Fund Flows and Income Risk of Fund Managers*

Xiao Cen Winston Wei Dou Leonid Kogan Wei Wu

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Abstract

Investment fund managers make asset allocation decisions on behalf of a significant segment of US households. To elucidate the incentives they operate under, as well as the income and career risks they face, we construct a unique and novel dataset, which encompasses detailed information on the compensation and career trajectories of managers within US active equity mutual funds. The dataset is compiled based on the US Census Bureau's LEHD program, leveraging various "big" textual data sources. Our causal evidence indicates that, contrary to fund disclosures, managers' pay is primarily driven by Assets Under Management (AUM), with performance influencing compensation only via AUM. Fund flows, although they do not align with client interests, have a significant 6% positive impact on compensation for every one-standard-deviation increase. Systematic flow components impact base salaries, while idiosyncratic elements alter bonuses. Crucially, fund flows, as opposed to fund performance, exert a strong impact on the career outcomes of fund managers, especially concerning their downside career risk. Specifically, large fund outflows elevate a manager's likelihood of job turnover (with a substantial decline in income) by 4 percentage points.

Keywords: Fund managers, Manager compensation, Career concerns, Mutual fund flows, Fund performance. (**JEL:** G11, G23, J24, J31, J33, J44)

*Cen is at Texas A&M University (Mays). Dou is at University of Pennsylvania (Wharton) and NBER. Kogan is at MIT (Sloan) and NBER. Wu is at Texas A&M University (Mays). Emails: xcen@mays.tamu.edu, wdou@wharton.upenn.edu, lkogan@mit.edu, and wwu@mays.tamu.edu. We are grateful to Jan Eberly, Richard Evans and Ron Kaniel for their comments and suggestions. We thank Gajendra Choudhary, Wenting Dai, Yijing Ren, Lorry Wu, Xiaoling Wu, Shuman Zhang, and Zitong Zhao for excellent research assistance. Cen and Wu acknowledge the financial supports from Mays Mini Research Grant. Dou is grateful for the financial supports from the Rodney L White Center for Financial Research and the Golub Faculty Scholar Award.

1 Introduction

In recent decades, the prominence of delegated asset management services, notably mutual funds and pension funds, has grown significantly in the United States (US) financial markets (e.g., French, 2008). Data from the Investment Company Institute reveals that approximately half of all US households have consistently invested in mutual funds across the past decades, spanning a broad range of age and income groups. In 2016, mutual and pension funds collectively held roughly 44% of the US equity market, maintaining a consistently high share of ownership over the past two decades. Given their considerable stake, the investment strategies and trading decisions of active equity funds – primarily active mutual and pension funds – not only wield significant influence over stock market valuations but also directly impact the wealth accumulation of a significant portion of US households.

Managers of active equity funds make daily trading and asset allocation decisions in the equity market, on behalf of a diverse cross-section of US households spanning various demographics and income levels. Their role is not merely unique; it's pivotal to the economic landscape. To understand the investment decisions of these fund managers and their implications for the capital market, it's imperative to examine the incentives they operate under, as well as the income and career risks they face. In particular, Dou, Kogan and Wu (2023) find that managers of active funds tilt their portfolios to hedge against fund flow shocks, even at the expense of performance. They further demonstrate that this flow-hedging behavior by active fund managers significantly influences stock market valuations. Central to their argument is the notion that fluctuations in a fund's assets under management (AUM) causally affect its managers' compensations. Given that fund flows are a primary driver of these AUM variations, managers are concerned about the inherent income risks associated with these flows. Drawing on Swedish data, Ibert et al. (2018) demonstrate a statistically significant but concave relationship between a fund manager's compensation and the fund's AUM. However, similar conclusive or causal evidence for US mutual funds is still lacking in the current literature.

This paper fills this gap by offering direct and causal evidence concerning the factors influencing fund managers' compensations in US active equity mutual funds. Undertaking this empirical exploration is challenging, largely owing to the scarcity of comprehensive and precise data on the compensation and career trajectories of individual managers. Consequently, prior research has predominantly concentrated on studying the advisory contracts between funds and their clients. Meanwhile, the intricacies of the compensation agreements between fund companies and their fund managers remain largely understudied, particularly in major economies like the US, where capital markets are instrumental in driving economic activities.

