Family Descent as a Signal of Managerial Quality: Evidence from Mutual Funds

Oleg Chuprinin
University of New South Wales

Denis Sosyura
Arizona State University

Using data from individual Census records on the wealth of managers' parents, we find that mutual fund managers from poor families outperform managers from rich families. We argue that managers born poor face higher entry barriers into asset management. Consistent with this view, managers born poor are promoted only if they outperform, while those born rich are more likely to be promoted for reasons unrelated to performance. Overall, we establish a first link between fund managers' family descent and their ability to create value. (*JEL* D14, G11, G23)

Received December 8, 2016; editorial decision November 20, 2017 by Editor Andrew Karolyi. Authors have furnished an Internet Appendix, which is available on the Oxford University Press Web Site next to the link to the final published paper online.

We thank Andrew Karolyi (the editor) and an anonymous referee for their valuable suggestions. For helpful comments, we also thank Ian Appel, Brian Baugh, Alex Butler, John Crosby, Pascal Gantenbein, Rawley Heimer, Joachim Inkmann, Yigitcan Karabulut, Elizabeth Kempf, Andy Kim, Lisa Kramer, Melissa Prado, Clemens Sialm, Johannes Stroebel, Boris Vallee, Jules van Binsbergen, Kelsey Wei, Han Xia, Scott Yonker, Eric Zitzewitz, and Leon Zolotoy and conference participants at the 2015 Nova-BPI Asset Management Conference, 2015 Miami Behavioral Finance Conference, 2015 Australasian Finance and Banking Conference, 2016 NBER Conference on New Developments in Long-Term Asset Management, 2016 Western Finance Association (WFA) Annual Meeting, 2016 NYU Stern and New York Fed Conference on Financial Intermediation, 2016 Society for Financial Studies (SFS) Finance Cavalcade, 2016 Arizona State University Sonoran Winter Conference, 2016 UNC-Jackson Hole Winter Finance Conference, 2016 University of Washington Summer Finance Conference, 2016 IDC Herzliya Conference in Financial Economics, 2016 Rotterdam Conference on Professional Asset Management, 2016 Fixed Income and Financial Institutions (FiFi) Conference, 2016 Mid-Atlantic Research Conference in Finance (MARC), 2016 Melbourne Conference on Financial Institutions, Regulation and Corporate Governance, 2016 World Finance and Banking Symposium, 2017 Spring Conference at the University of Texas at Dallas, 2017 Summer Symposium at the City University of Hong Kong, and seminar participants at Aalto University, Arizona State University, Boston College, Clemson University, Emory University, Federal Reserve Bank of Kansas City, Maastricht University, Queen's University at Kingston, Securities and Exchange Commission (SEC), Stockholm School of Economics, Tilburg University, University of Illinois at Urbana-Champaign, University of Melbourne, University of Nebraska, University of Toronto, University of Utah, and University of Wisconsin at Milwaukee. Erica Stewart and Lev Tyomkin provided excellent research assistance. Supplementary data can be found on *The Review of Financial Studies* Web site. Send correspondence to Denis Sosyura, W. P. Carey School of Business, 300 E. Lemon St., PO Box 873906, Tempe, AZ 85287; telephone: (480) 965-4221. E-mail: dsosyura@asu.edu.

doi:10.1093/rfs/hhy010 Advance Access publication January 30, 2018

In the majority of financial decisions, shareholders delegate decision rights to professional managers. Thus, one of the most important tasks of shareholders is to select the most capable and hardworking managers as their agents. Inferring managerial type ex ante is challenging. For example, the majority of chief executive officers (CEOs) at S&P 1500 firms have no prior CEO experience. Yet, given the costs of replacing managers, this task is of first-order importance for economic outcomes in all public firms.

We provide evidence that public information about a manager's family descent serves as a powerful signal of managerial ability in professions with high barriers to entry. We exploit the fact that individuals are endowed with different opportunities at birth and, as a result, differ in their ability to overcome these barriers. Individuals from wealthy families could obtain prestigious jobs using their families' resources, whereas those from poor families have to rely on skill. This mechanism imposes a more stringent selection among those born poor, ensuring that the more skilled individuals are able to build a career in a competitive profession. In such settings, we should expect to see more high performers among managers who had fewer resources that could substitute for skill during selection.

Delegated asset management provides a convenient setting to test this selection mechanism. First, in contrast to industrial firms where decisions are made by dozens of managers, fund managers have the principal authority over the fund's portfolio. Second, fund managers perform standardized professional tasks within a well-defined investment universe, and their outcomes are easily comparable in the time series and cross-section. Third and finally, mutual funds account for over half of financial wealth of the average U.S. household, indicating a question of broad public interest.

This paper studies the relation between mutual fund managers' family descent and their professional performance. We focus on family wealth as the main variable of interest, since family support could allow less skilled individuals to advance professionally, resulting in a biased selection into highly sought economic sectors. To identify managers' family characteristics, we hand-collect data on the households where the managers grew up by examining individual census records compiled by the National Archives. These records provide detailed information on the income, home value, and education of a manager's parents during his childhood, as well as other demographic characteristics.

We begin by providing the first descriptive evidence on the family descent of investment managers and document a sizable variation in their social backgrounds. In general, fund managers come from well-to-do families compared to the national or state benchmarks. The median income of managers' fathers is at the 87th percentile of the national distribution. The median value of a home where a fund manager grew up is 154% greater than the respective state median. At the same time, there is a wide variation in the managers' endowed family wealth. While the bottom quintile of managers sorted on parents' wealth come from families with incomes below the national average (42nd national percentile), the top quintile of managers come from ultra-rich families with the average income in the 99th national percentile. Furthermore, fund managers tend to come from well-educated families, and the income of the manager's parents predicts the type of education the manager receives. Managers from wealthier families attend more expensive universities, and the tuition for the manager's college is monotonically increasing in family wealth.

Our main finding is that fund managers from wealthy families underperform managers from poor families. For example, managers from families in the top quintile of wealth underperform managers in the bottom quintile by up to 1.36% per year (significant at 1%) on the basis of the four-factor gross alpha. Similar results hold for alternative measures of performance, such as benchmark-adjusted fund returns and the dollar value extracted from capital markets, a measure developed in Berk and Van Binsbergen (2015).

Our analysis accounts for a comprehensive set of controls which proxy for the quality and type of managers' education and demographics, their parents' education, and fund and management firm characteristics. While it is infeasible to control for all potentially relevant effects, most omitted variables, such as professional connections or access to information, should enhance the performance of the rich. Therefore, such variables are unlikely to explain our results. Consistent with this view, we find that the performance gap between managers from wealthy and poor families expands as additional controls are added to the regression, the effect predicted by a selection model we develop. Likewise, our results are unlikely to be driven by differences in risk attitudes, since our analysis focuses on risk-adjusted performance and controls for return volatility and skewness. Finally, in a test of another alternative explanation, we do not find that managers born poor are more likely to engage in unethical professional behavior, as reflected in window-dressing, risk shifting, or late trading.

Next, we investigate several barriers that prospective fund managers must overcome en route to the job, such as geographic distances and tight labor markets. We find that the negative wealth-performance relation is stronger for managers whose college was located further away from their parents' home and from the employment opportunities in asset management. This is consistent with the idea that skill plays a more important role in the selection of the poor. While candidates born wealthy are less constrained by long distances, those born poor would commit to high expenses of living away from home only if they are skilled and expect to succeed. Similarly, consistent with less egalitarian hiring in tight labor markets, the sensitivity of performance to wealth is higher for managers who enter the industry in years of high unemployment: it goes up by 39% for a 1-percentage-point increase in the unemployment rate at the time of entry.

After obtaining a job in asset management, managers endowed with greater family resources face less stringent performance thresholds in their career progression. In an analysis of managers' careers, we find that while strong performance increases promotion chances for all managers, this relation is significantly weaker for managers from wealthy families. In other words, managers born rich are more likely to be promoted for reasons unrelated to performance. An interquartile-range increase in family wealth nearly mutes the unconditional promotion-to-performance sensitivity. In contrast, the career progression of managers from poor families is strongly dependent on their performance.

We explore two nonmutually exclusive channels that may contribute to the performance gap between the rich and poor: (1) effort and (2) ability. The first channel posits that managers from poor families exert more effort because they obtain higher marginal utility from incentive pay under the assumption of a declining marginal utility of wealth. The second channel posits that managers from poor backgrounds have a higher innate ability, since only high-ability managers are able to overcome stringent selection.

Both channels are likely operative in our setting. Consistent with the effort channel, we find that managers from less wealthy families are more active on the job: they trade more frequently, have shorter holding horizons, and are less prone to herding. For example, an interquartile-range reduction in family wealth increases the fund's annual turnover by 4.5% relative to the average turnover in the sample. Next, we exploit an exogenous increase in managerial wealth from inheritances proxied by deaths of wealthy parents. As predicted by the effort channel, the deaths of rich parents are followed by a weak decline in a manager's portfolio activity. This result holds after skipping a one-year window around the death events to account for distractions and grievance. At the same time, we find that the performance gap does not diminish with the managers' career progressions (as managers born poor accumulate personal wealth), suggesting that response to incentives alone cannot explain the performance differential. In general, while both the effort and ability channels likely contribute to the performance gap, their effect is observationally equivalent from the perspective of an investor interested in total fund performance.

Next, we decompose investment performance into market timing and security selection, using the methods developed in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014). We find that the relative underperformance of the managers from wealthy families is concentrated in security selection. An interquartile-range decrease in family wealth improves the stock-picking component of fund returns by 39% relative to its sample mean. We find no difference in the market timing component of returns.

In our final analysis, we investigate whether mutual fund companies derive nonperformance benefits from employing managers from wealthy families. While we cannot rule out this possibility, we do not find reliable evidence of such benefits. In particular, neither capital flows nor management fees are significantly higher for funds run by wealthy managers. This result points to possible agency problems or frictions in the asset management industry that require further research.

The central contribution of this article is to provide the first evidence on how the family descent of investment professionals signals their ability to create value. Our findings contribute to research on (1) managerial characteristics that predict professional performance and (2) the effect of endowed wealth and social status on an individual's career progression.

We add to a small number of papers in asset management that identify the characteristics of fund managers that predict their performance. Chevalier and Ellison (1999) find that fund managers who attended colleges with higher average SAT scores deliver superior risk-adjusted returns, and Li, Zhang, and Zhao (2011) find similar evidence for hedge funds. Cohen, Frazzini and Malloy (2008) show that fund managers' educational networks yield valuable information that improves performance in connected stocks. Chaudhuri et al. (2017) provide evidence that funds managed by PhD graduates deliver superior risk-adjusted performance. Jagannathan, Jiao, and Karolyi (2017) find that the cultural heritage of international equity fund managers gives them an information advantage in stocks from their home countries. Our paper is the first in the investment literature to show that an individual's endowed wealth serves as a screening mechanism of managerial quality and contains a signal of skill.

We also extend the literature on the effect of an individual's family environment on subsequent economic outcomes. Chetty et al. (2011) find that a child's access to education predicts college attendance, earnings, and retirement savings. In two studies of Swedish twins, the socioeconomic status of an individual's parents helps explain future savings behavior (Cronqvist, and Siegel 2015) and preferences for value or growth stocks (Cronqvist, Siegel, and Yu 2015). In recent work, Duchin, Simutin, and Sosyura (2017) provide evidence on the family descent of U.S. CEOs and show that familial factors play an important role in the allocation of capital inside the firm. In complement to this work, we provide evidence on sophisticated financial intermediaries whose professional choices have large welfare implications.

More broadly, our paper is related to the literature at the intersection of labor markets and social economics. A number of studies find that an individual's income and labor market success are, to a large extent, determined by his parents' income, revealing surprisingly low levels of intergenerational mobility (Mazumder 2005; Dahl and DeLeire 2008; Chetty et al. 2014). In a nationally representative sample, Reeves and Howard (2013) find that individuals born into rich families end up in high-income professions even if these individuals are of mediocre quality, as measured by tests of cognitive ability and intrinsic motivation. The authors find that 43% of those born into families in the top income quintile remain in the top-quintile jobs against the predictions of ability scores and conclude: "Those born into more affluent families may be protected from falling by a 'glass floor,' even if they are only modestly skilled." Our paper demonstrates that such labor market frictions can affect important financial outcomes and the wealth of U.S. investors.

1. Motivation and Mechanism

We develop a simple model to describe selection and formalize the relation between fund managers' performance and endowed wealth. We discuss the intuition herein and present the model in Appendix A.

The basic premise of the model is that there exists a barrier (or several barriers) that individuals must overcome in order to become mutual fund managers. Individuals can overcome this barrier by either demonstrating a high level of skill s or relying on monetary resources, which we will denote w. A candidate passes the barrier and becomes a manager if $s+\beta_w w > \gamma$, where γ measures the barrier's stringency and β_w captures the power of the monetary factor to help the candidate pass the barrier. For example, if $\beta_w = 0$, then the barrier is completely egalitarian and selects only on skill.

Performance is a noisy function of skill: $\alpha = s + \varepsilon_\alpha$. We are interested in the manager's performance conditional on him passing the barrier: $\mathrm{E}[\alpha | s+\beta_w w > \gamma]$. The model is simple if s and w are independent. In this case, if $\beta_w$is positive, then the expected performance is a decreasing function of w. Intuitively, if we know that a manager had low wealth, then it must be that he had high skill that compensated for low wealth and enabled him to pass the barrier. Conversely, if a manager came from a wealthy family, then an ability to pass the barrier provides little information on his level of skill.

It is reasonable to allow w and s to be positively correlated. For example, genetic factors can account for high family wealth and skill of both a manager and his parents. Similarly, wealth facilitates access to good education and professional networks, which enhance skill. To model this case, we introduce drivers of skill d, such that $s = d + \varepsilon_s$ and $d = d_0 + \delta w + \varepsilon_d$. In this case, it is unclear whether expected performance is decreasing or increasing in w. The selection effect competes with the direct positive effect of wealth on performance, and which effect prevails is an empirical question.

At least some of the drivers of skill are observable (e.g., the education quality of the manager and his parents), and we can condition on them in the analysis. If we control for all of d, then $\mathrm{E}[\alpha | \{s+\beta_w w > \gamma, d\}]$ is a strictly decreasing function of w, as in the independence case. Otherwise, including some of d as controls should strengthen the negative effect of w on performance.

In the next section, we explain how we construct an empirical proxy for w (family wealth) and d (observable drivers of skill). In the empirical analysis, we investigate whether family wealth can signal managerial skill in the mutual fund industry, consistent with the predictions of the selection mechanism.

2. Data and Sample Construction

We begin our sample construction with the universe of U.S.-domiciled mutual funds covered by Morningstar in 1975–2012.[1] We include both defunct and active investment products (fund share classes), ensuring that any fund ever appearing in the Morningstar database during our time period is present in the initial sample. To ensure an equitable comparison basis for investment managers, we restrict our sample to domestic actively managed funds specializing in U.S. equity, thus excluding international funds, index funds, and funds specializing in bonds, commodities, and alternative asset classes.[2] To establish a clean correspondence between a fund manager's decisions and performance outcomes, we exclude funds that are always managed by a team of managers during our sample period. We also exclude observations in which the manager is linked to more than five funds (i.e., "figurehead" managers).

For each fund that passes the initial filters, we obtain its historical management data from Morningstar, which details the name of the manager and his starting and ending dates (months) in a fund. Patel and Sarkissian (2017) describe the Morningstar data set in detail and explain its advantages with respect to fund manager records. To provide a sufficient period for evaluating managerial performance, we limit our sample to managers with at least 24 monthly return observations. For the 1,762 managers who pass these initial criteria, we initiate the data collection process described below.

First, we obtain managers' education and employment histories from their biographies in Morningstar and FactSet and verify them against the employment records in the Nelson's Directory of Investment Managers. We complement our data on managers' education with records from university alumni publications and archived university yearbooks available from ancestry.com. In some cases, when information about a manager's degree is missing, we contact the registrar of the university attended or the National Student Clearinghouse, a degree-verification service provider. We are able to verify the undergraduate institution for 1,619 managers. We supplement this information with data on the academic quality of the institution (average SAT score of the entering class), its competitiveness (undergraduate acceptance rate), affordability (annual tuition), and elite status (Ivy League indicator). This information is obtained from the College Handbook of the College Entrance Examination Board, and most variables are based on the 2004 edition due to superior data availability.[3]

---

[1] Even though some funds have return series dating back to 1960, the data on net assets are generally not available before 1975.

[2] This filter excludes index funds, funds whose U.S. Broad Asset Class is not "U.S. Stock," funds for which Morningstar equity style classification is not available, and funds that have sector restrictions or specialty focus (Global Category includes the word "Sector" or Prospectus Objective includes the word "Specialty").

[3] In the subsample of colleges covered in both the 1979 and the 2004 editions, the cross-sectional correlations between the corresponding variables exceed 85%, indicating that measurements taken as of 2004 remain valid in the cross-section of colleges. For example, the correlation between the median SAT score (undergraduate instate tuition) in 1979 and 2004 is 86.5% (95.8%).

Second, we match fund managers to the Lexis Nexis Public Records database (LNPR), which aggregates information on nearly 500 million U.S. individuals (both alive and deceased) from sources such as birth and death records, property tax assessment records, voting records, and utility connection records. Prior research in finance has relied on this database to obtain personal data on fund managers (Pool, Stoffman, and Yonker 2012; Pool et al. 2017), corporate executives (Cronqvist, Makhija, and Yonker 2012; Yermack 2014), and financial journalists (Ahern and Sosyura 2015). All records in the database are linked to the individual's social security number (observable with the exception of the last four digits) and are assigned a unique ID. Using a manager's full name, age, and employment history, we establish reliable matches to LNPR for 1,670 (94.8%) of the managers from the initial sample. Appendix B shows the sample construction steps, and Internet Appendix 1 details our matching and verification procedures. The 5.2% of unmatched managers are those who live abroad and do not have a social security number (funds delegated to a foreign subadvisor) and those who have the most common combinations of first and last names (e.g., Robert Jones or John Miller) and no other information to establish an unambiguous match.

Next, we proceed to the main stage in our data collection—extracting personal census records for the households where fund managers grew up. Our sample construction is guided by regulatory constraints imposed on disclosures of individual census records. The U.S. public law prohibits the release of individual decennial census records with personally identifiable information for 72 years after these records are collected (92 Stat. 915, Public Law 95-416; Oct. 5, 1978). Because of the 72-year moratorium, the latest decennial census with personally identifiable information available at the time of writing is the 1940 federal census (and any earlier censuses), which constitutes our main data source. Appendix C shows the census form presented to households and provides an example of a completed form.

To ensure that the census record provides an accurate reflection of a manager's endowed social status at birth, we restrict our sample to managers born in or before 1945. Thus, we allow for a maximum delay of five years between the measurement of family wealth and the manager's birth. This filter restricts the sample to 434 managers. After investigating the managers' backgrounds, we find that 18 of these managers were raised outside the United States, and, as a result, their families were not covered in the U.S. census. After eliminating these cases, we end up with 416 managers with potential census records.

We follow a three-step algorithm to identify a manager's household in the census by sequentially checking three types of state records—birth, marriage, and death—for the manager and his relatives. To ensure a reliable match to the census, we require establishing a manager's parents and, in some cases, siblings. This criterion nearly eliminates the possibility of a spurious match, because the census record identified in this process contains the unique combination of the manager's parents and siblings who are further verified based on their year of birth. Internet Appendix 1 describes how we identify the manager's parents and siblings and provides examples of birth, marriage, death, and obituary records. In our final step, we use the combination of the manager's parents and siblings to identify the family's record in the 1940 census (for a small subset of older managers, we also obtain the 1930 census records). We obtain the image file of the family's census record (shown in Appendix C) from the digital archive maintained by the U.S. National Archives and Records Administration.

To compare the parents of fund managers with other U.S. households, we use the Integrated Public Use Microdata Series (IPUMS)—the anonymized set of household census records. We use the IPUMS data to construct some auxiliary variables, such as education attainment percentiles and state-level statistics. We also obtain tract-level census data from the Elizabeth Bogue File, a data set used extensively in social economics (e.g., Sugrue 1995; Elliott and Frickel 2013).[4] Tract-level records are available only for a subset of metropolitan areas and cover about one-third of our sample. For this reason, we use tract-level data for comparison and validation purposes but do not rely on them in our main analysis.

We are able to identify census records for 387 (93.0%) of the 416 managers that satisfy prior sample filters. The unmatched observations mainly result from transcription errors in the indexing of handwritten family names in the digital archive, which prevent us from being able to locate the record in the archive. We recover some of the misindexed records by identifying the manager's residential address during the census in the archives of white page directories (which are typed and free of handwriting issues) and then manually going through the manager's enumeration district in the census to extract the desired address. However, a full recovery of these observations is prohibitively costly. For a small number of observations, we are unable to locate the 1940 census record because the managers' parents were on an overseas trip (identified via vessel departure records) or on military duty abroad (identified via military enlistment records). Internet Appendix 1.B summarizes the sequence of steps in the data collection, and Internet Appendix 1.C provides examples of relevant records. Appendix B, Figure B1, shows the sample construction cascade and indicates the number of managers retained at each stage.

