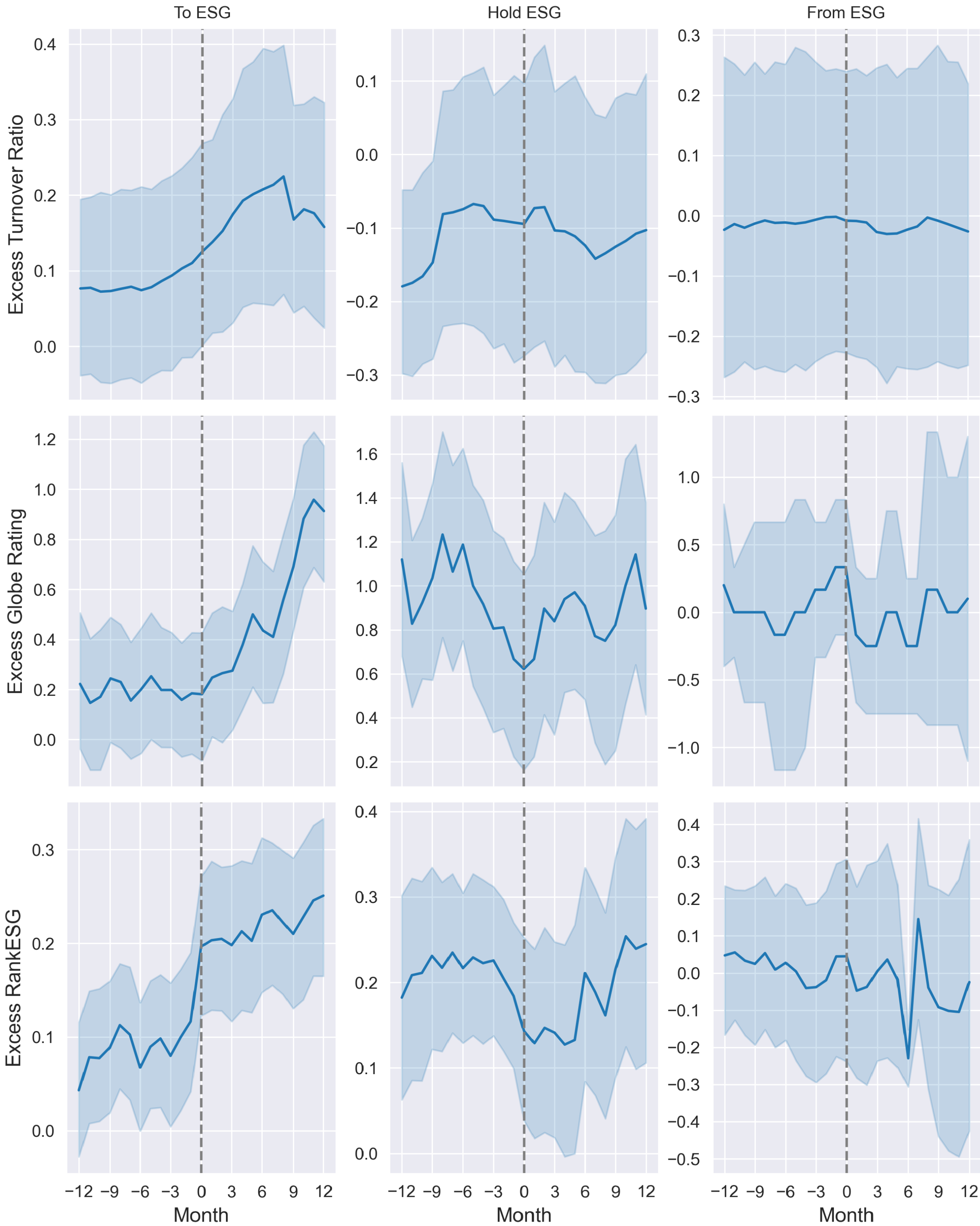

Figure 2. Excess Turnover Ratio and ESG Metrics Around Name Changes. This figure shows funds' excess turnover ratio, Globe Rating, and RankESG in the 24 months surrounding an ESG-related name change by event type (i.e., "To ESG", "Hold ESG", and "From ESG"). Excess values are calculated as the difference with respect to a fund's propensity-score matched fund (as described in Section IIB). The shaded area marks the 90% confidence interval.

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EDUCATION

Ph.D. in Finance, University of St. Gallen	Feb. 2017 - Apr. 2021
M.A. in Banking and Finance, University of St. Gallen	Sept. 2014 - Apr. 2017
Graduate Certificate, Boston University	Sept. 2015 - Dec. 2015
B.A. in Business Administration, University of St. Gallen	Sept. 2011 - Oct. 2016
B.A. in Economics, University of St. Gallen	Sept. 2011 - Sept. 2014

PROFESSIONAL EXPERIENCE

Visiting Researcher, Harvard Business School	Nov. 2021 - Present
Visiting Researcher, Cornell University	Sept. 2020 - Aug. 2021
Research Assistant, University of St. Gallen	Sept. 2016 - Aug. 2020
Research Analyst, Investnet AG	Sept. 2014 - Sept. 2016
Intern, Deutsche Bank AG	Jul. 2013 - Oct. 2013

CONFERENCE PRESENTATIONS AND TALKS

2021 German Finance Association, Innsbruck, AT
2020 Financial Management Association, New York, USA
2019 NBER Summer Institute, Boston, MA, USA
2019 Southern Finance Association, Orlando, FL, USA
2019 Swiss Finance Institute Research Days, Gerzensee, CH
2019 Cologne Colloquium on Financial Markets, Cologne, GER

TEACHING EXPERIENCE

Methods: Statistics (Undergraduate Course Exercises, Lecturer)	2019-2020
Financial Markets (Graduate Course, Teaching Assistant)	2017-2020
Research Seminar in Finance (Graduate Course, Teaching Assistant)	2017-2018
Statistics (Graduate Preparation Class, Lecturer)	2017-2020
Behavioral Finance (Executive Education, Lecturer)	2017-2020
Alternative Investments (Executive Education, Lecturer)	2017-2020
FinTech (Executive Education, Lecturer)	2018-2019
Fixed Income Instruments (Executive Education, Lecturer)	2017-2019
Options & Futures (Executive Education, Lecturer)	2017-2018
Derivatives (Graduate Course, Teaching Assistant)	2017-2018

REFEREE WORK

Review of Financial Studies
Financial Markets and Portfolio Management

SCHOLARSHIPS, AWARDS, AND ACCREDITATIONS

Southern Finance Association Outstanding Paper Award 2019
American Finance Association Travel Grant
Advanced Risk and Portfolio Management Bootcamp 2019, New York, NY, USA
Passed all three levels of the Chartered Financial Analyst (CFA®) Program
Passed both levels of the Chartered Alternative Investment Analyst (CAIA®) Program
Passed level 1 of the Financial Risk Manager (FRM®) Program
Awarded CFA® Fellowship, CAIA® Scholarship, GARP Fellowship, and FRM® Fellowship
UBS Prize for best degree result in 2017 (M.A. in Banking and Finance)