A primary contribution of this paper is the creation of a unique and novel dataset detailing the compensation and employment history of managers within US active equity mutual funds. Our data construction process starts with the entire universe of US active mutual funds. From there, we meticulously extracted the names of all fund managers using both the CRSP survivor-bias-free mutual fund database and the Morningstar direct mutual fund database. While the resulting dataset appears straightforward, the intricacies and challenges involved in its construction, even in the first step, are substantial. Approximately 13% of fund managers are not listed with their full names (with first names missing) in the combined CRSP-Morningstar dataset. To address this, we employ data scraping techniques, complemented by manual searches and verifications. We source this information from mutual fund prospectus, LinkedIn profiles, and the official websites of the mutual funds.

We further gather information regarding fund managers' age, partial social security number (SSN) information, and home address history from public record datasets such as LexisNexis and CoreLogic. Facilitated by these data, we are able to map fund managers to the Longitudinal Employer-Household Dynamics (LEHD) data to obtain their detailed compensation information and comprehensive employment history. The LEHD data is a large-scale confidential administrative dataset made available through the research data center of the US Census Bureau. The dataset provides a longitudinal match between employer and employee and tracks each individual's job history from 2000 to 2014 at a quarterly frequency. The LEHD data covers all individuals in the unemployment insurance wage records, which account for more than 95% of employment in the US over our sample period. In our analysis, we aggregate each manager's quarterly compensations annually. We then link this yearly compensation with the AUMs, performance, and fund flows of the funds overseen by that manager. The dataset we have assembled provides a unique opportunity to study the determinants of fund managers' compensations and career prospects. Furthermore, it allows us to examine the factors behind fund managers' portfolio choices and their implications for asset pricing in capital markets.

Leveraging our newly assembled dataset, we accomplish four key research goals. First, we demonstrate that fund managers' compensation intrinsically depends on both their performance and fund flows; yet, importantly, these dependencies primarily act through a fund's AUM. Specifically, the strong positive link between fund managers' compensation and their performance dissipates when we control for funds' AUMs. A similar pattern is observed for the link between fund managers' compensation and the fund flows they face. Furthermore, consistent with Ibert et al. (2018) who examine Swedish mutual funds, we find that the compensation of fund managers in the U.S. is significantly and monotonically associated with fund AUM, though the relationship exhibits a concave pattern. Our results, in conjunction with those presented in Ibert et al. (2018), robustly challenge the predictions of some existing contract theories. These theories suggest that a significant portion of a fund manager's compensation is directly linked to fund return performance, separate from the fund's AUM, particularly in situations where there is uncertainty regarding managers' ability. Interestingly, drawing from the U.S. data in the Statement of Additional Information (SAI), Ma, Tang and Gómez (2019) report that as many as 79% of funds purport to use compensation contracts that include a bonus contingent upon fund return performance. In contrast, fewer than 20% of funds explicitly claim that they have AUM-based managerial compensation. However, this seems to contradict our findings. This disparity may indicate that the assertions made in SAIs do not genuinely mirror the real-world compensation agreements between funds and their managers. Such a discrepancy is likely driven by the strategic marketing considerations of the fund companies. It is quite believable that funds would be highly motivated to present their managers' incentives as being perfectly aligned with the performance outcomes that potential investors desire.

Second, we show that fund flows, as opposed to fund performance, exert a strong impact on the career outcomes of fund managers, especially concerning their downside career risk. Understanding the impact of fund flows on fund managers' downside career risk is essential for unraveling the determinants of fund managers' asset allocation decisions, especially their flow hedging motivations. We explore the career risk along both intensive and extensive margins. For the intensive margin, we examine the percentage change in income before and after a fund manager's job turnover, given that the turnover has occurred. Our findings suggest that larger fund inflows prior to these turnovers are typically associated with bigger boosts in income, while larger outflows lead to more substantial income drops. In contrast, the changes in income that fund managers experience around these turnovers seem unrelated to their performance prior to these events. For the extensive margin, we examine the likelihood of a job turnover leading to a significant income promotion (20% increase or more) and the likelihood of one resulting in a significant income demotion (20% decrease or more). Our analysis reveals that enormous fund inflows elevate the likelihood of a turnover accompanied by a significant income promotion, while enormous fund outflows heighten the likelihood of a turnover accompanied by a significant income demotion. Interestingly, while severely negative fund performance minimally impacts the chances of a turnover with a significant income decline, very positive fund performance bolsters the likelihood of a turnover with a significant income increase.