Throughout the data collection, we almost exclusively rely on state and federal records. This approach serves two goals. First, we verify the information about a manager's parents contained in the census (e.g., age, education level, professional occupation) in other state and federal records, such as military enlistment records and death records (shown in Internet Appendix 1.C). This verification process serves to double check the census information and to ensure

[4] The digital copy of the data set was created by Dr. Donald Bogue and his wife Elizabeth Mullen Bogue, who manually entered information from printed publications released by the Bureau of the Census.

that it remains relevant beyond the census (e.g., if additional education is obtained, it is recorded).

Second, the reliance on state and federal records ensures an unbiased sample construction, where data availability and measurement error should be uncorrelated with managerial performance. We verify this pattern in Appendix B, Table B1, which compares a wide array of characteristics between managers with available and missing census records. The two groups of managers are statistically indistinguishable across the main characteristics, including gross and net alphas, career length, educational attainment, and university tuition. The only difference we are able to detect (significant at 10%) is that managers with available census records are, on average, 2.3 years older than their counterparts with missing records. This difference arises because for some managers born after 1940, the parents' household had not formed by 1940, and the individual parents' records could not be located.

Our sample is economically important. It includes 619 funds and, in the median sample year (1994), accounts for 33.4% of all assets of solo-managed domestic equity funds. Our sample compares favorably with other studies on older fund managers, such as Grinblatt, Titman, and Wermers (1995) (274 funds) and Chevalier and Ellison (1997) (398 funds). Our sample size is also comparable to that in some recent studies on fund managers, such as Hong and Kostovetsky (2012) (488 funds) and Pool et al. (2017) (778 funds).

Because of the statutory constraints on data availability, our sample is restricted to older managers, and our results may not provide an accurate description of today's mutual fund industry. Given this focus, our paper provides evidence on the genesis of the industry and the managers that had an influence on its development, an area where prior research is scarce. As the industry evolved, changes in selection mechanisms may have affected the empirical relations we document. In Section 7, we extend our analysis to the recent generations of fund managers and reexamine the relation between family wealth and managerial performance using a noisy proxy for endowed wealth available for younger managers.

Table 1, panel A, reports summary statistics for managers and funds in our sample. The average manager is born in 1938, shortly before we measure the endowed family wealth. The average (median) managerial career, measured by the period between the manager's first and last appearance in the sample, is 13.0 (11.3) years. Most managers have strong educational backgrounds. The average (median) manager attended an undergraduate college with an SAT percentile rank of 82.5 (88.0). The average (median) college admission rate is 46.8% (43.5%), but this variable has a wide distribution: from the 10th percentile of 13.0% to the 90th percentile of 83.0%, suggesting large variation in the education quality. About 60% of managers hold MBA degrees and 4% hold PhD degrees. Approximately two-thirds of managers hold undergraduate degrees from private universities and 18% graduated from the Ivy League institutions.

Table 1
Summary statistics

A. Managers and funds

	Mean	SD	10th perc.	25th perc.	Median	75th perc.	90th perc.
Managers							
Birth year	1938.4	6.7	1930.0	1936.0	1940.0	1943.0	1945.0
Career length (years)	13.02	9.04	3.33	6.17	11.33	18.33	26.08
Private university, indicator	0.65	0.48	0.00	0.00	1.00	1.00	1.00
Ivy League institution, indicator	0.18	0.39	0.00	0.00	0.00	0.00	1.00
SAT rank	82.5	15.5	62.0	73.0	88.0	97.0	98.0
Undergraduate admission rate (%)	46.8	26.1	13.0	23.0	43.5	70.0	83.0
Undergraduate in-state tuition ($)	18,659.4	11,036.7	3,916.0	5,670.0	23,775.0	28,400.0	29,318.0
MBA degree, indicator	0.60	0.49	0.00	0.00	1.00	1.00	1.00
PhD degree, indicator	0.04	0.19	0.00	0.00	0.00	0.00	0.00
Mutual funds							
Monthly return (pp)	0.985	5.146	−4.860	−1.710	1.230	3.905	6.713
Monthly gross alpha (pp)	0.040	2.115	−2.116	−0.936	0.029	0.994	2.182
Monthly net alpha (pp)	−0.054	2.112	−2.207	−1.025	−0.057	0.904	2.077
Volatility (three-year trailing; pp)	4.823	1.876	2.657	3.516	4.600	5.762	7.032
Total net assets, $mil	1,778.01	7,988.06	13.38	48.91	193.85	830.95	2,924.82

(continued)

Table 1
Continued

B. Households in which managers grew up

	Mean	SD	10th perc.	25th perc.	Median	75th perc.	90th perc.
Parents' household (1940 census records)							
Home value ($)	10,708.0	12,605.1	2,040.0	4,000.0	7,000.0	12,000.0	25,000.0
Monthly rent ($)	54.46	61.68	18.00	30.00	40.00	55.00	90.00
Number of siblings	1.43	1.39	0.00	0.00	1.00	2.00	3.00
Resident servants, indicator	0.16	0.37	0.00	0.00	0.00	0.00	1.00
Father							
Birth year	1906.2	9.9	1894.0	1902.0	1908.0	1913.0	1917.0
Income ($)	2,298.2	1,386.3	700.0	1,200.0	2,000.0	3,100.0	5,000.0
Years of education	13.3	3.2	8.0	12.0	14.0	16.0	17.0
Attended college, indicator	0.56	0.50	0.00	0.00	1.00	1.00	1.00
Mother							
Birth year	1909.7	8.9	1899.0	1906.0	1911.0	1916.0	1919.0
Income ($)	842.6	421.6	240.0	600.0	864.0	1,100.0	1,300.0
Years of education	12.7	2.8	8.0	12.0	12.0	15.0	16.0
Attended college, indicator	0.47	0.50	0.00	0.00	0.00	1.00	1.00
Tract-level demographics (1940 Bogue files)							
Median home value in the tract ($)	5,949.0	4,378.1	2,042.0	3,380.5	5,331.0	6,961.0	10,200.0
Median rent in the tract (gross; $)	46.25	15.49	30.75	37.24	46.27	53.69	62.19
Median education years in the tract	10.50	4.39	8.00	8.57	9.55	12.22	12.53
Household home value rel. to tract median	1.22	0.53	0.70	0.86	1.03	1.47	1.97
Household rent rel. to tract median	1.23	0.91	0.65	0.81	0.96	1.31	1.77
Father's education rel. to tract median (male)	1.31	0.38	0.92	1.03	1.30	1.45	1.86

This table shows summary statistics for the main sample of 387 managers born in or before 1945. Data on managers' careers and education are from Morningstar and FactSet biographies. University characteristics, such as tuition and SAT rank, are based on the 2004 figures reported in the College Handbook of the College Entrance Examination Board. Data on the households where fund managers grew up are from the 1940 census records, and monetary values are reported in the 1940 dollars. Tract-level demographic variables are computed from the summary files for the 1940 census compiled by Elizabeth Bogue. Mutual fund and family characteristics are from Morningstar.

Mutual fund statistics in our sample show patterns consistent with prior research. The distribution of fund size is right-skewed, with the mean total assets ($1,778 million) significantly greater than the median ($193.9 million). The average (median) monthly fund return is 0.99% (1.23%), reflecting a period of rapid stock market growth in 1975–2012. After adjusting for exposure to common risk factors (Section 4 provides the details), the average (median) fund manager earns a small positive gross four-factor alpha of 0.040% (0.029%) per month. After accounting for fees, the average (median) manager earns a negative net four-factor alpha of −0.054% (−0.057%) per month. These figures parallel prior evidence that fund managers, as a group, slightly outperform their benchmarks on a gross basis, but deliver negative net performance due to high fees (e.g., Gruber 1996; Barras, Scaillet, and Wermers 2010).

3. Descriptive and Univariate Evidence

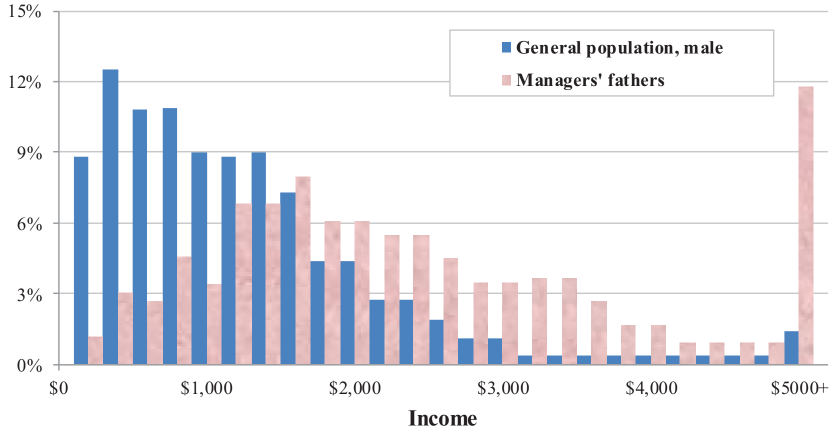
3.1 Which families do fund managers come from?

Before proceeding with formal analysis, we provide descriptive evidence on the family descent of mutual fund managers. To offer a comparative perspective, we juxtapose, where possible, their family characteristics with those of other households in the same census tract, state, or nationwide.

Table 1, panel B, shows summary statistics for the census data. Two conclusions emerge from these statistics. First, fund managers' families are, on average, relatively well-off compared to the general population. Second, there is a considerable variation of wealth and social status even within the sample. Managers' fathers report a median annual income of $2,000, which puts them at the 87th percentile of the national income distribution of adult males in 1940. Figure 1, panel A compares the sample and the national distributions graphically (the latter is based on the Census Labor Force summary files). Father's income shows a wide dispersion: the 10th (90th) percentile in the sample is $700 ($5,000), corresponding to the 40th (99th) percentile of the general population. Home value and rent have similar distribution patterns. The median home value (monthly rent) in the sample is $7,000 ($40), which is 233% (135%) higher than the median home value (rent) in the country. About 16% of managers' households employ resident servants, recorded in the census by the general title of servant or by their job function, such as butler, cook, or valet.

Managers generally come from well-educated families. The median father (mother) has 14 (12) years of education, which places them in the 92nd (81st) percentile of the national distribution for adult males (females). Figure 1, panel B compares the number of years of education between the managers' fathers and the general male population. About 56% of managers' fathers attended college, the number significantly higher than the 9.8% fraction of adult males with college education in 1940.

(A)



(B)

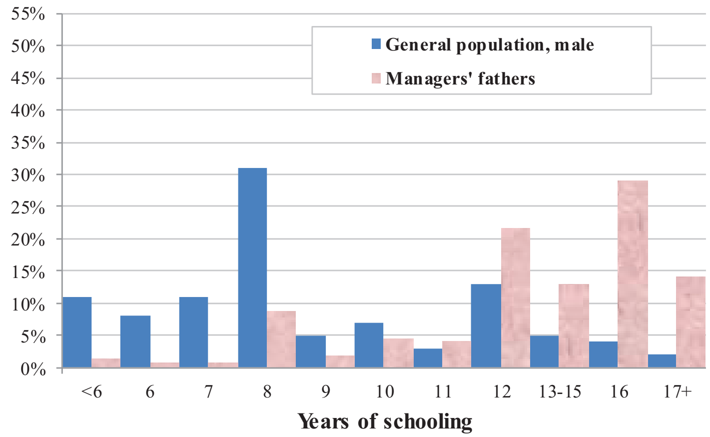


Figure 1
The distribution of annual incomes and schooling for managers' fathers and the general male population
Panel A compares the years of schooling between the fathers of fund managers and other males in the general population. The source of the data is the 1940 decennial federal census. Panel B compares the annual incomes of fund managers' fathers with those of other males in the general population. All values are shown in raw dollars based on the incomes reported in the 1940 decennial federal census.

Comparing our main statistics with their tract-level counterparts reveals that managers' households are marginally more affluent that those of their immediate neighbors: the average ratio of their home value (rent) to the respective tract median is 1.22 (1.23). Similarly, managers' fathers have slightly longer education records than the median male in the tract: the average ratio is 1.31.

Table 2, panel A, shows correlations among the main variables of interest. Different wealth proxies are strongly positively related to one another: father's income has a correlation of 0.445 with home value and 0.627 with rent. We cannot correlate home value and rent directly since these variables are available for complementary subsamples: owned and rented properties. We observe a robust positive relation between the manager's family wealth and the quality or exclusivity of his education. For example, father's income has a correlation of 0.362 with the university tuition and −0.354 with the university admission rate. The manager's education quality is positively related to his parents' education, while the parents' education, in turn, is positively related to the household wealth (correlation magnitudes range from 0.22 to 0.33). Finally, graduate education was more often pursued by managers from poorer backgrounds, as indicated by the negative correlations between the degree dummies and income.

3.2 Measuring the endowed economic status

Our objective is to construct a measure that would capture the family's ability to assist its children in career progression. Theoretical work on intergenerational mobility has focused on parents' earnings as a measure of family resources that could enhance a child's labor market outcomes over and above the effect of innate characteristics (e.g., Becker and Tomes 1979, 1986; Behrman et al. 1982). Consistent with theory, empirical work in labor economics demonstrates that parents' income is a key economic predictor of children's career success (see e.g., Black and Devereux 2011 for a review). When multiple proxies for a family's economic status are available, such as self-reported home values and net worth, researchers have focused on the annual income of the father as the main predictor of the children's labor market outcomes because of its precision and objective measurement (e.g., Solon 1992; Bjorklund and Jantti 1997; Couch and Dunn 1997).

The features of our data support using father's income as the main component in the measure of endowed economic status. First, in our sample period, the father is the primary wage earner in the family. The dominant majority of managers' mothers work as homemakers, and over 75% of mothers report no outside income. Second, father's income is unambiguously defined and measured in the year preceding the census. In contrast, the self-reported home values do not reflect the outstanding mortgage and could be reported at a historical cost or at a household's own estimate of the home value.

To construct a measure of a manager's economic status, we rely on the income of the father for all observations with available income data (69% of the sample). Income is usually missing for fathers who are proprietors, business partners, or entrepreneurs (based on the occupation description). To avoid losing this stratum, we construct an aggregate measure of economic status that is based on father's income, where available, and on its correlates—rent

Table 2
Univariate relationships

A. Correlations

	Father's income	Home value	Rent	Number of siblings	Tract home value	Tract rent	Parents' education	Private university	Ivy League inst.	SAT rank	Adm. rate	Tuition	MBA degree	PhD degree
Father's income	1.000													
Home value	0.445	1.000												
Rent	0.627		1.000											
Number of siblings	0.005	0.078	0.027	1.000										
Tract home value, median	0.369	0.094	0.228	0.151	1.000									
Tract rent, median	0.360	−0.138	0.499	0.164	0.589	1.000								
Parents' years of education	0.334	0.224	0.273	−0.074	0.209	0.224	1.000							
Private university	0.279	0.211	0.254	0.008	0.199	0.150	0.129	1.000						
Ivy League institution	0.307	0.315	0.218	−0.025	0.192	0.195	0.174	0.344	1.000					
SAT rank	0.396	0.312	0.263	0.012	0.231	0.174	0.242	0.422	0.462	1.000				
Admission rate	−0.354	−0.348	−0.238	−0.025	−0.191	−0.225	−0.206	−0.452	−0.575	−0.776	1.000			
Tuition	0.362	0.246	0.306	0.029	0.268	0.226	0.198	0.899	0.433	0.612	−0.590	1.000		
MBA degree, indicator	−0.195	−0.027	−0.195	−0.037	−0.213	−0.027	−0.002	−0.040	−0.041	−0.050	0.028	−0.041	1.000	
PhD degree, indicator	−0.076	−0.110	−0.035	0.037	−0.049	−0.059	0.040	−0.112	−0.094	−0.055	0.096	−0.096	−0.025	1.000

(continued)

Table 2
Continued

B. Family wealth quintiles

	Q1		Q2		Q3		Q4		Q5	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Wealth, main	0.75	0.78	1.49	1.48	2.17	2.19	3.30	3.25	6.69	5.10
Wealth, in-sample rank	12.55	10.50	35.87	35.50	54.60	58.00	69.72	75.00	85.03	91.00
Father's income ($)	752.8	728.0	1,524.1	1,560.0	2,191.2	2,240.0	3,133.7	3,200.0	4,641.4	5,000.0
Home value ($)	3,649.2	2,451.1	5,568.8	4,995.0	7,166.2	6,300.0	9,315.7	7,500.0	20,054.1	14,250.0
Monthly rent ($)	31.62	27.50	33.64	35.00	43.02	43.00	53.45	50.00	147.20	97.50
Number of siblings	1.80	1.00	1.18	1.00	1.41	1.00	1.18	1.00	1.64	1.00
Number of resident servants	0.03	0.00	0.05	0.00	0.10	0.00	0.21	0.00	0.96	1.00
Monthly gross alpha (pp)	0.069	0.041	0.094	0.059	0.049	0.053	0.020	0.012	−0.033	−0.022
Monthly net alpha (pp)	−0.031	−0.052	0.007	−0.027	−0.044	−0.030	−0.068	−0.068	−0.134	−0.111
Parents' years of education	11.5	12.0	12.4	12.5	12.9	13.0	13.7	14.0	14.6	15.0
Parents attended college, indicator	0.40	0.00	0.57	1.00	0.65	1.00	0.75	1.00	0.89	1.00
Private university, indicator	0.54	1.00	0.61	1.00	0.59	1.00	0.75	1.00	0.78	1.00
Ivy League institution, indicator	0.05	0.00	0.15	0.00	0.11	0.00	0.28	0.00	0.32	0.00
SAT rank	74.2	73.5	80.4	81.0	81.3	87.0	87.5	92.0	89.1	95.0
Admission rate (%)	56.9	64.0	49.7	54.0	50.3	49.0	40.3	35.0	36.9	24.5
Tuition ($)	15,349.4	17,137.0	17,285.3	18,505.0	17,153.5	20,193.0	21,596.3	27,535.5	22,602.4	28,090.0
MBA degree, indicator	0.64	1.00	0.70	1.00	0.58	1.00	0.64	1.00	0.42	0.00
PhD degree, indicator	0.06	0.00	0.04	0.00	0.03	0.00	0.01	0.00	0.03	0.00

This table provides descriptive statistics for the main sample. Panel A shows correlations among managers' and households' characteristics. Panel B shows mean and median values for the variables of interest for each quintile of the managers' household wealth distribution. Appendix D defines the variables.

and home value—if father's income is missing. In Section 4.2, we show that our conclusions are robust to using only father's income without any additional aggregation.

Since income, rent, and home value have different magnitudes, we measure them relative to their respective median values in the state of the family's residence. To construct our main measure, we scale father's income by the median male income in the state. Where father's income is missing, we replace it with similarly scaled rent or home value to avoid loss of observations.[5] The resulting measure covers the entire sample and is convenient to interpret. For example, it equals 1 for the median household, and it equals 2 for a household twice as wealthy as the median. This variable captures the economic status of the family where the fund manager grew up and is our main variable of interest. For ease of exposition, we will label this variable "family wealth" in lieu of the more precise but less parsimonious term "endowed economic status." Section 4.2 examines alternative measures.

Table 2, panel B, shows the breakdown of managers' characteristics and census variables across the quintiles of family wealth. The data reveal a large variation in family wealth in the sample. In the bottom quintile, the average manager comes from a family whose wealth is 25% below the state median, while in the top quintile, the average manager comes from a family that is 6.7 times wealthier than the state median. All three components of the wealth measure increase monotonically across the quintiles. The average father's income grows from $752.8 (42nd percentile of male income nationwide) in the bottom wealth quintile to $4,641.4 (99th percentile) in the top quintile. Similarly, the average home value in the top quintile is 5.5 times higher than in the bottom quintile, and the average rent is 4.7 times higher. The average number of servants in the household increases sharply from 0.03 in the bottom wealth quintile to 0.96 in the top quintile.

3.3 Univariate evidence

Table 2, panel B, provides univariate evidence on the relation between family wealth and measures of managerial performance without any controls or fixed effects. At this stage, we can note that managers from the top two quintiles deliver the worst performance and that this result holds for both gross and net alphas. For example, the gap in the mean gross alpha between the top and the bottom wealth quintile is 10.2 basis points (bps), or 1.22% annualized. However, the wealth-performance relation is not monotonic across the quintiles and is likely masked by confounding effects, some of which are apparent from the last block of the table. Specifically, all measures of the managers' education quality are increasing in wealth. For example, the average SAT rank increases from 74.2

[5] Since home value and rent cover nonoverlapping subsamples, the order in which they enter the aggregate measure does not matter.

in quintile 1 to 89.1 in quintile 5, while the average admission rate decreases from 56.9% in quintile 1 to 36.9% in quintile 5. Importantly, college tuition, a noisy proxy for wealth available for managers outside our core sample, is also increasing in the main wealth measure. These monotonic relations between wealth and education provide an external validation of the accuracy of our data, because data on family wealth and managers' education come from different sources.

A similar monotonic pattern is observed for the parents' education. While only 40% of families have a college-educated parent in the bottom wealth quintile, this fraction rises to 89% in the top quintile. Finally, PhD degrees are more often pursued by managers from the two bottom wealth quintiles, suggesting that some of these managers rely on education as a social lift. This is consistent with prior evidence in economics that education is a key driver of upward economic mobility (Brand and Xie 2010; Carneiro, Heckman, and Vytlacil 2011). All these variables are plausibly related to managerial performance and need to be included in the analysis. The main takeaway so far is that while natural drivers of performance are increasing in wealth, the performance itself shows the reverse pattern.

