What is in a Name? Mutual Fund Flows When Managers Have Foreign-Sounding Names*

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Abstract – This paper shows that stereotypes associated with a person's name affect the investment choices of U.S. mutual fund investors. Compared to managers with typical American names, fund managers with foreign-sounding names have lower fund flows, even though there are no significant differences in their investment style and performance. These managers also experience lower appreciation in flows following good performance and greater decline in flows following poor performance. The flow effects are stronger for funds that have more conservative investor clienteles or are located in regions where racial/ethnic stereotypes are more pronounced. Further, following the 9/11 terrorist attacks, fund managers with Middle-Eastern and South-Asian names experience a drop in fund flows relative to other managers with foreign-sounding names. Even in an experimental setting where managerial skill differences do not exist, individuals allocate 14% less money to an index fund managed by an individual with foreign-sounding name. Our rough calculations indicate that lower fund flows can reduce the annual compensation of managers with foreign-sounding names by over hundred thousand dollars. Collectively, our results provide evidence of taste-based discrimination and show that social biases affect capital allocations even in one of the largest and most liquid capital market segments.

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What is in a Name? Mutual Fund Flows When Managers Have Foreign-Sounding Names

Abstract – This paper shows that stereotypes associated with a person's name affect the investment choices of U.S. mutual fund investors. Compared to managers with typical American names, fund managers with foreign-sounding names have lower fund flows, even though there are no significant differences in their investment style and performance. These managers also experience lower appreciation in flows following good performance and greater decline in flows following poor performance. The flow effects are stronger for funds that have more conservative investor clienteles or are located in regions where racial/ethnic stereotypes are more pronounced. Further, following the 9/11 terrorist attacks, fund managers with Middle-Eastern and South-Asian names experience a drop in fund flows relative to other managers with foreign-sounding names. Even in an experimental setting where managerial skill differences do not exist, individuals allocate 14% less money to an index fund managed by an individual with foreign-sounding name. Our rough calculations indicate that lower fund flows can reduce the annual compensation of managers with foreign-sounding names by over hundred thousand dollars. Collectively, our results provide evidence of taste-based discrimination and show that social biases affect capital allocations even in one of the largest and most liquid capital market segments.

And I got my middle name from somebody who obviously didn't think I'd ever run for president.

– Barack Hussein Obama

Al Smith Dinner, New York, October 16, 2008.

1. Introduction

When people hear the name of a person, either consciously or sub-consciously, they typically assign a host of attributes to that person, which are related to the "group" (i.e., country of origin, religion, race, ethnicity, culture, etc.) associated with the name. Often, name-related stereotypes get activated almost spontaneously without much conscious effort (Kunda (1999)). These stereotypes consequently may color the initial impressions of the person. For example, names such as "Zaheer Sitabjhan" or "Toshihiko Tsuyusaki" is likely to invoke a different reaction than typical American names like "Michael Brown" or "Robert Stevens".

One of the main reasons for this differential perception based primarily on the name of a person is that a person with a less familiar, foreign-sounding name may trigger a strong sense of in-group bias.[1] As a result, that person may be trusted less, undergo closer scrutiny, and may even experience some form of discrimination. If these biases take an extreme form, they may even generate emotions of fear or hostility and induce xenophobic feelings (Hirshleifer (2008)).

A foreign name can also invoke stereotypes associated with the country of origin of the name. For example, when people hear an Indian name, they are more likely to believe that the person is a doctor or a computer engineer because such associations are more salient and more easily available. For similar reasons, people often assume that a person with an Asian last name must be good in science and mathematics.[2]

Of course, name-related stereotypes can also be negative. Using a field experiment in which names were randomly assigned to resumes, Bertrand and Mullainathan (2004) show that em-

[1] People systematically adopt favorable opinions about members of their own group and might be indifferent or have lower opinions about members who are outside of their group (e.g., Tajfel (1982), Hewstone, Rubin, and Willis (2002)). This form of in-group favoritism is likely to be the primary driver of social biases such as prejudice, stereotyping, and discrimination.

[2] As discussed in Kao (1995), some common positive stereotypes about minorities are: "Asians are good in technical fields." or "Asians are good with numbers."

ployers discriminate against candidates based on their name. Individuals with names such as "Lakisha" and "Jamal" that are distinctively African-American are less likely to be invited for a job interview.[3] While in that study there are no differences between candidates' resumes by design, it is still possible that names proxy for unobservable differences in productivity. In a related study, Fryer and Levitt (2004) show that Black names are correlated with parental behavior that is in turn negatively related to productivity of the child. Because job productivity is largely unobservable, in most labor market settings it is very hard to distinguish between social bias induced taste-based discrimination and pure statistical discrimination.

In this paper, we analyze whether potential stereotypes associated with a person's name affect the investment choices of mutual fund investors. Specifically, we examine whether investors are less likely to invest in mutual funds that are managed by individuals with foreign-sounding names. The mutual fund setting is particularly attractive for studying discrimination because fund management is one of the very few occupations where good measures of job performance are available. In particular, the performance of fund managers is observable from fund returns, which allows us to overcome challenges in the prior literature where it has been very difficult to account for productivity differences that might be correlated with the degree of foreignness of names.

We are not particularly interested in identifying fund managers who are U.S. citizens and those who are foreigners. What we want to capture is whether a name *sounds* foreign when heard, read in a fund prospectus, or found on a mutual fund web site.[4] Since information on nationality is rarely disclosed, the name of the fund manager is the only personal information that is available to most investors. The foreignness of a name is likely to be sufficient to invoke various social biases and influence the investment decisions of mutual fund investors.

Our key conjecture is that funds with "foreign" managers would experience lower flows even if managers of those funds do not have inferior investment skill or follow a different investment

[3]During the Presidential elections in 2008, several political commentators strategically highlighted President Barack Obama's Arab-sounding middle name "Hussein", perhaps to highlight his Islamic roots and affect voting behavior through ethnic intolerance.

[4]See Appendix E for an example of how fund manager names are usually displayed to potential investors.

style.[5] In particular, those managers would be "punished" more after bad performance and "rewarded" less after good past performance, i.e., compared to funds managed by individuals with non-foreign sounding names, funds with foreign managers would experience greater decline in flows following poor performance and lower appreciation in flows following good performance. Further, name-induced racial and ethnic stereotypes are likely to be stronger among individuals who are more conservative and, consequently, these name-induced flow patterns would be stronger for mutual funds that have more conservative investor clienteles.

We test our conjectures using a novel, hand-collected dataset that contains measures of foreignness of a large sample of mutual fund managers. We use the Amazon Mechanical Turk (AMT), an anonymous Internet platform, to hire several paid "workers" from the U.S. who classify names into foreign and non-foreign categories. Each name is evaluated by ten different workers and they indicate whether a name sounds foreign or domestic from the perspective of a U.S. resident. We aggregate the classifications of all workers into a foreign name index, which is defined as the percentage of workers who classified a name as foreign. Using these estimates, we classify each manager into the foreign-sounding name category if at least 75% of workers indicate that the name sounds foreign.

We use the foreign name classification obtained from the AMT to examine the influence of name-induced stereotypes on mutual fund flows. Our evidence indicates that funds managed by individuals with foreign-sounding names are very similar to other funds in terms of performance levels and investment styles. In some tests, there is weak evidence that a portfolio of foreign funds outperforms a portfolio of non-foreign funds on a risk-adjusted basis. These findings suggest that a foreign-sounding name is not a signal of worse managerial skill. Therefore, the foreignness of fund manager names cannot be used to engage in effective statistical discrimination where an investor could separate good fund managers from bad managers based only on their names.

In spite of these similarities among funds, the perceived foreignness of fund manager names influences fund flows. Specifically, our baseline results show that compared to funds managed

[5] A manager with a foreign-sounding name may be a U.S. citizen and need not be a foreigner, but for brevity, we refer to managers with foreign-sounding names as "foreign" managers. Similarly, we refer to funds managed by individuals with foreign-sounding names as "foreign" funds.

by individuals with typical American names, mutual fund flows are around 10 percentage points lower for funds managed by individuals with foreign-sounding names. Further, managers with foreign-sounding names experience lower appreciation in flows following good performance and greater decline in flows following poor performance. Compared to an otherwise identical fund managed by an individual with an American name, managers with foreign-sounding names experience 11.7 percentage points higher outflows and a 44.5 percentage points lower inflows when their recent performance is in the bottom or the top decile of all mutual funds, respectively.

The results from additional tests suggest that these flow patterns are induced by taste-based discrimination among fund investors. First, we show that name-induced flow patterns are stronger for funds headquartered in regions that are more conservative and where racial and ethnic stereotypes are more pronounced. Because fund location is mostly exogenous, these findings provide strong support for the view that discrimination is induced by social biases and is likely to be taste-based.

Second, we find evidence of taste-based discrimination using the exogenous event of 9/11 terrorist attacks when negative stereotypes against individuals of South-Asian and Middle-Eastern origin were amplified. Specifically, we demonstrate that following the 9/11 terrorist attacks, fund managers with Middle-Eastern and South-Asian names experience a drop in fund flows relative to other managers with foreign-sounding names. Last, even in an experimental setting where we assign fund manager names to index funds and managerial skill differences do not exist by design, individuals allocate 14% less money to an index fund run by a manager with a foreign-sounding name.

In the last part of the paper, we examine directly whether the foreignness of fund manager names influences the mutual fund investment decisions of individual investors. Using a small sample of brokerage customers at a large U.S. discount brokerage house, we show that household characteristics are important determinants of mutual fund investment decisions of U.S. investors. While older, conservative households are less willing to invest in funds that are managed by individuals with foreign-sounding names, individuals who live in regions with a greater proportion of foreign-born individuals are more likely to invest in those funds. Even the level of investments in “foreign” funds is influenced by investors’ demographic characteristics. Overall, we find that both the degree of conservatism and in-group bias affect the mutual fund choices of individual investors.

We do not find empirical support for alternative explanations for our findings such as discrimination at the fund management level or information asymmetry between managers with foreign-sounding names and other managers. Bias against foreign-sounding names at the fund management company level could be relevant for our results if, for example, managers with foreign sounding names were systematically assigned to worse funds that are expected to attract lower flows. However, our finding that the fund attributes and performance levels of funds with managers with foreign-sounding names is not very different from other funds does not support this hypothesis. The fund company could also advertise these funds less, which could explain our flow results. But we find that foreign funds have larger marketing expenses than other funds. Hence, our results are most consistent with the conjecture that social biases such as discrimination, stereotyping, and in-group bias influence the behavior of mutual fund investors.

One of the key implicit assumptions in our analysis is that investors are aware of the identities of their fund managers. To examine whether this assumption is appropriate, we conduct an online survey in the U.S. and ask individuals whether they are aware of the fund manager when they pick a mutual fund. About 64% of survey respondents mention that fund manager identity is an important determinant of their fund choices and 57% of respondents knew their fund managers.[6] This evidence suggests that a sizeable proportion of mutual fund investors are likely to be aware of fund manager identities. Therefore, fund manager names could influence people’s investment decisions and aggregate fund flows.

Taken together, our empirical results suggest that name-induced social biases such as in-group bias and stereotyping affects the behavior of mutual fund investors. If managers with foreign-sounding names face greater hurdles in the labor market, only superior managers would be able to enter the profession. Thus, ex ante they may be expected to have superior abilities and, in fact, managers with foreign-sounding names are better educated (a larger proportion

[6]Our survey focuses on smaller retail investors. The degree of awareness about fund managers is likely to be higher among larger and relatively more sophisticated retail investors.

hold a Ph.D. degree). From this perspective, our evidence of taste-based discrimination is quite surprising.

Our results challenge the belief that liquid and competitive capital markets can fully absorb the potential adverse effects of social biases and other types of biases. Examining the economic costs of these social biases to a fund manager, we find that mutual fund managers with foreign-sounding names incur a significant cost for the foreignness of their names. Our estimates indicate that the typical fund with a size of about \$175 million can incur an annual average cost of \$143,000, although this cost can be as high as \$600,000. Even if only a fraction of this cost is experienced by the fund manager, the cumulative cost of having a foreign-sounding name over the entire career span of a fund manager can be significant.

These empirical findings contribute to the growing literature in behavioral finance that examines the effects of social biases such as discrimination and stereotyping on financial markets (e.g., Wolfers (2006), Kumar (2010), Niessen-Ruenzi and Ruenzi (2011)). To our knowledge, this is the first paper to demonstrate that social biases such as in-group bias and stereotyping can aggregate and have the potential to influence aggregate-level variables like fund flows. Several previous papers have examined the impact of psychological biases such as overconfidence and the disposition effect on aggregate-level variables such as turnover, liquidity, and returns. However, none of these studies study the impact of social biases on portfolio decisions and aggregate-level variables, which is the main focus of our study.

Our results also contribute to a broader literature in economics that provides evidence of in-group bias and discrimination in a variety of settings. Specifically, this literature documents that employers discriminate against minority groups in the labor market (e.g., Becker (1957), Bertrand and Mullainathan (2004)). Similarly, consumers discriminate against products sold by or associated with individuals of other races (e.g., Nardinelli and Simon (1990), Ouellet (2007)). Race-based discrimination influences decisions in sporting events (e.g., Price and Wolfers (2010), Parsons, Sulaeman, Yates, and Hamermesh (2011)). Even in courtrooms, studies consistently find that race matters (e.g., Abrams, Bertrand, and Mullainathan (2012)). In this paper, we provide strong evidence of taste-based discrimination and demonstrate that social biases such as in-group bias and stereotyping affect capital allocations in the mutual fund industry, which is one of the most liquid and competitive capital markets in the U.S.

The rest of the paper is organized as follows. We summarize our data sources and the foreign names classification method in Section 2. We present our main empirical results in Section 3 and present additional experimental results in Section 4. In Section 5, we provide supporting evidence using data from a discount brokerage house in the U.S. We conclude in Section 6 with a brief discussion.

2. Data and Summary Statistics

We use data from multiple sources. This section provides a brief summary of all those datasets. In Appendix A, we provide a brief summary of all variables used in the empirical analysis.

2.1. Mutual Fund Data

We obtain data on mutual funds from the Center for Research on Security Prices (CRSP) survivorship bias free mutual fund database. This database covers virtually all U.S. open-end mutual funds. It contains information about fund returns, fund management structure, total net-assets, investment objectives, fund manager identity, and other fund characteristics. Our sample spans from 1993 to 2009.

We focus on funds that are not team-managed. Baer, Kempf, and Ruenzi (2011) and Patel and Sarkissian (2012) show that fund managers behave very differently if they work together in a management team as compared to managing a fund on their own. To avoid these confounding effects of group behavior versus individual behavior, we focus on single managed funds only and exclude all funds for which CRSP provides multiple manager names. This selection allows us to isolate the potential effects of foreignness of fund manager names on the investment choices of mutual fund investors.

Our sample consists of actively managed equity funds that invest more than 50% of their assets in stocks and exclude bond and money market funds. We exclude fixed-income funds from the sample because these funds have very different performance benchmarks and would not be comparable to equity funds. Following Daniel, Grinblatt, Titman, and Wermers (1997), we aggregate all share classes of the same fund to avoid multiple counting of the same portfolio. We aggregate Strategic Insight (SI) and Lipper fund objective codes to define the market segment of all funds. This aggregation generates the following eleven distinct equity fund segments: AG (Aggressive Growth), BAL (Balanced Funds), GE (Global Equity), GI (Growth and Income), IE (International Equity), IN (Income), LG (Long-term Growth), REG (Regional Funds, e.g., Asia-Pacific, Europe etc.), SE (Sector Funds), UT (Utility Funds) and TR (Total Return).

All mutual fund variables used in the empirical analysis are similar to those used in the prior literature. The main variable of interest in most of our tests is the net inflow ("fund flow") for fund i in year t defined as

$$\text{Fund Flow} = \frac{TNA_{i,t} - TNA_{i,t-1}}{TNA_{i,t-1}} - r_{i,t},$$

where $TNA_{i,t}$ denotes fund i's total net assets at the end of year t and r_t denotes fund i's return (net of fees) in year t as reported in CRSP.

Beyond the CRSP mutual fund database, we obtain various fund manager attributes such as age and education from Morningstar. We also supplement the Morningstar data with hand-collected data on managerial attributes.

Table 1, Panel A provides the summary statistics for the CRSP sample. The average fund grows its net assets by 28.8% a year net of returns and the median fund by 5.7%. On average fund returns net of fees have been 3.8% (median is 3.1%). The average log fund size is 5.152, which corresponds to a raw size of $174.5 million.

2.2. Identifying Managers with Foreign-Sounding Names

To identify fund managers that have foreign-sounding names, we survey a random sample of the U.S. population via Amazon Mechanical Turk (AMT).[7] AMT is an online platform similar to a labor market, in which "requesters" can list tasks called "human intelligence tasks" (or HITs) along with a specified compensation. Individual "workers" can then elect to work on the

[7]See https://www.mturk.com/mturk/welcome for additional details.

task. They first click on a link to view a brief description of the task. This link can be tied to requirements that a worker has to fulfill (e.g., only U.S. workers can open the link). After seeing the preview, workers can choose to accept the HIT, at which point the work is officially assigned to them and they can begin working on the task. Requesters can set a time frame in which the task needs to be completed.

Once a worker completes a task, the requester examines the quality of the work and the payment amount. If the worker completed the task properly, she will get the specified compensation. But if the task is not completed in a satisfactory manner, requesters can withhold the payment. The requester can also pay a bonus if a worker completes a task extremely well.

We identify a list of all fund manager names for our sample of single managed equity funds from the CRSP mutual fund database. This list contains 4,118 individual first and last names.[8] We then upload this list on AMT. Our task submitted to AMT involved going through the list of fund manager names and marking all names that sounded foreign to the worker.[9] Specifically, we asked workers to indicate for each name in the list whether it sounds foreign from the perspective of a U.S. resident by inserting "Yes" or "No" into the corresponding field. If workers were unsure, they were allowed to indicate "Unsure" into the field.

To ensure that workers completed the task carefully, we told them that we would analyze their answers and if we detected any pattern indicating that they gave their answers randomly, they would not get paid. Workers were required to fulfill the task in two business days. They were paid $20 for their work. In addition, we required that workers who register to work on our task are located in the United States and that their reliability rank is at least 95. This threshold is recommended by AMT and reflects the reliability of a worker based on the ratings from previous requesters.

Ten different workers classified each fund manager name. Workers were able to give us feedback on the task and all of them indicated that they enjoyed working on the task as they considered it more interesting than the average task provided on the AMT platform. They also

[8]We drop names that appear several times in the database due to spelling errors, etc. However, these managers are not excluded from the sample.