Third, we delve deeper by decomposing fund flows into two distinct components: the systematic fund flow and the idiosyncratic fund flow, as outlined by Dou, Kogan and Wu (2023). This decomposition allows us to isolate and measure the effects of each type of fund flow on the career risk of fund managers. Our analysis reveals that both the systematic and idiosyncratic components of fund flows consistently and significantly influence the career risk of fund managers. We show that both systematic and idiosyncratic components of fund flows affect the compensation of fund managers. Intriguingly, while the systematic fund flow component predominantly influences the base-pay segment of a manager's compensation, the idiosyncratic fund flow component mainly sways the bonus segment.

Next, we examine whether manager compensations and career outcomes depend on the performance and fund flows of other peer funds in the same fund family. Based on Swedish data, Ibert et al. (2018) find that the sensitivity of manager compensation to fund family revenue is comparable to that of manager revenue. Their findings suggest that the compensation of fund managers contains one component that depends on manager-level revenues and another component that comes out of a fund-family-wide bonus pool. A natural question is whether the same pattern exists for U.S. mutual fund managers and, if so, whether the compensation structure can help rationalize the cross-fund subsidization phenomena documented by previous studies (e.g., Gaspar, Massa and Matos, 2006; Bhattacharya, Lee and Pool, 2013) and reconcile the observed competition and cooperation patterns in mutual fund families (e.g., Evans, Prado and Zambrana, 2020). Our findings provide strong support for the cross-fund subsidization hypothesis. Specifically, we observe a significant positive comovement between fund family flows and a fund manager's compensation growth. Consequently, the notable exposure of a manager's compensation to common fund flow shocks can be partly attributed to the cross-fund subsidization and the strong comovement between fund family flows and the common flows.

Finally, we present compelling evidence supporting a causal relationship between fund manager compensation and the corresponding fund AUM and revenues. Our findings demonstrate a robust positive correlation between fund manager compensation and the lagged AUM and revenue of the funds under their management. However, it's essential to recognize that this evidence, by itself, does not suffice to establish a definitive causal link, indicating that fund manager compensation is primarily driven by the AUM or revenue of the funds they oversee. This limitation arises due to an endogeneity issue. Specifically, the observed positive correlation between fund manager compensation and the lagged AUM and revenue of the funds they manage may be influenced by unaccounted-for variables. For instance, both manager compensation and fund AUM (and revenue) can be simultaneously affected by the skill level of fund managers, regardless of whether these skills are reflected in the fund's returns. On one hand, manager compensation is, to some extent, determined by the skill level of fund managers. On the other hand, fund AUM experiences accelerated growth with higher levels of fund manager skills, not only due to the potential for superior fund returns but also because of capital inflows from clients who recognize the skills of these fund managers (e.g., Berk and Green, 2004).

To establish a definitive causal relationship, indicating that mutual funds primarily compensate their managers based on fund AUM (or revenue), even though the pass-through from fund revenue to manager compensation is not complete, we rely on variations in a fund's AUM (or revenue) that go beyond the inherent skill level and influence of its fund managers. These variations in fund AUM (or revenue) are often attributed to luck, whether it's in a favorable or unfavorable direction. If mutual funds actively adjust manager compensation based on fluctuations in fund AUM (or revenue) that are independent of the perceived skill levels of fund managers — commonly referred to as "non-fundamental" variations in fund AUM (or revenue) — then the positive correlation observed between fund manager compensation and the lagged AUM and revenue of the funds they oversee is likely to signify a causal relationship.

To capture non-fundamental fluctuations in fund AUM and revenue, we adopt an instrumental variable approach inspired by the idea of heterogeneous demand-driven price impacts, as originally introduced by Koijen and Yogo (2019). This instrumental variable is designed to capture the changes in a fund's AUM and revenue that stem from exogenous shifts in demand by other institutions, which are beyond the control of the fund family.

Related Literature. Our study contributes to the literature on managerial incentives in the delegated asset management industry. Owing to a dearth of data on individual fund manager incentives, most existing literature has concentrated on advisory contracts between fund shareholders and investment advisors (e.g., Starks, 1987; Grinblatt and Titman, 1989; Golec, 1992; Tufano and Sevick, 1997; Coles, Suay and Woodbury, 2000; Das and Sundaram, 2002; Deli, 2002; Elton, Gruber and Blake, 2003; Golec and Starks, 2004; Dass, Massa and Patgiri, 2008; Massa and Patgiri, 2009; Warner and Wu, 2011). There's limited research on the compensation structures of individual portfolio managers, despite their significance in understanding managerial incentives in the mutual fund industry. However, two studies stand out. Ibert et al. (2018) collate a registry-based dataset on the compensation of Swedish mutual fund managers. They observe a positive relationship between pay and revenue and identify a surprisingly weak sensitivity of pay to performance, even after considering the indirect effects of performance on revenue. While Ibert et al. (2018)'s results are intriguing, it remains to be seen how applicable they are to the larger and differently-regulated U.S. mutual fund industry. In contrast, Ma, Tang and Gómez (2019) source data on portfolio manager compensation structures from the SAI for U.S. open-end mutual funds between 2006 and 2011. Their findings indicate that approximately 79% of these funds disclose that a component of their fund managers' compensation is tied to the funds' investment performance. However, the