4. Family Wealth and Managerial Performance

4.1 Main results

This section investigates the relation between the family wealth of fund managers and their performance. Our main dependent variable is the gross fund alpha, calculated as follows. For each fund j and month t, we estimate the coefficients in the four-factor model, which includes the three Fama-French factors (Fama and French 1993) and the Carhart momentum factor (Carhart 1997), using monthly fund gross returns from the trailing 36 months (t-36 to t-1).[6] We compute the alpha as the difference between the actual fund return in month t and the return predicted by the model. This procedure yields rolling alphas at a monthly frequency which we express in percentage points in all our tests. To reduce noise due to occasional extreme estimates of the loadings, we require at least 30 nonmissing observations in the estimation window.

Alpha is a standard measure of fund performance and fits the objectives of our study: (1) it quantifies the percentage value created over the salient benchmark portfolios, and (2) it is based on the actual fund return data. However, it is not without issues. First, alpha can be dynamically altered. Although such alterations cannot be directly inferred from the return magnitudes, they tend

[6] The data come from Kenneth French's Web site. Our results are robust to the choice of the estimation window. However, many funds in our sample have long return series that stretch across different market cycles. The three-year period allows for a reasonable statistical accuracy in the estimation without requiring that the factor loadings must remain constant over a long period.

to increase the volatility and skewness of returns. We therefore control for fund volatility and skewness in all tests. Second, funds are restricted in their portfolio choice by investment mandates. To accommodate these constraints, our regressions include fund style fixed effects. We also include year fixed effects. While the market trend is cleansed in the construction of alpha, the inclusion of time fixed effects allows for the possibility that alpha might be easier to earn in some market conditions more than others.

Formally, we estimate the following regression specification:

$$Alpha_{mjt} = \beta Wealth_m + \boldsymbol{\Gamma_1} \times \mathbf{FControls_{mjt-1}} + \boldsymbol{\Gamma_2} \times \mathbf{MControls_{mt-1}} + \alpha_{Yt} + \delta_s + \varepsilon_{mjt}, \quad (1)$$

where j indexes funds, t indexes months, m indexes managers, and s denotes Morningstar fund style.

FControls is a vector of fund and fund family controls comprising *FundSize* (the natural log of the fund's total net assets (TNA) in millions of dollars), *FundAge* (time in years since the fund's first appearance in Morningstar), *ManagerTenure* (duration in years of the manager's tenure with the fund), *FirmSize* (the natural log of the fund family TNA in millions of dollars), *FirmLogNumFunds* (the natural log of the number of funds in the family), *Volatility* (standard deviation of fund returns over the trailing twelve months), and *Skewness* (skewness of fund returns over the trailing twelve months). **MControls** is a vector of manager controls comprising *UniSATRank* (percentile rank of the median SAT score for the manager's undergraduate college), *UniAdmissionRate* (undergraduate admission rate for the manager's college), *HasPhD* (an indicator equal to one if the manager holds a PhD), and *ParentsEdu* (the average education attainment score for the manager's parents, defined as follows: education attainment equals 3 if the person attended college, 2 if he attended high school but not college, 1 if he attended elementary school but not high school, and 0 if he has no formal education). All controls variables are measured at the end of month t-1 and are defined in Appendix D. In these and subsequent tests, the standard errors are clustered at fund manager level to allow for serial correlation in performance resulting from unobservable managerial characteristics.

We perform this analysis for our main measure of wealth as well as the percentile rank of wealth in the sample, defined as the percentile rank of father's income, if available, and the percentile rank of rent or home value otherwise. Table 3, panel A, reports the estimation results, beginning with specifications without manager controls (Columns 1 and 6) and gradually adding controls for manager characteristics correlated with wealth. Both measures of wealth are reliably negatively related to alpha, and this relation becomes stronger and economically larger as we add controls for manager characteristics. This pattern is consistent with the predictions of the model.

Table 3
Family wealth and managerial performance

A. Main analysis

Dependent variable	*Gross four-factor alpha*					*Gross four-factor alpha*				
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Wealth	−0.0136***	−0.0161***	−0.0160***	−0.0159***	−0.0191***					
	(−3.72)	(−4.26)	(−4.20)	(−4.12)	(−4.64)					
Wealth, rank						−0.0589*	−0.0901**	−0.0903**	−0.0840**	−0.1075***
						(−1.72)	(−2.58)	(−2.55)	(−2.38)	(−2.91)
FundSize	−0.0633***	−0.0623***	−0.0636***	−0.0645***	−0.0637***	−0.0606***	−0.0595***	−0.0607***	−0.0619***	−0.0609***
	(−5.96)	(−5.78)	(−5.89)	(−6.15)	(−5.79)	(−5.76)	(−5.55)	(−5.67)	(−5.93)	(−5.57)
FundAge	−0.0008	−0.0011	−0.0012	−0.0007	−0.0009	−0.0008	−0.0010	−0.0011	−0.0006	−0.0009
	(−0.44)	(−0.61)	(−0.66)	(−0.36)	(−0.50)	(−0.44)	(−0.60)	(−0.64)	(−0.34)	(−0.48)
ManagerTenure	0.0028*	0.0029*	0.0030**	0.0039**	0.0039**	0.0023	0.0023	0.0025*	0.0032**	0.0032**
	(1.82)	(1.88)	(1.96)	(2.39)	(2.40)	(1.52)	(1.58)	(1.67)	(2.07)	(2.07)
FirmSize	0.0536***	0.0508***	0.0512***	0.0489***	0.0457***	0.0531***	0.0499***	0.0501***	0.0489***	0.0453***
	(4.59)	(4.28)	(4.28)	(4.19)	(3.76)	(4.58)	(4.23)	(4.21)	(4.21)	(3.77)
FirmLogNumFunds	−0.0753***	−0.0719***	−0.0704***	−0.0656***	−0.0648***	−0.0766***	−0.0734***	−0.0715***	−0.0688***	−0.0691***
	(−3.68)	(−3.47)	(−3.34)	(−3.16)	(−2.99)	(−3.77)	(−3.57)	(−3.43)	(−3.34)	(−3.23)
Volatility	−0.0465***	−0.0463***	−0.0465***	−0.0453***	−0.0489***	−0.0461***	−0.0459***	−0.0462***	−0.0446***	−0.0483***
	(−4.07)	(−4.04)	(−4.04)	(−3.97)	(−4.44)	(−4.05)	(−4.04)	(−4.05)	(−3.92)	(−4.38)
Skewness	0.0013***	0.0013***	0.0013***	0.0013***	0.0013***	0.0013***	0.0013***	0.0013***	0.0013***	0.0013***
	(4.48)	(4.50)	(4.55)	(4.39)	(4.36)	(4.52)	(4.53)	(4.58)	(4.41)	(4.35)
UniSATRank		0.1731**			0.1156		0.1812**			0.1305
		(2.09)			(1.33)		(2.16)			(1.49)
UniAdmissionRate			−0.1090**					−0.1164**		
			(−2.48)					(−2.56)		
ParentsEdu				0.0442***	0.0385**				0.0376**	0.0310*
				(2.63)	(2.15)				(2.25)	(1.73)
HasPhD					−0.0119					−0.0130
					(−0.26)					(−0.28)
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund style FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	46,492	46,221	45,989	45,236	43,376	47,018	46,747	46,515	45,762	43,902
Adj. R-sq	0.0153	0.0155	0.0156	0.0151	0.0161	0.0151	0.0153	0.0154	0.0149	0.0159

(continued)

Table 3
Continued

B. Alternative proxies of wealth

Dependent variable	Gross four-factor alpha									
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
FIncome, actual	−0.0285**	−0.0304***								
	(−2.45)	(−2.62)								
FIncome, after taxes			−0.0310**	−0.0328***						
			(−2.51)	(−2.67)						
AccumulatedSavings					−0.0023**	−0.0023**				
					(−2.54)	(−2.57)				
Housing							−0.0072**	−0.0081**		
							(−2.40)	(−2.58)		
WealthQ2									0.0226	0.0130
									(0.80)	(0.45)
WealthQ3									−0.0472	−0.0508
									(−1.42)	(−1.55)
WealthQ4									−0.0749**	−0.1015***
									(−2.12)	(−2.78)
WealthQ5									−0.1086***	−0.1134***
									(−3.33)	(−3.49)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager's controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parents' controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund style FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	30,447	30,447	29,591	29,591	28,594	28,594	42,999	41,755	44,620	43,376
Adj. R-sq	0.0165	0.0165	0.0170	0.0170	0.0171	0.0171	0.0157	0.0155	0.0164	0.0162

(continued)

Table 3
Continued

C. Alternative measures of performance

Dependent variable	*Benchmark-adjusted return*		*Abnormal return over benchmark*		*Value extracted*	
Model	(1)	(2)	(3)	(4)	(5)	(6)
Wealth	−0.0169***	−0.0172***	−0.0131***	−0.0123**	−0.2865**	−0.4316***
	(−3.29)	(−3.18)	(−2.77)	(−2.49)	(−2.42)	(−2.93)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
Manager's controls	Yes	Yes	Yes	Yes	Yes	Yes
Parents' controls	No	Yes	No	Yes	No	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Fund style FEs	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	43,573	42,397	43,337	42,161	44,609	43,365
Adj. R-sq	0.0128	0.0124	0.0151	0.0146	0.0041	0.0041

This table studies the relation between the family wealth of fund managers and their performance. Panel A shows regressions of the funds' four-factor monthly alphas (in percentage points) on two relative measures of the manager's family wealth. The dependent variable is the gross fund alpha, defined as the gross return of the fund minus the return predicted by the four-factor model estimated over the trailing 36 months. The main independent variable, *Wealth*, is a measure of the relative economic status of the household where the manager grew up, expressed in multiples of the state median. This variable is equal to the father's income scaled by the median male income in the state (when the father's income is available), and to the home value or rent scaled by the respective state median (when the father's income is unavailable). Wealth rank is equal to the percentile rank in the sample (in percentage points) of the father's income, if available, and to the percentile rank of the home value or rent (these variables are defined on nonoverlapping subsamples), if the father's income is unavailable. Panel B shows the results for additional proxies of wealth. *FIncome, actual* is the actual father's income in 1940 (in thousands of dollars). *FIncome, after taxes* is the father's income after federal and state taxes (historical tax data is from The Tax Foundation). *AccumulatedSavings* is the measure of the family's accumulated savings, computed as one-third of the father's total after-tax income earned from the year the father joined the workforce to the year the manager turned 18. *WealthQx* are the dummy variables indicating quintiles of the wealth distribution (main measure). Panel C shows the results for alternative measures of investment performance. *Benchmark-adjusted return* (in percentage points) is the fund's return net of the prospectus benchmark index return. *Abnormal return over benchmark* (in percentage points) is the fund's return minus the return predicted by the benchmark-based one-factor model. *Value extracted* is the dollar measure of the value extracted from capital markets (in millions of dollars) computed as the product between the fund's gross alpha and the fund's inflation-adjusted TNA (expressed in 2012 dollars) at the end of the previous month. The values of time-varying control variables are taken at the end of the month preceding the observation month. Appendix D defines the variables. All regressions include Morningstar fund style fixed effects and time fixed effects. Standard errors are clustered at the fund manager level, and the corresponding t-statistics are reported in parentheses. Statistical significance levels for this test are indicated as follows: *, 10%; **, 5%; and ***, 1%.

Correlates of wealth, such as education, tend to improve performance, and failure to control for them in the regression weakens the signalling effect of wealth. When these controls are added, the selection effect is identified more precisely, and the results get stronger.

These results are economically important. According to the full specification in Column 5, an interquartile range increase in family wealth (2.27 multiples of the state median) is associated with a reduction in alpha of 4.34 bps per month (0.0191*2.27) or about 0.52% per year, a result significant at 1% with a t-statistic of 4.64. We obtain similar results for the percentile rank measure of wealth in Columns 6–10. According to the full specification in Column 10, an increase in the wealth rank of 50 percentiles reduces the four-factor alpha by 5.38 bps per month or 0.65% per year, a relation significant at 1%. Given the long careers of fund managers in our sample, the resulting difference in the compounded risk-adjusted returns is substantial, underscoring the importance of the quality signalling mechanism we study.

The effects of the control variables are largely consistent with prior work. Managers with a higher-quality education, measured by their college's admission rate or SAT score, perform better, as shown in Chevalier and Ellison (1999). In Column 2, an increase in the SAT rank of 10 percentiles (or 0.1) increases annual alpha by 0.21%. In addition, the education of a manager's parents has a significant positive effect, confirming the importance of congenital drivers of performance (Barnea, Cronqvist, and Siegel 2010). In Column 4, a one-level increase in the educational attainment score of the manager's parents (e.g., from high school to college) is associated with an increase in the fund alpha of 4.42 bps per month or 0.53% per year. Managerial experience is positively related to performance, as shown in Kempf, Manconi, and Spalt (2017), while fund size is negatively related, consistent with diseconomies of scale in asset management (Berk and Green 2004; Chen et al. 2004). Finally, we control for the PhD degree, which was shown to affect fund managers' performance (Chaudhuri et al. 2017). The PhD effect is almost zero in our sample, probably due to a smaller sample size and the rarity of PhD degrees.

4.2 Alternative measures of family wealth

This subsection examines the robustness of our findings to alternative proxies for family wealth, which are available for different subsamples of our main sample.

We begin with the raw father's income. Columns 1 and 2 in panel B of Table 3 show that the effect of father's income on gross alpha is strongly negative, and its economic magnitude exceeds that of our main measure of family wealth. An interquartile range increase in father's income ($1,900) reduces alpha by 5.78 bps per month or 0.69% per year. In Columns 3 and 4, we account for the cross-sectional variation in state income taxes in our sample and focus on father's income net of federal and state taxes.[7] The effect of the after-tax income is about 8% larger than that of the raw income and has a higher statistical significance. In Columns 5 and 6, we consider a proxy for the cumulative savings of the family from the time the father joined the workforce to the time the manager turned 18. This measure, motivated by the importance of parental lifetime earnings in the theoretical models of intergenerational mobility (e.g., Becker and Tomes 1979, 1986), assumes that the father earned the same income for said period and saved one-third of his after-tax earnings. The cumulative savings are negatively related to performance, and this effect is similar to our baseline estimates: an interquartile-range increase in savings reduces annualized alpha by 0.56%.

Columns 7 and 8 focus on nonincome proxies for the endowed economic status. In these columns, family wealth is measured by home value or monthly rent, scaled by their state medians. As discussed, these proxies are noisier, and their economic effect on performance is about 42% that of the main wealth measure (0.0081/0.0191 = 42%, according to Column 8).[8] For all wealth proxies, the results are stronger in specifications that control for parents' education—the principal correlate of family wealth.

In Columns 9 and 10, we switch from the linear measure of wealth to its quintile dummies to provide more detail on the structure of the wealth-performance relation. The omitted category is the bottom wealth quintile, and quintiles are arranged in the increasing order of family wealth so that *WealthQ5* corresponds to managers from the wealthiest families. The results reveal two patterns. First, the coefficients on the quintile dummies decrease monotonically across the wealth quintiles. Second, the wealth-performance relation is mostly driven by the underperformance of the wealthy, as indicated by the sizable gap in coefficients between the top two and the bottom three quintiles. In particular, the strongest relation, significant at 1%, is observed for managers from the wealthiest families in the top quintile. In Column 10, the top wealth group underperforms the bottom (omitted) group by 11.3 bps per month or 1.36% per year.

The economic importance of these results is underscored by the fact that various unobservable effects should enhance the performance of the rich. Although we strive to control for different characteristics of the manager and his family, potentially important omitted variables may exist in our study. However, a reasonable endogeneity argument would point to a positive relation between a manager's performance and his family wealth. For example, those from wealthier families have better connections and access to resources, which should aid their professional tasks. And yet, these same privileges make it

[7] We use historical tax rates for the year when the father's income is measured. In 1939, 20 states imposed no income tax, whereas some states had double-digit tax rates (e.g., California and North Dakota had maximum income tax rates of 15%). We obtain historical state tax rates from the tax policy firm The Tax Foundation: https://files.taxfoundation.org/legacy/docs/pn29.pdf

[8] Actual rent or home value can only be used in nonoverlapping subsamples for which these variables are available. In these subsamples, both variables are negatively related to performance but are not statistically significant.

possible to embark on a career in asset management with only modest skill. Consistent with the model predictions, the selection effect of wealth must be strong to offset the benefits of wealth for performance and reveal a negative wealth-performance relation even in the absence of full controls.

In summary, family wealth is negatively related to managerial performance, and this result is robust to various wealth proxies. This relation is driven by the underperformance of managers from the richest families, and it gets stronger after we control for managerial characteristics correlated with wealth.

4.3 Alternative measures of fund performance

This subsection examines several alternative measures of mutual fund performance.

First, we consider fund performance net of the fund's benchmark index, since it is debatable whether factors commonly used in the construction of alpha capture risk or should be viewed as part of the abnormal fund return. We define *Benchmark-adjusted return* as the difference between the fund's monthly gross return and the return on the fund's benchmark index as per the fund prospectus recorded by Morningstar. We also consider the abnormal return net of the benchmark (*Abnormal return over benchmark*), computed as the difference between the fund's return and the return predicted by the factor model in which the factor is the index return series (as before, the model is estimated over the trailing 36 months). The results for these two measures, reported in Columns 1–4 of panel C in Table 3, confirm the strong negative association between family wealth and managerial performance. This relation has stable economic magnitudes and high levels of statistical significance across the four specifications.

Next, we use the dollar measure of the value extracted from capital markets introduced in Berk and Van Binsbergen (2015). Following the authors, we define this measure as the product of the fund's beginning-of-the-month TNA (inflation-adjusted and expressed in millions of 2012 dollars) and its gross alpha. This variable is different from the return-based measures of performance as it explicitly takes into account fund size. The size component is important, since the neoclassical framework posits that fund size adjusts endogenously to the manager's ability via flows, thus driving down the return-based measures of performance under the assumption of decreasing returns to scale. However, as long as the equilibrium is not reached, the value-added measure would understate the ability of managers constrained by fund size. Moreover, the equity market grew rapidly in our sample period, offering new investment opportunities for fund managers every year, thus relaxing the effect of diminishing returns to scale. For these reasons, we rely on the return-based measures of performance in our main analysis and use the value extracted measure as a robustness check. Columns 5 and 6 in panel C show that family wealth is reliably negatively related to the value extracted from capital markets, and this relation is significant at 1% in the full specification.

In summary, the relation between family wealth and managerial performance is robust to a variety of performance measures and fund characteristics. While some fund characteristics are unobservable, they are unlikely to explain our results. We exclude non-U.S. and specialty funds, making it difficult to predict fund performance based on fund type. If anything, we would expect managers from wealthier families to seize the more obvious investment opportunities, in contrast to their actual underperformance.

4.4 Mediating effects

This subsection examines how the strength of the wealth-performance relation varies by additional characteristics expected to amplify or attenuate the precision of the wealth signal.

We first focus on the number of a manager's siblings collected from a combination of census records and obituaries for the managers' parents. Our focus on siblings is motivated by a literature in household economics, reviewed in Black, Devereux, and Salvanes (2005), which shows theoretically and empirically that, for a given amount of family wealth, an increase in the number of children leads to a smaller amount of resources—temporal, familial, and monetary—allocated to each child. This pattern, labeled "resource dilution," has been shown to have a significant effect on individuals' education, incomes, and career outcomes. If family wealth helps overcome entry barriers into high-income jobs, this effect should be stronger for families with one child and weaker in families with a large number of children.

The results in Column 1 in Table 4 confirm this prediction. The underperformance of managers from wealthy families is greater for the most privileged individuals—those who have no siblings. When we focus on such one-child families, the magnitude of the wealth-performance relation increases compared to that in our baseline analysis. The point estimate on *Wealth* (-0.0305) indicates that an interquartile range increase in wealth (2.27) corresponds to a reduction in alpha of 6.9 bps per month or 83 bps per year. The positive and statistically significant interaction term *Wealth∗NumberOfSiblings* shows that an addition of an extra sibling to a family weakens the negative wealth-performance relation by 22% (0.0067/0.0305).

Columns 2 and 3 focus on the effect of market cycles on the performance gap between managers from rich and poor families. Prior work establishes theoretically and empirically that economic downturns reveal the differences in managerial skill (Kosowski 2006; Sun, Wang, and Zheng 2009; Glode 2011; Schmalz and Zhuk 2017). If the endowed economic status contains information about skill, its effect on performance should be stronger in economic downturns. To test this hypothesis, we define two dummy variables: *UpMarket* to indicate months when the return on the S&P 500 Index was positive and *HighMarket* to indicate months when the return on the S&P 500 Index was above average in the sample.