[9]See Appendix D for a screen-shot of the task description.

commented that the task was well paid. All workers were paid $20 as they submitted their task on time and completed it satisfactorily.

We aggregate the foreign classification scores of each fund manager, and calculate the percentage of workers who classified the name as foreign. We define the Foreign75 variable, which is a dummy variable that is set to one for names where at least 75% of workers indicated that the name sounds foreign. Appendix B provides the list of the 168 fund manager names that were identified as foreign-sounding according to this definition.[10] We use a cutoff of 75% because it is an effective way to trade off noise, which we get for lower cutoffs, versus a small number of observations, which we get if we require that all workers classify a name as foreign. As expected, we find weaker results for lower cutoffs and very similar results for higher cutoffs.

A significant fraction (40.3%) of fund companies have at least one of their funds run by a manager with foreign sounding name. However, in most fund families, the fraction of funds run by "foreign" managers is small (on average 4.41%). As shown in Table 1, Panel A, 2.1% of fund-years in our sample come from foreign funds. Altogether, there are 3,902 individual funds and 3,159 unique managers in our full sample. Within this set, 192 of the funds (4.92% of total) are managed by 168 unique individuals (5.32% of total) with foreign-sounding names.

There may be concerns that there is a bias in our foreign name classification procedure. For example, there may be a concern that the AMT population is a group with access to the Internet and with skills to download and open an Excel file. Thus, the AMT population may not be representative of the average investor population, which includes a large fraction of older individuals. We think this is a minor concern because older investors and less educated individuals are more likely to stereotype and discriminate. Thus, the bias in our workers sample towards more educated and younger subset of the population would work against us finding an effect.

Second, the AMT workers might not take their task seriously. We try to mitigate such concerns by selecting only workers with a reliability rank above 95. Since these workers receive compensation from various tasks and since previous work performance is an important criterion

[10]For comparison, Appendix C provides a partial list of fund manager names that were not identified as foreign by any AMT worker.

for receiving future tasks, reputation should be important for them.

The third potential concern is that ten workers might not be enough to minimize potential noise in the evaluation process. We try to eliminate this noise by defining a manager as "foreign" only if at least 75% of all workers classified the name as foreign. Further, we find that the correlations among the foreign-name classification measures of AMT workers are significantly positive (average is 0.40) and, therefore, our procedure is unlikely to have systematic biases that would skew our results.

2.3. Individual Investor Data

To provide sharper tests of our main conjectures, we use mutual fund holdings of individual investors from a major U.S. discount brokerage house. This data set contains all mutual fund trades and end-of-month portfolio positions of a set of individual investors during the 1991 to 1996 period. In this paper, we use the data only for the 1993 to 1996 period because not all control variables from the CRSP database are available before 1993. For a subset of households, demographic measures such as age, income, location (zip code), total net worth, occupation, marital status, family size, and gender are also available.

We enrich the individual investor database using data from other sources. Specifically, to identify sample investors' racial and ethnic characteristics and education level, we obtain the racial and ethnic compositions of each zip code using data from the 1990 U.S. Census. We assign each investor the appropriate zip code-level racial and ethnic characteristics. We also assume that investors who live in more educated zip codes are likely to be more educated.[11]

We use the investor-level brokerage data to directly measure fund inflows and outflows. We aggregate the mutual fund trades of all households in the brokerage dataset and compute Inflow, Outflow, and Netflow (= Inflow − Outflow) by fund, household, and year. Our ability to measure inflows and outflows separately using the investor-level data is a major advantage over the CRSP mutual fund database, which does not allow us to decompose total flows into inflows and outflows.

[11] Additional details on the individual investor database are available in Barber and Odean (2000) and Barber and Odean (2001). Bailey, Kumar, and Ng (2011) provides additional information about the mutual funds sample.

Table 1, Panel B provides the summary statistics for the brokerage sample.

2.4. Other Data Sources

We gather data from several additional sources to construct other variables used in our empirical analysis. For our performance regressions, we use monthly values of the market (RMRF), size (SMB) and value (HML) factors from Professor Kenneth French's web site.[12]

For the location tests using the CRSP dataset and for assigning investor attributes using the brokerage data, we obtain demographic characteristics from the U.S. Census Bureau. Specifically, we consider the total population of an area, the level of education (the proportion of county population above age 25 that has completed a bachelor's degree or higher), the male-female ratio, the proportion of households in the region with a married couple, the minority population (the proportion of the local population that is non-white), the median age of the population, and the proportion of residents who live in urban areas. From the same data source we obtain files that link counties, states, MSAs, and zip-codes and we use different levels of aggregation for different tests.

The Presidential elections data used in our location tests are from David Leip's web site (`www.uselectionatlas.org`). The religion data are obtained from two sources. First, we collect data on religious adherence using the "Churches and Church Membership" files from the American Religion Data Archive (ARDA) available at `www.thearda.com`. The data set compiled by Glenmary Research Center contains county-level statistics for 133 Judeo-Christian church bodies, including information on the number of churches and the number of adherents of each church. During our 1993 to 2009 sample period, the county-level religion data are available only for years 1990 and 2000. Following the approach in the recent literature (e.g., Alesina and La Ferrara (2000), Hilary and Hui (2009)), we linearly interpolate the religion data to obtain the values in the intermediate years. Following Kumar, Page, and Spalt (2011), the main religion variable we consider is the Protestant to Catholic ratio (PCRATIO) to capture the relative proportions of Protestants and Catholics in a county.

[12]See `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

The second source for religiosity data is the General Social Survey, which is conducted biannually since 1974 by the National Opinion Research Corporation at the University of Chicago. This dataset provides information on the share of residents in a geographical region, who go to church at least once a week.

We obtain state-level data on stereotypes from the 2008 wave of the American National Election Studies (ANES).[13] Specifically we make use of the questions numbered beginning with V083208, which use a representative sample of the U.S. population to rate whether or not they perceive Whites, Blacks, or Asians as intelligent on a scale between one (intelligent) and seven (unintelligent).

Last, we compute name fluency measures using a list of the 10,000 most common U.S. last names.[14]

3. Main Empirical Results

In this section, we present our main empirical findings. Our main objective is to establish that aggregate mutual fund flows are affected by social bias induced taste-based discrimination by U.S. mutual fund investors. We also provide rough estimates of the potential costs of discrimination against fund managers with foreign-sounding names.

3.1. Attributes of Funds with "Foreign" Managers

We start our empirical analysis by examining the attributes of funds that have managers with foreign-sounding names and other funds. Table 2 presents the univariate sorting results. Consistent with our main conjecture, we find that funds managed by individuals with foreign-sounding names have 10.9 percentage point lower average fund flows. While fund flows are different, fund returns are not. The mean raw returns of foreign funds is slightly lower but statistically insignificant, while the risk-adjusted returns are effectively identical.

[13] The American National Election Studies (ANES) 2008: Pre- and Post-Election Survey (computer file: ICPSR25383-v1), Ann Arbor, MI. Inter-university Consortium for Political and Social Research (distributor), 2009-06-10, doi:10.3886/ICPSR25383.

[14] http://names.mongabay.com/most_common_surnames.htm.

Among the other fund attributes, we find that on average funds with "foreign" managers are smaller, slightly riskier, and have somewhat higher expense ratios. Marketing expenses as proxied by the 12b-1 fees are higher for "foreign" funds, which suggests that flows are not lower because fund management companies spend less resources on marketing these funds. There are no significant differences in the average fund turnover and fund age estimates of the two groups.

Comparing the fund manager characteristics across the two groups, we find that there are no significant differences in age, gender, and undergraduate education. But "foreign" managers have shorter average tenure (4.69 versus 5.87 years) and are more likely to hold a Ph.D. degree.

3.2. Comparing Fund Performance and Investment Styles

In the next set of tests, we take a closer look at the performance and investment styles of foreign funds. We start by computing equal-weighted and value-weighted portfolios based on monthly returns of all funds with and without managers with foreign sounding names, respectively. We compute the return of a portfolio that is long in all foreign funds and short in all non-foreign funds in our sample. We assign funds to the foreign and non-foreign portfolios at the beginning of every month.

Table 3, Panel A reports estimates of risk-adjusted alphas from this Long−Short strategy. Irrespective of the factor model used to obtain risk-adjusted performance, the alpha is always close to zero, i.e., there is no significant difference in the returns of foreign and non-foreign funds. If anything, funds with foreign managers perform better than other funds on a risk-adjusted basis when we use value-weighted portfolios. This evidence suggests that only more skilled foreign managers enter the profession because of perceived discrimination in the fund manager labor market.

Panel B of Table 3 presents results using an alternative approach, where we regress individual fund alphas on our main Foreign75 indicator variable and various control variables. We use one year of daily returns (columns (1) to (3)) and three years of monthly returns (columns (4) to (6)) to compute the alphas in these tests. The set of independent variables includes lagged fund size, expense ratio, fund age, and managerial tenure. In all regressions, we include year and segment fixed effects and cluster standard errors at the fund level. Because the standard risk factors may not be adequate for international stock portfolios, we also repeat the analysis in Panel C for the subset of funds that invests mainly in U.S. equities. The results in all panels portray a consistent picture. There are no significant differences in the performance of foreign funds, irrespective of the method or benchmark used.[15]

Table 4 looks at differences in investment style. We again find no significant differences between foreign and non-foreign funds for most of the standard style variables we consider. Specifically, total risk, the CAPM beta, the HML and momentum factor loadings, and the tracking error estimates are all statistically indistinguishable between the two groups. Foreign funds are more exposed to SMB, but at the same time they have lower idiosyncratic risk. They also have a larger active share, which has been shown to positively affect fund performance (e.g., Cremers and Petajisto (2009)). This form of active management may therefore be beneficial to investors.

Overall, the results reported in Tables 3 and 4 suggest that funds managed by individuals with foreign-sounding names are similar to other funds in terms of performance and only marginally different in terms of investment style. The managerial characteristics are also roughly similar across the two groups, although foreign managers are more educated. Thus, it may be difficult to engage in effective "statistical" discrimination using the foreignness of fund manager names where an investor could separate good fund managers from bad managers based only on their names. In particular, a foreign name does not signal systematically lower abilities in generating risk-adjusted returns. This evidence also suggests that fund management companies are not systematically assigning individuals with foreign-sounding names to inferior funds.

3.3. Foreign-Sounding Names and Fund Flows

Since funds with managers with foreign-sounding names and other funds do not differ significantly along the dimensions of style and performance, capital allocations across funds should not be different after we account for the observable differences in fund and managerial characteristics.

[15]Other performance measures such as the raw returns, Sharpe ratios, or appraisal ratios also delivers insignificant results. They are not reported to save space.

In particular, the foreignness of fund manager names should not influence fund flows. However, if social biases such as discrimination, stereotyping, and in-group bias affect investment decisions of mutual fund investors, the foreignness of fund manager names could drive capital away from those funds. Investors may skew their investments more toward funds that are managed by individuals with names that sound more familiar.

To examine the relation between the foreignness of fund managers and fund flows, we estimate flow regressions where the annual fund flow is the dependent variable. The main independent variable is the Foreign75 dummy variable. We also include measures of fund size, fund risk, expense ratio, segment flow (i.e., the aggregate flow to funds that are in the same SI/Lipper fund segment during the year), and fund manager tenure. In addition, we consider different measures of lagged fund returns, which includes the raw fund performance (specifications (1) and (2)), performance rank as well as squared performance rank (specifications (3) and (4)) or performance quintiles (specifications (5) and (6)). Here, performance ranks and quintiles are formed by ranking all funds in the same market segment in the previous year.

Last, flow regression specifications include fund turnover, lagged fund flow, fund age, and family flow (i.e., the aggregate flow to all funds in the same fund family during the year) as additional control variables. In all flow regression specifications, we lag the control variables by a year. We estimate the flow regressions as a panel that includes year and segment fixed effects where we cluster the standard errors at the fund-level. For robustness, we estimate Fama-MacBeth regressions.

Table 5, Panel A presents the flow regression estimates. Consistent with the view that investors discriminate among funds based on fund manager names, we find that the Foreign75 variable is significantly negatively related to fund flows across all specifications. These estimates are also significant in economic terms. The fund flows are between 8.50 to 11.40 percentage points lower for a fund that is managed by an individual with a foreign-sounding name. Compared to the mean fund flow of 28.80%, these estimates are economically meaningful. In these specifications, we control for fund return, fund risk as well as other well-known determinants of fund flows, and include segment fixed effects. Therefore, these results cannot be explained by differences among funds along these dimensions. The evidence is more consistent with name-induced stereotypes and taste-based discrimination, which we examine further in the following sections.

3.4. Flow Regression Estimates Using a Matched-Sample

One potential concern with the flow regression results may be that our findings are spuriously induced by unobservable fund or managerial attributes. Because the set of foreign funds is small, our regressions might implicitly compare very different types of funds that would then also differ on those unobservable attributes. To mitigate these potential concerns, we identify a matched sample where we match the subset of foreign funds with similar non-foreign funds at the same point in time. We then re-estimate the baseline regressions using only the sample of foreign funds plus matched funds. If our results are truly due to the foreignness of the name, then restricting the analysis to more similar funds should increase the precision of our estimates. In addition, because the foreign and matched funds are more similar on observable characteristics, they are also likely to be more similar on the unobservable characteristics.

We perform this matching analysis as follows. First, we identify a set of matching attributes such as fund size, fund location, manager education, etc. Then, each year, for each foreign fund in the sample, we identify all non-foreign funds that match the foreign fund on the chosen dimensions. We keep these non-foreign funds in the sample and drop all non-foreign funds that do not have a matching foreign fund in the chosen year. This matching procedure produces a set of funds that closely resemble our sample of foreign funds.

Panel B presents the fund flow regression results for several alternative ways of performing the match. The results are based on specification (3) in Panel A, where for brevity we only report the estimates of the Foreign75 dummy. The matched-sample results indicate that restricting the sample to better matches in terms of observable attributes increases the point estimates of the Foreign75 indicator variable. In most cases, the statistical significance increases substantially despite the considerable reduction in sample size.

Specifically, we continue to find lower flows for funds managed by individuals with foreign-sounding names when we match funds on year, fund segment, and fund size. Our results get substantially stronger when we additionally match on fund age and manager age. Although the sample size shrinks significantly, the point estimates double and the statistical significance increases. These results are similar when we match on lagged performance or focus only on funds that are headquartered in the same MSA. Even when we compare foreign funds to other non-foreign funds in the same fund family, we find the same stronger patterns. Thus, unobservable fund family attributes are unlikely to explain our results. Last, we show that even though foreign managers are slightly more educated (see Table 2), we do not find that our effects go away when we consider a subsample of matched funds that are managed by individuals with either a Ph.D., an MBA, or a professional degree (e.g., CFA).

Overall, our flow regression estimates in Table 5 indicate that flows are significantly lower when fund managers have foreign-sounding names. Our matched-sample analysis shows that benchmarking foreign funds to funds that are more similar on observable fund and managerial characteristics strengthens our results. The matching analysis also minimizes concerns that unobservable fund and managerial attributes are somehow spuriously generating these results.

3.5. Basic Robustness Checks

In this section, we show that our results on fund flows are robust to sensible alterations of our main setup and line up with a discrimination-based interpretation of our findings. We use specification (3) in Table 5, Panel A as the benchmark. The results from these tests are summarized in Table 6.

We start by estimating the flow regressions for different subsamples (see Panel A). We first separate funds in the international and global equities segments from funds that focus primarily on U.S. equities. We find that the Foreign75 dummy variable has a significant negative estimate only for the subsample of funds that do not focus predominantly on international markets. One potential explanation for this pattern is that investors perceive "foreign" managers to be more knowledgeable about foreign investments, while managers with more familiar "American" names are perceived to be more skillful in analyzing domestic U.S. stocks. Hence, a foreign name is less of a disadvantage when managing a portfolio of non-domestic stocks. However, this type of statistical discrimination is unlikely to be effective since Tables 3, Panel C, and Table 4, Panel B, show that U.S. equity funds managed by "foreigners" do neither differ with respect to their returns nor with respect to their riskiness.

Next, we split the sample into two time periods. This test is designed to examine whether our results are driven by the earlier sample years in which mangers with foreign-sounding names were less common. The results in Panel A show that this is not the case. In fact, the results are more pronounced in the latter part of the sample. These findings could also be consistent with the idea that following the terrorist attacks of September 2001 and the subsequent wars in Iraq and Afghanistan, the in-group bias was stronger and foreignness was more salient.[16]

Panel B presents the results from various robustness checks. We first show that our results are essentially unchanged if we classify a name as foreign-sounding if at least 85% of AMT workers classify it as foreign. The results from test (1) shows that our findings are unchanged when we replace the Foreign75 variable with the Foreign85 measure.

In the second test, we investigate if our results are driven by name fluency rather than the foreignness of a name. Green and Jame (2011) show that people prefer to trade company stocks if the name of the company is more fluent and easier to process mentally. In our setting, investors might discriminate against foreigners not necessarily because foreign-sounding names are associated with negative stereotypes but because a name like "Yosawadee Polchareon" is harder to memorize, less salient, or otherwise less convenient to handle mentally than "David White". Motivated by Green and Jame (2011), we define a name fluency dummy that is equal to one if the number of characters in the name is below the median number of characters or the name does not appear in the 10,000 most commonly-used names in the US.[17]

The results from test (2) in Table 6 show that name fluency is indeed related to fund flows. Names with lower fluency are associated with lower fund flows. Importantly, however, if we use the name fluency variable as a control variable, we find that the size and significance of the Foreign75 measure is largely unaffected. This evidence demonstrates that our foreignness measure is not simply a proxy for name fluency.

[16]We provide additional results related to these ideas in Section 3.7.

[17]See `http://names.mongabay.com/most_common_surnames.htm`.

In the third test, we employ additional controls for fund size. The evidence in Table 2 indicates that funds managed by foreign managers are smaller. Since it is well known that fund size is related to fund flows, we replace our fund size control variable with a non-parametric control for fund size. To do this, we assign funds to size deciles in its market segment for each year and include this set of dummy variables instead of fund size in our regression specification. The results from test (4) show that our choice of size control is not influencing our inferences. In fact, our results become economically larger when we use non-parametric controls for fund size.

In the next test, we exclude index funds because for index funds the identity of the fund manager is less likely to matter. The evidence from test (5) shows that excluding index funds does not influence our results.