SAIs don't provide information on the magnitude of the compensation, leaving a gap in understanding the exact magnitude of the performance-sensitive pay. It's also ambiguous whether the disclosures in the SAIs genuinely mirror the actual compensation structures in practice. Our paper complements both Ibert et al. (2018) and Ma, Tang and Gómez (2019) by examining the actual compensation amounts of fund managers in the U.S. mutual fund industry. Contrary to their self-disclosures, we find that the AUMs of U.S. funds primarily determine their managers' compensation. Both fund flows and performance play a role in influencing this compensation through AUM, a finding consistent with those of Ibert et al. (2018) in their Swedish dataset. We go beyond topics studied by their paper to further document the impact of fund performance, flows and their systematic and idiosycratic components on compensation growth.

Our study further contributes to the literature on the effects of fund performance and fund flows on the career outcomes of fund managers. Hu, Hall and Harvey (2000) analyze 307 managerial changes over the period from 1976 to 1996. They find that fund performance has a positive correlation with promotions and an inverse one with demotions. In contrast, fund flows do not significantly predict either outcome. Examining a sample of U.S. equity funds from 1995 to 2002, Evans (2006) determines that fund return alphas are significant predictors for both promotions and demotions, while fund flows are not. However, Evans (2006) also observes that fund flows play a crucial role in predicting fund terminations, after which managers often depart from the fund family. With an expanded dataset in terms of time series and cross-section, Barber, Scherbina and Schlusche (2017) support previous findings, emphasizing fund performance as a strong predictor of managers' career trajectories. They further underscore a notable association between career outcomes and fund flows. Our research augments this body of literature by exploiting the actual compensation information after job turnovers. We show that, contrary to fund performance, fund flows exert a significant influence on the career outcomes of fund managers, particularly regarding their downside career risk.

Our study further enriches the literature on cross-fund subsidization. Chevalier and Ellison (1997) posit that the primary goal of a mutual fund family is to enhance the value of the entire firm rather than focusing solely on individual funds. Gaspar, Massa and Matos (2006) demonstrate that mutual fund families strategically reallocate performance among member funds to prioritize those that bolster the overall family profits. Bhattacharya, Lee and Pool (2013) highlight that affiliated funds serve as an insurance mechanism against transient liquidity shocks impacting other funds within the family. Meanwhile, Berk, van Binsbergen and Liu (2017) explore capital reallocation decisions of mutual fund firms, revealing that fund executives possess keen insights into their managers' capabilities and duly reward the most adept with larger portfolios. Our paper adds to this stream of literature on by evaluating how fund manager incentives might drive such cross-fund subsidization behaviors. Specifically, we establish that manager compensation is influenced by the fund flows within the same fund family. Our results elucidate the internal incentive dynamics within fund families that shape managers' portfolio choices.

Lastly, our study connects with the emerging literature on the role of intermediaries, especially in the context of delegated portfolio management, and its implications for asset pricing (e.g., Brennan, Jegadeesh and Swaminathan, 1993; Goldman and Slezak, 2003; Asquith, Pathak and Ritter, 2005; Cornell and Roll, 2005; Nagel, 2005; Cuoco and Kaniel, 2011; He and Krishnamurthy, 2011, 2013; Basak and Pavlova, 2013; Kaniel and Kondor, 2013; Vayanos and Woolley, 2013; Adrian, Etula and Muir, 2014; Koijen, 2014; He, Kelly and Manela, 2017; Drechsler, Savov and Schnabl, 2018; Koijen and Yogo, 2019; Gabaix and Koijen, 2021; Haddad, Huebner and Loualiche, 2021; Dou, Wang and Wang, 2022). Dou, Kogan and Wu (2023) show that common fund flow shocks play an important role in the financial markets. They highlight the role of endogenous fund flows as an invisible hand in the capital market, connecting the asset allocation choices of institutions, as well as their asset pricing implications, to the aggregate economic shocks affecting households. Our paper adds to this literature by documenting that common fund flows and the systematic component of manager-level flows significantly and positively comove with compensation growth. This suggests that fund managers possess pronounced incentives to hedge against flow risks, thereby lending direct empirical support to Dou, Kogan and Wu (2023).