Table 4
Mediating effects

Dependent variable	*Gross four-factor alpha*			
Model	(1)	(2)	(3)	(4)
Wealth	−0.0305***	−0.0302***	−0.0241***	−0.0251***
	(−3.76)	(−4.19)	(−3.95)	(−3.71)
NumberOfSiblings	−0.0319***			
	(−2.98)			
*Wealth * NumberOfSiblings*	0.0067**			
	(2.07)			
UpMarket		−0.0465		
		(−1.58)		
*Wealth * UpMarket*		0.0176**		
		(2.07)		
HighMarket			−0.0126	
			(−0.42)	
*Wealth * HighMarket*			0.0093	
			(1.07)	
ManagerTenure				0.0019
				(0.81)
*Wealth * ManagerTenure*				0.0006
				(1.38)
Fund controls	Yes	Yes	Yes	Yes
Manager's controls	Yes	Yes	Yes	Yes
Parents' controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Fund style FEs	Yes	Yes	Yes	Yes
Num. obs.	39,515	43,376	43,376	43,376
Adj. R-sq	0.0159	0.0161	0.0161	0.0161

This table studies how the relation between family wealth and managerial performance varies with manager and market characteristics. The dependent variable is the gross fund alpha (in percentage points), defined as the gross return of the fund minus the return predicted by the four-factor model estimated over the trailing 36 months. *NumberOfSiblings* is the number of siblings of the manager. *UpMarket* (*HighMarket*) is an indicator variable equal to one in months when the return on the S&P 500 Index was positive (above average in the sample). *ManagerTenure* is the duration in years of the manager's tenure with the fund. The control variables are the same as in Table 3 (suppressed for brevity). Appendix D defines the variables. All regressions include Morningstar fund style fixed effects and time fixed effects. Standard errors are clustered at the fund manager level, and the corresponding t-statistics are reported in parentheses. Statistical significance levels for this test are indicated as follows: *, 10%; **, 5%; and ***, 1%.

The performance gap between managers from rich and poor families expands in down markets. The interaction term of the market cycle indicator with family wealth is positive for both measures of market performance and significant at 5% for *UpMarket*. The sensitivity of alpha to wealth in the down market is 58% greater than the unconditional (average) sensitivity (−0.0302/−0.0191−1). Yet, while the magnitude of the performance gap varies by market cycle, this gap remains economically relevant at all times. In up-markets, the sensitivity of alpha to wealth is negative and is about two-thirds of its unconditional value.

In Column 4, we study how the performance gap varies by the manager's experience and do not find a significant effect. We revisit this result in Section 6 which investigates channels of value creation.

Overall, the wealth-performance relation is strengthened by the presence of factors that increase the precision of the wealth signal. In the cross-section, the signal is stronger when the manager is the sole benefactor of family resources. In the time series, it is stronger in periods when skill has the greatest impact.

4.5 Alternative explanation for the performance gap

So far, we have viewed the relatively stronger performance of managers from less wealthy families as evidence of superior skill. We conclude this section by testing an alternative explanation—that this performance can be attributed to unethical behavior of managers coming from poor backgrounds. For example, if it is harder for the poor to advance in the profession, they could engage in illicit trading practices to even the odds. To test this hypothesis, we study the relation between family wealth and three questionable practices in asset management: (1) window-dressing, (2) risk shifting, and (3) late trading.

First, we consider window-dressing—a portfolio manipulation strategy that involves buying stocks with high trailing returns before disclosure dates to convey the impression that they were purchased before appreciating in value. Following Agarwal, Gay, and Ling (2014) and Solomon, Soltes, and Sosyura (2014), we construct a window-dressing measure, *Backward-looking return gap* (*BLRG*), defined as the difference between the weighted average return of the fund's holdings (disclosed at the end of the quarter) and the actual return of the fund. If a fund buys past winners shortly before reporting dates, the realized returns of reported holdings would exceed the actual returns of the fund, resulting in a higher *BLRG*.

Table 5, panel A, shows that family wealth is unrelated to *BLRG*. The point estimates on family wealth are small and statistically insignificant across the specifications. If anything, wealthier managers tend to window-dress more, as evidenced by the positive coefficients on wealth and high-wealth quintile dummies in the full specifications (Columns 2, 4, and 6).

In our second test, we investigate how managers adjust the risk of their portfolios in response to past performance. We follow Huang, Sialm, and Zhang (2011) and for each fund-quarter compute the measure of risk shifting as the difference between the 36-month volatility of the fund's current holdings and the actual volatility of fund returns over the past 36 months. Risk shifting is positive if the fund has increased its volatility risk as of late. Risk shifting by itself is not necessarily value-destroying or unethical. However, risk shifting in response to past performance can be indicative of strategic flow-management rather than forward-looking value considerations.

Table 5, panel B, studies whether managers from less wealthy families are more likely to engage in performance-driven risk shifting. We regress risk shifting on family wealth interacted with past fund performance. We consider both absolute performance (past returns) and relative performance (fund rank within its investment style) measured over a one- or a three-year horizon. The interaction terms between family wealth and past performance are economically small, statistically insignificant, and have the opposite sign of that predicted by the alternative explanation. If anything, wealthier managers are slightly more likely to risk shift in response to past performance.

Our third test focuses on late trading—the practice of allowing some investors to trade mutual fund shares after the market close but disguising them as trades

Table 5
Family wealth and investment practices

A. Window-dressing

Dependent variable	*Backward-looking return gap*					
Model	(1)	(2)	(3)	(4)	(5)	(6)
Wealth	−0.0061	0.0201				
	(−0.48)	(1.50)				
Wealth, rank			−0.0515	0.1252		
			(−0.35)	(0.82)		
WealthQ2					−0.0889	0.0144
					(−0.84)	(0.14)
WealthQ3					−0.0306	0.0105
					(−0.22)	(0.08)
WealthQ4					0.1288	0.3106*
					(0.82)	(1.89)
WealthQ5					−0.0915	0.1134
					(−0.76)	(0.95)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
Manager’s controls	Yes	Yes	Yes	Yes	Yes	Yes
Parents’ controls	No	Yes	No	Yes	No	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Fund style FEs	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	30,337	29,434	30,688	29,785	30,337	29,434
Adj. R-sq	0.2137	0.2230	0.2126	0.2212	0.2149	0.2250

(continued)

Table 5
Continued

B. Risk shifting in response to past performance

Dependent variable	*Risk shifting*							
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wealth	−0.0042	−0.0055	−0.0165	−0.0165	0.0021	−0.0013	0.0008	−0.0027
	(−0.21)	(−0.28)	(−0.79)	(−0.75)	(0.12)	(−0.07)	(0.04)	(−0.14)
Past return, 12 months	0.1676***	0.1640***						
	(5.58)	(5.38)						
*Wealth * Past return, 12 months*	0.0093	0.0106						
	(1.13)	(1.23)						
Past return, 36 months			0.1885**	0.1913**				
			(2.38)	(2.38)				
*Wealth * Past return, 36 months*			0.0219	0.0212				
			(1.58)	(1.51)				
In-style rank, 12 months					0.4475***	0.4258***		
					(3.49)	(3.37)		
*Wealth * In-style rank, 12 months*					0.0058	0.0143		
					(0.16)	(0.40)		
In-style rank, 36 months							0.1871	0.1771
							(1.07)	(1.01)
*Wealth * In-style rank, 36 months*							0.0050	0.0121
							(0.11)	(0.27)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager’s controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parents’ controls	No	Yes	No	Yes	No	Yes	No	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund style FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	3,697	3,570	3,697	3,570	3,697	3,570	3,697	3,570
Adj. R-sq	0.3225	0.3283	0.2903	0.2970	0.2862	0.2926	0.2746	0.2815

(continued)

Table 5
Continued

C. Involvement in the 2003 late-trading scandal

Dependent variable	*Tainted*					
Model	(1)	(2)	(3)	(4)	(5)	(6)
Wealth	0.0166	0.0150				
	(1.07)	(1.00)				
Wealth, rank			0.0194	0.0056		
			(0.25)	(0.07)		
WealthQ2					0.0075	0.0061
					(0.13)	(0.10)
WealthQ3					0.0074	0.0143
					(0.13)	(0.26)
WealthQ4					0.0260	0.0266
					(0.43)	(0.42)
WealthQ5					0.1972**	0.1896**
					(2.34)	(2.28)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
Manager's controls	Yes	Yes	Yes	Yes	Yes	Yes
Parents' controls	No	Yes	No	Yes	No	Yes
Fund style FEs	No	Yes	No	Yes	No	Yes
Num. obs.	261	258	264	261	261	258
Adj. R-sq	0.2399	0.2451	0.2257	0.2323	0.2498	0.2534

This table studies the relation between a fund manager's family wealth and three questionable practices in asset management: (1) window-dressing (panel A), (2) risk shifting in response to past performance (panel B), and (3) late trading (panel C). Panel A shows regressions of the fund's backward-looking return gap (measure of window-dressing) on the manager's family wealth. The dependent variable is the backward-looking return gap, computed as the difference between the return of a hypothetical portfolio, in which the weights of the stocks are equal to the weights reported in the end-of-quarter disclosure, and the actual fund gross return. In panel B, the dependent variable is the fund's quarterly risk shifting measure, computed as the difference between the 36-month volatility of the fund's current holdings and the actual volatility of fund returns over the past 36 months. The main independent variable of interest is the interaction of the manager's family wealth and past fund performance (raw return and rank in the Morningstar style). Panel C shows linear-probability regressions which relate family wealth to the "tainted" indicator variable, a proxy for the manager's involvement in the 2003 late-trading scandal (McCabe 2009). The dependent variable, *Tainted*, is a binary indicator equal to one if the fund belonged to one of the fund families implicated in the 2003 late-trading scandal and if the fund was active in 2001–2003. The control variables (suppressed for brevity) are the same as in Table 3. Appendix D defines the variables. The inclusion of Morningstar fund style fixed effects and time fixed effects is indicated at the bottom of the table. Standard errors are clustered at the fund manager level, and the corresponding t-statistics are reported in parentheses. Statistical significance levels for this test are indicated as follows: *, 10%; **, 5%; and ***, 1%.

that had been placed earlier. Such trades would use information available after the market closure but would execute at the old price, giving a trader an unfair information advantage. For identification, we exploit the 2003 late-trading scandal which revealed the identity of firms involved in this illegal practice. Following McCabe (2009), we classify a mutual fund as ‘tainted’ if it belonged to one of the implicated fund families and was active in 2001–2003.[9] Among the funds in our sample that were active during this period, 13.2% are tainted.

In Table 5, panel C, we run the linear-probability regression of the tainted dummy on the fund manager’s family wealth. Contrary to the alternative hypothesis, the coefficients on family wealth are positive across all specifications, albeit few are statistically significant. Only the top wealth quintile in Columns 5 and 6 stands out: the wealthiest managers were 19% more likely than the least wealthy to be implicated in the scandal, a result significant at 5%. Because late trading was based on unofficial agreements between mutual funds and large trading firms, it is possible that managers from wealthier backgrounds were more likely to have connections with large traders.

In summary, our evidence does not support the view that managers from less wealthy backgrounds are more likely to engage in unethical behavior. This result is consistent with prior work on the drivers of academic cheating, a strong predictor of professional misconduct (Sims 1993; Ogilby 1995; Nonis and Swift 2001). For example, focusing on the same generation of people as our paper and using individual-level data on the endowed economic status, Bowers (1964) finds no relation between parents’ income and an individual’s likelihood of academic cheating, whether measured within or across colleges.

5. Family Wealth and Career Progression

This section studies managerial careers to provide evidence on the selection mechanism. The first subsection focuses on barriers to entry on the path to asset management. The second subsection studies career progression following the entry into the industry.

5.1 Barriers to entry into asset management

An aspiring portfolio manager has to pass multiple barriers on his way to the job. To test whether the selection mechanism in our model contributes to the performance differential between managers from wealthy and poor families, we study entry barriers to asset management that are easier to pass for the wealthy than for the poor. If the selection mechanism is operative, the negative wealth-performance relation should be magnified in the presence of such barriers.

[9] The implicated mutual fund complexes include Alliance, Bank One, Bank of America/Nations, Columbia/Fleet/Liberty, Deutsche/Scudder/Kemper, Federated, Franklin Templeton, Fred Alger, Fremont, Invesco/AIM, Janus, Massachusetts Financial Services, Pilgrim Baxter (PBHG), PIMCO, Putnam, RS Investments, Seligman, Strong, Wachovia Evergreen, and Waddell & Reed.

The first barrier we consider is the geographic distance to education and employment opportunities. Candidates from wealthier families can travel more easily. In contrast, it is costly for poor candidates to travel and live away from home, particularly given the high cost of air travel during managers' early careers. A poor candidate would commit to high travel and living expenses only if he is confident of his skill. The less skilled poor candidates would be discouraged from committing to high expenses, since they are less likely to pay off. Under this hypothesis, the negative wealth-performance relation should be stronger (1) the greater the distance between the manager's parent home and the college the manager attended and (2) the greater the distance between that college and employment opportunities in asset management.

We compute distances in thousands of kilometers based on geographical coordinates from the U.S. Census Bureau's gazetteer files. We consider a continuous distance measure and an indicator which equals one if the distance exceeds 1,000 kilometers, a conservative threshold for required air travel. To proxy for the distance to employment opportunities, we compute the distance between the manager's college campus and Manhattan, New York—the principal location of asset management firms at the outset of the industry.

In Columns 1–4 of Table 6, we interact the distance measures with family wealth and rerun our main regression. The coefficients on the interaction terms are consistently negative and significant at 10% or better in three of the four specifications, indicating that the negative relation between family wealth and performance is stronger for managers who had to overcome greater distances. For example, compared to the unconditional effect (coefficient of −0.0191), the effect of family wealth on performance is 45.0% (0.0086/0.0191) stronger for every thousand kilometers separating the manager's home from college and 52.9% stronger for every thousand kilometers separating the college from New York.

Next, we study the role of specialized education as an entry barrier into asset management. We posit that a college degree in business or economics facilitates an individual's entry into asset management, since the majority (60%) of fund managers have this specialization. We focus on undergraduate degrees because they immediately precede the entry into the workforce and indicate the initial career path chosen on the basis of skill and family support. If the endowed economic status is more important for a candidate's entry into business compared with the entry into other fields, such as science or engineering, candidates from lower-income families would self-select out of business programs unless they are confident of their skill. Similarly to the distance barrier, a candidate facing greater challenges in a given career path would commit to it only if he is confident that this investment will pay off. Thus, under this mechanism, the wealth-performance relation should be stronger among those who elect to pursue business education.

Table 6
Barriers on a path to asset management

Dependent variable	*Gross four-factor alpha*					
Model	(1)	(2)	(3)	(4)	(5)	(6)
Wealth	−0.0128**	−0.0157***	−0.0081*	−0.0142***	−0.0183***	0.0268
	(−2.31)	(−3.73)	(−1.66)	(−3.79)	(−4.30)	(1.39)
HomeUniDistance	0.0291					
	(1.49)					
*Wealth * HomeUniDistance*	−0.0086					
	(−1.62)					
HighHomeUniDistance		0.0709*				
		(1.72)				
*Wealth * HighHomeUniDistance*		−0.0174*				
		(−1.68)				
UniNYDistance			0.0432***			
			(3.67)			
*Wealth * UniNYDistance*			−0.0101**			
			(−2.34)			
HighUniNYDistance				0.0787**		
				(2.40)		
*Wealth * HighUniNYDistance*				−0.0195*		
				(−1.73)		
BusinessDegree					0.0040	
					(0.11)	
*Wealth * BusinessDegree*					−0.0223**	
					(−2.03)	
UnemploymentAtEntry						0.0338**
						(2.51)
*Wealth * UnemploymentAtEntry*						−0.0075**
						(−2.21)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
Manager's controls	Yes	Yes	Yes	Yes	Yes	Yes
Parents' controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Fund style FEs	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	43,376	43,376	43,376	43,376	29,622	43,376
Adj. R-sq	0.0161	0.0161	0.0163	0.0162	0.0172	0.0162

This table shows how the relation between a manager's family wealth and performance is affected by various barriers on a path to asset management. The dependent variable is the gross fund alpha (in percentage points), defined as the gross return of the fund minus the return predicted by the four-factor model estimated over the trailing 36 months. The main independent variable of interest is the interaction term between family wealth (*Wealth*) and the proxies for entry barriers defined below. *HomeUniDistance* is the distance, in thousands of kilometers, between the manager's parent home and his undergraduate college. *HighHomeUniDistance* is a binary indicator that equals one if the distance between the manager's parent home and his undergraduate college exceeds 1,000 kilometers. *UniNYDistance* is the distance, in thousands of kilometers, between the manager's undergraduate college and Manhattan, NY. *HighUniNYDistance* is a binary indicator equal to one if the distance between the manager's undergraduate college and Manhattan, NY exceeds 1,000 kilometers. *BusinessDegree* is a binary indicator equal to one if the manager's undergraduate degree is in finance, economics, accounting, or business. *UnemploymentAtEntry* is the average monthly unemployment rate (in percentage points) in the year when the manager joined the mutual fund industry. The control variables are the same as in Table 3 (suppressed for brevity). Appendix D defines the variables. All regressions include Morningstar fund style fixed effects and time fixed effects. Standard errors are clustered at the fund manager level, and the corresponding t-statistics are reported in parentheses. Statistical significance levels for this test are indicated as follows: *, 10%; **, 5%; and ***, 1%.

We are able to obtain undergraduate majors for 243 of the 387 fund managers by submitting written information requests to university registrars and using the archive of college yearbooks. We classify a manager as holding a business degree if he majored in business, finance, accounting, or economics. Column 5 in Table 6 shows that the performance gap between the managers born wealthy and poor is wider among those who pursued business degrees, as predicted by the selection hypothesis. The negative interaction term of family wealth with the business degree indicator, significant at 5%, shows that the wealth-performance sensitivity is more than twice (0.0223/0.0183 = 122%) as high among those who pursued business degrees.

Finally, we consider unfavorable economic conditions as a barrier to entry into asset management. At times of high unemployment, publicly available employment opportunities dry up, and informal channels play a more important role in job search (Calvó-Armengol, and Jackson 2004). This suggests that economic downturns increase entry barriers more steeply for the less privileged candidates, and the wealth-performance relation should be stronger for managers hired in years of high unemployment.

In Column 6 of Table 6 we study the dynamics of the managers' entries into the mutual fund industry and exploit the variation in selection stringency induced by the fluctuations in the national unemployment rate (from the Bureau of Labor Statistics). The results show that the negative wealth-performance relation is magnified by high unemployment at entry. This effect, significant at 5%, is economically meaningful: the negative sensitivity of managerial performance to family wealth increases by 39.2% of its unconditional value (0.0075/0.0191) for every percentage-point increase in the national unemployment rate.

Overall, the negative relation between family wealth and performance is likely linked to selection. Consistent with the selection mechanism, this relation is magnified by entry barriers into asset management, such as specialized education, distance to employment opportunities, and job availability.

5.2 Career progression in asset management

An ideal test of the effects of wealth and skill in selection would examine the entire pool of candidates—both those who were hired and those who were rejected—and evaluate how an individual's characteristics affect his likelihood of being hired. This test is typically infeasible for two reasons. First, the pool of rejected candidates cannot be observed. Second, even if the rejected candidates could be identified, their skill would be hard to measure because their performance as fund managers is unobservable. Although hiring decisions cannot be studied, it is reasonable to assume that similar selection criteria would apply to promotion decisions. We thus examine the career progressions of fund managers and study the determinants of their promotions and exits from the industry. In this setting, we not only observe the pool of portfolio managers, but also obtain accurate measures of each manager's professional performance.

In the analysis of career advancement, we focus on the assets delegated to the manager and the management fees to which he is entitled. The total amount of management fees serves as an upper bound for the pool of funds available for managerial pay, as the actual amount of pay is not disclosed. Following

Chapman and Evans (2010), we identify discontinuities in these statistics that usually arise from the assignment of additional assets to the manager. We use these events as proxies for managerial promotions and define two indicator variables. *Promotion, AUM inferred* is a binary indicator that equals one if the total amount of assets delegated to the manager at the end of the month more than doubles since the previous month. *Promotion, fee inferred* is a binary indicator that equals one if the combined management fee for the assets delegated to the manager more than doubles since the previous month.[10] The high thresholds imposed in these measures reflect conservatism in their construction and ensure that they capture significant events associated with tangible monetary benefits rather than lateral moves. These proxies identify important, relatively infrequent career events. The unconditional probability of being promoted in any given month is 0.63% and 0.69% for the asset- and fee-based measures, respectively.

We examine the relation between promotions and managerial performance and introduce specifications where past performance is interacted with family wealth. We define past performance (*PastGAlpha*) as the average gross monthly alpha earned by the manager over the trailing 60 months, ending in month t-1. The regression specification is a linear probability model with fixed effects, defined below:

$$\begin{aligned} Promotion_{mjt} = {} & \beta_1 PastGAlpha_{mt} + \beta_2 Wealth_m + \beta_3 PastGAlpha_{mt} * Wealth_m \\ & + \boldsymbol{\Gamma_1} \times \mathbf{FControls_{mjt-1}} + \boldsymbol{\Gamma_2} \times \mathbf{MControls_{mt-1}} + \alpha_{Yt} + \delta_s + \varepsilon_{mjt}. \end{aligned} \tag{2}$$

Table 7 shows that past performance is a strong driver of promotions, as indicated by the positive and significant coefficients on *PastGAlpha* in Columns 1–6. According to Column 1, an increase in *PastGAlpha* of 10 bps improves promotion chances by 0.044% or by 6% relative to the unconditional promotion probability. These results are consistent with the evidence in prior work that past performance is an important driver of career progression in the mutual fund industry (Khorana 1996; Hu, Hall, and Harvey 2000). The coefficients on the control variables indicate that the number of funds in the mutual fund family is positively related to the likelihood of promotion, consistent with a greater number of available promotion opportunities. The coefficients on the manager's tenure indicate that managers in the earlier stages of their careers are more likely to be promoted, suggesting a steeper career trajectory early on.

The interaction terms between a manager's performance and his family wealth show that promotions of managers from wealthier families are less

[10] The management fee is calculated as the sum (over all the funds managed by the manager) of the product of the fund TNA and the expense ratio divided by the number of managers running the fund.