Test (6) controls for the known effects of various managerial attributes such as gender, age, and education on mutual fund flows. In particular, if some foreign names such as "Ivka", "Tetsuya", or "Fariba" are perceived as female names, and if investors perceive female fund managers as less knowledgeable, then our Foreign75 variable might be a proxy for gender effects (e.g., Niessen-Ruenzi and Ruenzi (2011)). Similarly, the lower fund flows may reflect the effects of other managerial attributes such as age and education, which are known to be correlated with managerial skill (e.g., Chevalier and Ellison (1997)).

Our results show that gender bias does not influence our main findings. Consistent with the finding in Niessen-Ruenzi and Ruenzi (2011), we find that female fund managers receive lower flows but the effect of Foreign75 remains statistically and economically significant. Similarly, our results do not reflect the effects of other managerial attributes, including age and education.[18]

In test (7), we control for marketing expenses of funds as proxied by 12b-1 fees. To the extent that 12b-1 fees are an adequate proxy for marketing expenses, these results show that our results are not driven by fund management companies that spend less on advertising funds that are managed by individuals with foreign-sounding names. This evidence is consistent with the univariate results presented in Table 2.

[18]We assign the mean age and education level of all foreign managers to foreign managers with missing age and education data. We perform a similar data-filling exercise for non-foreign managers. Our results are qualitatively similar but somewhat weaker when we exclude about 25% of observations with missing managerial attributes.

To mitigate potential concerns that names which sound foreign to less than 75% of all AMT workers might bias our main result, we remove them from our sample in test (8). Consequently, we only compare flow differences between fund managers who were rated as foreign by at least 75% AMT workers and fund managers who were rated as foreign by not even one AMT worker, respectively. Our main result is unaffected.

In test (9) we investigate whether differences in distribution channels might drive our result of lower inflows into "foreign" funds. To that end, we define a dummy variable equal to one if a fund does not charge load fees, and zero otherwise. We interact this variable with our foreignness measure and find that our main result is unaffected by a fund's distribution channel.

Finally, in test (10) we replace managerial tenure with the specific fund with tenure in the mutual fund industry. We define industry experience as the difference between the current year and the year a manager first entered the CRSP mutual fund database. Controlling for industry experience does not affect our results.

Based on these findings from various additional tests, we conclude that our baseline results are robust to reasonable alterations to the main empirical specification. Overall, the baseline flow regression results and the evidence from various robustness tests jointly indicate that managers with a foreign sounding name have different flows despite essentially identical performance and styles. This finding makes statistical discrimination unlikely and suggests an explanation based on taste-based discrimination. In the next two sub-sections, we use other approaches to provide further evidence that taste-based discrimination is the most plausible explanation for our findings.

3.6. Evidence Based on Fund Headquarters Locations

First, we exploit geographical variation in conservatism and stereotypes among investors to provide evidence for a taste-based explanation of our baseline results. Specifically, we present a test for taste-based discrimination using cross-sectional variation in the propensity to discriminate. We exploit the well-documented local bias in equity investments among both institutions and retail investors (e.g., Coval and Moskowitz ((1999), (2001)), Ivković and Weisbenner (2005)).

Bailey, Kumar, and Ng (2011) provide direct evidence that there is local bias among retail investors in mutual fund investment.

Given the existence of fund-level local bias, the foreignness-fund flow relation should be more pronounced for funds headquartered in regions where discrimination, stereotyping, and in-group bias are stronger. Since the regional characteristics can be thought of as exogenous in our setting, this procedure can identify a causal role of the fund manager name, and makes it harder for alternative omitted variable bias stories to explain our findings.

To conduct these tests, we use CRSP to obtain data on the headquarters location for the set of mutual funds in our sample. We are able to obtain the headquarters locations for about half of the funds in our sample. We then match these data with regional characteristics that are likely to reflect conservatism and in-group bias. In these regions, we expect greater sensitivity to foreign-sounding names. Our econometric approach is to regress fund flows on one or more interaction variables defined using the Foreign75 dummy variable and various regional characteristics. A significant coefficient estimate of the interaction term would indicate that fund managers with foreign-sounding names have greater flow sensitivity if those funds are located in more conservative regions. Except for the addition of these interaction terms, our regression specifications in this section are identical to the baseline specification in column (3) of Table 5, Panel A.

The estimates from these extended flow regression specifications are presented in Table 7. In the first test, we investigate whether frequent exposures to people from different cultural backgrounds and races would attenuate the tendency to discriminate. We posit that investors in large metropolitan statistical areas (MSAs) in the U.S. are likely to be less responsive to the foreignness of manager names.[19] Similarly, we expect that investors in more rural areas, on average, are more conservative. We obtain data on the fraction of the county population that lives in rural areas from the U.S. Census and define a dummy variable that is set to one for counties with above-median rural population in our sample.

The results reported in specifications (1) and (2) of Table 7 provide evidence consistent with

[19]The ten largest MSAs based on the population in the year 2000 are New York, Los Angeles, Chicago, Miami, Philadelphia, Dallas, Boston, San Francisco, Detroit, and Houston.

this conjecture. The interaction term is negative in both specifications, which indicates that fund flows are significantly lower for "foreign" funds when these funds are located outside the ten largest MSAs or in rural areas. The results are also economically significant. The coefficient estimates of the interaction terms imply that flows are 30.20 and 28.20 percentage points lower in regions outside of top ten MSAs and rural areas, respectively.

A potential alternative explanation for this finding is that foreign-named fund managers are more likely to work for funds that are located in large metropolitan areas. Since investors are known to exhibit local bias in their equity (e.g., Coval and Moskowitz (1999)) as well as mutual fund (Bailey, Kumar, and Ng (2011)) holdings, one might expect that investors in small metropolitan areas invest less in funds with foreign managers. To examine this alternative conjecture, we perform the matched sample analysis using the location of funds. The results reported in Panel B of Table 5 show that the Foreign75 dummy has a significantly negative coefficient estimate even when we compare flows into foreign and non-foreign funds located in large metropolitan areas. Thus, the combination of geographical concentration of foreign managers in large metropolitan areas and local bias is unlikely to explain these results.

Another potential proxy for local conservatism is the age of the local population. Specification (3) shows that funds located in counties with above-median average age have substantial 47.70 percentage points lower flows when they are managed by individuals with foreign-sounding names than otherwise identical funds run by fund managers with more familiar American names. As before, the results are also significant statistically (t-statistic = 4.19).

In the next test, we use state-level data on Presidential elections to measure conservatism directly. Specifically, we define a Republican state dummy that is set to one for funds that are located in a state that voted for the Republican presidential candidate in the most recent presidential election. Specification (4) shows again that there is a stronger sensitivity to foreignness to fund manager names for funds that are located in more conservative regions. The estimates are significant both statistically and economically.

For additional robustness, we use two religion-based measures to gauge local conservativeness. We first get data on church attendance from the General Social Survey and define a Church

Attendance dummy variable that is set to one for a region if the share of residents in that region who go to church at least once a week is higher than the sample median. The second data source is the American Religious Data Archive which provides county-level data on the fraction of the population that adheres to protestants and Catholic faiths.[20]

These tests are motivated by the evidence in Kumar, Page, and Spalt (2011) who show that investors in Protestant denominated areas are less likely than Catholics to engage in speculative trading activities. If investing in a fund managed by an individual with an unfamiliar name is perceived to be riskier, a higher ratio of Protestants to Catholics in a county (we label this ratio PCRATIO) would predict greater reluctance to invest in such funds. The results in specifications (5) and (6) are consistent with this hypothesis and show that "foreign" funds have significantly lower flows when they are located in areas where church attendance is higher or the local tendency to take speculative risks is lower.

In the final set of location-based tests, we use a direct measure of ethnic stereotypes in a region. The 2008 wave of the American National Election Studies (ANES) asks a representative sample of the U.S. population about whether or not they rate Whites, African-Americans, or Asians as intelligent on a scale between one (intelligent) and seven (unintelligent). We construct a state-level stereotype measure by dividing the average rating assigned to African-Americans and Asians by the average number assigned to Whites. This produces a relative state-adjusted measure of how much the local population is likely to have stereotypes against non-Whites. This measure should provide a good proxy for the tendency of local population to dislike managers that have foreign-sounding names.

The last two specifications in Table 7 report the estimates. We find that funds managed by managers with foreign-sounding names have flows that are about 38 percentage points lower and highly statistically significant flows when stereotypes among the local investor population are particularly pronounced. As this measure directly captures local stereotypes, these results provide strong support for our interpretation that the observed differences between the two groups of managers are likely to be due to in-group bias and discrimination.

[20]Since both, the GSS and the ARDA denominations survey, are not conducted every year, we extrapolate the yearly values between the different survey waves before matching it to our mutual fund dataset.

An alternative interpretation of the results in this subsection could be that the geographical patterns we observe reflect taste-based discrimination on the fund management company level. Such a management company channel, if it exists, would further strengthen our argument that flow differences are induced by taste-based discrimination. However, because foreign funds perform as well as other funds and they have *higher* marketing expenses, it is not entirely obvious how that channel would operate.[21]

Taken together, these results from our location-based tests show that foreignness of fund manager names affect fund flows more strongly when the local investor population is more conservative and is more likely to be influenced by racial or ethnic stereotypes. Because our regression specifications ensure that the funds are otherwise comparable and since the fund location is likely to be exogenous to the name of the fund manager, it is difficult to identify reasonable alternative explanations for our findings. The differences in fund flows that are associated with foreignness of managers' names are most likely driven by racial or ethnic stereotypes and in-group bias of mutual fund investors.

3.7. A Natural Experiment: The 9/11 Terrorist Attacks

In this subsection, we use the terrorist attacks of September 11, 2001 as a natural experiment to examine the taste-based explanation for our findings. Specifically, we exploit the fact that the attacks generated an exogenous shock to the negative stereotypes against a subset of the foreign names sample. These are funds managed by individuals with names that could be associated with the Middle East (e.g., Saudi Arabia, Syria, Iraq, Iran) and South-East Asia (e.g., Afghanistan, India, Pakistan). For brevity, we refer to these names as "Middle Eastern" names. We test if flows into funds with Middle Eastern named managers decline abnormally after 9/11.

This test is based on the observation that following the 9/11 terrorist attacks, through the enhanced focus on national security and the wars in Iraq and Afghanistan, the perceived distinc-

[21] Fund-level discrimination could be important in hiring and promotion decisions. This channel presents an additional layer of discrimination that we would not capture in our tests. Nevertheless, discrimination in hiring and promotion decisions, if it exists, cannot explain our 9/11 evidence (see next section), our experimental evidence (see Section 4.2), and the brokerage data evidence (see Section 5.2). Rather, it would complement the investor channel we identify.

tion between foreigners and U.S. nationals has become stronger (e.g. Vlopp (2002), Abowitz and Harnish (2006)). In particular, individuals of Middle Eastern origin as well as South Asians, or more broadly speaking, individuals perceived to be associated with Islam, were reportedly subject to increased levels of xenophobia and sometimes even outright violence following the 9/11 event (e.g., American-Arab Anti-Discrimination Committee (2003) and Human Rights Watch (2002)).[22] Further, prior research establishes that this xenophobic sentiment affected economic behavior. For example, Davila and Mora (2005) show a significant abnormal decrease in earnings of men from Middle Eastern decent in the U.S. labor market between 2000 and 2002, which they argue is consistent with increased taste-based discrimination after the 2001 events.

Motivated by these observations, we conduct the 9/11 tests by manually identifying those names that could be perceived as Middle Eastern or South Asian. These names are marked with an asterisk in Appendix B. One-third of managers (56 out of 168) with foreign-sounding names is identified as "Middle Eastern". As before, the focus here is on the *perception* of being Middle Eastern or South Asian rather than truly being from those countries.[23]

The split sample test in Table 6, Panel A, already shows that the negative impact of foreignness on flows became much stronger after 2001. Our main prediction in this section is that after 9/11, flows into funds with managers with Middle Eastern names would decline abnormally relative to the flows of non-foreigners and, importantly, relative to the flows of managers with a name that sounds foreign but not Middle Eastern (we call this latter group "Non-Middle Eastern Foreigners").

We use monthly flow data to isolate the effects of 9/11. We only include control variables with a monthly variation into these regressions. Specifically, we control for lagged fund size, lagged performance rank and squared performance rank, flows into the fund's market segment

[22]According to a CNN report from September 16, 2001: "Reports of hate crimes against Muslims and Southeast Asians have risen exponentially across the U.S. in the wake of Tuesday's terror attacks." This article was retrieved from `http://articles.cnn.com/2001/sep/16.`

[23]India is a good example of the impact of perceptions following 9/11. While there are more than 150 million Indians with Islamic faith, many Indians adhere to other religions. Nevertheless, following the 9/11 attacks, the number of hate crimes against Indians in the U.S. were sufficiently alarming for the former Indian Prime Minister Atal Bihari Vajpayee to intervene with President George W. Bush to ensure the safety of Indians living in the United States. See the CNN article cited above.

and flows into the fund's company. We also include segment and year-month fixed effects.[24] The overall sample consists of 230,149 monthly fund observations out of which 2,830 observations (2.17% of the sample) are associated with managers with Middle Eastern names.

Table 8 presents the results. Columns (1) to (3) focus only on the subsample of managers with foreign sounding names. Hence, in these specifications we are comparing Middle Eastern named managers (e.g., Zaheer Sitabjhan or Ajit Dayal) with non-Middle Eastern foreigners (e.g., Klaus Kaldermorgen or Taizo Ishida). The first column shows results when we regress flows on a Middle Eastern dummy interacted with a dummy that is one for all months including and after September 2001. The results show that flows for funds managed by individuals with Middle Eastern names experience an abnormal monthly 2.6 percentage point decline after 9/11. This is about 22% of the standard deviation of monthly flows and therefore economically large.

One potential channel through which economic fundamentals could induce the observed difference between the two set of foreigners might be that managers with Middle Eastern names run portfolios that invest predominantly in the Middle East, and that 9/11 adversely affected the economic outlook for the region. To address this concern, we re-estimate the regression but include only funds that invest primarily in U.S. equities. Column (2) shows that although we lose more than a third of our sample, the results are essentially unchanged, which is inconsistent with the fundamentals-based explanation.

Last, we focus further on the period around 9/11 and re-estimate the flow regressions using only the flows in the 24 months window around the event. We observe that, despite the small sample, our results become even stronger in magnitude (see column (3)). This finding indicates that our results are unlikely to be induced by events before 2000 or after 2002. We also rerun this test by centering the 24 month window around September 2000 or September 2002, excluding September 2001 in both cases, and by redefining the dummy variable accordingly. In both cases, the interaction terms are insignificant and have opposite signs, which again indicate that our results do not merely reflect a secular trend.

[24]Alternatively, we use annual flow data with the complete set of control variables and define a dummy variable equal to one for the 2001 to 2009 period, and zero otherwise. These results are similar but weaker due to the less precise cutoff.

For additional robustness, we conduct two placebo tests and estimate the flow regression in which we move the 24 month window to one year before or one year after the 2001 terrorist attacks. First, we only consider observations before the 2001 terrorist attacks and use a 24 month window from September 1999 to September 2001. The results show that after September 2000 there is no significant difference between the flows of funds with Middle Eastern named managers and funds with non-Middle Eastern named managers (coefficient estimate = 0.006, t-statistic = 0.52).

Second, we only consider observations after the 2001 terrorist attacks and use a 24 months window from September 2001 to September 2003. Again, the interaction term between our Middle Eastern dummy and a post September 2002 dummy is not significant (coefficient estimate = 0.102, t-statistic = 0.95). These results suggest that it is indeed the terrorist attacks of 9/11, which caused lower flows into funds managed by individuals with Middle Eastern and South Asian names.

These 9/11 regression results indicate that Middle Eastern named managers experience a drop in flows relative to non-Middle Eastern named managers around 9/11.[25] To illustrate this finding graphically, Figure 1 presents average flows for the two groups around September 2001. Consistent with the regression results, flows into funds managed by individuals with Middle Eastern names dropped, while the flows into non-Middle Eastern funds were largely unaffected.

In the last 9/11 related test, we consider the full sample of managers and include dummies for Middle Eastern named managers, non-Middle Eastern named foreigners, and the interactions of these variables with the Post-9/11 dummy that is equal to one for months including and after September 2001. In these tests, we compare two sets of foreigners to non-foreigners before and after 9/11. The results again show that non-Middle Eastern named managers are unaffected, while Middle Eastern named managers experience a 2.3 percentage point decline in flows relative to non-foreigners. The results hold for both the full sample as well as for the sample that focuses only on funds that invest primarily in U.S. equities.

[25]To make sure that our main results are not entirely driven by the 9/11 terrorist attacks, we re-estimate the baseline specification in Table 5 after excluding all observations in 2001 and 2002. We find that the Foreign75 dummy variable remains significantly negative (coefficient estimate = -0.097, t-statistic = -1.80).

Taken together, the results from 9/11 tests show that around 9/11, a subset of foreign funds with Middle Eastern named managers experience an abnormal decrease in fund flows. This finding provides additional support for the view that the flow results we document earlier including the baseline results are induced by taste-based discrimination.

3.8. Foreign-Sounding Names and the Flow-Performance Relation

Our evidence so far establishes that, all else equal, fund flows are lower when fund managers have foreign-sounding names. In this section, we gather support for our more specific conjecture, which posits that managers with foreign-sounding names are likely to be "punished" more after bad performance and "rewarded" less after good performance. Consequently, funds that are managed by individuals with foreign-sounding names would experience greater outflows and lower inflows following bad and good performance, respectively. This conjecture is based on the observation that investors react more strongly to both extreme positive and negative performance than to average performance (e.g., Chevalier and Ellison (1997)).

To test this conjecture, we re-estimate the baseline flow regressions presented in Table 5. We define interaction variables using the Foreign75 dummy variable and various measures of past performance. We also include an interaction between fund size and Foreign75 to rule out that we are picking up differences in the flow-performance relationship due to size, rather than due to the foreignness of the fund manager name.

The regression results are presented in Table 9. The first two specifications interact the Foreign75 dummy with fund return in the past year. We find a significant and negative interaction effect, whether we account for lagged fund flows (specification (2)) or not (specification (1)). These estimates indicate that the largest differences in flows are due to lower inflows into funds with "foreign" managers following good performance.