2 Data and Empirical Measures

We assemble a unique dataset on the compensation and career trajectory of US mutual fund managers, drawing from multiple sources. This dataset encompasses information on their quarterly compensation and employment history, extracted from the Longitudinal Employer-Household Dynamics (LEHD) data. The LEHD is an extensive administrative dataset on individual-level employment, provided by the US Census Bureau. With the support from the Census Bureau, we combine the administrative data from the Census with our manually collected data from multiple "big" textual sources. This effort enables us to integrate the LEHD data with both the CRSP Survivor-Bias-Free US Mutual Fund and Morningstar databases, which provide extensive details on fund asset size, fund returns, expense ratios, and other pertinent information on funds.

In addition to the data on fund managers' compensation and employment histories, we also manually gather information on the compensation structure for each mutual fund from the Statement of Additional Information (SAI). In Sections 2.1 through 2.4, we delve into the aforementioned datasets, as well as the intermediate datasets used for merging. In Sections 2.5, we outline the empirical measures and present their summary statistics.

2.1 Longitudinal Employer-Household Dynamics (LEHD) Data

We use the LEHD dataset to gather information on the compensation and employment histories of mutual fund managers. The LEHD data is a comprehensive administrative dataset provided to researchers by the US Census Bureau. This dataset offers a longitudinal linkage between employers and employees, recording job transitions for individuals from 2000 to 2014. Notably, it includes all individuals listed in the unemployment insurance wage records, representing more than 95% of employment in the United States.[1]

The LEHD data proves to be exceptionally well-suited for our project for several compelling reasons. First, as a confidential administrative employment dataset, LEHD provides precise and accurate metrics concerning the actual compensation of fund managers. To the best of our knowledge, this paper represents the first-ever endeavor to construct an individual-level fund manager compensation and employment panel dataset based on authentic income data within the US. Second, the LEHD data allows for the meticulous tracking of career transitions for each fund manager over time. This capability enables us to determine the subsequent employers and income levels of fund managers once they depart from their roles in fund management. Such information is instrumental in gaining insight into the implications of job turnovers for fund managers, thereby facilitating a deeper understanding of their career motivations and incentives in making portfolio management decisions.

The LEHD dataset comprises a vast panel that provides income information at the individual-employer-quarter level. Moreover, it includes comprehensive demographic information for each individual, encompassing details such as date of birth, gender, race, educational attainment, and precise residence location denoted by six-decimal-digit precision longitudes and latitudes. Crucially, the dataset is longitudinally linked at both the individual and the employer levels. Each individual is assigned a unique Personal Identification Key (PIK), while every employer is identified by a distinct State Employer Identification Number (SEIN), which remains constant throughout the sample period.

The income data derived from the LEHD combines the total compensation, including base salary and bonuses, for each specific individual-employer pair in every quarter. Con-

[1] For this particular project, our access to the LEHD data covers 17 states, namely Arizona, Arkansas, California, the District of Columbia, Delaware, Illinois, Indiana, Iowa, Kansas, Maine, Maryland, Nevada, New Mexico, Oklahoma, Pennsylvania, Tennessee, and Texas.

sequently, this dataset accurately reflects the actual compensation of individuals. However, it is essential to acknowledge two important considerations. First, the dataset does not encompass equity-based compensation elements such as option grants or restricted-stock grants, as noted by Kerr et al. (2015). Fortunately, for our study's purposes, this omission is of lesser significance since mutual fund managers typically receive such stock-related compensation far less frequently than individuals in roles like CEOs or other executives at the company level. Second, the dataset does not differentiate between base salary and bonuses. To address this limitation, we employ a method to decompose compensation into base pay and bonuses by leveraging the quarterly time-series variations in the LEHD data. Specifically, in order to estimate a fund manager's annual bonus, we identify the highest-earning quarter of the year as the "bonus quarter" if the compensation during that period exceeds the average of its two adjacent quarters by at least 20%. It's worth noting that, in most cases, this bonus quarter aligns with the first quarter of the year, which is quite intuitive. We calculate a fund manager's bonus pay for year t by taking the difference between their compensation during the bonus quarter of year t and the average pay over the two neighboring quarters. Year t's base pay is then determined as the fund manager's total annual compensation, with the bonus for that same year subtracted.