Table 7
Managerial promotions and exits

Dependent variable	*Promotion, AUM inferred*			*Promotion, fee inferred*			*Exit from asset management*		
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PastGAlpha	0.0044**	0.0086**	0.0078**	0.0050**	0.0094**	0.0092**	−0.0036***	−0.0047**	−0.0046***
	(2.02)	(2.31)	(2.21)	(2.21)	(2.41)	(2.48)	(−2.78)	(−2.57)	(−2.69)
Wealth		−0.0003			−0.0003			0.0002	
		(−0.81)			(−0.95)			(0.88)	
WealthHigh			−0.0014			−0.0014			0.0019**
			(−0.86)			(−0.84)			(2.10)
*PastGAlpha * Wealth*		−0.0018**			−0.0019**			0.0003	
		(−2.11)			(−2.20)			(0.49)	
*PastGAlpha * WealthHigh*			−0.0078**			−0.0098**			0.0017
			(−2.06)			(−2.49)			(0.66)
FundSize	−0.0001	−0.0001	−0.0001	−0.0003	−0.0004	−0.0003	−0.0007*	−0.0007	−0.0007
	(−0.19)	(−0.24)	(−0.16)	(−0.56)	(−0.68)	(−0.59)	(−1.77)	(−1.63)	(−1.62)
FundAge	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000
	(0.73)	(0.71)	(0.71)	(0.49)	(0.49)	(0.50)	(0.38)	(0.38)	(0.48)
ManagerTenure	−0.0003***	−0.0003***	−0.0003***	−0.0002***	−0.0002**	−0.0002**	0.0000	0.0000	0.0000
	(−4.19)	(−3.55)	(−3.46)	(−2.92)	(−2.34)	(−2.28)	(0.18)	(−0.04)	(−0.29)
FirmSize	−0.0007	−0.0008	−0.0009	−0.0009	−0.0009	−0.0010	−0.0003	−0.0003	−0.0003
	(−1.16)	(−1.22)	(−1.32)	(−1.31)	(−1.31)	(−1.41)	(−0.62)	(−0.72)	(−0.62)
FirmLogNumFunds	0.0035**	0.0036**	0.0037**	0.0041***	0.0042***	0.0043***	0.0026***	0.0025***	0.0024***
	(2.48)	(2.48)	(2.48)	(2.80)	(2.75)	(2.74)	(3.29)	(3.15)	(3.11)
Volatility	0.0000	0.0000	0.0000	0.0001	0.0001	0.0002	−0.0003	−0.0003	−0.0003
	(−0.13)	(−0.08)	(0.14)	(0.19)	(0.27)	(0.50)	(−0.98)	(−1.00)	(−1.13)
Skewness	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(1.47)	(1.42)	(1.42)	(1.28)	(1.14)	(1.13)	(0.36)	(0.10)	(0.12)
UniSATRank	0.0023	0.0030	0.0031	0.0049	0.0055	0.0056	0.0015	0.0007	−0.0001
	(0.77)	(0.89)	(0.87)	(1.52)	(1.56)	(1.46)	(0.50)	(0.22)	(−0.02)
HasPhD	−0.0026	−0.0030*	−0.0033*	−0.0008	−0.0013	−0.0015	−0.0046***	−0.0042***	−0.0036**
	(−1.59)	(−1.66)	(−1.70)	(−0.40)	(−0.60)	(−0.66)	(−2.93)	(−2.67)	(−2.23)
ParentsEdu	0.0002	0.0004	0.0006	0.0004	0.0006	0.0007	−0.0003	−0.0006	−0.0008
	(0.16)	(0.32)	(0.41)	(0.31)	(0.44)	(0.53)	(−0.38)	(−0.83)	(−1.08)
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund style FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	41,026	40,218	40,218	41,026	40,218	40,218	37,503	36,825	36,825
Adj. R-sq	0.0054	0.0058	0.0060	0.0047	0.0050	0.0054	0.0012	0.0013	0.0015

This table studies how family wealth affects managerial promotions and exists from the mutual fund industry, using linear probability regressions. In Columns 1–6, the dependent variable is a promotion dummy, *Promotion, AUM inferred* (*Promotion, fee inferred*), defined as a binary indicator equal to one if the total dollar assets managed by the manager (total management fee accruing to the manager) more than doubles since the previous month. In Columns 7–9, the dependent variable is an exit dummy, *Exit from asset management*, defined as a binary indicator equal to one if the observation month is the last month for the manager in the sample. This variable is undefined if the observation month is December 2012 or if either of these two conditions hold: (1) the manager appears as either an insurance fund or a hedge fund manager in Morningstar in the next twelve months after leaving or (2) the manager dies in the same or next year after leaving. The main independent variable of interest is the interaction term between the manager's family wealth (*Wealth*) and his past performance (*PastGAlpha*). *PastGAlpha* is the average gross monthly alpha (in percentage points) earned by the manager over the trailing 60 months. *WealthHigh* is a binary indicator equal to one if the manager's family wealth is above the sample median. The control variables include the characteristics of the mutual fund and fund family, as well as those of the manager and his parents. Appendix D defines the variables. All regressions include Morningstar fund style fixed effects and time fixed effects. Standard errors are clustered at the fund manager level, and the t-statistics are reported in parentheses. Statistical significance levels for this test are indicated as follows: *, 10%; **, 5%; and ***, 1%.

sensitive to past performance. This effect is significant at 5% in all specifications and is economically strong. According to the interaction coefficient in Column 2, an interquartile-range increase in wealth mutes over 90% of the overall sensitivity (−0.0018*2.27/0.0044). Similar conclusions apply to the binary wealth variable and the fee-based measure of promotion. These results suggest that managers from poor families are promoted when they outperform, whereas those born rich are more likely to be promoted for reasons unrelated to performance.

Next, we study how managerial performance and family wealth are related to exits from the industry. To identify likely involuntary exits from asset management, we exclude lateral moves to hedge funds and insurance funds. To this purpose, we match our managers to those in the Morningstar universes of insurance funds and hedge funds (which comprise different data sets) using managers' names and then confirming the matches by the managers' biographies. We find that a significantly greater fraction of managers move from mutual funds to the insurance sector (9.2%) than to hedge funds (1.2%). The fraction of mutual fund managers in our sample that switch to hedge funds is similar to the estimates in prior work, such as the fraction of 1.28% in Deuskar et al. (2011), indicating that the labor market flows in our sample are comparable to those in a larger universe of managers.

We also exclude industry exits for natural causes that we can reliably identify—namely, those related to terminal health issues or death. The date of a manager's death, which comes from the Social Security Administration Death Registry, is linked to the manager's social security number and appears in the Lexis Nexis Public Records Database. We view the exits in the year of the manager's death or one year prior as those related to natural causes and exclude them from our analysis.

In Columns 7–9 of Table 7 we study the determinants of fund managers' exits from asset management. The dependent variable, *Exit from asset management*, is a binary indicator that equals one if the manager leaves the mutual fund universe in the observation month for reasons other than lateral employment moves and terminal health issues, as defined above. To the extent that some of the remaining exits in our sample contain noise as proxies for involuntary separations, it would bias our estimation against identifying significant effects. We estimate the following specification:

$$\begin{aligned} Exit_{mjt} = {} & \beta_1 PastGAlpha_{mt} + \beta_2 Wealth_m + \beta_3 PastGAlpha_{mt} * Wealth_m \\ & + \mathbf{\Gamma_1} \times \mathbf{FControls_{mjt-1}} + \mathbf{\Gamma_2} \times \mathbf{MControls_{mt-1}} + \alpha_{Yt} + \delta_s + \varepsilon_{mjt}. \quad (3) \end{aligned}$$

Table 7 shows that industry exits are preceded by poor performance. This relation is reliably significant across all specifications in Columns 7–9. Consistent with the argument that managers from wealthy families are less likely to lose jobs due to weak performance, the results suggest that wealth reduces the sensitivity of exits to past performance, as indicated by the positive interaction coefficients in Columns 8 and 9. However, this effect falls short of statistical significance at conventional levels, likely due to a relatively small number of exits and an imperfect proxy for involuntary separations.[11]

In summary, strong investment performance is a key driver of managerial promotions, and weak performance precipitates exits from the industry. The promotion-performance relation is significantly steeper for managers from poor families, suggesting that their careers are more dependent on skill. Similar criteria likely hold for hiring decisions too, albeit they cannot be tested directly. If family wealth partially substitutes for skill as a hiring factor, thus reducing the effect of skill on the hiring probability, then some unskilled wealthy managers can enter the industry.

6. Value Channels: Ability and Effort

This section focuses on two nonmutually exclusive channels that may contribute to the performance gap between managers from wealthy and poor families. The first channel posits that managers from wealthy families have weaker incentives to apply effort due to the diminishing utility of additional earnings. The second channel suggests that managers from wealthy backgrounds have a lower innate ability as a result of the less stringent selection. We acknowledge that ability and effort are difficult to define precisely. We view effort as something that a manager chooses to apply or not apply in response to incentives. In contrast, ability determines whether, conditional on exerting effort, the manager is able to deliver superior returns.

We first examine proxies for professional activity. In these tests, we do not assume that greater activity creates value, but rather regard activity as a sign that a manager does not opt for a “quiet life,” a low-effort style documented in other settings (Bertrand and Mullainathan 2003). We compute three proxies for managerial activity. *Turnover* is defined as the annualized ratio of the sum of absolute values of dollar changes in the fund’s equity positions over the quarter to the average dollar value of the fund’s portfolio, as in Gaspar, Massa, and Matos (2005). *Holding horizon* measures how many months, on average, shares are held in the fund’s portfolio. This variable is computed as in Lan, Moneta, and Wermers (2017), using the assumption that shares bought first are sold first. *Herding* is equal to the correlation between changes in fund holdings over the quarter (measured by the percentage change in the number of shares held) and the corresponding changes in the holdings of a hypothetical average fund in the style, whose portfolio position in a given stock is calculated as the

[11] The higher likelihood of exit by poorly performing managers from less wealthy families does not introduce a sample composition bias to our analysis. This bias would only result if either the wealth measure were time dependent or if alpha had a time trend, so that managers who are more likely to stay in the sample had a higher chance of performing well. Neither of these is the case. Furthermore, we include time fixed effects in all the regressions to eliminate any possible composition issues.

sum of the aggregate positions in the stock of all the funds in the style. Higher values indicate funds whose trades are closer to the style's average in direction and magnitude.

We examine how these portfolio variables are related to the manager's family wealth by estimating the following regression specification:

$$Activity_{mjT} = \beta Wealth_m + \mathbf{\Gamma_1} \times \mathbf{FControls_{mjT-1}} + \Gamma_\mathbf{2} \times \mathbf{MControls_{mT-1}} + \alpha_{Yt} + \delta_s + \varepsilon_{mjT}, \quad (4)$$

where the right-hand side variables are defined as in Equation (1) and the left-hand side variables are the measures of activity for fund j in quarter T. We run this regression with and without controls for volatility and skewness, because some dependent variables can be related to volatility and skewness by construction.

The results, reported in Columns 1−6 of Table 8, panel A, are directionally consistent across all the activity measures. Managers from less wealthy families are more active: they trade more, have shorter holding horizons, and are less prone to herding. The results on turnover and holding horizon are statistically significant at least at 10%. An interquartile-range increase in wealth decreases annual turnover by 1.43 (based on Column 2), or by 4.5% of its mean of 32.2, and increases the holding horizon by 1.96 months (based on Column 4), or by 5% of its mean of 39.1.

Higher turnover and shorter horizon could be value-enhancing or destroying, depending on the timing of the trades and the stocks traded. To understand the drivers of the performance gap, we follow the ideas of Henriksson and Merton (1981) and the methodology of Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) and decompose fund returns into the stock selection and market timing components. For example, *Market timing* is defined as the sum across the fund's holdings of the term $(w_{in\ fund} - w_{in\ benchmark})^{*}\beta * r_M$, where $w_{in\ fund}$ is the weight of the stock in the fund portfolio, $w_{in\ benchmark}$ is the weight of the stock in the market (benchmark) portfolio, r_M is the market return in the quarter, and β is the stock beta computed from the one-factor model over the trailing 36 months. Appendix D defines the variables.

We run regression (4) with *Stock picking* and *Market timing* as dependent variables and report the results in Columns 7−10 of Table 8, panel A. The evidence indicates that less wealthy managers are not significantly better at market timing but have superior stock-picking skills. The coefficient on *Stock picking* is significant at 1% and economically large. In Column 8, an interquartile-range increase in family wealth decreases the stock-picking return by 11.2 bps per quarter (38.8% of the sample mean). Combined with the earlier results, this evidence supports the view that active trading adds value as long as the manager has skill (Pastor, Stambaugh, and Taylor 2017). In Internet Appendix Table 1, we study how managers'

Table 8
Family wealth and portfolio activity

A. Baseline effect

Dependent variable	*Turnover*		*Holding horizon*		*Herding*		*Stock picking*		*Market timing*	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Wealth	−0.6100*	−0.6315**	0.8966*	0.8615*	0.2746	0.2612	−0.0488***	−0.0494***	0.0078	0.0054
	(−1.91)	(−2.20)	(1.76)	(1.79)	(1.08)	(1.05)	(−2.72)	(−2.93)	(0.31)	(0.21)
FundSize	−1.8683**	−2.1347***	−0.0680	0.1528	4.2439***	4.0979***	−0.1186**	−0.1106**	0.0048	−0.0046
	(−2.27)	(−2.95)	(−0.08)	(0.18)	(8.47)	(8.40)	(−2.55)	(−2.35)	(0.11)	(−0.11)
FundAge	−0.0364	0.0441	0.4974**	0.4175*	0.0341	0.0620	−0.0042	−0.0065	0.0037	0.0043
	(−0.21)	(0.28)	(2.16)	(1.96)	(0.33)	(0.62)	(−0.55)	(−0.88)	(0.46)	(0.52)
ManagerTenure	−0.2656*	−0.2239	0.4910**	0.4634**	0.1790*	0.1980*	0.0165**	0.0155**	0.0066	0.0079
	(−1.70)	(−1.55)	(2.02)	(1.96)	(1.73)	(1.93)	(2.38)	(2.25)	(0.87)	(1.03)
FirmSize	−0.5642	−0.4538	1.2181	1.1055	−0.4203	−0.3792	0.0257	0.0220	−0.1207**	−0.1199**
	(−0.63)	(−0.57)	(1.33)	(1.28)	(−0.72)	(−0.66)	(0.52)	(0.44)	(−2.49)	(−2.45)
FirmLogNumFunds	4.0281**	3.9514**	−5.9871***	−5.9059***	−0.0469	−0.0726	−0.0672	−0.0647	0.2022**	0.2020**
	(2.23)	(2.42)	(−3.08)	(−3.25)	(−0.05)	(−0.07)	(−0.81)	(−0.77)	(2.31)	(2.29)
UniSATRank	−2.3869	−0.6164	12.6310	11.4685	0.8415	0.7179	0.3755	0.3484	−0.1108	−0.1677
	(−0.29)	(−0.08)	(1.46)	(1.46)	(0.20)	(0.17)	(1.17)	(1.08)	(−0.38)	(−0.56)
HasPhD	4.8825	4.4912	−7.2772***	−6.8686***	−1.3171	−1.6960	−0.0941	−0.0756	−0.2114	−0.2431
	(1.43)	(1.43)	(−2.96)	(−2.74)	(−0.58)	(−0.73)	(−0.45)	(−0.35)	(−1.02)	(−1.16)
ParentsEdu	−0.1573	0.1287	−4.4731	−4.5394*	−2.5214**	−2.4993**	0.0253	0.0219	0.0810	0.0819
	(−0.08)	(0.08)	(−1.54)	(−1.65)	(−2.36)	(−2.43)	(0.31)	(0.27)	(1.00)	(1.02)
Volatility		3.7071***		−3.6169***		1.3885***		−0.1062***		0.0360
		(5.06)		(−5.67)		(4.40)		(−3.10)		(0.78)
Skewness		0.0357***		−0.0298*		−0.0253***		−0.0004		−0.0037***
		(3.12)		(−1.92)		(−2.61)		(−0.29)		(−2.63)
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund style FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	6,499	6,499	8,723	8,723	8,692	8,692	8,440	8,440	8,440	8,440
Adj. R-sq	0.1235	0.1735	0.2488	0.3013	0.2714	0.2791	0.1043	0.1053	0.3524	0.3528

(continued)

Table 8
Continued

B. Inheritances of wealth

Dependent variable	*Turnover*		*Holding horizon*		*Herding*		*Stock picking*		*Market timing*	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Wealth	−0.4951	−0.4369	−0.6104	−0.6831	0.1587	0.1277	−0.0421	−0.0469	−0.0169	−0.0202
	(−0.75)	(−0.75)	(−1.05)	(−1.39)	(0.36)	(0.29)	(−1.14)	(−1.32)	(−0.41)	(−0.50)
ParentsDead	4.8669	4.2317	−6.7523*	−6.3561*	−1.9155	−1.9079	−0.1726	−0.1528	0.2276	0.2266
	(1.47)	(1.38)	(−1.91)	(−1.88)	(−0.82)	(−0.85)	(−1.16)	(−1.04)	(1.19)	(1.22)
Wealth * *ParentsDead*	−0.5290	−0.7124	1.7533**	1.9567**	0.3554	0.3313	−0.0024	0.0063	0.0354	0.0319
	(−0.74)	(−1.05)	(2.16)	(2.38)	(0.51)	(0.49)	(−0.06)	(0.15)	(0.81)	(0.74)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager's controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parents' controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vol. and skew controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund style FEs.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	4,257	4,257	5,636	5,636	5,616	5,616	5,452	5,452	5,452	5,452
Adj. R-sq	0.1346	0.1692	0.2239	0.2701	0.2949	0.2991	0.1100	0.1117	0.3493	0.3499

This table studies the relation between a manager's family wealth and his portfolio activity. The dependent variable is one of the measures of portfolio activity, as described below. *Turnover* is the annualized ratio (in percentage points) of the sum of the absolute dollar changes in the fund's positions over the quarter to the average fund portfolio value in these adjacent quarters. *Holding horizon* (in months) measures the average duration that the shares are held in the fund's portfolio. It is based on the first-in, first-out (FIFO) assumption about share purchases and sales, as in Lan, Moneta, and Wermers (2016). *Herding* is the correlation (in percentage points) between the changes in positions of the fund and the changes in positions of the hypothetical average fund in the same style. *Stock picking* and *Market timing* denote the component of fund performance attributable to stock selection and market timing, respectively, as in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014). All the regressions are run at quarterly frequency. Panel A shows the baseline relation between family wealth and portfolio activity. Panel B shows the effect of an increase in managerial wealth from inheritances proxied by the death of the last parent. In panel B, the indicator variable *ParentsDead* is equal to one if both of the manager's parents had died before the observation year and zero otherwise. This variable is set to missing if either parent died in the observation year. Appendix D defines the variables. All regressions include Morningstar fund style fixed effects and time fixed effects. Standard errors are clustered at the fund manager level, and the t-statistics are reported in parentheses. Statistical significance levels for this test are indicated as follows: *, 10%; **, 5%; and ***, 1%.

family wealth is related to the characteristics of their funds' portfolios. There is weak evidence that managers from wealthier families hold bigger and lower book-to-market stocks. Other portfolio characteristics, such as momentum, illiquidity, volatility, and beta are not significantly related to family wealth.

As a further test of the effort channel, we exploit an exogenous increase in a manager's own wealth from an inheritance, an event proxied by the death of the last parent. Under the effort channel, a manager's incentives to apply effort should decrease after the inheritance, but only for wealthy managers. We define an indicator variable *ParentsDead*, which equals one if both of the manager's parents died before the observation year and zero otherwise. We set this variable to missing if either parent died in the observation year. This approach omits one year of observations around the death event to account for possible effects of emotional distress and personal distractions associated with the loss of a parent.

We rerun regression (4) with *ParentsDead* and its interaction with *Wealth* as independent variables and report the results in panel B of Table 8. The interaction term captures the difference in the response of the activity variables to the inheritance events between the rich and the poor. The results are directionally consistent with the predictions of the effort channel: managers from wealthier families become relatively less active after the inheritance. For example, in Column 2, the negative effect of family wealth on turnover increases by 163% (0.7124/0.4369) post-inheritance.

Unlike effort, innate ability is not directly observable. Absent a direct proxy for ability, a natural question is to what extent the performance gap between the rich and poor is driven by differential incentives. To the extent that value creation is driven by stronger incentives of the poor, the performance gap should decrease as managers from poor families accumulate personal wealth throughout their careers. We revisit the results in Column 4 of Table 4. They show that the interaction between *Wealth* and *ManagerTenure* is positive, but economically small and statistically insignificant. In other words, the performance differential between managers from rich and poor backgrounds remains economically stable across the course of their careers, suggesting that it is related to inherent, time-invariant aspects of managerial ability.

In summary, both the effort and ability channels are likely operative in our setting. Viewed broadly, our findings are consistent with the work in labor economics that singles out an individual's "smarts" and "drive" as the key determinants of professional performance (Heckman, Stixrud, and Urzua 2006).

7. Discussion and Extensions

This section discusses the implications of our findings, their external validity, and possible extensions.