To get a sense of the economic magnitudes of our results, consider two otherwise identical funds at the 20th performance percentile. If one of these funds is managed by a "foreign" manager, then the estimates in specification (2) imply a flow difference between the foreign fund and a non-foreign fund in the same performance rank of 19.20 percentage points.[26] The same calculation for funds that have performance at the 80th percentile of the performance rank distribution, this value would be as high as 50.50 percentage points. Therefore, these effects are economically large. While having a foreign-sounding name is associated with lower flows for both funds, these results suggest that managers with foreign-sounding names are particularly rewarded less after good performance.

The linear specification for the interaction will not be appropriate if the true flow-performance relation is non-linear. We therefore examine extended versions of specifications (3) and (4) from Table 5, which use performance rank and squared performance rank to capture the potential non-linearity. As before, performance rank (PRank) is the ranking of the fund by return relative to all funds in the same segment in the previous year, rescaled to lie between zero and one. We estimate the corresponding flow regressions using both OLS and the Fama and MacBeth (1973) method.

The results presented in columns (3) and (4) of Table 9 show that the flow-performance relation is indeed non-linear and more pronounced for the extreme return rank quintiles. For additional robustness, in the last two specifications of Table 9, we replace the performance ranks by performance quintiles. As before, we find that investors react most to the two extreme return quintiles, with somewhat more pronounced effects following very good performance.

To examine the economic significance of these results, we plot in Figure 2 the difference in fund flows conditional on performance ranks implied by the estimates in specification (3) of Table 9. The plot shows that the relation between flow differential and performance has an inverse U-shape. This graphical evidence is consistent with our hypothesis that investors do not reward "foreign" managers as much after good performance but punish them more severely after bad performance. The economic magnitudes of these effects are large. The fund flow differential due to the foreignness of the manager's name is -11.70% for the lowest performance rank and a striking -44.50% for the most extreme out-performers. Similar to the linear specification, we again see that the effects are more pronounced for inflows, which usually follow good performance.

[26] This is calculated as $-0.180 - 0.052 \times 0.2 + 0.018 \times 5.162$ and assumes that the log of fund size is equal to the mean log of the fund size in the sample (5.162).

Collectively, the results from extended flow regressions show that the flow-performance relation is altered by the foreignness of fund manager names. Consistent with our conjecture, we show that fund managers with foreign-sounding names experience lower appreciation in fund flows following good performance and greater decline in flows following poor performance.

3.9. Economic Costs of Discrimination

Our flow regression estimates suggest that managers with foreign sounding names receive lower inflows and that this effect is strong for both better and poorly performing funds. In this section, we provide rough estimates for the potential economic costs to fund managers with foreign-sounding names.

We suspect that the economic costs associated with discrimination are faced primarily by the individual fund manager with foreign-sounding name. One complication in analyzing this conjecture is that we do not observe the actual compensation contracts of mutual fund managers. We obtain estimates of discrimination-induced pay differentials using the results in Deli (2002). Using all mutual fund advisory contracts that filed form NSAR-B with the SEC in 1998, Deli (2002) finds that for 93% of all funds, advisory fees depend exclusively on total net assets. This evidence suggests that our results could have significant impact on the pay of mutual fund managers.

Specifically, based on the SEC filings, Deli (2002) estimates a "marginal compensation rate" across funds, which equals 0.767% for equity funds. This number means that for every additional \$100 million in fund assets, the fund advisor (e.g., Fidelity) receives an additional \$767,000 in fees. Our baseline estimates in Table 5, specification (3) then indicate that the difference in fund flows between "foreign" and other funds translates into \$143,000 ($= 0.107 \times 174.5 \times 0.767\%$) lower fees if a manager has a foreign-sounding name. This calculation assumes that the fund size is equal to the mean fund size in the sample, i.e., \$174.5 million.

The cost estimate of \$143,000 is likely to overstate the actual cost to an individual manager with foreign sounding name for two reasons. First, it ignores administrative costs incurred by the management company in managing the fund. Second, if individual contracts have a bonus component that is based on the total performance of the firm, then this cost will be spread out over many fund managers, thus decreasing the impact for the actual foreign manager managing the fund. The cost of $143,000 reflects the actual cost to an individual manager most closely if the bonus component of pay is based mainly on the fee generated for the fund company and if the administrative costs to run the fund are low.

The flow-performance regressions in Table 9 provide a closer look at how these cost estimates change with the level of fund performance. Because the differentials in flows are greatest for funds that have either very good or particularly poor performance, the actual costs for these funds are larger. In contrast, for a fund with average performance, the costs are small. Table 10 presents an estimate of costs associated with foreign-sounding names, conditional on performance levels. The cost estimates are obtained as follows. First, we calculate the average flow differential from specification (3) in Table 9. Then, we multiply this number with $174.5 million, which is the average size of funds in our sample, and the marginal compensation rate of 0.767%.

As shown in Table 10, for the fund with median performance level, there would be no economic cost of discrimination because our non-linear estimates suggest virtually no difference in fund flows between foreign and non-foreign funds. For the worst performing funds the cost of estimate increases to $154,000 because the difference in flows increases. Similarly, among the best performing funds, the cost is substantial. For example, a fund at the 80th percentile of the performance distribution would incur a striking $267,000 difference in advisory fees, while for the extreme out-performers this number can amount to almost $600,000.

Our cost estimates indicate that the cost of discrimination based on manager names is likely to be economically significant. However, these cost estimates should be interpreted with some caution because in the absence of compensation contracts of fund managers, our estimates are coarse. While the cost to the fund advisor may be attenuated by the fact that they usually employ only a small fraction of managers with foreign sounding names, the cost to the individual manager can be large if the individual contract is closely tied to the flow-based advisory fees estimated here. In addition, all our estimates are based on the mean fund size in our sample. For larger funds, these differentials would widen further.

4. Evidence From Online Experiments

In this section, we use evidence from two online experiments to complement the results obtained using the CRSP sample.

4.1. Do Investors Know Their Fund Managers?

In the first online experiment, we investigate whether mutual fund investors are aware of their fund managers. The results so far indicate that managers with a foreign sounding name have different flows despite essentially identical performance and styles. This makes statistical discrimination unlikely and suggests an explanation based on taste-based discrimination. However, for taste-based discrimination to work, investors must be aware of fund manager identities when they make their investment decisions.

As can be seen from Appendix E, investors are directly exposed to manager names when they search for product descriptions on fund web sites. The name of the fund manager is always prominently presented on the main fund page.[27] Thus, it is very likely that an investor is exposed to the fund manager name when she is making her investment decision, even if she might not recall the fund manager name at a later point in time.

To directly investigate whether investors consider the identity of the fund manager to be an important piece of information in their investment decisions, we conduct an online survey. We request 100 Amazon Mechanical Turk (AMT) workers to evaluate the importance of different fund attributes in their investment decisions.[28] Most of the respondents (71%) have invested in mutual funds. We also asked survey participants directly whether it is important for them to know who is managing the fund when they make their investment choices. The results of this survey are reported in Appendix F.

We find that 64% of the survey respondents thought that it was important for them to know the fund manager and 57% actually knew the identities of the fund managers (see Panel A).[29]

[27]All major search platforms such as Yahoo Finance, Morningstar, Fundresearch, and Google Finance display information about the fund manager on the first page of the product description.

[28]See Mason and Suri (2007) for validity of experimental results obtained using Amazon Mechanical Turk.

[29]These results are very similar if we restrict the sample to survey participants who have invested in a mutual fund before.

Thus, the identity of the fund manager is an important determinant of an investor's decision to buy a fund and investors are keen to know their fund managers. This evidence is consistent with the findings in Massa, Reuter, and Zitzewitz (2011) who show that funds with named managers have greater inflows than funds with anonymous management, and that departures of named managers reduce inflows.

Among the other fund and managerial attributes, we find that investors consider fund risk as the most important fund attribute as 90% of respondents consider this attribute "very important" or "important" (see Panel B). This evidence is not surprising in light of the most recent turmoil in financial markets world wide. This attribute is followed by historical fund performance and fund fees. Examining the importance of the fund manager, we find that 59% of respondents indicate that this information is "very important" or "important" for their investment decision. Interestingly, the fund company is considered to be less important than the fund manager.

When asked directly about the importance of managerial attributes such as gender, national origin, age, and race/ethnicity, survey respondents indicated that those attributes are irrelevant for their investment decisions. Only one survey respondent indicated that the fund manager's ethnicity would be an important factor in her investment decision. This evidence is not surprising as social biases such as taste-based discrimination typically operate subconsciously and are unlikely to be revealed when investors are questioned directly. Very few individuals would directly admit to having these biases. In the next section, we conduct an online experiment as an implicit test for the presence of social biases such as taste-based discrimination.

4.2. Additional Evidence of Taste-Based Discrimination

We use a different set of 100 Amazon Mechanical Turk (AMT) workers to complete a hypothetical fund investment task where they allocate money between two index funds. All participants are presented with descriptions of two identical index funds (fund A and fund B). Appendix G shows the fund descriptions that are presented to these individuals. The workers are asked how they would split 100 dollars between two S&P500 index funds, which we label "fund A" and "fund B". We use two index funds because managerial skill is irrelevant for managing this type of fund. Choi, Laibson, and Madrian (2010) conduct a similar experiment and show that investors typically fail to minimize fees when choosing among different index funds.

The first group of 50 workers observes that fund A is managed by "Mustafa Sagun", while fund B is managed by "William R. Andersen". The other group of 50 workers observes that fund A is managed by "William R. Andersen", while fund B is managed by "Mustafa Sagun". All other information regarding the two index funds are similar. After AMT workers observe both funds and decide how they would split 100 dollars between the two funds, we gather information about their age, gender, and their prior experience in mutual fund investing. Each AMT worker is paid 2 U.S. dollars for participating in the experiment, where the suggested time to complete the experiment is five minutes although participants could take longer if necessary.

Because we randomly assign fund manager names to funds and funds to subjects, all fund characteristics other than manager's name would not matter by design. Thus, there should be no difference in the amounts invested in both funds if the name of a fund manager is indeed irrelevant. But if taste-based discrimination affects investment decisions, the money allocated to fund A should be lower when that fund is managed by an individual with a foreign-sounding name.

Panel A of Figure 3 presents the univariate results. Consistent with our taste-based discrimination hypothesis, AMT workers invest about 14 dollars less in fund A if the manager name of fund A is foreign (t-statistic $= -2.56$). Supporting the general validity of our experimental design, these results also show that AMT workers split their money between both index funds, rather than investing it in the cheaper index fund, which is always fund B. We can therefore replicate a main finding of Choi, Laibson, and Madrian (2010) in our experimental setting.

Panel B of Figure 3 shows that our results are stronger for relatively older AMT workers. These workers are above the median age of 35 years. This result is consistent with our previous evidence (see Table 7) and the literature in sociology, which shows that conservatism escalates rapidly during later decades of life (e.g., Truett (1993), Nilsson, Ekehammar, and Sidanius (1985)). Older households, who are likely to be more conservative, appear less willing to invest in a fund that is managed by a foreign manager. We also find that our results are somewhat stronger for female AMT workers and for those AMT workers who have never invested in a mutual fund before (see Panels C and D).

Table 11 demonstrates that these results also hold in a multivariate setting. Controlling for the AMT worker characteristics, the results in column (1) show that AMT workers allocate significantly less money to the first index fund if the manager name is foreign-sounding. This result gets even stronger if we exclude AMT workers from our sample who spent less than one minute (column (2)) or two minutes (column (3)) on the experiment. Spending little time on the task could indicate that the workers did not carefully look at all the available information. These findings show that our results are not spuriously induced by AMT workers who did not take the task seriously.

In column (4) we use interactions to show that our results are stronger for older AMT workers than for younger AMT workers, consistent with the idea that older people who are likely to be more conservative are more sensitive to the foreignness of a name. Across all specifications, we find that the effect of a simple name change on the amount allocated to a fund is economically meaningful.

Overall, the experimental results indicate that investors are likely to be aware of fund manager identities at the time of their investment decisions. We also find additional support for our taste-based discrimination hypothesis. Consistent with our conjecture, we find that the foreignness of a fund manager name influences the investment choices of investors. Interestingly, our survey results indicate that investors are not consciously aware of this impact or are not willing to admit it. Further, the personal characteristics of investors, especially age, further amplify the perceived ability differences between managers with foreign-sounding and U.S. names.

5. Evidence Using Investor-Level Data

In this section, we analyze whether the foreignness of managers' names influence the mutual fund investment decisions of retail investors. We obtain a sample of brokerage customers from a large U.S. discount brokerage house, which allows us to directly examine their investment choices. Specifically, we can observe the fund-level investment amounts of each household at the end of each month. Unlike the CRSP database that only allows us to observe net flows, the brokerage data allow us to separate inflows and outflows. Even though the brokerage sample spans a short 1993 to 1996 time period, it complements our results obtained using aggregate flows by providing micro-level evidence consistent with our main taste-based discrimination hypothesis.

5.1. Inflows versus Outflows

We start our analysis of the brokerage data by examining the differences in inflows and outflows between funds that have managers with foreign-sounding names and other funds. We compute several quarterly fund flow measures for each household. Specifically, we obtain fund inflows as the logarithm of the amount of fund shares a household bought in a particular quarter times the price of the fund's shares in that quarter (LN(Inflows)). Similarly, we compute fund outflows as the logarithm of the amount of fund shares a household sold in a given quarter times the price of the fund's shares in that quarter (LN(Outflows)). Last, we compute net fund flows as the difference between inflows and outflows (NetFlow).

We relate these household-level fund flow measures to the measure of foreignness of fund manager names.[30] We control for several fund characteristics such as the fund's return, size, turnover, risk, expense ratio and age. These variables are defined as in the previous regressions. We cluster standard errors at the fund level.[31]

The inflow and outflow regression results are presented in Table 12, Panel A. The evidence reported in column (1) suggests that households invest significantly less in a mutual fund if the fund is managed by a foreign manager. This result is also economically significant. Foreign managed funds receive about $e^{5.955} - e^{(5.955-0.499)} = \$151$ lower inflows per household per quarter. Relative to the mean inflow of $e^{5.955} = \$386$, this reflects about 39% lower inflow. Further, we find that households invest significantly more in smaller funds. This result is consistent with the literature on investor sentiment showing that retail investors are more likely to invest in small

[30]We have to use a different definition of foreignness of fund manager name as only very few funds during this sample are managed by a foreign manager. We classify a fund as foreign managed if at least one worker identifies the manager as foreign. An alternative definition of foreignness requiring 50% of workers to classify a fund manager name as foreign yield similar results. If we require 75% of all workers to define a fund as foreign, only 0.004% of all observations in the brokerage sample are associated with foreign funds.

[31]Our results are very similar when we cluster by household, or household and fund level.

stocks (Baker and Wurgler (2007)).

We do not find a significant impact of the fund manager's foreignness on households' decision to withdraw money from a mutual fund (see column (2)). This result might be due to the fact that fund outflows in general are very sticky as some investors do not withdraw their money from a mutual fund even after bad fund performance (Ippolito (1992)). Last, in column (3), we aggregate inflows and outflows into a mutual fund as net flows and find that net flows are lower if a fund is managed by a manager with foreign-sounding name. These results indicate that retail investors shy away from mutual funds that are managed by foreign managers and this evidence is mainly driven by inflows into those funds.

5.2. Investor Characteristics and In-Group Bias

We next investigate whether household characteristics influence the sensitivity of mutual fund investment choices to foreignness of fund manager names. Our goal is to examine whether investor attributes associated with conservatism and in-group bias affect the mutual fund choices of individual investors. We consider several attributes such as age, gender, education, and foreignness to capture investor conservatism and the potential for in-group bias. We relate these investor attributes to our foreignness variable to identify the propensity of a particular household to invest into a mutual fund with a foreign manager. The set of control variables used in these regressions are identical to those used previously in the flow regressions.

The marginal effects from logit regressions are presented in Table 12, Panel B. The estimates in column (1) show that older households are significantly less likely to invest in a fund with a foreign manager. This result is consistent with the results from our experiment and the results based on fund locations. In contrast to the effects of age, examining the effects of education and gender, we find that these attributes do not significantly influence the propensity to invest in foreign mutual funds (see columns (2) and (3)). However, individuals who live in regions with greater proportion of foreign-born individuals are more likely to invest in foreign funds (see Column (4)). To the extent that investors in these regions are themselves more likely to be foreign, this evidence reveals in-group bias among individual investors. Alternatively, the evidence may indicate that investors who are more exposed to foreign-born individuals exhibit lower sensitivity to foreignness of manager names. These estimates remain significant when we include all household characteristics in one regression (see column (5)).

To further investigate the impact of household characteristics on the decision to invest in a foreign mutual fund, we focus on the subset of foreign funds and obtain household-level flow measures. The dependent variable in these regressions is the level of flow into funds with foreign managers. The regression results are presented in Table 12, Panel C.

We again find that older households invest significantly less in foreign mutual funds than younger households. However, the result is not statistically significant (see column (1)). We also find that better educated households invest significantly more in foreign funds than less educated households (see column (2)). Further, we find that male investors invest significantly less in foreign funds than female investors (see column (3)). Last, we find a significantly positive coefficient on foreignness of households, i.e., households with members more likely to be born outside of the U.S. invest significantly more in foreign mutual funds than other households, which is again consistent with in-group bias and familiarity.

In sum, the evidence in Table 12 shows that household characteristics are important determinants of mutual fund investment decisions of U.S. retail investors. Both the propensity to invest in foreign funds and the level of investments in those funds are influenced by investors' demographic characteristics. While our evidence using the brokerage sample alone may not be extremely strong due to the short sample period and various data approximations, these results clearly support the evidence obtained from the CRSP sample. In addition, we demonstrate *directly* that both the degree of conservatism and in-group bias affects the mutual fund choices of individual investors.

6. Summary and Conclusion

In this paper, we study whether social biases induced by a person's name affect the investment choices of mutual fund investors. Specifically, we examine whether investors are less likely to invest in mutual funds that have managers with foreign-sounding names. Our key finding is that funds with “foreign” managers experience lower flows even though these managers do not differ in the risk-adjusted returns they generate from managers who have typical American names. We also document that foreign-sounding names alter the flow-performance relation. Investors “punish” fund managers more after bad performance by withdrawing more capital and “reward” them less after good performance by additional investment if the fund-manager name sounds foreign.

While the absence of a performance difference makes statistical discrimination unlikely, we provide several tests that all support an interpretation based on taste-based discrimination against managers with foreign-sounding names. First, we show that the flow effects are stronger for funds that have more conservative investor clienteles or are located in regions where racial/ethnic stereotypes are more pronounced. Further, following the 9/11 terrorist attacks, fund managers with Middle-Eastern and South-Asian names experience a drop in fund flows relative to other managers with foreign-sounding names. Even in an experimental setting where managerial skill differences do not exist, individuals allocate 14% less money to an index fund run by a manager with foreign-sounding name. Last, using investor-level data, we document that investors who live in regions with high concentration of foreign-born individuals invest less in funds managed by individuals with more familiar American names.