2.2 CRSP and Morningstar Mutual Fund Databases

We obtain fund names, monthly returns, monthly total net assets (TNAs), investment objectives, and other fund characteristics from the CRSP Survivorship-Bias-Free Mutual Fund Database. In line with prior studies (e.g., Kacperczyk, Sialm and Zheng, 2008; Huang, Sialm and Zhang, 2011), we classify actively managed US equity mutual funds using their objective codes and disclosed asset compositions.[2] Because data coverage on

[2]We first select funds with the following Lipper objectives: CA, CG, CS, EI, FS, G, GI, H, ID, LCCE, LCGE, LCVE, MC, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, MR, NR, S, SCCE, SCGE, SCVE, SG, SP, TK, TL, UT. If a fund does not have any of the above objectives, we select funds with the following strategic insight (SI) objectives: AGG, ENV, FIN, GMC, GRI, GRO, HLT, ING, NTR, SCG, SEC, TEC, UTI, GLD, RLE. If a fund has neither the Lipper nor the SI objective, then we use the Wiesenberger fund type code to select

monthly TNAs prior to 1991 is scarce and poor, our CRSP sample starts from January 1991. Following the approach of earlier studies (e.g., Elton, Gruber and Blake, 2001), we focus on active mutual funds with AUM larger than $15M.

The CRSP mutual fund database lists manager names for both individually-managed funds and team-managed funds. However, for team-managed funds, CRSP only provides the managers' last names. To substantiate the CRSP dataset, we further collect manager names and their tenure histories from the Morningstar Direct mutual fund database. By combining the CRSP and Morningstar data, we obtain full manager names for 90% of the fund-year observations.

2.3 Intermediate Datasets to Bridge LEHD and CRSP-Morningstar

To establish a connection between the CRSP-Morningstar mutual fund data and the LEHD data at the fund manager level, we initiate the process by preprocessing the fund manager data. This preprocessing step involves addressing incomplete fund manager names through information gathered from mutual fund prospectuses, LinkedIn profiles, and company websites. Subsequently, we locate each fund manager within the LEHD data through a combined intermediate dataset. This dataset is created by leveraging individual real estate transaction information from the CoreLogic data and individual demographic information from the LexisNexis data. These two datasets serve as intermediary sources that connect the fund manager databases to the LEHD data. Further details about each dataset will be elaborated upon in the following paragraphs.

Mutual Fund Prospectuses, LinkedIn Profiles, and Company Websites. By merging the CRSP and Morningstar datasets, we are able to retrieve full manager names for approximately 87% of the fund-year observations concerning active equity funds. For

funds with the following objectives: G, G-I, G-S, GCI, IEQ, ENR, FIN, GRI, HLT, LTG, MCG, SCG, TCH, UTL, GPM. If none of these objectives is available and the fund holds more than 80% of its value in common shares, then the fund will be included. After finishing the procedure described above, we further identify and exclude index funds based on their names and the index fund identifiers in the CRSP data.

those instances where manager names remain incomplete, we employ a manual search process to gather their full names. This search involves consulting mutual fund prospectuses, LinkedIn profiles, and other online resources. A comprehensive description of the procedure used to acquire complete manager names is available in Appendix A. This meticulous approach guarantees the accuracy and comprehensiveness of the collected full names, resulting in our dataset containing full names for over 98% of the fund-year observations related to active equity funds.

CoreLogic Deeds and Listings Data. Using the pre-processed fund manager names, we employ CoreLogic as an intermediary dataset to bridge the CRSP-Morningstar mutual fund data with the Census LEHD data. CoreLogic is a prominent dataset covering deed records for over 147 million residential and commercial properties in the US. It offers detailed information about property transactions and mortgage terms spanning from 1980 to 2017. Relevant variables for our matching method include property owners' names, sellers' names, comprehensive property street addresses (encompassing street names, numbers, suite numbers, cities, counties, states, zip codes, and so forth), and property's geographical coordinates (latitude and longitude).