7.1 Side benefits and agency

It is natural to ask whether managers from wealthier families deliver their employers other benefits uncaptured by investment returns. If so, one can envision a rational equilibrium where it is optimal for financial firms to employ such managers even at the expense of weaker performance. This question is difficult to address comprehensively because many benefits are unobservable. Most asset management firms are private and do not disclose their financial data. Furthermore, some benefits might accrue not to the firm itself but to its senior management, making them difficult to detect. Given these challenges, we investigate two measurable mechanisms through which managers from wealthy families can add value for their firms: attracting capital flows and earning revenues through high fees.

First, we focus on fund flows—changes in fund assets resulting from the contributions and redemptions of capital by investors. Table 9 examines the relation between a fund manager's family wealth and the net capital flow into the fund, computed as the percentage change in fund assets unexplained by fund returns. Since a manager's family wealth is related to performance, we consider specifications with and without controls for performance—a key driver of fund flows (Chevalier and Ellison 1997; Sirri and Tufano 1998). Past performance is defined as the average net alpha of the fund over the trailing three years.

Without controls for past performance, *Wealth* is weakly negatively related to flow, as indicated by the marginally significant negative coefficient on *Wealth* in Column 1. However, this effect is largely explained by the response of flows to past performance: the coefficient on past performance is highly significant in Column 2, whereas the coefficient on family wealth is not. Columns 3 and 4 accommodate the convexity in the flow-performance relation by allowing the flow sensitivity to be different over different ranges of past performance. In Column 3, the higher slope in the positive range indicates that flow is convex in past performance. In Column 4, we fit a continuous piecewise linear regression with three segments and continue to observe different effects for low and high levels of performance. As we refine the specification, the negative effect of *Wealth* on flow weakens, indicating that the manager's family wealth affects flows only via performance but not by itself. Importantly, we never observe a positive effect of family wealth on flows.

It is perhaps not surprising that mutual fund managers of higher social status are not able to attract more flows. A mutual fund manager has no direct communication with investors, and most investors are likely unaware of the manager's familial background. While a manager from a wealthy family could in theory attract the family's capital, this effect is less likely if the manager has poor skill. Prior work in household economics shows that parents understand their children's ability and use this knowledge in the allocation of capital and other resources (see Behrnan 1997 for a review). This suggests that wealthier families (and their friends) would likely avoid entrusting large sums of capital to a child of modest skill.

Table 9
Family wealth and capital flows

Dependent variable	*Flow*					
Model	(1)	(2)	(3)	(4)	(5)	(6)
Wealth	−0.0555*	−0.0286	−0.0275	−0.0228	−0.0368	−0.0136
	(−1.94)	(−1.03)	(−1.00)	(−0.79)	(−1.29)	(−0.35)
PastAlpha		2.5259***			2.7627***	
		(10.56)			(7.21)	
*PastAlpha * Wealth*					−0.1024	
					(−0.98)	
PastAlphaLow			1.4578***			1.4386***
			(5.86)			(3.25)
PastAlphaHigh			3.3648***			3.6939***
			(7.22)			(4.86)
PastAlphaT1				0.4188		
				(1.53)		
PastAlphaT2				5.2614***		
				(7.65)		
PastAlphaT3				2.8985***		
				(5.40)		
*PastAlphaLow * Wealth*						0.0098
						(0.07)
*PastAlphaHigh * Wealth*						−0.1509
						(−0.72)
FundSize	−0.2892***	−0.2982***	−0.2741***	−0.2677***	−0.2997***	−0.2746***
	(−3.62)	(−3.68)	(−3.50)	(−3.41)	(−3.66)	(−3.47)
FundAge	−0.0633***	−0.0462***	−0.0422***	−0.0393***	−0.0457***	−0.0421***
	(−5.94)	(−4.73)	(−4.32)	(−4.05)	(−4.68)	(−4.30)
ManagerTenure	0.0080	0.0017	0.0038	0.0016	0.0023	0.0043
	(0.73)	(0.18)	(0.40)	(0.17)	(0.23)	(0.45)
FirmSize	0.4478***	0.4006***	0.3852***	0.3619***	0.4009***	0.3852***
	(4.87)	(4.55)	(4.47)	(4.20)	(4.53)	(4.44)
FirmLogNumFunds	−0.8208***	−0.6980***	−0.6722***	−0.6278***	−0.6996***	−0.6742***
	(−4.77)	(−4.51)	(−4.42)	(−4.15)	(−4.50)	(−4.40)
Volatility	−0.0368	0.0244	−0.0211	−0.0195	0.0241	−0.0200
	(−0.65)	(0.44)	(−0.37)	(−0.35)	(0.43)	(−0.35)
Skewness	0.0028*	0.0020	0.0018	0.0018	0.0020	0.0018
	(1.71)	(1.35)	(1.21)	(1.24)	(1.35)	(1.22)
UniSATRank	−0.8459	−1.0209*	−0.9901*	−1.0404**	−1.0190*	−0.9800*
	(−1.56)	(−1.93)	(−1.89)	(−2.00)	(−1.93)	(−1.88)
HasPhD	0.4297	0.2233	0.2632	0.2740	0.2164	0.2511
	(1.19)	(0.68)	(0.80)	(0.82)	(0.65)	(0.76)
ParentsEdu	−0.0161	−0.0348	−0.0310	−0.0338	−0.0329	−0.0274
	(−0.14)	(−0.30)	(−0.27)	(−0.29)	(−0.29)	(−0.24)
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Fund style FEs	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	40,334	39,776	39,776	39,776	39,776	39,776
Adj. R-sq	0.0121	0.0337	0.0352	0.0368	0.0338	0.0353

This table shows the regressions of monthly capital flows into the fund on the manager's family wealth and the fund's past performance. The dependent variable is the fund's capital flow (in percentage points), computed as the ratio of the net dollar flow into the fund over the month to the previous-month fund TNA. The net dollar flow into the fund is the difference between the end-of-month fund TNA and the previous-month fund TNA multiplied by one plus the gross return of the fund over the month. *PastAlpha* is the fund's average net monthly alpha (in percentage points) over the past 36 months. *PastAlphaLow* (*PastAlphaHigh*) is equal to *PastAlpha*, if *PastAlpha* is negative (positive), and zero otherwise. *PastAlphaT1*, *PastAlphaT2*, and *PastAlphaT3* are defined so that the regression fits a continuous piecewise linear function with kinks at the terciles of the *PastAlpha* distribution, following Sirri and Tufano (1998). Appendix D defines the variables. All regressions include Morningstar fund style fixed effects and time fixed effects. Standard errors are clustered at the fund manager level, and the t-statistics are reported in parentheses. Significance levels are indicated as follows: *, 10%; **, 5%; and ***, 1%.

Table 10
Family wealth and management fees

Dependent variable	*Expense ratio*			
Model	(1)	(2)	(3)	(4)
Wealth	0.0020	−0.0013		
	(0.27)	(−0.17)		
Wealth, rank			0.0385	0.0175
			(0.64)	(0.30)
FundPastPerformance		0.0149*		0.0145*
		(1.79)		(1.71)
FundSize		−0.0510***		−0.0533***
		(−4.06)		(−4.24)
FundAge	−0.0023	0.0016	−0.0020	0.0021
	(−0.84)	(0.59)	(−0.74)	(0.78)
ManagerTenure	−0.0092***	−0.0082***	−0.0093***	−0.0083***
	(−3.84)	(−3.59)	(−3.97)	(−3.78)
FirmSize	−0.0839***	−0.0538***	−0.0851***	−0.0532***
	(−7.87)	(−3.87)	(−7.89)	(−3.81)
FirmLogNumFunds	0.1024***	0.0855***	0.1030***	0.0837***
	(3.59)	(2.93)	(3.63)	(2.90)
Volatility	0.0347***	0.0394***	0.0335***	0.0385***
	(3.01)	(3.45)	(2.91)	(3.38)
Skewness	0.0000	0.0000	0.0000	0.0000
	(0.09)	(−0.15)	(0.14)	(−0.13)
UniSATRank	0.0993	0.0965	0.0802	0.0803
	(0.79)	(0.79)	(0.61)	(0.63)
HasPhD	0.0133	−0.0036	0.0199	0.0011
	(0.25)	(−0.07)	(0.37)	(0.02)
ParentsEdu	−0.0466*	−0.0582**	−0.0458*	−0.0585**
	(−1.67)	(−2.09)	(−1.66)	(−2.11)
Time FEs	Yes	Yes	Yes	Yes
Fund style FEs	Yes	Yes	Yes	Yes
Num. obs.	3,514	3,372	3,556	3,413
Adj. R-sq	0.3033	0.3259	0.2998	0.3240

This table studies the relation between a fund manager's family wealth and the expense ratio of his fund. The dependent variable is the fund's annual expense ratio, expressed in percentage points. Appendix D defines the variables. All regressions include Morningstar fund style fixed effects and time fixed effects. Standard errors are clustered at the fund manager level, and the t-statistics are reported in parentheses. Significance levels are indicated as follows: *, 10%; **, 5%; and ***, 1%.

Next, we investigate whether, despite their inferior performance, managers from wealthier families still charge high fees (for example, by developing better customer relations and trust, as in Gennaioli, Shleifer, and Vishny 2015). We focus on the expense ratio (available at an annual frequency)—the fraction of the fund's TNA charged as management fee. In Table 10, we regress the expense ratio on the manager's family wealth. We consider specifications with and without controls for fund size and performance, because (1) the expense ratio is generally lower for larger funds and higher for better performing funds and (2) both fund size and performance are partly endogenous to the manager's wealth, since poorer managers grow their funds quicker due to the positive flow-performance relation. We do not find a significant relation between the manager's family wealth and the fund's expense ratio. This relation is weakly positive in the absence of size and performance controls and becomes even weaker after these controls are added.

Overall, we are unable to detect tangible benefits that would compensate for the inferior performance of wealthy managers. These findings point to possible frictions and agency problems in the mutual fund industry. However, extensive research is needed to quantify the extent of these problems. Recent developments indicate that hiring practices related to candidates from wealthy families remain an important regulatory focus. For example, on August 18, 2015, the SEC issued a cease-and-desist order to Bank of New York Mellon Asset Management regarding the preferential recruiting of wealthy candidates. The SEC has concluded that applicants from wealthy families faced lower selection stringency in the recruiting process: "An SEC investigation found that BNY Mellon did not evaluate or hire the family members through its existing, highly competitive internship programs that have stringent hiring standards and require a minimum grade point average and multiple interviews. The family members did not meet the rigorous criteria yet were hired with the knowledge and approval of senior BNY Mellon employees..."[12]

The SEC suggests one explanation for why these hiring practices could persist at financial firms. In particular, managers making the hiring and promotion decisions obtain additional benefits, whether intangible or pecuniary, which do not accrue to the end investor. Some of these benefits are familial, as when the fund manager is a relative of other portfolio managers or fund family founders.[13] Others may include access to social networks and political connections or a manifestation of homophily—an affinity for similar others (McPherson, Smith-Lovin, and Cook 2001). While it is difficult to draw a reliable link between a manager's family descent and these outcomes—a task beyond the scope of our paper—we believe that a likely explanation for the wealth-performance relation is the occasional divergence between the interests of the principal and its agents in delegated asset management. Such labor market frictions have been documented in other settings. For example, Fracassi and Tate (2012) find that powerful CEOs favor the appointment of directors based on personal preferences, a bias that damages the firm's performance. Duchin and Sosyura (2013) show that social connections to the CEO affect the appointment of managers to divisions. Using detailed personnel data and measures of individual productivity, Bandiera, Barankay, and Rasul (2009) find evidence of managerial favoritism in hiring lower-ability employees.

7.2 Large sample analysis

Our core analysis focuses on older managers and provides evidence on an important selection mechanism at the genesis of the mutual fund industry. A natural follow-up question is whether the relation between wealth and

---

[12] Securities and Exchange Commission Press (release no. 2015-170, dated August 18, 2015).

[13] For example, Carole S. Kinney succeeded her father Charles Walters Steadman as a manager at Ameritor. Similarly, Christine M. Baxter, a former manager of PBHG Emerging Growth Fund, is the daughter of Harold J. Baxter, the founder of the company.

performance applies to younger managers and whether the composition of managers by family wealth changed over time. In this subsection, we provide suggestive evidence on these issues.

To circumvent data limitations on the endowed wealth of younger managers, we consider a crude wealth proxy—college tuition. This simple proxy is intended to facilitate replication of our results, but it comes with limitations. While the median tuition increases monotonically across the wealth quintiles (Table 2, panel B), its correlation with the income of the manager's father is a moderate 0.362. This proxy misses a part of variation in wealth because some capable students from poor families obtain scholarships to attend expensive colleges and because the actual tuition paid by the student is unobservable. We believe that the precise measurements from the census records cannot be easily substituted with alternative proxies.

Our tuition data come from the 2004 College Handbook and reflect the costs of education as of 2004. Yet the ranking of colleges by tuition has remained relatively stable since the 1970s. We therefore rank all colleges by undergraduate tuition and study the relation between tuition rank and managerial performance. Columns 1–3 in Table 11, panel A, focus on the entire sample and consider different controls for education quality that correlate with tuition, such as the college's SAT rank and admission rate. We find a consistent negative effect of tuition on managerial performance, significant at 5% in Columns 1 and 3. In contrast, education quality (higher SAT scores and lower admission rates) has a strong positive effect on performance. As expected, the economic effect of tuition is weaker (by about 60%) than the effect of the father's income in our main analysis. In the full specification in Column 3, an interquartile range increase in tuition (50 percentiles) reduces the four-factor alpha by 2.4 bps a month or 0.28% per year.

This difference in magnitudes could be attributed to a less precise measurement of wealth, or it might reflect a more egalitarian selection into asset management in recent years. We examine the latter conjecture by splitting our sample into two subsamples by the manager's year of birth and reestimating the regression. Column 4 (5) shows the results for the managers born before (in or after) 1960. The relation between performance and tuition is negative in both subsamples and has similar economic magnitudes. The lack of statistical significance in the younger sample can be explained by its smaller size which compounds the measurement error problem. Yet the economic magnitudes do not diminish in the younger sample, indicating that the effect remains relevant beyond our sample period. However, we caution the reader that this evidence is at best suggestive, given the lack of precision in the wealth proxy.

Finally, we investigate the composition of managers by family wealth over time and in the cross-section of firms. We consider two proxies for family wealth: raw tuition and the residual of this tuition when regressed on the admission rate. The latter measure allows us to identify wealth more directly without contaminating it with education quality. In each year and for each

Table 11
Large sample analysis and the characteristics of mutual fund companies

A. College tuition as a proxy for family wealth

Dependent variable	*Gross four-factor alpha*				
	Entire sample			Birth year <1960	Birth year ⩾ 1960
Model	(1)	(2)	(3)	(4)	(5)
UniTuitionRank	−0.0437**	−0.0308	−0.0474**	−0.0455*	−0.0489
	(−1.99)	(−1.32)	(−2.15)	(−1.71)	(−1.23)
FundSize	−0.0297***	−0.0296***	−0.0306***	−0.0388***	−0.0162***
	(−7.18)	(−7.21)	(−7.36)	(−6.82)	(−2.89)
FundAge	−0.0004	−0.0004	−0.0004	−0.0008	−0.0003
	(−0.67)	(−0.61)	(−0.59)	(−0.85)	(−0.32)
ManagerTenure	0.0010	0.0008	0.0010	0.0022**	−0.0024
	(1.09)	(0.92)	(1.09)	(2.11)	(−1.05)
FirmSize	0.0179***	0.0193***	0.0178***	0.0307***	−0.0117
	(3.30)	(3.56)	(3.23)	(4.35)	(−1.27)
FirmLogNumFunds	−0.0192*	−0.0201*	−0.0200*	−0.0464***	0.0385**
	(−1.85)	(−1.94)	(−1.90)	(−3.58)	(2.12)
Volatility	−0.0575***	−0.0582***	−0.0565***	−0.0476***	−0.0662***
	(−9.05)	(−9.22)	(−8.90)	(−7.11)	(−5.40)
Skewness	0.0014***	0.0015***	0.0014***	0.0013***	0.0017***
	(9.70)	(10.20)	(9.51)	(6.89)	(6.95)
UniSATRank	0.1917***		0.1895***	0.1884***	0.1906**
	(4.29)		(4.21)	(3.54)	(2.34)
UniAdmissionRate		−0.1040***			
		(−3.60)			
HasPhD			0.0107	0.0063	0.0387
			(0.43)	(0.27)	(0.34)
Time FEs	Yes	Yes	Yes	Yes	Yes
Fund style FEs	Yes	Yes	Yes	Yes	Yes
Num. obs.	198,789	202,414	193,765	125,827	67,439
Adj. R-sq	0.0157	0.0157	0.0162	0.0145	0.0205

B. Temporal trends in the employment of managers, relative measures of family wealth

	Employed managers		Newly hired managers	
Decade	Tuition	Residual tuition	Tuition	Residual tuition
1970–1979	3.232	2.992	3.119	3.054
1980–1989	3.041	2.924	3.041	3.038
1990–1999	2.917	2.928	2.951	3.028
2000–2009	2.800	2.834	2.886	2.910
>2009	2.840	2.875	2.800	2.948

C. Characteristics of mutual fund companies

	Employed managers		Newly hired managers	
	Tuition	Residual tuition	Tuition	Residual tuition
Company size (log of TNA in $000)	0.111	0.048	0.117	0.058
Investment style concentration	−0.095	−0.044	−0.033	−0.011
Managers' TNA concentration	−0.063	−0.061	−0.030	−0.010
Academic selectivity	−0.106	−0.102	−0.045	−0.027
Manager turnover	0.072	0.100	0.054	0.065

(continued)

Table 11
Continued

This table studies the relation between a fund manager's family wealth and his professional performance in the full sample of managers unrestricted by birth year. In panel A, the dependent variable is the gross fund alpha (in percentage points), defined as the gross return of the fund minus the return predicted by the four-factor model estimated over the trailing 36 months. The main independent variable of interest is the percentile rank of the annual tuition at the manager's undergraduate institution (*UniTuitionRank*), a large-sample proxy for the manager's endowed family wealth. Columns 4 and 5 show the results in the subsamples split by the manager's year of birth. Standard errors are clustered at the fund manager level, and the t-statistics are shown in parentheses. Panel B studies how the prevalence of wealthy managers in the asset management industry has changed over time. This panel reports the average tuition quintile of employed and newly hired managers for every decade in our sample period: 1975–2012. Quintile 5 denotes the wealthiest managers. Panel C shows correlations between the characteristics of mutual fund companies and the weighted-average tuition or residual tuition (net of the admission rate) of the employed and newly hired managers. *Investment-style concentration* is the Herfindahl concentration index of dollar assets managed by the company in different Morningstar styles. *Managers' TNA concentration* is the Herfindahl concentration index of dollar assets managed by different managers. *Academic selectivity* is the Herfindahl concentration index of dollar assets managed by managers from different universities. *Manager turnover* is the arithmetic average between the number of managers who joined the company and the number of managers who left the company over the past three years divided by the number of managers employed by the company in the year of observation.

mutual fund company, we compute two composition measures: the weighted (by TNA) average tuition of all managers employed by the company and the weighted average tuition of managers who joined that company in the last three years (i.e. "newly hired managers"). High values of these variables in a given year indicate that the company employed or recently hired people from wealthy backgrounds.

Table 11, panel B, investigates the time-series pattern and reports the average tuition quintile of employed and newly hired managers (quintile 5 denotes the wealthiest managers) for every decade of our sample period. The pattern for the raw tuition suggests that preference for wealthier managers has diminished monotonically with time. The average family wealth of newly hired managers decreased by 10.2% ([2.800–3.119]/3.119) from the 1970 decade to the 2010 decade. However, this effect becomes substantially weaker if we consider tuition net of education quality: the average family wealth decreased by 3.4% ([2.948–3.054]/3.054) in this case. Overall, it appears that, as the industry grew, its hiring policies became less exclusive, but this pattern is not specific to family wealth.

Next, we examine the relations between mutual fund company characteristics and the composition of their managerial workforce. Since the vast majority of asset management firms are private and do not disclose their financial data, we focus on the characteristics that do not require such data. We compute three Herfindahl concentration measures. *Investment style concentration* is the Herfindahl concentration of dollar assets managed in different Morningstar styles. This measure is high if the firm specializes in few styles and low if the firm is more diversified across styles. *Managers' TNA concentration* is high if most of the firm's assets are managed by a handful of managers and low if the assets are divided among managers more evenly. *Academic selectivity* is high if the firm's managers come from a selected few colleges and low if the firm employs managers from different colleges.

In addition, we compute a measure of managerial turnover. Each year, we calculate the average between the number of managers who joined and who left the company over the past three years and divide this result by the number of managers employed in the year of observation.

Table 11, panel C, shows correlations between the characteristics of mutual fund firms and the average family wealth of employed and newly hired managers, where each observation is firm-year. The correlations are modest but suggest a pattern. Wealthier managers are more likely to be employed by larger firms and those that have a more diverse clientele (low style concentration). Less wealthy managers are employed by firms where each manager's performance has a bigger impact on the firm (high managers' TNA concentration) and where managerial turnover is low. To the extent that less wealthy managers are on average more skilled, these results suggest that a firm is more careful in its hiring policies if it is less diversified. Put differently, firms that diversify their performance risks over a larger pool of styles, managers, and expertise sets have weaker incentives to screen for top performers in each hiring decision. These less sharp hiring policies are consistent with a higher personnel turnover in such firms.