Taken together, these results suggest that social biases such as in-group bias, stereotyping, and discrimination affect mutual fund investments of U.S. investors. Consequently, mutual fund managers with foreign-sounding names incur an economically significant cost for the foreignness of their names. The typical fund with a size of about $175 million can incur an annual average cost of $143,000, although this cost can be as high as $600,000. Even if only a fraction of this cost is experienced by the fund manager, the cumulative cost of having a foreign-sounding name over the entire career span of a fund manager can be significant. A manager with foreign-sounding name may be able to avoid this large cost by adopting a common American name.

These findings add to the literature on discrimination, which shows that despite growing public awareness, discrimination influences decision-making in many areas, including legal courts, sports refereeing, consumer choice, and labor markets. Our paper adds a new dimension to this debate. We demonstrate that social biases affect capital allocations even in one of the largest and most liquid segments of U.S. capital markets. We are also able to provide rough estimates of the economic costs associated with those social biases.

In future work, we hope to examine whether social biases influence skill perceptions of market participants when they evaluate CEOs, equity analysts, and hedge fund managers. It would also be interesting to examine whether other aspects of names beyond foreignness (e.g., social or economic class indicated by the name) exacerbate investors' social biases.

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Table 1: Sample Statistics

This table presents summary statistics for the CRSP Mutual Funds Database sample (Panel A) and the brokerage sample (Panel B). In Panel A, Foreign75 is a dummy variable that takes the value one if more than 75% of AMT workers indicate that the name of the manager as foreign-sounding, and zero otherwise. Fund Flow is the net inflow into the fund in the current year defined as: $(TNA_{i,t} - TNA_{i,t-1})/TNA_{i,t-1} - r_{i,t}$, where $TNA_{i,t}$ denotes fund i's total net assets in year t and r_t denotes fund i's return in year t as reported in CRSP. Return denotes fund i's return in year $t-1$ as reported in CRSP. PRank is the performance rank of the fund in the previous year relative to all other funds in the same market segment. PRank is rescaled to lie between 0 (lowest performance) and 1 (highest performance). PRank^2 is the square of PRank. Fund Size is the lagged natural logarithm of the fund's size in million USD. Turnover is the fund's lagged turnover rate. Fund Risk is the lagged return time series standard deviation of the fund return using the past 12 monthly return observations. Expense Ratio is the logarithm of the fund's total expense ratio. Fund Age is the natural logarithm of fund age in years at the beginning of year t. Segment Flow is the growth rate of fund i's market segment due to flows in year t. Family Flow is the growth rate of fund i's fund family due to flows in year t. Segment Flow and Family Flow are calculated excluding flows into fund i. Tenure is the difference of the current year to the start year of the fund manager reported in CRSP plus one. The level of observation in Panel A is fund-years. In Panel B, Foreign is a dummy variable that takes the value of one if any AMT worker indicates that the name of the manager as foreign sounding, and zero otherwise. Net Flow is the USD value of inflows minus outflows per fund in a given quarter for a given household. The variable ln(Inflows) is the natural logarithm of the total USD volume of inflows in a given fund for a given household and quarter. The variable ln(Outflows) is defined analogously. Fund Size, Turnover, Fund Risk, Expense Ratio, and Fund Age are defined above. HHAge is the age of the household. HHEducation is the education of the household proxied for by the proportion of the population over the age of 25 with a bachelor's degree or higher in the zip code of the household and year. HHMale is set to one for male investors. HHForeign is the probability of the household-investor being foreign proxied by the fraction of foreign born residents in a given zip code and year. The level of observation in Panel B is household-fund-quarter. The sample period is from 1993 to 2009 for Panel A, and from 1993 to 1996 for Panel B.

Table 1: Sample Statistics (Continued)

Panel A: CRSP Mutual Funds Database Sample

Variable	Mean	S.D.	Median	1^{st} Perc.	99^{th} Perc.	N
Foreign75	0.021	0.144	0.000	0.000	1.000	12,259
Fund Flow	0.288	1.099	0.057	–0.554	4.682	12,259
Return	0.038	0.310	0.042	–0.532	0.770	12,259
PRank	0.499	0.287	0.500	0.015	1.000	12,259
$PRank^2$	0.331	0.298	0.250	0.000	1.000	12,259
Fund Size	5.162	1.934	5.138	0.833	9.515	12,259
Turnover	1.052	2.224	0.652	0.022	7.440	12,259
Fund Risk	0.048	0.028	0.042	0.014	0.150	12,259
Expense Ratio	0.014	0.010	0.013	0.002	0.035	12,259
Fund Age	2.245	0.741	2.197	1.099	4.205	12,259
Segment Flow	0.088	0.257	0.074	–0.572	1.379	12,259
Family Flow	1.195	9.256	0.059	–0.990	55.300	12,259
Tenure	5.307	4.494	4.000	0.000	22.000	12,259

Panel B: Brokerage Data

Variable	Mean	S.D.	Median	1^{st} Perc.	99^{th} Perc.	N
Foreign	0.358	0.479	0.000	0.000	1.000	78,559
Net Flow	1.690	15.862	1.199	–46.466	51.459	78,559
ln(Inflows)	5.955	4.039	7.824	0.000	10.991	78,559
ln(Outflows)	3.823	4.433	0.000	0.000	10.900	78,559
Fund Size	6.509	1.855	6.538	0.032	10.364	78,559
Turnover	0.914	0.899	0.740	0.000	3.858	78,559
Fund Risk	0.030	0.013	0.028	0.000	0.062	78,559
Expense Ratio	0.012	0.005	0.012	0.003	0.025	78,559
Fund Age	0.963	0.942	0.693	0.000	3.401	78,559
HHAge	50.486	12.224	50.000	28.000	82.000	29,356
HHEducation	24.701	12.417	23.340	4.353	57.317	45,742
HHMale	0.897	0.304	1.000	0.000	1.000	42,638
HHForeign	10.061	9.104	7.272	0.311	43.933	45,742

Table 2: Fund Manager Names and Fund Characteristics

This table reports the mean fund and managerial characteristics of funds sorted by foreignness of fund manager name. Foreign75 is a dummy variable that takes on the value of one if more than 75% of AMT workers indicate that the name of the manager is foreign-sounding, and zero otherwise. All other variables have been previously defined in Table 1 and in Appendix A. The table shows group means in the first two columns and the difference between the group means and corresponding t-statistics in the last two columns.

Variable	"Foreign" Funds	Other Funds	Difference	t-statistic
Fund Attributes				
Fund Flow	0.181	0.290	–0.109	–1.58
Return	0.033	0.039	–0.006	–0.66
CAPM Alpha	–0.055	–0.056	–0.001	–0.99
PRank	0.488	0.500	–0.012	–0.61
PRank^2	0.323	0.332	–0.001	–0.46
Fund Size	4.646	5.173	–0.527	–4.36
Turnover	0.962	1.054	–0.092	–0.66
Fund Risk	0.056	0.048	0.008	4.69
Expense Ratio	0.016	0.014	0.002	3.65
Fund Age	2.235	2.246	–0.011	–0.23
Segment Flow	0.031	0.089	–0.058	–3.59
Family Flow	0.938	1.201	–0.263	–0.45
Marketing Expenses (12b-1 Fees)	0.300	0.270	0.030	2.43
Fund Manager Attributes				
Age	45.47	46.56	–1.09	–1.79
Gender	0.109	0.109	0.000	0.48
Bachelor	1.000	0.998	0.002	0.58
MBA	0.555	0.557	–0.002	–0.06
PhD	0.090	0.052	0.038	2.47
Professional Education	0.478	0.521	–0.043	–1.23
Fund Tenure	4.690	5.871	–1.181	–4.11

Table 3: Performance of "Foreign" Funds and Other Funds

This table presents performance results. Panel A shows the monthly returns of a portfolio that is Long in funds with managers with foreign-sounding names and Short in funds managed by individuals with non-foreign names. Panels B and C show the estimates of fund performance regressed on a foreign fund manager dummy (Foreign75) and a set of fund characteristics. The set of fund attributes used as control variables include lagged return, fund size, expense ratio, fund age, and managerial tenure. The performance of a fund is defined as the CAPM alpha (columns (1) and (4)), the Fama and French (1993) three-factor Alpha (columns (2) and (5)), and its four-factor extension (columns (3) and (6)). In all regressions in Panels B and C, we include year and segment fixed effects. U.S. equity (USE) funds are defined as all funds not classified as Global Equity, International Equity, and Regional funds according to the SI/Lipper classification. All control variables are lagged by one year and have previously been defined in Table 1. Standard errors are clustered at the fund level.

Panel A: Fund Performance: Portfolio Evidence (Foreign − Non-Foreign)

	Equal-Weighted (1-3)			Value-Weighted (4-6)		
	CAPM	3-Factor	4-Factor	CAPM	3-Factor	4-Factor
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha_t	0.000	0.000	0.000	0.000	0.001	0.001
	(0.05)	(0.77)	(0.09)	(0.10)	(1.80)	(1.61)
MKTRF_t	0.019	0.010	0.019	–0.147	–0.168	–0.167
	(3.40)	(1.77)	(3.23)	(–11.34)	(–14.94)	(–13.20)
SMB_t		0.011	0.009		–0.002	–0.002
		(1.60)	(1.33)		(–0.18)	(–0.22)
HML_t		–0.034	–0.028		–0.098	–0.097
		(–4.62)	(–3.77)		(–8.77)	(–8.56)
MOM_t			0.019			0.003
			(4.16)			(0.37)
Adj. R^2	0.047	0.165	0.225	0.599	0.748	0.748
Observations	216	216	216	216	216	216

Panel B: Fund Performance: Multivariate Evidence

	1 Year of Daily Returns (1-3)			3 Years of Monthly Returns (4-6)		
	CAPM	3-Factor	4-Factor	CAPM	3-Factor	4-Factor
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign75	0.000	–0.000	0.000	–0.006	–0.011	–0.003
	(0.12)	(–0.07)	(0.07)	(–0.46)	(–0.97)	(–0.24)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.096	0.105	0.108	0.109	0.077	0.084
Observations	12,026	12,026	12,026	9,802	9,802	9,801

Panel C: Fund Performance: Multivariate Evidence, USE Funds only

	1 Year of Daily Returns (1-3)			3 Years of Monthly Returns (4-6)		
	CAPM	3-Factor	4-Factor	CAPM	3-Factor	4-Factor
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign75	0.005	0.002	0.004	–0.002	–0.010	–0.004
	(0.99)	(0.51)	(0.85)	(–0.17)	(–0.92)	(–0.33)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.095	0.091	0.099	0.087	0.051	0.055
Observations	9,348	9,348	9,348	7,635	7,635	7,635

Table 4: Comparison of Investment Styles

This table shows the estimates of various investment style measures regressed on a foreign fund manager dummy (Foreign75) as well as fund characteristics. The fund's total risk is measured by its return time series standard deviation using the past 12 monthly returns. The fund's systematic risk is defined as the CAPM beta. HML, SMB, and MOM are the standard Fama French factors. The fund's idiosyncratic risk is defined as the standard deviation of the residuals from the four-factor model. The table also shows as dependent variables the fund's Turnover, the fund's active share, and the fund's tracking error. Panel A presents results for all available funds, while Panel B shows results for U.S. equity funds only. U.S. equity (USE) funds are defined as all funds not classified as Global Equity, International Equity, and Regional funds according to the SI/Lipper classification. Panel B includes the same control variables as those in Panel A but, for brevity, their coefficient estimates are not reported.

Panel A: All Funds

	Total Risk	CAPM Beta	HML	SMB	MOM	Idio. Risk	Turnover Ratio	Active Share	Tracking Error
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Foreign75	0.002	0.047	–0.050	0.093	–0.011	–0.188	1.146	0.052	–0.003
	(1.28)	(1.27)	(–0.98)	(2.10)	(–0.40)	(–1.90)	(0.92)	(2.18)	(–0.57)
(Lagged) Return	0.010	0.193	–0.085	0.065	0.094	0.421	3.547	0.022	0.015
	(5.71)	(6.65)	(–2.40)	(4.04)	(4.96)	(2.24)	(2.29)	(2.49)	(4.32)
Fund Size	0.000	0.012	–0.017	–0.013	0.006	–0.093	–0.867	–0.022	–0.004
	(0.07)	(3.55)	(–4.17)	(–3.79)	(3.00)	(–6.05)	(–2.60)	(–8.10)	(–7.43)
Fund Age	–0.001	–0.015	0.006	–0.028	0.010	–0.020	0.584	–0.001	0.001
	(–1.63)	(–2.09)	(0.67)	(–3.41)	(2.30)	(–0.70)	(0.80)	(–0.15)	(0.45)
Tenure	–0.000	–0.005	0.005	–0.000	–0.002	–0.025	0.081	0.004	0.001
	(–2.03)	(–3.58)	(2.89)	(–0.30)	(–3.06)	(–5.93)	(2.47)	(4.18)	(3.94)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.507	0.197	0.090	0.123	0.064	0.065	0.157	0.205	0.395
Observations	15,231	15,200	15,200	15,200	15,200	15,125	15,200	6,207	6,074

Panel B: U.S. Equity Funds Only

	Total Risk	CAPM Beta	HML	SMB	MOM	Idio. Risk	Turnover Ratio	Active Share	Tracking Error
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Foreign75	0.001	0.072	0.024	0.115	–0.020	–0.262	–0.189	0.052	–0.003
	(0.58)	(1.40)	(0.29)	(1.62)	(–0.46)	(–0.15)	(–1.19)	(2.18)	(–0.57)
Adj. R^2	0.495	0.158	0.055	0.102	0.039	0.116	0.070	0.205	0.395
Observations	11,861	11,835	11,835	11,835	11,835	11,835	11,779	6,206	6,073

Table 5: Fund Flow Regression Estimates

This table shows the estimates of percentage fund flows regressed on Foreign75 and control variables. The dependent variable is Fund Flow, defined as the net inflow into the fund in the current year: $(TNA_{i,t} - TNA_{i,t-1})/TNA_{i,t-1} - r_{i,t}$, where $TNA_{i,t}$ denotes fund i's total net assets in year t and r_t denotes fund i's return in year t as reported in CRSP. Foreign75 is a dummy variable that takes on the value one, if more than 75% of AMT workers indicated the name of the manager as foreign sounding, and zero otherwise. All other variables are lagged by one year and have previously been defined in Table 1. In Panel A, the model is estimated by OLS (columns (1), (2), (3), and (5)) as well as Fama and MacBeth (1973) (columns (4) and (6)). Panel B presents results from estimating specification (3) from Panel A on a sample of matched funds. We construct the matched fund sample by keeping for each fund with a foreign manager only the subset of funds with the same set of matching criteria in a given year. The following matching attributes are used: year, fund size, fund segment, fund family, fund location, manager age, managerial performance, and education. MSA denotes funds headquartered in the same metropolitan statistical area. Standard errors of OLS regressions are clustered at the fund level. The corresponding t-statistics are given in brackets below the coefficient estimates.

Panel A: Main Results

	OLS	OLS	OLS	FMB	OLS	FMB
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign75	–0.107	–0.114	–0.107	–0.085	–0.102	–0.103
	(–2.08)	(–2.15)	(–2.30)	(–2.59)	(–1.99)	(–2.77)
Return	0.332	0.273				
	(4.64)	(3.53)				
PRank			–0.916	–0.852		
			(–6.00)	(–5.99)		
PRank^2			1.653	1.580		
			(9.38)	(9.57)		
PQuintile 1					0.309	0.520
					(1.18)	(2.05)
PQuintiles 2 to 4					0.364	0.305
					(7.37)	(3.40)
PQuintile 5					2.383	2.340
					(6.82)	(5.15)
Fund Size	–0.059	–0.064	–0.056	–0.058	–0.069	–0.069
	(–7.19)	(–7.70)	(–7.11)	(–7.92)	(–8.33)	(–11.04)
Turnover	0.051	0.047	0.049	0.034	0.050	0.040
	(3.95)	(3.87)	(4.03)	(1.95)	(4.09)	(2.29)
Fund Risk	–2.046	–2.107	–2.108	–1.726	–1.558	–0.059
	(–3.19)	(–3.23)	(–3.19)	(–1.81)	(–2.39)	(–0.05)
Expense Ratio	–0.098	–0.178	–0.039	–3.240	–0.404	–4.278
	(–0.04)	(–0.07)	(–0.02)	(–1.79)	(–0.15)	(–2.22)
Fund Age	–0.133	–0.089	–0.075	–0.073	–0.068	–0.066
	(–10.15)	(–6.86)	(–6.17)	(–3.94)	(–5.40)	(–3.33)

(Continued...)

Table 5: Fund Flow Regression Estimates (Continued)

Panel A: Main Results (Continued)

	OLS	OLS	OLS	FMB	OLS	FMB
	(1)	(2)	(3)	(4)	(5)	(6)
Segment Flow	0.190	0.171	0.179	0.295	0.178	0.280
	(4.03)	(3.87)	(4.13)	(3.82)	(4.12)	(3.40)
Family Flow	0.004	0.003	0.003	0.096	0.003	0.095
	(2.59)	(2.23)	(2.39)	(2.35)	(2.32)	(2.42)
Tenure	–0.003	–0.002	–0.004	–0.005	–0.004	–0.004
	(–1.69)	(–1.58)	(–2.91)	(–3.07)	(–2.91)	(–2.98)
Lagged Fund Flow		0.073	0.075	0.085	0.054	0.065
		(7.42)	(8.14)	(5.78)	(5.71)	(4.53)
Year FE	Yes	Yes	Yes	No	Yes	No
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj/Avg. R^2	0.062	0.071	0.117	0.178	0.093	0.157
Observations	13,215	12,255	12,255	12,310	12,307	12,307

Panel B: Results Using Matched Samples

	Coefficient	t-value	Observations
Baseline (Table 5, Panel A, Specification (3))	–0.107	–2.30	12,255
Matching Attributes			
Year, Segment, and Size	–0.135	–2.49	3,550
Year, Segment, Size, and Fund Age	–0.203	–2.64	913
Year, Segment, Size, and Manager Age	–0.229	–2.68	1,001
Year, Segment, Size, and Performance	–0.165	–1.90	685
Year, Segment, Size, and MSA	–0.157	–2.70	1,593
Year, Size, and Fund Family	–0.156	–2.39	1,235
Year, Segment, Size, and Fund Family	–0.186	–1.64	496
Year, Segment, Size, and Education	–0.132	–1.95	1,687

Table 6: Fund Flow Regression Estimates: Robustness Checks

This table presents flow regression estimates for subsamples (Panel A) and robustness checks (Panel B) to our baseline results. Unless otherwise mentioned, all regressions estimates are based on specification (3) in Table 5. The table only shows the main coefficient estimates. Control variables are included but not reported for brevity. The corresponding t-statistics are obtained using standard errors clustered at the fund level. The number of observation are also reported. Panel A shows results when the sample is split by fund type and year. U.S. equity (USE) funds are defined as all funds not classified as Global Equity, International Equity, and Regional funds according to the SI/Lipper classification. Panel B presents robustness checks. The name fluency measure follows Green and Jame (2011) and is defined as a dummy variable equal to one if the length of the name as measured by the number of letters is greater than the median in the sample and/or the last name does not appear in the list of the 10,000 most common last name sin the US. In the specification with non-parametric size controls, we include dummies for ten size deciles instead of fund size. Index funds are all funds classified as S&P 500 Index funds in the CRSP Mutual Fund Database. Marketing expenses are measured using 12b-1 fees as provided in CRSP. Industry experience is computed as the difference between the current year and the year a manager first appeared in the CRSP mutual fund database.