In our efforts to identify fund managers within the LEHD, our initial step involves matching each fund manager from the CRSP and Morningstar databases with deed records in CoreLogic. We consider a match valid when a fund manager's first, middle, and last names correspond with those of a property owner or seller in the records. Subsequently, our second step entails associating each property owner (or seller) from the deed records with an individual listed in the LEHD data. To facilitate this process, we utilize a bridge connecting the CoreLogic data to the unique individual identifiers in the LEHD, known as PIK. This bridge is established by the Person Identification Validation System (PVS) office at the US Census Bureau (Cen, 2021). The establishment of a match between an individual in the LEHD and an owner (or seller) in CoreLogic necessitates an exact match of both the individual's full name and residential address, as these are shared data fields in both CoreLogic and the PVS database.

The two-step individual-level matching process outlined above enables us to identify a set of unique individual identifiers in the LEHD data that may correspond to fund managers in the CRSP and Morningstar datasets. To further refine the identification of these fund managers within the LEHD, we take advantage of the available employment information. Among the individuals matched in the LEHD, we require that they be employed by the same fund management company that employs the fund managers, as indicated in the CRSP and Morningstar datasets for a given year. Consequently, our bridging file between fund managers and LEHD individuals is created based on an exact match of three distinct criteria: the manager's name, residential address, and the fund management company where they are employed during a specific year.

LexisNexis Public Records. In addition to the CoreLogic data, we incorporate individual demographic information from LexisNexis Public Records to enhance the bridging process between the CRSP-Morningstar mutual fund data and the LEHD data. Solely relying on CoreLogic might result in incomplete coverage for active equity fund managers employed by fund management companies operating in the 17 states covered by the LEHD data at our disposal. This limitation arises for several reasons. First, CoreLogic does not possess residential addresses for fund managers who reside in rented places rather than purchased properties. Many fund managers may have their residential addresses recorded as rentals in the Census LEHD. Second, CoreLogic may not cover active equity fund managers if they own houses for which property transactions occurred before CoreLogic began recording such data. Third, not all fund managers working for a fund family operating in the 17 states necessarily live within those specific states, although the majority do. To address these limitations, we employ the LexisNexis data to expand the set of matched active equity fund managers between the Census LEHD and the CRSP-Morningstar mutual fund datasets. Additionally, the supplemental information from LexisNexis, including partial Social Security Numbers (SSN) and birth month and year, enhances the accuracy of the matching process.

LexisNexis Public Records serves as a leading data source providing comprehensive information on individuals' demographics, identification information, contact details, employment histories, and residential address histories. This extensive dataset encompasses more than 84 billion public records related to individuals. To compile comprehensive information on fund managers, we employ the "People Search" feature available within the LexisNexis online public record database. Similar to Pool, Stoffman and Yonker (2012), we utilize name, age, and location information to identify fund managers in the LexisNexis data. For instance, we begin by using the "People Search" function to search for a fund manager's name. Next, we utilize their location details obtained from their LinkedIn profiles or company websites to refine the search results. Finally, we confirm the fund manager's identity through a meticulous manual review of their employment history within the LexisNexis individual public record report.

After identifying fund managers in the LexisNexis database, we collect their year and month of birth, the first 5 digits of their social security number (SSN), and their entire residential history from the reports. Using these details, we map each fund manager from the LexisNexis data to an individual in the LEHD data using a matching service provided by the Person Identification Validation System (PVS) office at the US Census Bureau. This matching process requires an exact match on four individual characteristics: the fund manager's full name, residential address, the first 5 digits of the SSN, and year and month of birth.

2.4 Self-Disclosed Fund Manager Compensation Structure

Information regarding the compensation structure of each mutual fund's manager is sourced from the Statement of Additional Information (SAI), which is a part of Form

N-1A filed by open-end management investment companies.[3] Following Ma, Tang and Gómez (2019), we access Form N-1A from the SEC EDGAR database and manually gather annual information on manager compensation for actively managed U.S. equity mutual funds from 2005 to 2018. Additionally, we collect fund names and fund tickers/CUSIPs (when available) and utilize this information to match the compensation structure data to the CRSP Mutual Fund database. We successfully obtain the compensation structure for 28,359 fund share-year observations out of the 44,285 fund share-year observations in our CRSP active mutual fund data sample for the period from 2005 to 2018, resulting in 64.0% coverage.

2.5 Sample Overview and Summary Statistics

The merge of CRSP-Morningstar mutual fund data with LEHD data results in approximately 2,400 observations at the manager-year level, spanning from 2000 to 2014.[4] This dataset comprises roughly 450 fund managers and approximately 200 distinct fund management companies as employers. As the newly constructed data panel of income and employment histories for active equity fund managers is a major contribution of this paper, we summarize and illustrate the process of data construction in Figure 1. Table 1 provides summary statistics for the key variables in our paper, which we will elaborate on below.