8. Conclusion

We find that managers from wealthy families deliver lower risk-adjusted returns than managers from poor families. Our evidence suggests that managers endowed with higher wealth at birth face lower entry barriers into asset management, and some of the less skilled managers succeed in entering the profession. Consistent with the selection mechanism, the presence of additional entry barriers, either cross-sectional (geographical distances) or time series (high unemployment), enhances the negative wealth-performance relation. This explanation is further supported by the evidence on managers' career progressions, which shows that less objective promotion criteria apply to managers from wealthier families.

Recent work suggests that our findings may extends to other settings. Reeves and Howard (2013) find that over 40% of people born into wealthy families obtain high-income jobs despite having low scores of cognitive ability and internal drive. Bennedsen et al. (2007) and Mehrotra et al. (2013) show that managers who become CEOs via their inherited family status underperform those hired externally. Lee, Shin, and Yun (2017) find a decline in firm performance around family successions in Korean chaebols. Du (2017) shows that CEOs born into poor families outperform those born into wealthy families according to operating performance, stock returns, and merger outcomes. We hope that an increased focus on an agent's family background will continue to yield valuable insights in different economic settings.

Appendix A. The Model

This appendix presents a simple model that describes selection in the mutual fund industry and formalizes the relation between fund managers' family wealth and their professional performance.

For each manager, his performance level α is determined by a combination of skill s and noise ε_α (everywhere in the model, all noise components denoted ε are independent of the main variables):

$$\alpha = s + \varepsilon_\alpha,$$

Each candidate seeking to become a manager is endowed with family wealth w and some level of skill s. Initially, we will investigate a baseline case in which s is independent of w.

On their path to the job, candidates face a selection barrier. Both skill and family wealth help candidates overcome this barrier. A candidate passes the barrier and becomes a manager if

$$s + \beta_w w > \gamma,$$

where γ measures the barrier's stringency and β_w measures the influence of family wealth. For example, if $\beta_w = 0$, then the barrier is completely egalitarian and only filters on skill.

We face a trade-off of convenience in our choice of distributions for s and w. A uniform distribution is convenient for studying selection, because it is robust under truncation; that is, a truncated uniform distribution is still a uniform distribution. However, a uniform distribution is not convenient to formalize statistical dependencies among variables because it is not stable; that is, a sum or a mean of uniformly distributed random variables is not uniformly distributed. For this reason, we will illustrate the baseline case (in which s is independent of w) assuming that s and w are uniformly distributed, but will assume normal distributions in the more general case.

Our analysis is conducted conditional on a candidate becoming a manager. Specifically, we are interested in the manager's level of performance $E[\alpha|pass]$, where *pass* indicates that the manager passed the selection barrier (in practice, several such barriers):

$$E[\alpha|pass] = E[s|s + \beta_w w > \gamma] = E[s|s > \gamma - \beta_w w].$$

The last term represents the expected value of a truncated random variable. If s is uniformly distributed on $[0, s_{max}]$, then

$$E[s|s > \gamma - \beta_w w] = \frac{\gamma + s_{max}}{2} - \frac{\beta_w}{2} w.$$

Therefore, to the extent that wealth helps overcome the barrier ($\beta_w > 0$), the relationship between $E[\alpha|pass]$ and w is negative.

Next, we allow managerial skill to vary with wealth. For example, access to good education and professional networks depends on family wealth but also enhances skill. We model this case as follows.

Skill s is a noisy function of the drivers of skill d:

$$s = d + \varepsilon_s.$$

The inclusion of ε_s indicates that some component of skill cannot be explained by any observable drivers.

The drivers of skill, in turn, depend on wealth

$$d = d_0 + \delta w + \varepsilon_d,$$

Here, δ captures the strength of dependency of these drivers on wealth. In this part of the model, we assume normal distributions for all exogenous variables: ε_s, ε_d, w. This means that s as a function of w is also normally distributed with mean $d_0 + \delta w$ and variance $\sigma_d^2 + \sigma_s^2$.

We first investigate the relationship between performance and wealth in a specification where we don't control for any wealth-related drivers of skill. That is, as before, we are interested in $E[\alpha|pass] = E[s|s > \gamma - \beta_w w]$.

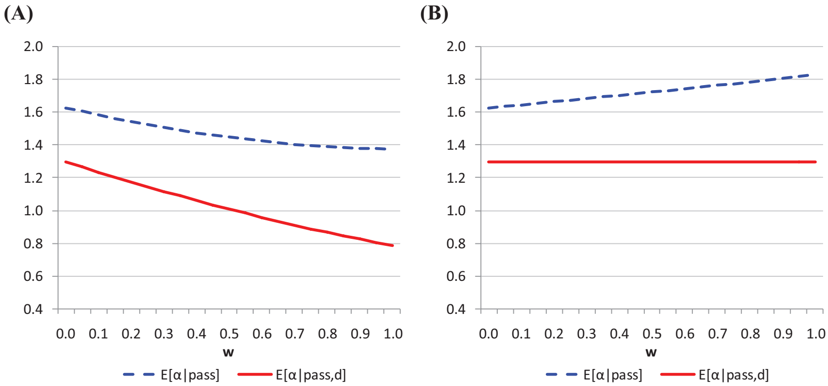


Figure A1

The expected value of a truncated normal distribution with parameters μ and σ and truncation point a is given by

$$\mu+\sigma\frac{\phi((a-\mu)\sigma)}{1-\Phi((a-\mu)/\sigma)},$$

where ϕ is the pdf and Φ is the cdf of the standard normal distribution. This expression is a monotonically increasing function of a.

Substituting our parameters into this expression and denoting $\sigma=\sqrt{\sigma_d^2+\sigma_s^2}$, we get

$$\mathrm{E}[\alpha|pass]=d_0+\delta w+\sigma\frac{\phi((\gamma-d_0-(\delta+\beta_w)w)/\sigma)}{1-\Phi((\gamma-d_0-(\delta+\beta_w)w)/\sigma)}.$$

The third term captures the selection effect and decreases in w. The second term captures the direct beneficial effect of wealth on performance and increases in w. Which effect would dominate in this specification is an empirical question. However, it is clear that the presence of skill drivers that correlate with wealth attenuates the selection effect.

Conditioning on the skill drivers would allow us to identify the selection effect more precisely. The better we are able to control for d, the stronger the relationship between α and w becomes. If we assume that the whole of d is observable and condition E[α|*pass*] on d, we get

$$\mathrm{E}[\alpha|pass,d]=d+\sigma_s\frac{\phi((\gamma-d-\beta_w w)/\sigma_s)}{1-\Phi((\gamma-d-\beta_w w)/\sigma_s)}.$$

This case is similar to the baseline independence case we considered earlier. The expected performance is decreasing in wealth and the strength of this relationship is governed by β_w. It is notable that for most parameter values the expected performance increases in d, because the linear first term dominates the second term. However, the presence of the second term, which decreases in d, means that the relationship between performance and skill drivers in the sample of managers is weaker than the direct effect of d on s.

In Figure A1, we plot E[α|*pass*] and E[α|*pass,d*] as functions of w. In panel A, we take $\beta_w=1$, and in panel B, we take $\beta_w=0$; that is, consider an egalitarian barrier. The other parameters are as follows: $\gamma=0.5$, d_0 (or d in the conditioning case) = 0.5, $\delta=0.5$, $\sigma_d=1$, and $\sigma_s=1$.

The main predictions of the model can be summarized as follows:

(1) To the extent that family wealth plays an important role in helping prospective fund managers overcome selection barriers, we should expect a negative relation between family wealth of managers and their performance.

(2) The selection effect is identified more precisely when one controls for wealth-correlated skill drivers, such as education. Controlling for these drivers should increase the strength of the negative wealth-performance relation.

(3) There should be a positive relation between wealth-correlated skill drivers and performance even as one includes wealth as a separate independent variable.

Appendix B. Sample Construction

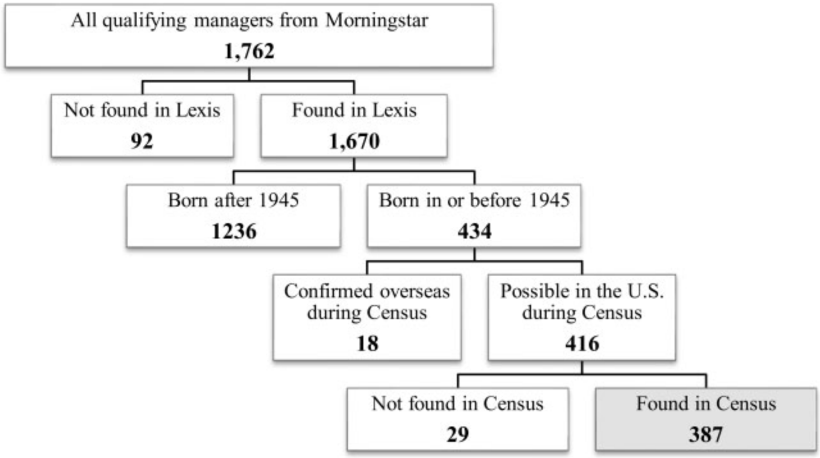


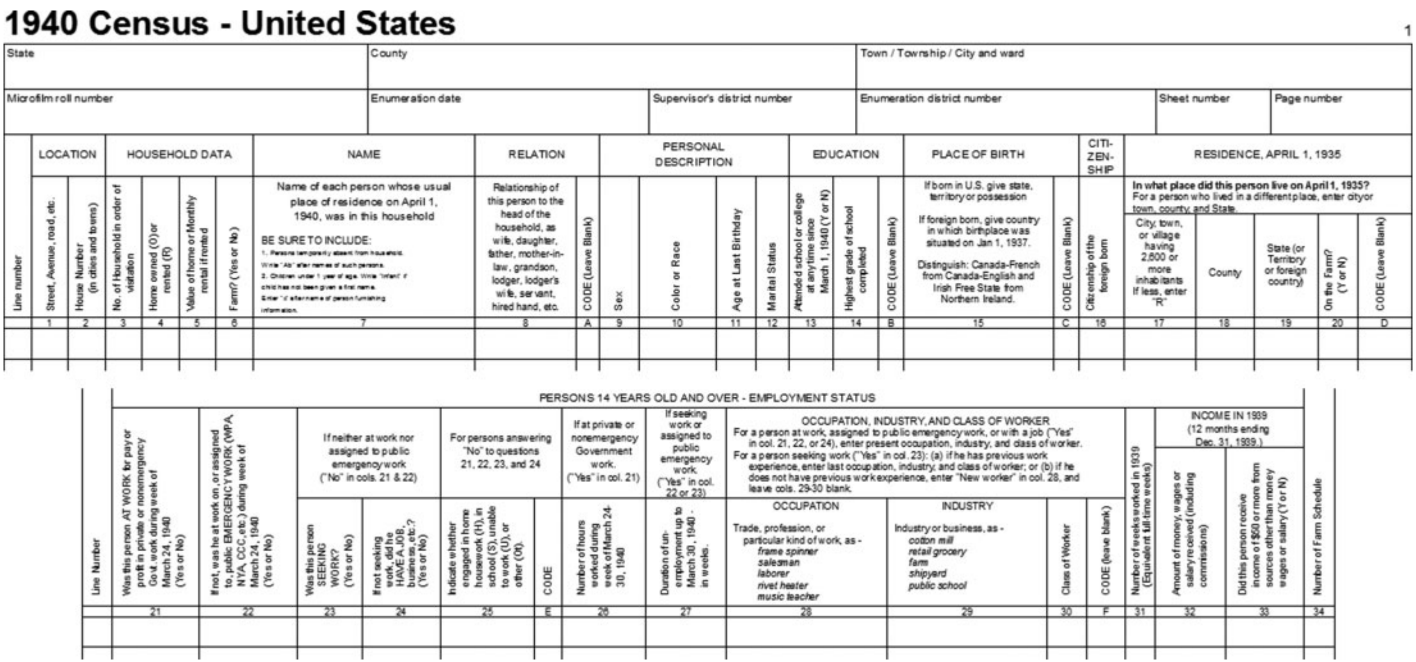
Figure B1
Sample construction cascade
This figure describes the construction of the main sample which consists of 387 mutual fund managers with available census records. The cascade shows the sample selection criteria and indicates the number of managers retained after each sample filter.

Table B1
Comparison of the managers found in the census with those not found in the census

	Not found		Found		
	Mean	Median	Mean	Median	Diff. (t-stat)
Monthly gross alpha (pp)	0.073	0.018	0.040	0.029	−0.0328 (−1.07)
Monthly net alpha (pp)	−0.026	−0.073	−0.054	−0.057	−0.0275 (−0.90)
Year of birth	1,940.7	1,942.0	1,938.4	1,940.0	−2.3* (−1.83)
Career length, years	12.67	11.25	13.02	11.33	0.35 (0.20)
Private university, indicator	0.67	1.00	0.65	1.00	−0.02 (−0.17)
Ivy League institution, indicator	0.11	0.00	0.18	0.00	0.07 (0.92)
SAT rank	77.2	81.0	82.5	88.0	5.3 (1.64)
Admission rate (%)	49.5	50.0	46.8	43.5	−2.7 (−0.49)
Tuition ($)	17,165.8	18,797.0	18,659.4	23,775.0	1,493.6 (0.67)
MBA degree, indicator	0.52	1.00	0.60	1.00	0.08 (0.83)
PhD degree, indicator	0.07	0.00	0.04	0.00	−0.03 (−0.90)

This table compares the characteristics of fund managers in the main sample with those of managers who passed the sample criteria but could not be identified in the federal census. The last column indicates the difference between these groups of managers and shows the t-statistics for the test of the difference in means. Statistical significance levels for this test are indicated as follows: *, 10%; **, 5%; and ***, 1%.

Appendix C. The 1940 Decennial Federal Census



1940 Census - United States

1

State | County | Town / Township / City and ward

Microfilm roll number | Enumeration date | Supervisor's district number | Enumeration district number | Sheet number | Page number

Line number

LOCATION: Street, Avenue, road, etc. (1); House Number (in cities and towns) (2)

HOUSEHOLD DATA: No. of Household in order of visitation (3); Home owned (O) or rented (R) (4); Value of home or Monthly rental if rented (5); Farm? (Yes or No) (6)

NAME: Name of each person whose usual place of residence on April 1, 1940, was in this household

BE SURE TO INCLUDE:
1. Persons temporarily absent from household. Write "Ab" after names of such persons.
2. Children under 1 year of age. Write "Infant" if child has not been given a first name.
Enter "x" after name of person furnishing information. (7)

RELATION: Relationship of this person to the head of the household, as wife, daughter, father, mother-in-law, grandson, lodger, lodger's wife, servant, hired hand, etc. (8); CODE (Leave Blank) (A)

PERSONAL DESCRIPTION: Sex (9); Color or Race (10); Age at Last Birthday (11); Marital Status (12)

EDUCATION: Attended school or college at any time since March 1, 1940 (Y or N) (13); Highest grade of school completed (14); CODE (Leave Blank) (B)

PLACE OF BIRTH: If born in U.S. give state, territory or possession

If foreign born, give country in which birthplace was situated on Jan 1, 1937.

Distinguish: Canada-French from Canada-English and Irish Free State from Northern Ireland. (15); CODE (Leave Blank) (C)

CITIZENSHIP: Citizenship of the foreign born (16)

RESIDENCE, APRIL 1, 1935: In what place did this person live on April 1, 1935? For a person who lived in a different place, enter city or town, county, and State.
City, town, or village having 2,500 or more inhabitants If less, enter "R" (17); County (18); State (or Territory or foreign country) (19); On the Farm? (Y or N) (20); CODE (Leave Blank) (D)

PERSONS 14 YEARS OLD AND OVER - EMPLOYMENT STATUS

Line Number

Was this person AT WORK for pay or profit in private or nonemergency Govt. work during week of March 24, 1940 (Yes or No) (21)

If not, was he at work on, or assigned to, public EMERGENCY WORK (WPA, NYA, CCC, etc.) during week of March 24, 1940 (Yes or No) (22)

If neither at work nor assigned to public emergency work ("No" in cols. 21 & 22): Was this person SEEKING WORK? (Yes or No) (23); If not seeking work, did he HAVE A JOB, business, etc.? (Yes or No) (24)

For persons answering "No" to questions 21, 22, 23, and 24: Indicate whether engaged in home housework (H), in school (S), unable to work (U), or other (Ot). (25); CODE (E)

If at private or nonemergency Government work. ("Yes" in col. 21): Number of hours worked during week of March 24-30, 1940 (26)

If seeking work or assigned to public emergency work. ("Yes" in col. 22 or 23): Duration of unemployment up to March 30, 1940 - in weeks. (27)

OCCUPATION, INDUSTRY, AND CLASS OF WORKER
For a person at work, assigned to public emergency work, or with a job ("Yes" in col. 21, 22, or 24), enter present occupation, industry, and class of worker.
For a person seeking work ("Yes" in col. 23): (a) if he has previous work experience, enter last occupation, industry, and class of worker; or (b) if he does not have previous work experience, enter "New worker" in col. 28, and leave cols. 29-30 blank.

OCCUPATION: Trade, profession, or particular kind of work, as - *frame spinner*, *salesman*, *laborer*, *rivet heater*, *music teacher* (28)

INDUSTRY: Industry or business, as - *cotton mill*, *retail grocery*, *farm*, *shipyard*, *public school* (29)

Class of Worker (30); CODE (leave blank) (F)

Number of weeks worked in 1939 (Equivalent full-time weeks) (31)

INCOME IN 1939 (12 months ending Dec. 31, 1939.): Amount of money, wages or salary received (including commissions) (32); Did this person receive income of $50 or more from sources other than money wages or salary (Y or N) (33)

Number of Farm Schedule (34)

Figure C1
Blank census form
This figure shows an excerpt from a blank census form which describes the main information collected in the 1940 decennial federal census. This form is completed by a designated census official via in-person household visits. The complete census form, record symbols, and explanatory notes appear on the Web site of the National Archives and Records Administration: https://www.archives.gov/files/research/census/1940/1940.pdf.

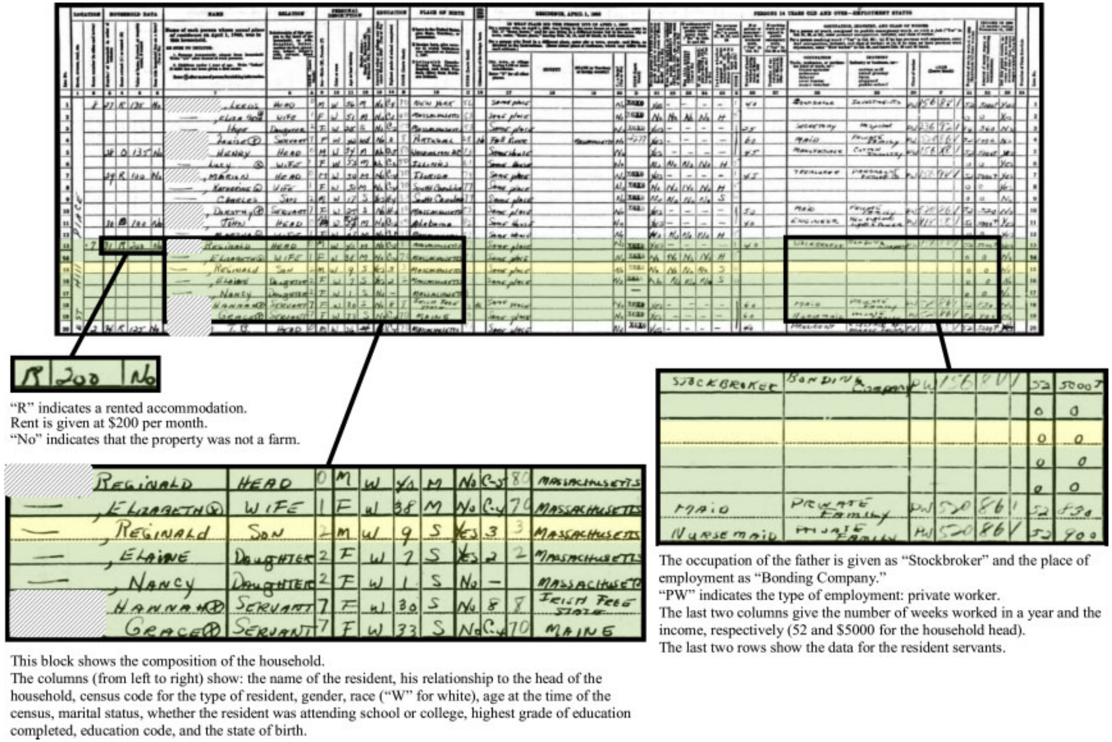


Figure C2
Example of a completed census record

Appendix D. Variable Definitions

This appendix provides variable definitions. The indexing convention is as follows: m denotes a manager, j denotes a fund, t denotes a month, and T denotes a calendar quarter.