Panel A: Subsample Estimates

	Coefficient	t-value	Observations
Baseline (Table 5, Specification (3))	–0.107	–2.30	12,255
(1) USE Funds Only	–0.128	–2.10	9,617
Non-USE Funds Only	–0.009	–0.12	2,638
(2) Year > 2001	–0.132	–2.76	5,666
Year $\leq$ 2001	–0.043	–0.52	6,589

Panel B: Estimates From Other Robustness Checks

	Coefficient	t-value	Observations
Baseline (Table 5, Specification (3))	–0.107	–2.30	12,255
(1) Alternative Foreignness Measure (Foreign85)	–0.107	–2.25	12,255
(2) Name Fluency Instead of Foreignness	–0.028	–2.07	12,255
(3) Control for Name Fluency			
Coefficient on Foreign75	–0.100	–2.04	12,255
Coefficient on Fluency Measure	–0.027	–2.01	
(4) Nonparametric Size Control	–0.122	–2.02	12,255
(5) Exclude Index Funds	–0.108	–2.32	12,174
(6) Control for Other Managerial Attributes			
Gender	–0.099	–2.12	12,255
Gender and Age	–0.099	–2.14	12,255
Gender, Age, and Education	–0.098	–2.11	12,255
(7) Control for Marketing Expenses (12b-1 Fees)	–0.127	–2.47	8,878
(8) Exclude Mixed Names	–0.109	–2.27	5,977
(9) Distribution Channels			
Coefficient Estimate of Foreign75	–0.143	–2.66	12,255
Coefficient Estimate of Foreign75 $\times$ No Load	0.084	0.86	
Coefficient Estimate of No Load Dummy	0.020	0.96	
(10) Industry Experience			
Coefficient on Foreign75	–0.109	–2.33	12,255
Coefficient on Industry Tenure	–0.004	–1.48	

Table 7: Regional Characteristics Around Fund Headquarters and Fund Flows

This table shows the estimates of percentage fund flows regressed on Foreign75 interacted with regional characteristics at the fund location. Small MSA is a dummy variable that is equal to one for all MSAs other then the ten largest MSAs by population in 2000. Rural Area is the proportion of the county population that lives in rural areas. Old Population is a dummy variable equal to one if the average household age in the county of the fund headquarter is larger than the median age across counties in our sample. Republican State is one if the majority of voters in a state voted for the Republican party in the last presidential elections. Church Attendance is a dummy equal to one if the share of residents in a state who go to church at least once a week based on the General Social Survey is higher than the sample median. PCRATIO is one if the ratio of Protestants to Catholics in a county is above the sample median. Black (Asian) Stereotype is a state-level dummy variable for the prevalence of stereotypes against Blacks (Asians) based on the degree of agreement with the statement "Blacks (Asians) are intelligent" from the ANES survey. Additional control variables are included as in specifications (3) in Table 5. All control variables are lagged by one year and have previously been defined in Table 1. Standard errors are clustered at the fund level. The corresponding t-statistics are given in brackets below the coefficient estimates.

	Location Variable:			
	Small MSA	Rural Area	Old Population	Republican State
	(1)	(2)	(3)	(4)
Foreign75	–0.264	0.015	0.044	0.045
	(–2.45)	(0.20)	(0.62)	(0.57)
Foreign75 × Location Variable	–0.302	–0.282	–0.477	–0.394
	(–2.34)	(–2.22)	(–4.19)	(–2.52)
Location Variable	–0.052	–0.102	–0.009	–0.046
	(–2.46)	(–3.98)	(–0.35)	(–2.09)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes
Adj. R^2	0.127	0.129	0.116	0.117
Observations	5795	5802	5792	5490

	Location Variable:			
	Church Attendance	PCRATIO	Black Stereotype	Asian Stereotype
	(5)	(6)	(7)	(8)
Foreign75	0.100	–0.323	0.050	0.049
	(0.91)	(–3.08)	(0.70)	(0.68)
Foreign75 × Location Variable	–0.262	–0.353	–0.387	–0.380
	(–2.11)	(–3.06)	(–2.70)	(–2.62)
Location Variable	–0.039	–0.017	–0.029	–0.037
	(–1.46)	(–0.69)	(–1.21)	(–1.26)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes
Adj. R^2	0.116	0.116	0.120	0.121
Observations	5315	5792	5385	5385

Table 8: Fund Flow Regressions Around 9/11 Terrorist Attacks

This table shows estimates of monthly fund flows regressed on a dummy variable equal to one for fund managers with Middle Eastern and South Asian names, and zero otherwise. Fund manager names that are classified as Middle Eastern names are marked with an asterisk in Appendix B. The dependent variable is the Fund Flow, defined as the net inflow into the fund in the current month: $(TNA_{i,m} - TNA_{i,m-1})/TNA_{i,m-1} - r_{i,m}$, where $TNA_{i,m}$ denotes fund i's total net assets in month m and r_m denotes the return of fund i in month m, as reported in CRSP. Post-9/11 is a dummy variable that takes the value of one for September 2001 and all subsequent months ending in December 2009. It is zero for all months beginning in January 1992 and ending in August 2001. The results in column (1) are based on all funds classified as a "Foreign Fund" according to at least 75% of Amazon Mechanical Turk raters. In column (2), we restrict the sample of foreign funds to those with an investment focus on U.S. equities. U.S. equity (USE) funds are defined as all funds not classified as Global Equity, International Equity, and Regional funds according to the SI/Lipper classification. In column (3), we restrict the sample of foreign funds to a time period of 12 month around September 2001. The results in column (4) are based on the full sample of mutual funds, while results in column (5) are based on all mutual funds with an investment focus on U.S. equities. Non-MidEast-Foreigner is a dummy variable equal to one for all fund manager names that have been classified as foreign by at least 75% of Amazon Mechanical Turk raters but are not part of the Middle Eastern name category, and zero otherwise. All other variables are lagged by one year and have previously been defined in Table 1. Standard errors are clustered at the fund level. The corresponding t-statistics are shown in brackets below the coefficient estimates.

	Foreign Funds	Foreign Funds, Only USE	Foreign Funds +/− 12 Months	Full Sample	Full Sample, Only USE
	(1)	(2)	(3)	(4)	(5)
MidEast	0.014	0.003	0.008	0.011	0.009
	(1.60)	(0.34)	(0.66)	(1.54)	(1.05)
MidEast × Post-9/11	−0.026	−0.022	−0.030	−0.020	−0.023
	(−2.66)	(−1.90)	(−1.90)	(−2.72)	(−2.50)
Non-MidEast-Foreigner				−0.002	0.003
				(−0.61)	(0.62)
Non-MidEast-Foreigner × Post-9/11				0.008	0.004
				(1.39)	(0.52)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.060	0.070	0.060	0.050	0.040
Observations	8,109	5,049	1,272	230,149	185,954

Table 9: Flow Performance Relation Among "Foreign" Funds

This table shows the estimates of percentage fund flows regressed on Foreign75 interacted with lagged performance indicators. The dependent variable is Fund Flow, defined as the net inflow into the fund in the current year: $(TNA_{i,t} - TNA_{i,t-1})/TNA_{i,t-1} - r_{i,t}$, where $TNA_{i,t}$ denotes fund i's total net assets in year t and r_t denotes fund i's return in year t as reported in CRSP. Foreign75 is a dummy variable that takes on the value one, if more than 75% of AMT workers indicated the name of the manager as foreign sounding, and zero otherwise. Additional control variables are included as in specifications (1) to (6) in Table 5. All control variables are lagged by one year and have previously been defined in Table 1. The model is estimated by a pooled regression approach with time and segment fixed effects (Columns (1), (2), (3), and (5)) as well as Fama and MacBeth (1973) regressions (Columns (4) and (6)). Standard errors of OLS regressions are clustered at the fund level. The corresponding t-statistics are given in brackets below the coefficient estimates.

	OLS	OLS	OLS	FMB	OLS	FMB
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign75	–0.183	–0.180	–0.205	–0.025	0.226	0.413
	(–0.97)	(–0.88)	(–0.86)	(–0.12)	(0.65)	(1.68)
Foreign75× Return	–0.379	–0.523				
	(–2.84)	(–3.20)				
Return	0.336	0.280				
	(4.64)	(3.53)				
Foreign 75 × PRank			0.800	1.046		
			(1.12)	(1.44)		
Foreign 75 × PRank^2			–1.128	–1.589		
			(–1.70)	(–2.05)		
PRank			–0.145	–0.042		
			(–0.91)	(–0.19)		
PRank^2			0.750	0.635		
			(4.38)	(2.57)		
Foreign 75 × PQuintile 1					–1.103	–2.464
					(–0.60)	(–2.24)
Foreign 75 × PQuintile 2 to 4					–0.001	0.615
					(–0.00)	(2.16)
Foreign 75 × PQuintile 5					–4.022	–7.892
					(–3.36)	(–2.26)
PQuintile 1					0.337	0.553
					(1.27)	(2.14)
PQuintile 2 to 4					0.364	0.302
					(7.27)	(3.42)
PQuintile 5					2.463	2.405
					(6.93)	(5.11)
Foreign 75 ×Fund Size	0.018	0.016	0.017	–0.012	–0.011	–0.034
	(0.54)	(0.44)	(0.48)	(–0.29)	(–0.33)	(–0.96)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj/Avg. R^2	0.062	0.071	0.094	0.159	0.095	0.160
Observations	13,215	12,255	12,233	12,288	12,307	12,307

Table 10: Cost Estimates

This table shows the estimates of cost to the mutual fund company due to lower flows to funds that have mangers with foreign-sounding names. These estimates are based on the implied flow difference (Δ Flow) from specification (3), Table 9. We assume that the fund size equals \$174.5 million, which is the average fund size in our sample. The calculations are based on the estimate of 0.767% for the marginal compensation rate in Deli (2002).

PRANK	Δ Flow (%)	Estimated Cost (\$)
0.00	−11.72	−156,936
0.10	−4.85	−64,953
0.20	−0.24	−3,167
0.30	2.12	28,422
0.40	2.23	29,814
0.50	0.08	1,009
0.60	−4.33	−57,993
0.70	−11.00	−147,191
0.80	−19.92	−266,587
0.90	−31.09	−416,179
1.00	−44.52	−595,969

Table 11: Fund Allocation Regression Estimates Using Experimental Data

This table shows estimates of experimental monetary units allocated to an index fund regressed on fund characteristics and Amazon Mechanical Turk (AMT) worker characteristics. The dependent variable is the fraction of 100 monetary units that AMT workers allocated to a randomly assigned S&P500 index fund in an online experiment. Foreign Fund is a dummy variable equal to one if the manager name of the index fund is "Mustafa Sagun" and zero if the manager name of the otherwise identical fund is "William R. Andersen". Female is a dummy variable equal to one if the AMT worker is female, and zero otherwise. Old Investor is a dummy variable equal to one if the AMT worker's age is larger than the median age of 35 years, and zero otherwise. MF Investor is a dummy variable equal to one if the AMT worker indicated that she invested in a mutual fund before, and zero otherwise. Column (1) presents results for the full sample of AMT workers. Columns (2) and (3) exclude AMT workers who completed the experiment in less than one minute and two minutes, respectively. The results in column (4) are based on the full sample. The t-statistics are reported in parentheses below the coefficient estimates.

	Full Sample	Work Time > 1 min	Work Time > 2 mins	Inter-actions
	(1)	(2)	(3)	(4)
Fund Manager Characteristic				
Foreign Fund	–12.713	–12.977	–17.230	–2.571
	(–2.36)	(–2.35)	(–2.56)	(–0.32)
AMT Worker Characteristic				
Female	11.929	11.915	3.611	14.112
	(2.42)	(2.39)	(0.59)	(2.08)
Old Investor	–8.944	–8.945	–9.499	2.622
	(–1.66)	(–1.64)	(–1.42)	(0.36)
MF Investor	–6.850	–6.825	–4.510	–9.656
	(–1.30)	(–1.29)	(–0.71)	(–1.39)
Interactions				
Female × Foreign Fund				–3.170
				(–0.32)
Old Investor × Foreign Fund				–23.010
				(–2.15)
MF Investor × Foreign Fund				5.493
				(0.53)
Adj. R^2	0.113	0.114	0.085	0.134
Observations	100	98	66	100

Table 12: Investor-Level Regression Estimates

This table presents estimates from investor-level regressions. Foreign is a dummy variable equal to one if at least one AMT worker indicated the name as foreign sounding. Panel A regresses flow measures on Foreign and controls. Inflows (outflows) are buys (sells) of fund shares aggregated by household, fund and quarter, in the brokerage dataset. Net Flow is defined as Inflow minus Outflow. Panel B presents results from Logit regressions. The dependent variable is Foreign. Panel C shows OLS estimates. The dependent variable are inflows into "foreign" funds. In Panels B and C, the main independent variables are HHAge, HHEducation, HHMale, and HHForeign, which are defined in Table 1. Control variables in all three Panels are lagged fund return, fund size, turnover, fund risk, expense ratio, and fund age. Standard errors are clustered at the fund level in Panel A and at the household level in Panels B and C. The corresponding t-statistics (z-statistics) are given in brackets below the coefficient estimates.

Panel A: Flows into "Foreign" Funds

	LN(Inflows)	LN(Outflows)	Net Flow
Foreign	–0.499	0.083	–1.039
	(–2.09)	(0.41)	(–1.70)
Additional Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes
Adj. R^2	0.051	0.023	0.020
Observations	78,559	78,559	78,559

Panel B: Probability of Investing in "Foreign" Fund

	(1)	(2)	(3)	(4)	(5)
HHAge	–0.003				–0.003
	(–2.02)				(–2.37)
HHEducation		–0.000			–0.001
		(–0.05)			(–0.37)
HHMale			0.026		–0.048
			(0.58)		(–0.82)
HHForeign				0.005	0.004
				(3.34)	(2.31)
Additional Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.149	0.138	0.137	0.138	0.150
Observations	29,356	45,741	42,637	45,741	27,927

Panel C: "Foreign" Fund Inflows and Retail Investor Characteristics

	(1)	(2)	(3)	(4)	(5)
HHAge	–0.006				–0.003
	(–1.39)				(–0.64)
HHEducation		0.008			0.009
		(3.05)			(2.44)
HHMale			–0.187		–0.043
			(–1.94)		(–0.32)
HHForeign				0.010	0.008
				(2.21)	(2.16)
Additional Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.078	0.082	0.082	0.082	0.079
Observations	11,028	16,801	15,748	16,801	10,482

Figure 1: Monthly Fund Flows around Terrorist Attacks in September 2001

This figure shows the average monthly net inflows into funds that are managed by individuals with South Asian and Middle Eastern sounding names (Flow (ME)), net inflows into funds managed by individuals with other foreign-sounding names (Flow (NME)), and the difference between them (Flow Difference (ME−NME)). The fund flows are measured at the last day of each month.

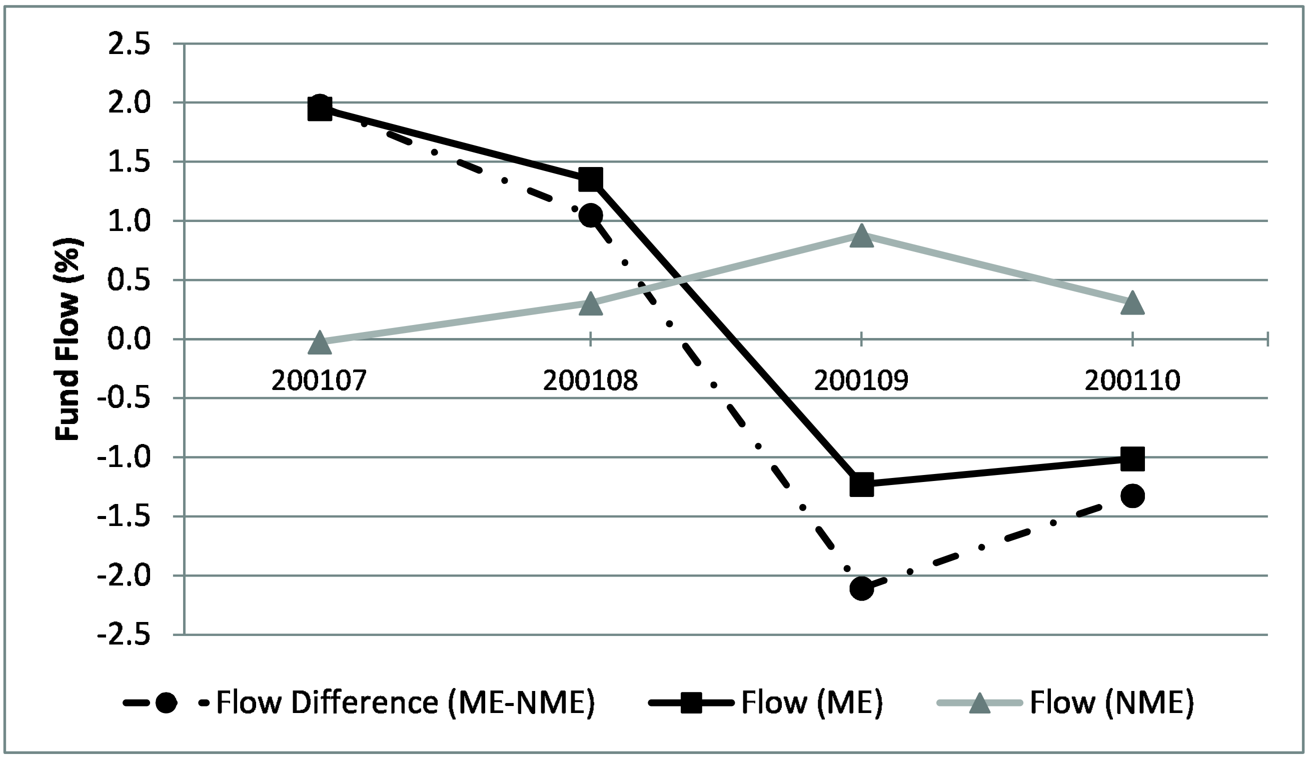


Figure 2: Differences in Fund Flow Conditional on Performance

This figure shows the predicted difference (in percentage points) in fund flow conditional on lagged fund performance between funds with and without managers with foreign sounding names. The graph is based on specification (3) in Table 5. The negative values indicate lower flows into fund managed by individuals with foreign-sounding names.

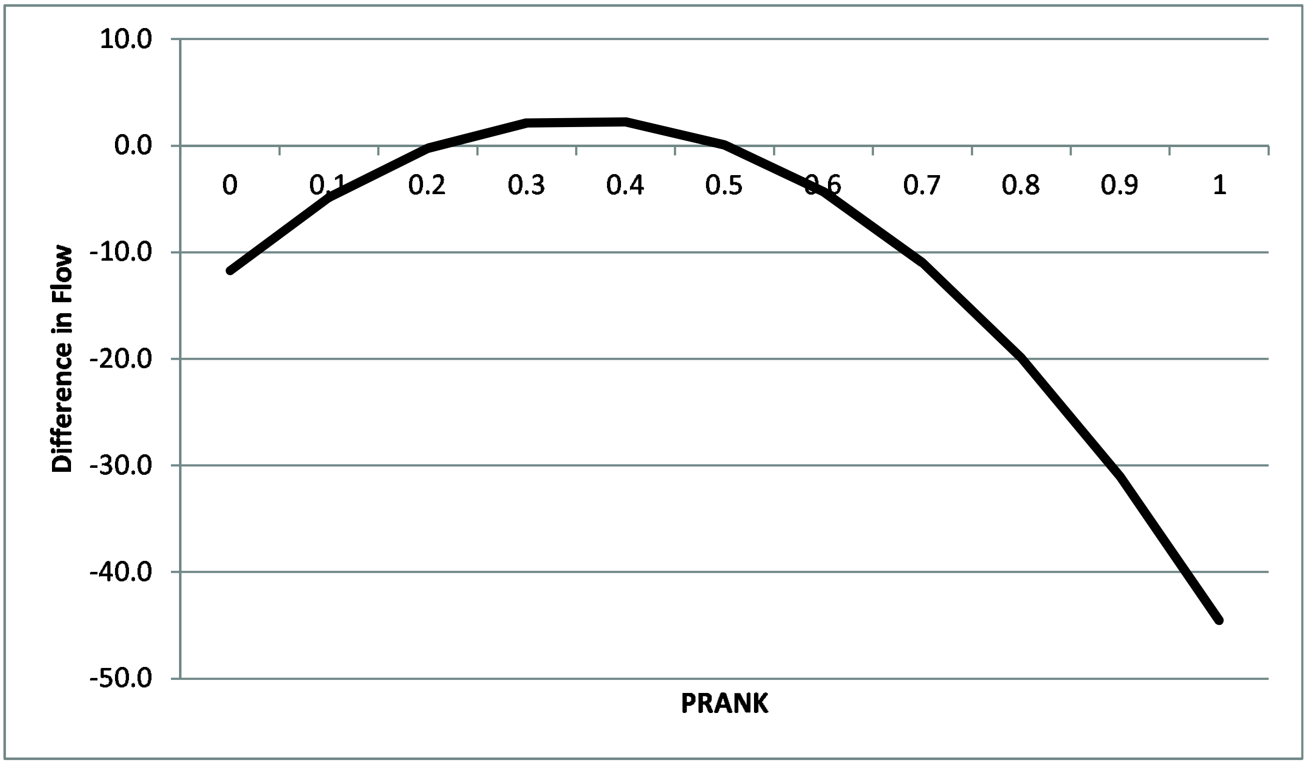
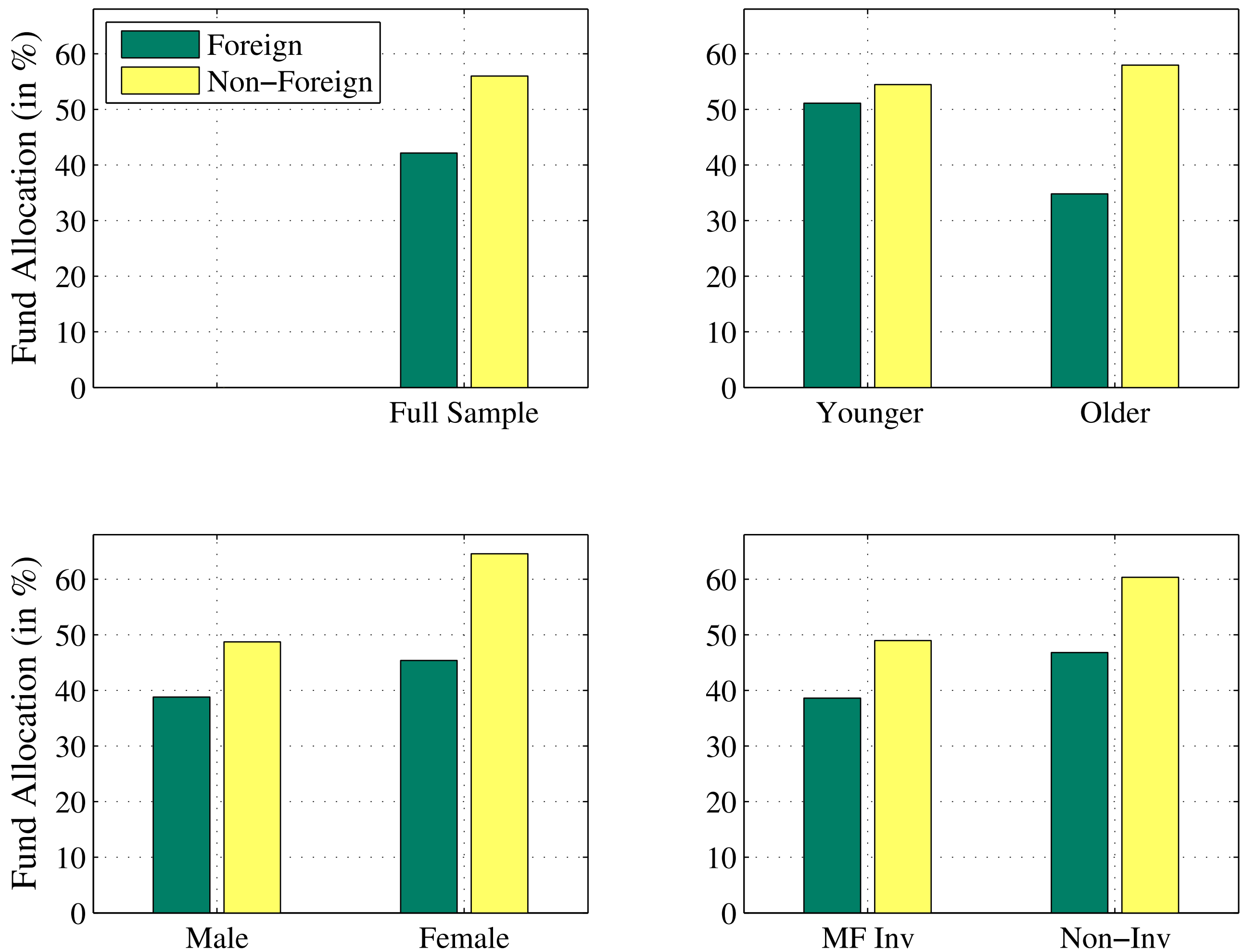


Figure 3: Experimental Results

This figure shows the allocations of Amazon Mechanical Turk (AMT) paid participants to index fund A when the fund manager name is foreign and non-foreign. Young (old) denotes AMT workers who are younger (older) than the median age of 35 years. Female is a dummy variable that is equal to one if the AMT worker is female, and zero otherwise. MF Inv is a dummy variable that is equal to one if the AMT worker indicates that he has invested in mutual funds before, and zero otherwise.



Appendices

A Brief Definitions and Sources of Main Variables

This table briefly defines the main variables used in the empirical analysis. The data sources are:
(i) CRSP: CRSP Survivorship Bias Free Mutual Fund Database
(ii) ARDA: Association of Religion Data Archives,
(iii) GSS: General Social Survey,
(iv) Brokerage: Large U.S. discount brokerage,
(v) Estimated: Estimated by the authors,
(vi) AMT: Amazon Mechanical Turk,
(vi) PT: http://www.petajisto.net/data.html,
(vii) Census: U.S. Census County Files,
(viii) KF: Kenneth French Data Library,
(ix) David Leip: www.uselectionatlas.org,
(x) ANES: American National Election Studies,
(xi) MS: Morningstar Database, and
(xii) HC: Hand-collected by the authors.

Panel A: Main Dependent Variables

Variable Name	Description	Source
Fund Flow	Computed as $(TNA_{i,t} - TNA_{i,t-1})/TNA_{i,t-1} - r_{i,t}$ where $TNA_{i,t}$ denotes fund i's total net assets in year t and r_t denotes fund i's return in year t as reported in CRSP.	CRSP, estimated
LN(Inflows)	Logarithm of absolute USD inflows into fund i by household h in year t.	Brokerage, Estimated
LN(Outflows)	Logarithm of absolute USD money withdrawals from fund i by household h in year t.	Brokerage, Estimated
Net Flows	Inflows$_{i,h,t}$ minus Outflows$_{i,h,t}$.	Brokerage, Estimated

Panel B: Main Independent Variables

Variable Name	Description	Source
Foreign75	Dummy variable equal to one if at least 75% of respondents indicated that the fund manager's name sounds foreign, and zero otherwise.	AMT
Foreign	Dummy variable equal to one if any respondent indicated that the fund manager's name sounds foreign, and zero otherwise.	AMT

Panel C: Other Measures

Variable Name	Description	Source
Fund Characteristics		
Return	Annual fund return.	CRSP
Fund Size	Logarithm of a fund's total net assets.	CRSP
Turnover	A fund's annual turnover ratio in %.	CRSP
Expense Ratio	A fund's annual expense ratio in %.	CRSP
Fund Risk	A fund's annualized standard deviation based on twelve monthly fund returns.	CRSP, Estimated
Fund Age	Logarithm of a fund's age computed from the date a fund was first offered (variable $first\_offer\_dt$).	CRSP, Estimated
Segment Flow	Computed as $(TNA_{j,t} - TNA_{j,t-1})/TNA_{j,t-1} - r_{j,t}$ where $TNA_{j,t}$ denotes segment j's total net assets in year t and $r_{j,t}$ denotes segment j's equal weighted return in year t.	CRSP, Estimated
Family Flow	Computed as $(TNA_{f,t} - TNA_{f,t-1})/TNA_{f,t-1} - r_{f,t}$ where $TNA_{f,t}$ denotes fund company f's total net assets in year t and $r_{f,t}$ denotes fund company f's equal weighted return in year t.	CRSP, Estimated
Active Share	A fund's active share in % as computed in Petajisto (2010).	PT
Tracking Error	A fund's active share in % as computed in Petajisto (2010).	PT
Location Data		
HHAge	Age of the household.	Brokerage
HHGender	Dummy variable equal to one for male investors.	Brokerage
HHEducation	Proportion of residents in investor's zip code with a Bachelor's or higher educational degree.	Brokerage, Census
HHForeign	Proportion of foreign born residents in the investor's zip code.	Brokerage, Census
Small MSA	Dummy equal to one for a fund located in one of the ten largest MSAs based on the population in the year 2000: New York, Los Angeles, Chicago, Miami, Philadelphia, Dallas, Boston, San Francisco, Detroit, and Houston.	Census
Republican State	dummy that is one for funds located in a state that voted for the Republican presidential candidate in the most recent presidential election.	David Leip
Rural Area	Proportion of MSA residents living in rural areas.	Census
Old Population	Dummy equal to one if fund is located in county with above-median average age in the sample.	Census
Church Attendance	Dummy variable equal to one if share of people in a state who go to church at least once a week is larger than median share of people across all states, and zero otherwise. The survey is conducted every second year. We use interpolated values for years in which no survey was conducted.	GSS
PCRATIO	Ratio of Protestant population to Catholic population in a county.	ARDA
Black Stereotype	Dummy based on average rating assigned to Blacks divided by the average number assigned to whites in the question "Blacks (whites) are ..." on a scale from one (intelligent) to (unitelligent).	ANES
Asian Stereotype	Dummy based on average rating assigned to Asians divided by the average number assigned to whites in the question "Asians (whites) are ..." on a scale from one (intelligent) to (unitelligent).	ANES

Panel C: Other Measures (Continued)

Variable Name	Description	Source
Performance Measures		
CAPM Alpha	Performance alpha from a market model estimated for one year of monthly returns.	CRSP, KF, Estimated
CAPM Beta	Loading on the market portfolio from a market model estimated for one year of monthly returns.	CRSP, KF, Estimated
3-Factor Alpha	Performance alpha from a Fama-French 3-factor model estimated for one year of monthly returns.	CRSP, KF, Estimated
SMB	Loading on the SMB portfolio.	CRSP, KF, Estimated
HML	Loading on the HML portfolio.	CRSP, KF, Estimated
4-Factor Alpha	Performance alpha from a Fama-French 3-factor model augmented by the Carhart factor estimated for one year of monthly returns.	CRSP, KF, Estimated
MOM	Loading on the momentum factor.	CRSP, KF, Estimated
Idiosyncratic Risk	A fund's unsystematic risk, estimated as the standard deviation from a market model estimated using one year of monthly returns.	CRSP, KF, Estimated
AR	A fund's 4-factor alpha divided by idiosyncratic risk as defined above.	CRSP, KF, Estimated
SR	A fund's excess annual return divided by the annualized return standard deviation.	CRSP, Estimated
PRank	Performance rank of a fund based on its annual return relative to its market segment in a given year. This variable is bound between zero and one.	CRSP, Estimated
PRank^2	Squared performance rank of a fund based on its annual return relative to its market segment in a given year. This variable is bound between zero and one.	CRSP, Estimated
PQuintile 1	Computed as min(Perf. Rank; 0.2).	CRSP, Estimated
PQuintiles 2 to 4	Computed as min(PRank-PQuintile 1; 0.8).	CRSP, Estimated
PQuintile 5	Computed as min(PRank-(PQuintile 1+PQuintiles 2 to 4)).	CRSP, Estimated
Fund Manager Characteristics		
Age	Age of a fund manager in years.	MS, HC
Gender	Dummy variable equal to one if fund manager is female, and zero otherwise.	MS, HC
Bachelor's	Dummy variable equal to one if fund manager holds a Bachelor degree, and zero otherwise.	MS, HC
MBA	Dummy variable equal to one if fund manager holds an MBA degree, and zero otherwise.	MS, HC
PhD	Dummy variable equal to one if fund manager holds a PhD degree, and zero otherwise.	MS, HC
Prof Education	Dummy variable equal to one if fund manager holds a CFA (or equivalent), and zero otherwise.	MS, HC
Fund Tenure	Tenure of manager at specific fund, computed as difference between current year and year in which the manager started working for this fund.	CRSP, Estimated
Industry Experience	The difference between the current year and the year a manager first appeared in the CRSP mutual fund database.	CRSP, Estimated

B Mutual Fund Managers with Foreign-Sounding Names

South Asian and Middle-Eastern names are identified using an asterisk mark.