Table D1

Variable name	Description
Family wealth	
$Wealth_m$	Is equal to manager m's father's income in the Census record, if reported, expressed in multiples of the median male income in the state of the household; is equal to the home value or the rent expressed in multiples of the state median, if the father's income is not available
$Wealth, rank_m$	Is equal to 0.01 times the percentile rank of manager m's father's income, if reported, and to 0.01 times the percentile rank of either the home value or the rent, if the father's income is not available
$WealthQx_m$	Indicator variable equal to 1 if $Wealth_m$ falls in the xth quintile of the distribution
$WealthHigh_m$	Indicator variable equal to 1 if $Wealth_m$ is above the median in the sample
$FIncome, actual_m$	Annual income of manager m's father as per the Census record. This variable is expressed in $000
$FIncome, after taxes_m$	Annual income of manager m's father less federal and state taxes on that income
$AccumulatedSavings_m$	Is equal to one-third times the total after-tax income of manager m's father earned from the year the father joined the workforce to the year the manager turned 18
Barriers	
$HomeUniDistance_m$ ($HighHomeUniDistance_m$)	Distance in 000 km between manager m's parents' home and his undergraduate educational institution (an indicator variable equal to 1 if this distance is greater than 1,000 km)
$UniNYDistance_m$ ($HighUniNYDistance_m$)	Distance in 000 km between manager m's undergraduate educational institution and New York county, New York (an indicator variable equal to 1 if this distance is greater than 1,000 km)
$BusinessDegree_m$	Indicator variable equal to 1 if manager m's undergraduate specialization references any of the following: "finance," "economics," "accounting," "business"
$UnemploymentAtEntry_m$	Average monthly unemployment rate (in pp) in the year that manager m joined the mutual fund industry.
Managers' and parents' characteristics	
$UniSATRank_m$	0.01 times the 2004 national percentile rank of manager m's undergraduate educational institution by median SAT score
$UniAdmissionRate_m$	2004 undergraduate admission rate of manager m's undergraduate educational institution
$UniTuitionRank_m$	0.01 times the 2004 percentile rank of manager m's undergraduate educational institution by undergraduate in-state tuition
$HasPhD_m$	Indicator variable equal to 1 if manager m holds a PhD degree
$ParentsEdu_m$	Average education attainment score of manager m's mother and father. The education attainment score is equal to 3 if the person attended college, 2 if he attended high school, but not college, 1 if he attended elementary school but not high school, and 0 if he has no school education
$NumberOfSiblings_m$	Number of siblings for manager m
$ParentsDead_{mT}$	Indicator variable equal to 1 if both manager m's father and mother died before the year of quarter T. This variable is set to missing if either the mother or the father died in the year of quarter T
Performance measures	
$Gross\ four\text{-}factor\ alpha_{jt}$	Fund j's gross return in month t minus the fitted value from the four-factor model for which the loadings are estimated over the period [t-1, t-36]. If the estimation period contains fewer than 30 nonmissing observations, the variable is set to missing

(continued)

Table D1

Variable name	Description
Benchmark-adjusted return $_{jt}$	Fund j's gross return in month t minus the return on the fund's prospectus benchmark index
Abnormal return over benchmark $_{jt}$	Fund j's gross return in month t minus the fitted value from the one-factor model, where the factor is the fund's benchmark index return. The loadings in the model are estimated over the period [t-1, t-36]. If the estimation period contains fewer than 30 nonmissing observations, the variable is set to missing
Value extracted $_{jt}$	Dollar value extracted from capital markets computed as the product between fund j's gross alpha in month t and the fund's TNA at the end of month t-1. The fund's TNA is standardized to 2012 dollars by the Consumer Price Index of the Federal Reserve Bank of St. Louis. This variable is expressed in $mil
Fund and fund family variables	
$FundSize_{jt(T)}$	Log(1 + fund j's TNA in $000 at the end of month t (quarter T))
$FundAge_{jt(T)}$	Time in years from the month of fund j's first appearance in the sample to the end of month t (quarter T)
$ManagerTenure_{mjt(T)}$	Time in years from the month of manager m's first appearance in the sample as a manager of fund j to the end of month t (quarter T)
$FirmSize_{jt(T)}$	Log(1 + fund j's total family TNA in $000 at the end of month t (quarter T))
$FirmLogNumFunds_{jt(T)}$	Log(the number of funds in fund j's fund family at the end of month t (quarter T))
$Volatility_{jt(T)}$	Standard deviation of fund j's monthly returns (in pp) over the period [t-35, t] ([T-35, T])
$Skewness_{jt(T)}$	Skewness of fund j's monthly returns (in pp) over the period [t-35, t] ([T-35, T])
Expense ratio $_{jT}$	Annual expense ratio (in pp) of fund j in year T
Promotion and exit indicators	
Promotion, AUM inferred $_{mjt}$	Indicator variable equal to 1 if the total dollar assets managed by manager m of fund j at the end of month t is more than double the assets at the end of month t-1
Promotion, fee inferred $_{mjt}$	Indicator variable equal to 1 if the total management fee accruing to manager m of fund j at the end of month t is more than double this fee at the end of month t-1. The total management fee is calculated as the sum (across all the funds managed by the manager) of fund TNA * fund expense ratio / number of managers running the fund
Exit from asset management $_{mjt}$	Indicator variable equal to 1 if month t is the last month that manager m of fund j appears in the sample. This variable is undefined if month t is December 2012 (end of the sample period). This variable is undefined if either of these two conditions hold for manager m: (1) the manager appears as either an insurance fund or a hedge fund manager in Morningstar in the next 12 months after leaving or (2) the manager dies in the same or next year after leaving
Portfolio activity and flows	
$Turnover_{jT}$	Annualized ratio (in pp) of the sum of the absolute dollar changes in fund j's stock positions over quarter T to the average fund portfolio size in these adjacent quarters. Formally, $$4*\frac{\sum_{i\in j_T}\frac{P_{iT-1}+P_{iT}}{2}\lvert NS_{jiT}-NS_{jiT-1}\rvert}{\frac{TNA_{jT-1}+TNA_{jT}}{2}},$$ where NS_{jiT} is the number of shares of stock i held by fund j at the end of quarter T, P_{iT} is the price of stock i at the end of quarter T, and TNA_{jT} is the dollar total net assets of fund j at the end of quarter T
Holding horizon $_{jT}$	For each stock i in fund j's portfolio at the end of quarter T, we calculate the average number of months that its shares are held in the portfolio using the FIFO assumption of Lan, Moneta, and Wermers (2016). Next, we aggregate this variable to the fund level as the weighted average measure in which the weights are proportional to the stocks' portfolio weights

(continued)

Table D1

Variable name	Description
Herding $_{jT}$	We construct a hypothetical style portfolio by aggregating (for each stock and quarter) the dollar positions of all funds in the style. Next, for fund j in quarter T we compute the correlation (across all the stocks in the style portfolio) of the percentage changes in the number of shares held by fund j from the beginning to end of quarter T with the corresponding changes in positions of the style portfolio.
Stock picking $_{jT}$	Is equal to $$\sum_{i\in j_T}(w_{jiT}-w_{MiT})*(r_{iT+1}-\beta_{iT}r_{MT+1}),$$ where w_{jiT} is the weight of stock i in fund j's portfolio at the end of quarter T, w_{MiT} is the weight of stock i in the market portfolio (the benchmark portfolio of all funds in the Morningstar investment style), r_{iT} is the return of stock i in quarter T, r_{MT} is the market (CRSP value-weighted index) return in quarter T, and β_{iT} is the beta of stock i (computed from the one-factor model over the period of the past 36 months). See (Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2014) for details.
Market timing $_{jT}$	Is equal to $$\sum_{i\in j_T}(w_{jiT}-w_{MiT})*\beta_{iT}r_{MT+1}$$ See the previous item for details
Flow $_{jt}$	Percentage flow (in pp) for fund j in month t computed as $$\frac{TNA_{jt}-(1+r_{jt})TNA_{jt-1}}{TNA_{jt-1}},$$ where TNA_{jt} is the dollar total net assets of fund j at the end of month t and r_{jt} is fund j's gross return over month t
Other	
UpMarket $_t$ *(HighMarket* $_t$*)*	Indicator variable equal to 1 if the return on the S&P 500 Index is positive (above average in the sample) in month t
Backward-looking return gap $_{jt}$	Is equal to $$\sum_{i\in j_T}w_{jiT}*r_{it}-r_{jt},$$ where w_{jiT} is the weight of stock i in fund j's portfolio at the end of quarter T, r_{it} is the return of stock i in month t (inside quarter T), and r_{jt} is the gross return of fund j in month t
Risk shifting $_{jT}$	Is equal to the difference between the current holdings volatility of fund j based on its holdings in quarter T and the volatility of actual gross fund j's returns. Both volatilities are measured over the past 36 months. See (Huang, Sialm, and Zhang, 2011) for details
Past return, 12 (36) months $_{jt}$	Fund j's average monthly return (in pp) in the period [t-12,t-1] (period [t-36,t-1])
In-style rank, 12 (36) months $_{jt}$	0.01 times the percentile rank of fund j in the Morningstar style by average monthly return in the period [t-12,t-1] (period [t-36,t-1])
Tainted $_j$	Indicator variable equal to 1 if fund j belonged to one of the fund families implicated in the 2003 late-trading scandal (and was active in 2001–2003), see (McCabe, 2009)
PastGAlpha $_{mt}$	Manager m's average gross monthly alpha (in pp) in the period [t-60,t-1]
PastNAlpha $_{jt}$	Fund j's average net monthly alpha (in pp) in the period [t-36,t-1]
PastNAlphaLow $_{jt}$	Is *PastNAlpha* $_{jt}$, if *PastNAlpha* $_{jt}\leqslant 0$; is 0, if *PastNAlpha* $_{jt}>0$
PastNAlphaHigh $_{jt}$	Is 0, if *PastNAlpha* $_{jt}\leqslant 0$; is *PastNAlpha* $_{jt}$, if *PastNAlpha* $_{jt}>0$
PastNAlphaT1 $_{jt}$	Is *PastNAlpha* $_{jt}$, if *PastNAlpha* $_{jt}\leqslant$ p33 (of *PastNAlpha* $_{jt}$); is p33, if *PastNAlpha* $_{jt}>$ p33
PastNAlphaT2 $_{jt}$	Is 0, if *PastNAlpha* $_{jt}\leqslant$ p33; is *PastNAlpha* $_{jt}-$ p33, if *PastNAlpha* $_{jt}$ is between p33 and p66; is p66 − p33, if *PastNAlpha* $_{jt}>$ p66
PastNAlphaT3 $_{jt}$	Is 0, if *PastNAlpha* $_{jt}\leqslant$ p66; is *PastNAlpha* $_{jt}-$ p66, if *PastNAlpha* $_{jt}>$ p66

References

Agarwal, V., G. Gay, and L. Ling. 2014. Window dressing in mutual funds. *Review of Financial Studies* 27:3133–70.

Ahern, K., and D. Sosyura. 2015. Rumor has it: Sensationalism in financial media. *Review of Financial Studies* 28:2050–93.

Bandiera, O., I. Barankay, and I. Rasul. 2009. Social connections and incentives in the workplace: Evidence from personnel data. *Econometrica* 77:1047–94.

Barnea, A., H. Cronqvist, and S. Siegel. 2010. Nature or nurture: What determines investor behavior? *Journal of Financial Economics* 98:583–604.

Barras, L., O. Scaillet, and R. Wermers. 2010. False discoveries in mutual fund performance: Measuring luck in estimated alphas. *Journal of Finance* 65:179–216.

Becker, G., and N. Tomes. 1979. An equilibrium theory of the distribution of income and intergenerational mobility. *Journal of Political Economy* 87:1153–89.

———. 1986. Human capital and the rise and fall of families. *Journal of Labor Economics* 4:1–39.

Behrnan, J. 1997. Intrahousehold distribution and the family. In *Handbook of population and family economics*. Eds. O. Stark and M. R. Rosenzweig. Amsterdam: North-Holland.

Behrman, J., R. Pollak, and P. Taubman. 1982. Parental preferences and provision for progeny. *Journal of Political Economy* 90:52–73.

Bennedsen, M., K. Meisner Nielsen, F. Perez-Gonzalez, and D. Wolfenzon. 2007. Inside the family firm: The role of families in succession decisions and performance. *Quarterly Journal of Economics* 122:647–91.

Berk, J., and R. Green. 2004. Mutual fund flows and performance in rational markets. *Journal of Political Economy* 112:1269–95.

Berk, J., and J. Van Binsbergen. 2015. Measuring managerial skill in the mutual fund industry. *Journal of Financial Economics* 118:1–20.

Bertrand, M., and S. Mullainathan. 2003. Enjoying the quiet life? Corporate governance and managerial preferences. *Journal of Political Economy* 111:1043–75.

Bjorklund, A., and M. Jantti. 1997. Intergenerational income mobility in Sweden compared to the United States. *American Economic Review* 87:1009–18.

Black, S., and P. Devereux. 2011. Recent developments in intergenerational mobility. In *Handbook of labor economics*, vol. 4b. Eds. O. Ashenfelter and D. Card, pp. 1487–541. Amsterdam: North-Holland.

Black, S., P. Devereux, and K. Salvanes. 2005. The more the merrier? The effect of family size and birth order on children's education. *Quarterly Journal of Economics* 120:669–700.

Bogue, D. 2000. Census tract data, 1940: Elizabeth Mullen Bogue File. ICPSR02930-v1. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor].

Bowers, W. 1964. Student dishonesty and its control in college. Dissertation at Columbia University, Bureau of Applied Social Research, New York City, NY.

Bowles, S., H. Gintis, and M. Osborne. 2005. *Unequal chances: Family background and economic success*. Princeton, NJ: Russell Sage and Princeton University Press.

Brand, J., and Y. Xie. 2010. Who benefits most from college? Evidence for negative selection in heterogeneous economic returns to higher education. *American Sociological Review* 75:273–302.

Calvó-Armengol, A., and M. Jackson. 2004. The effects of social networks on employment and inequality. *American Economic Review* 94:426–54.

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

Carneiro, P., J. Heckman, and E. Vytlacil. 2011. Estimating marginal and average returns to education. *American Economic Review* 101:2754–81.

Chapman, D., and R. Evans. 2010. The portfolio choices of young and old active mutual fund managers. Working Paper.

Chaudhuri, R., Z. Ivković, J. Pollet, and C. Trzcinka. 2017. A tangled tale of training and talent: PhDs in institutional money management. Working Paper.

Chen, J., H. Hong, M. Huang, and J. Kubik. 2004. Does fund size erode mutual fund performance? The role of liquidity and organization. *American Economic Review* 94:1276–1302.

Chetty, R., J. Friedman, N. Hilger, E. Saez, D. Schanzenbach, and D. Yagan. 2011. How does your kindergarten classroom affect your earnings? Evidence from Project STAR. *Quarterly Journal of Economics* 126:1593–660.

Chetty, R., N. Hendren, P. Kline, and E. Saez. 2014. Where is the Land of Opportunity? The geography of intergenerational mobility in the United States. *Quarterly Journal of Economics* 129:1553–623.

Chevalier, J., and G. Ellison. 1997. Risk taking by mutual funds as a response to incentives. *Journal of Political Economy* 105:1167–200.

———. 1999. Are some mutual fund managers better than others? Cross-sectional patterns in behavior and performance. *Journal of Finance* 54:875–99.

Cohen, L., A. Frazzini, and C. Malloy. 2008. The small world of investing: Board connections and mutual fund returns. *Journal of Political Economy* 116:951–79.

Couch, K., and T. Dunn. 1997. Intergenerational correlations in labor market status: A comparison of the United States and Germany. *Journal of Human Resources* 32:210–32.

Cronqvist, H., A. Makhija, and S. Yonker. 2012. Behavioral consistency in corporate finance: CEO personal and corporate leverage. *Journal of Financial Economics* 103:20–40.

Cronqvist, H., and S. Siegel. 2015. The origins of savings behavior. *Journal of Political Economy* 123:123–69.

Cronqvist, H., S. Siegel, and F. Yu. 2015. Value versus growth investing: Why do different investors have different styles? *Journal of Financial Economics* 117:333–49.

Dahl, M., and T. DeLeire. 2008. The association between children's earnings and fathers' lifetime earnings: Estimates using administrative data. Institute for Research on Poverty Discussion Paper, no. 1342-08.

Deuskar, P., J. Pollet, Z. Wang, and L. Zheng. 2011. The good or the bad? Which mutual fund managers join hedge funds? *Review of Financial Studies* 24:3008–24.

Du, F. 2017. From playground to boardroom: Endowed social status and managerial performance. Working Paper.

Duchin, R., M. Simutin, and D. Sosyura. 2017. The origins and real effects of the gender gap: Evidence from CEOs' formative years. Working Paper.

Duchin, R., and D. Sosyura. 2013. Divisional managers and internal capital markets. *Journal of Finance* 68:387–429.

Elliott, J., and S. Frickel. 2013. The historical nature of cities: A study of urbanization and hazardous waste accumulation. *American Sociological Review* 78:521–43.

Fama, E., and K. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33:3–56.

Fracassi, C., and G. Tate. 2012. External networking and internal firm governance. *Journal of Finance* 67:153–94.

Gaspar, J., M. Massa, and P. Matos. 2005. Shareholder investment horizons and the market for corporate control. *Journal of Financial Economics* 76:135–65.

Gennaioli, N., A. Shleifer, and R. Vishny. 2015. Money doctors. *Journal of Finance* 70:91–114.

Glode, V. 2011. Why mutual funds "underperform." *Journal of Financial Economics* 99:546–59.

Grinblatt, M., S. Titman, and R. Wermers. 1995. Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *American Economic Review* 85:1088–105.

Gruber, M. 1996. Another puzzle: The growth in actively managed mutual funds. *Journal of Finance* 51:783–810.

Heckman, J., J. Stixrud, and S. Urzua. 2006. The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics* 24:411–82.

Henriksson, R., and R. Merton. 1981. On market timing and investment performance. II. Statistical procedures for evaluating forecasting skills. *Journal of Business* 54:513–33.

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

Hu, F., A. Hall, and C. Harvey. 2000. Promotion or demotion? An empirical investigation of the determinants of top mutual fund manager change. Working Paper.

Huang, J., C. Sialm, and H. Zhang. 2011. Risk shifting and mutual fund performance. *Review of Financial Studies* 24:2575–616.

Jagannathan, M., W. Jiao, and A. Karolyi. 2017. Home field advantage: Fund manager national origin and U.S. international mutual fund performance. Working Paper.

Kacperczyk, M., S. Van Nieuwerburgh, and L. Veldkamp. 2014. Time-varying fund manager skill. *Journal of Finance* 69:1455–84.

Kempf, E., A. Manconi, and O. Spalt. 2017. Learning by doing: The value of experience and the origins of skill for mutual fund managers. Working Paper.

Khorana, A. 1996. Top management turnover: An empirical investigation of mutual fund managers. *Journal of Financial Economics* 40:403–27.

Kosowski, R. 2006. Do mutual funds perform when it matters most to investors? U.S. mutual fund performance and risk in recessions and expansions. Working Paper.

Lan, C., F. Moneta, and R. Wermers. 2017. Mutual fund investment horizon and performance. Working Paper.

Lee, J., H. Shin, and H. Yun. 2017. Family feud: Succession tournaments and risk-taking in family firms. Working Paper.

Li, H., X. Zhang, and R. Zhao. 2011. Investing in talents: Manager characteristics and hedge fund performances. *Journal of Financial and Quantitative Analysis* 46:59–82.

Mazumder, B. 2005. Fortunate sons: New estimates of intergenerational mobility in the United States using social security earnings data. *Review of Economics and Statistics* 87:235–55.

McCabe, P. 2009. The economics of the mutual fund trading scandal. Federal Reserve Board Finance and Economics Discussion Series Paper.

McPherson, M., L. Smith-Lovin, and J. Cook. 2001. Birds of a feather: Homophily in social networks. *Annual Review of Sociology* 27:415–44.

Mehrotra, V., R. Morck, J. Shim, and Y. Wiwattanakantang. 2013. Adoptive expectations: Rising sons in Japanese family firms. *Journal of Financial Economics* 108:840–54.

Nonis, S., and C. Swift. 2001. An examination of the relationship between academic dishonesty and workplace dishonesty: A multicampus investigation. *Journal of Education for Business* 77:69–77.

Ogilby, S. 1995. The ethics of academic behavior: Will it affect professional behavior? *Journal of Education for Business* 71:92–6.

Pastor, L., R. Stambaugh, and L. Taylor. 2017. Do funds make more when they trade more*? Journal of Finance* 72:1483–528.

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

Pool, V., N. Stoffman, and S. Yonker. 2012. No place like home: Familiarity in mutual fund manager portfolio choice. *Review of Financial Studies* 25:2563–99.

Pool, V., N. Stoffman, S. Yonker, and H. Zhang. 2017. Do shocks to personal wealth affect risk taking in delegated portfolios? Working Paper.

Reeves, R., and K. Howard. 2013. The glass floor: Education, downward mobility, and opportunity hoarding. Brookings Institution research report.

Schmalz, M., and S. Zhuk. 2017. Revealing downturns. Working Paper.

Sims, R. 1993. The relationship between academic dishonesty and unethical business practices. *Journal of Education for Business* 68:207–11.

Sirri, E., and P. Tufano.1998. Costly search and mutual fund flows. *Journal of Finance* 53:1589–622.

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

Solon, G. 1992. Intergenerational income mobility in the United States. *American Economic Review* 82:393–408.

Sugrue, T. 1995. Crabgrass-roots politics: Race, rights, and the reaction against liberalism in the urban North, 1940-1964. *Journal of American History* 82:551–78.

Sun, Z., A. Wang, and L. Zheng. 2009. Do active funds perform better in down markets? New evidence from cross-sectional study. Working Paper.

Yermack, D. 2014. Tailspotting: Identifying and profiting from CEO vacation trips. *Journal of Financial Economics* 113:252–69.