A Rama Krishna*	Hao-Hung (Peter) Liao	Rajiv Jain*
Acquico Wen	Harish Kumar*	Ralf Oberbannscheidt
Adeline Ko	Hiroshi Motoki	Ram Kolluri*
Agus Tandiono	Hitesh (John) P. Adhia*	Ramesh Jhaveri*
Agustin J Fleites	Hokeun Chung	Ramin Arani*
Ajit Dayal*	Huachen Chen	Ramona Persaud*
Amit Khandwala*	Hyun Jong Nan	Remy Trafelet
Anh Lu	Ilario Di Bon	Ren Y. Cheng
Anmol Mehra*	Ira L. Unschuld	Renaud Saleur
Antonio Intagliata	Ivka Kalus-Bystricky	Rimmy Malhotra*
Arjun Divecha*	Ivo Kovachev	Rohit Sah*
Armon Bar-Tur	Iwao Komatsu	Rudolph Kluiber
Arnab Kumar Banerji*	James D. Oelschlager	Rupal J. Bhansali*
Arpad Pongracz	Jean-Pierre Conreur	S. Irfan Ali*
Arsen Mrakovcic	Jolanta Wysocka	Saker Nusseibeh*
Arvind K Sachdeva*	June-Yon Kim	Sal Diaz-Verson Jr
Ashi Parikh*	Kara Than Bhala	Samir Mehta*
Ashutosh Sinha*	Kenji Chihara	Sandip A. Bhagat*
Aziz Hamzaogullari*	Klaus Kaldemordgen	Sandip Bjagat*
B. Padmanabha Pai*	Kooi Cho Yu	Sandor Cseh
Bala Iyer*	Kunihiko Sugio	Sanjeev Makan*
Benedict E Capaldi	Lauriann Kloppenburg	See Wee Tan
Beso Sikharulidze	Liaquat Ahamed*	Seung Kwak
Bin Shi	Liu-Er Chen	Seung Miinn
Boaz Rahav	Lon Schreue	Shahreza Yusof*
Boniface A. Zaino	Loris Muzzatti	Shigeki Makino
Bruno Desforges	Luca Parmeggiani	Shigemi Takagi
Chetan Joglekar*	Madhav Dhar*	Shiv Mehta*
Christopher Matyszewski	Magali Azema-Barac	Siew-Hua Thio
Conrad Saldanha	Manind V. Govil*	Sonu Kalra*
Constantinos G. Mokas	Manraj Sekhon	Sonya Thadhani*
Craigh A. Cepukenas	Marcel Houtzager	Spiros Sig Segalas
Daizo Motoyoshi	Maurits E Edersheim	Stavros Koutsantonis
Daniel Tranchita	Miki Sugimoto	Sudhir Nanda*
David Y. S. Chiueh	Minyoung Sohn	Suhas Kundapoor*
Dirk H Van Dijk	Mitzi Malevich	Sujatha R. Avutu*
Domenic Colasacco	Morris B. Ajzenman	Suresh L. Bhirud*
Dutch Handke	Morty Schaja	Taizo Ishida
Duy Nguyen	Mustafa Sagun*	Takeo Nakamura
Ean Wah Chin	Narayan Ramachandran*	Telis D. Bertsekas
Emilio Bassini	Nitin Mehta*	Tetsuya Itoh
Fabrizio Pierallini	Noor Kamruddin*	Thierry Wuilloud
Farha-Joyce Haboucha	Olessia Denissiouk	Thyra Zerhusen
Fariba Talebi*	Olivier Rudigoz	Tin Y. Chan
Fayez Sardfim*	Ophelia Barsketis	Toshihiko Tsuyusaki
Feng Chang	Oscar Vermeulen	Venkat Chidambaram*
Fernando Garip	Paolo Vassalli	Victor Filatov
FIJ-Joseph Tse	Patrice Conxicoeur	Vik Mehrotra*
George Gianarikas	Pavlos Alexandrakis	Vikram J. Kuriyan*
Giampaolo G Guarnieri	Pedro Verdu	Wolodymyr Wrsonskyj
Gijs Dorresteijn	Piergaetano Iaccarino	Yi Zhang
Giri Bogavelli	Pratima Abichandani*	Yoko Ishibashi
Giri Devulapally	Praveen Abichandani*	Yosawadee Polchareon
Guido Guzzetti	Praveen K Gottipalli*	Yun Jae Chung
Guru M. Baliga*	Rajeev Bhaman*	Yun-Min Chai
Hans Van den Berg	Rajendra Prasad*	Zaheer Sitabjhan*

C Managers with Non-Foreign-Sounding Names (Incomplete List)

Aaron Harris
Adrian Holmes
Al Stewart
Alexander Denner
Alfred Harrison
Alison Larkin
Allan Conway
Andrew Brown
Andrew Jenner
Andrew Mason
Andrew Parry
Andrew Preston
Andy Hood
Anthony R Gray
Art McQueen
Arthur Q. Johnson
B. J. Willingham
Barbara Knapp
Barbara L. Bowles
Bernard Zimmerman
Beth Cotner
Betsy Palmer
Bill Fries
Bill Hickes
Bill Maher
Bill McAdams
Bill Whitlow
Bob Thompson
Brad Greenleaf
Brad Snyder
Bret W. Stanley
C. K. Lawson
C. Thomas Clapp
Cameron Hinds
Cathy Dudley
Charles G Watson
Charles T. Happel
Charlie Fish
Charlie Jacklin
Cheryl Smith
Chris Turner
Christine M Baxter
Christopher D. Brown
Christopher Faber
Christopher M.V Jones
Chuck Craig
Courtney Smith
Craig J. Hardy
Curtiss Scott
D. Gary Richardson
Dale Nicholls
Dan Cantor
Dan Rice
Daniel L. Jacobs
Daniel Lew
Daniel P. Brown
Daryl Weber
Dave Bagby
David A. Semple
David D. Basten
David D. Tripple
Debbie McCabe
Deborah Miller
Dennis P. Lynch
Donald Jones
Donna Baggerly
Donna M. Calder
Doris Kelley-Watkins
Douglas M. Larson
Duane F. Kelly
Ed Makin
Ellen R. Harris
Eric N. Perkins
Francis D. Gannon
Frank Holmes
Frank Jolley
Fred Meserve
Frederrick Moran
G. Paul Matthews
G. Rusty Johnson III
Gardner Jackson
Garry M. Allen
Gary Craven
Gary Sandel
George F. Foley
George Foster
George Roche
Gerald J. Moran
Gerald R. Sparrow
Gerald Reid Jordan
Gerry Bennett
Greg A. McCrickard
Greg A. McGrickard
Greg Johnson
Greg Ratte
Guy W. Pope
Hank Hermann
Harry D. Cohen
Helen Degenger
Helen Potter
Hilary R. Woods
Irene D. O'Neill
Irving Levine
J. Randy Valentine
Jack McCue
Jack Orben
Jackie M. Benson
James A. MacMillan
James Behrmann
James Burns
James C. Perkins, Jr.
James H. Gibson
James L. Savage
James Margard
James P. Craig
James Tilton
Jane P. Lucas
Jason D. Weiner
Jason S. Maxwell
Jay Morley
Jean Ledford
Jeffrey G Morris
Jeffrey L. Knight
Jenny B. Jones
Jocelin A. Reed
Joe Huber
Joe Stocke
Johathan White
John B. Leo
John Bailey
John C. Knox
John C. Maxwell
John Christopher Whitaker
John Church
John D. Avery
John Dowd
John E. Steiner
John G. Marshall
John J. Geewax
John Kane
John L. Keeley, Jr.
John M. Chambers
John Morton
John P. Robinson
John Porter
John S. Force
Jonathan D. Coleman
Jonathan F. Weed
Jonathan Neil
Joseph C. Ford
Julie Hale
Justin Thomson
Karen E McGrath
Katherine Buck
Kathleen T Millard
Kathryn L. Langridge
Kelli K. Hill
Kelly Cardwell
Kenneth G Mertz II
Kenneth L. Abrams
Kevin L Wenck
L. Gordon Croft
Leslie Ferris
Lynda Johnstone
Marcus Smith
Margaret Reynolds
Maria McCormack
Mark A. Coffelt
Mark Corbett
Mark F. Trautman
Mark Fawcett
Mark Goldstein
Mark J. Beckwith
Mark Johnson
Mark Mitchell
Mark Westman
Martin C. Schulz
Matthew Cheyney
Matthew G Thomsom
Matthew Hart
Matthew S. Wright
Michael Cowan
Michael Crowe
Michael J. Donnelly
Michael J. Hogan
Michael Landry
Michael P. Bradshaw
Michael R. Hamilton
Michael T. Carmen
Michael T. Kennedy
Michael W. Holton
Nate Carter
Nathan A. Chapman, Jr.
Norman Fidel
Pamela R. Holding
Patty McKenna
Paul M. McMahon
Paul McEntire
Paul Michael Frank
Paul T. Cook
Peter E. Robbins
Peter J. Wilby
Peter Mitchelson
Peter Welles
R. Scott Berg
Ralph E. Whitman
Rand L. Alexander
Raymond Haines
Richard A. Begun
Richard J. Gessner
Richard Kost
Richard Lawson
Richard P. Howard
Richard R. Foulkes
Richard T. Whitney
Richard Williams
Robert B. Cameron
Robert Corbett
Robert Gardiner
Robert H. Bergson
Robert J. Mancuso
Robert J. Rhodes
Robert J. Vile
Robert Levy
Robert M. Mitchell
Roger E. King
Roger Ellis
Roger J. Sit
Ron Weiss
Ronald Steele
Samuel H. Baker
Scott Scatterwhite
Shawn Ridley
Sheldon Simon
Stephen C. Rogers
Stephen J. Cohen
Stephen Jones
Stephen Peterson
Stephen S. Petersen
Stephen Watson
Steve Kaye
Steve Reynolds
Steven Sinclair
Stuart E. Teach
Susan D. Everly
Susan French
Thomas A. Frank
Thomas Christopher
Thomas Connelly
Thomas Hudson
Thomas Maguire
Thomas Michael
Thomas P. Callan
Thomas S Henderson
Thomas Sweeney
Timothy Clift
Timothy R. H. Love
Timothy Woods
Todd Sanders
Tom Hesslein
Tom Jones
Tom Laming
Tracy McCormick
Trevor Forbes
Valerie Larson
Walter C. Price
William Anderson
William C. Field
William F. Gadsden
William Landers
William M. Hughes
William M. Berger
William M. Garrison

D Task Description

The Amazon Mechanical Turk Workers were provided with the following set of instructions.

Name classification

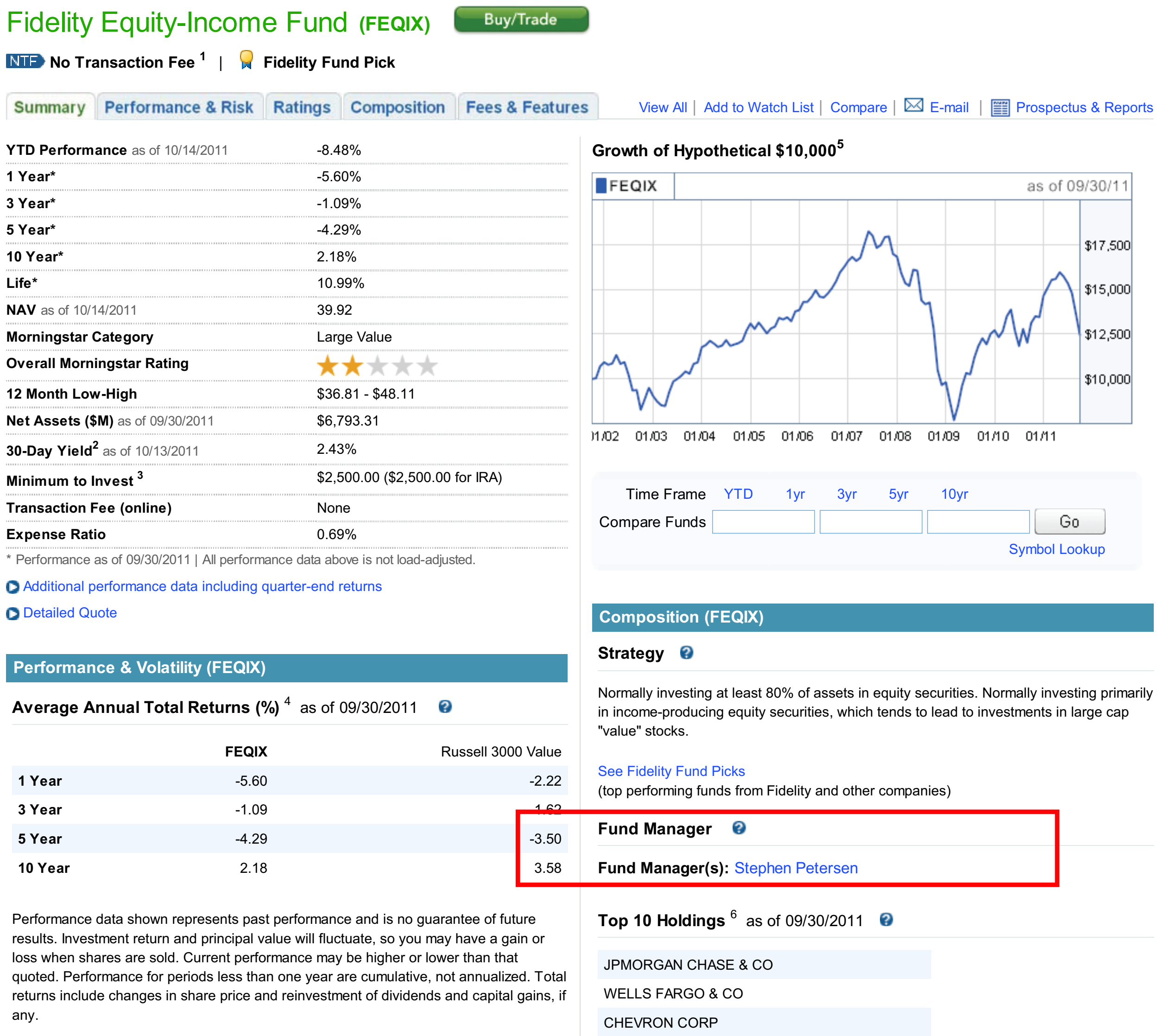
- Go to the following website:
  https://docs.google.com/leaf?id=0B1pB2izBAbyTMDJlMTU5NjgtYTM0Zi00M2RmLWExNzYtZGNhMGU1YWQ1MGM1&hl=en&authkey=Cl
- Download the Excel file and save it on your computer.
- Open the Excel file.
- For each name in the list, indicate whether **from the perspective of a United States resident**, this name sounds foreign to you or not. Indicate your classification by inserting an "x" or "yes" into the corresponding column. If you are unsure, insert "unsure", **do not leave any names unclassified.**
- Save your classification and email the completed Excel file to foreignnames@gmail.com
- Please note: The classification has to be done carefully. Any pattern (such as providing the same classification for all names) indicating that you classified the names randomly will not be paid.

Please indicate that you have read and agree to the previous text:

- agree
- don't agree

E Salience of Fund Manager Names – Fidelity Example

Mutual fund manager names are salient and easily accessible information for investors. Below is an example of a fund description obtained from `http://fundresearch.fidelity.com/mutual-funds/summary/316138106`. The fund manager name is displayed on the first page of the fund description.



Fidelity Equity-Income Fund (FEQIX) Buy/Trade

NTF No Transaction Fee [1] | Fidelity Fund Pick

Summary | Performance & Risk | Ratings | Composition | Fees & Features

View All | Add to Watch List | Compare | E-mail | Prospectus & Reports

YTD Performance as of 10/14/2011	-8.48%
1 Year*	-5.60%
3 Year*	-1.09%
5 Year*	-4.29%
10 Year*	2.18%
Life*	10.99%
NAV as of 10/14/2011	39.92
Morningstar Category	Large Value
Overall Morningstar Rating	
12 Month Low-High	$36.81 - $48.11
Net Assets ($M) as of 09/30/2011	$6,793.31
30-Day Yield[2] as of 10/13/2011	2.43%
Minimum to Invest [3]	$2,500.00 ($2,500.00 for IRA)
Transaction Fee (online)	None
Expense Ratio	0.69%

* Performance as of 09/30/2011 | All performance data above is not load-adjusted.

Additional performance data including quarter-end returns

Detailed Quote

Growth of Hypothetical $10,000[5]

Time Frame YTD 1yr 3yr 5yr 10yr

Compare Funds Go

Symbol Lookup

Performance & Volatility (FEQIX)

Average Annual Total Returns (%) [4] as of 09/30/2011

	FEQIX	Russell 3000 Value
1 Year	-5.60	-2.22
3 Year	-1.09	-1.62
5 Year	-4.29	-3.50
10 Year	2.18	3.58

Performance data shown represents past performance and is no guarantee of future results. Investment return and principal value will fluctuate, so you may have a gain or loss when shares are sold. Current performance may be higher or lower than that quoted. Performance for periods less than one year are cumulative, not annualized. Total returns include changes in share price and reinvestment of dividends and capital gains, if any.

Composition (FEQIX)

Strategy

Normally investing at least 80% of assets in equity securities. Normally investing primarily in income-producing equity securities, which tends to lead to investments in large cap "value" stocks.

See Fidelity Fund Picks
(top performing funds from Fidelity and other companies)

Fund Manager

Fund Manager(s): Stephen Petersen

Top 10 Holdings [6] as of 09/30/2011

JPMORGAN CHASE & CO
WELLS FARGO & CO
CHEVRON CORP

F Online Survey: Importance of Fund and Managerial Attributes

We asked 100 AMT workers to evaluate the importance of different fund and managerial attributes in their investment decisions. Ratings were provided on a 5 point Likert Scale ranging from very important to unimportant. Two questions only had the possibility of a Yes or No response. Respondents could skip an attribute if they were unsure about its meaning. We report the results from this survey below.

Panel A: Awareness of Fund Manager

	Yes	No
Important to know fund manager	64%	36%
Typically know the fund manager	57%	43%

Panel B: Importance of Fund and Managerial Attributes

	Very Imp	Imp	Moderately Imp	Little Imp	Unimp
Fund Attributes					
Historical Fund Performance	45%	44%	9%	2%	0%
Fees and expenses	50%	38%	12%	0%	0%
Fund risk	68%	22%	7%	2%	0%
Fund manager	20%	39%	28%	13%	0%
Price per share	21%	33%	26%	14%	5%
Types of securities held by fund	29%	44%	24%	3%	0%
Tax consequences	32%	37%	20%	8%	1%
Minimum investment	20%	31%	32%	14%	2%
Company offering the fund	21%	28%	34%	16%	0%
Investment objectives	38%	33%	22%	6%	1%
Portfolio turnover rate	15%	34%	35%	12%	2%
Fund's rating from rating services	33%	45%	18%	4%	0%
Fund Manager Characteristics					
Education	31%	41%	19%	8%	1%
Age	2%	14%	35%	35%	14%
National origin	2%	3%	9%	39%	47%
Race/Ethnicity	0%	1%	9%	26%	64%
Gender	1%	1%	6%	26%	65%
Industry experience	59%	29%	10%	1%	0%
Length of time manager is responsible for fund	34%	41%	22%	2%	0%
Works with a team when managing the fund	17%	45%	19%	16%	3%
Other funds this manager currently manages	22%	37%	33%	6%	2%

G Funds Used in the Online Experiment

In the experiment described in Section 4.1, half of the Amazon Mechanical Turk workers were asked to split 100 dollars between index funds A and B. The fund descriptions provided to the participants are shown below. "Mustafa Sagun" managed fund A and "William R. Andersen" managed fund B. The second group of AMT workers received exactly the same fund description as below but with one key change. We switched the fund manager names such that fund A was managed by "William R. Andersen" and fund B was managed by "Mustafa Sagun".

	Fund A	**Fund B**
Fund Segment	S&P 500 Index Fund	S&P 500 Index Fund
Fund Manager	Mustafa Sagun	William R. Andersen
About the Fund		
Size	$77.49 Million	$75.35 Million
Inception Date	02.10.1998	18.02.2005
Annual Expense Ratio	0.70%	0.64%
Trading Activity (Annual Turnover Ratio)	1.98%	2.03%
Fund Facts	The investment seeks to replicate the total return of the S&P 500 index, before fees and expenses. The fund invests primarily in common stocks issued by companies in the Standard & Poor's 500 Composite Stock Price index.	The investment seeks to replicate the total return of the S&P 500 index, before fees and expenses. The fund invests primarily in common stocks issued by companies in the Standard & Poor's 500 Composite Stock Price index.
Top Five Stock Holdings		
1	Exxon Mobil CP	Exxon Mobil CP
2	General Electric CO	General Electric CO
3	Microsoft Corporation	Microsoft Corporation
4	Chevron Corp	Chevron Corp
5	AT&T Inc.	AT&T Inc.