Compensation and Compensation Growth of Fund Managers. In Panel A of Table 1, we present the summary statistics for the natural log of the yearly compensation level, denoted as $\ln(Pay_{m,t})$. The median of $\ln(Pay_{m,t})$ is 12.90, corresponding to approximately \$400 thousand. We calculate the growth rate of the yearly compensation as $\ln(Pay_{m,t}/Pay_{m,t-1})$.

[3] In 2004, the SEC introduced a new regulation requiring mutual funds, starting from March 2005, to disclose the compensation structure of its portfolio managers in the SAI.

[4] To comply with U.S. Census Bureau disclosure requirements, observation counts are rounded to the nearest hundred if they fall between 1,000 and 10,000, and to the nearest fifty if they range from 100 to 1,000. This rounding convention applies to all tables in our study.

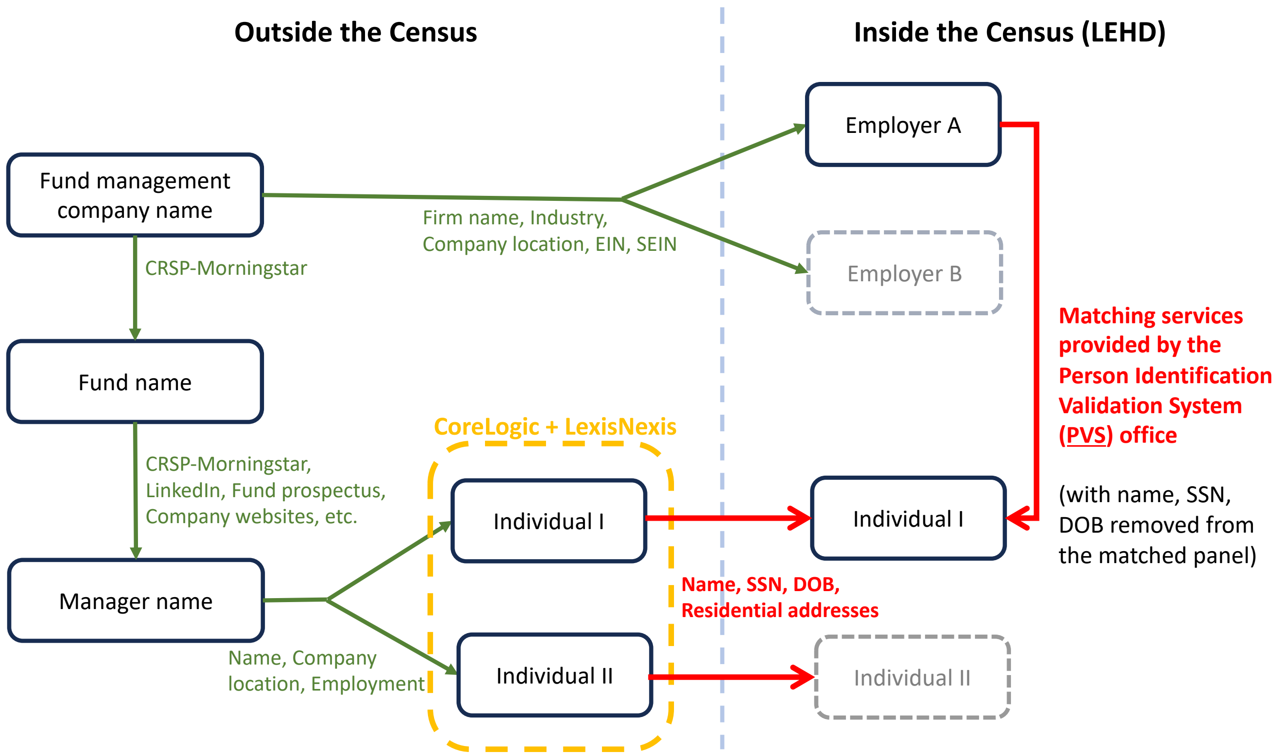

Figure 1: Illustration of data construction.

When there are no job turnovers, the median growth rate of the yearly compensation is 4.5% (refer to Panel B of Table 1). When job turnovers occur (i.e., when there are changes of employers), the median growth rate stands at 7.2%. Intriguingly, the distribution appears to have a pronounced left tail. When no job turnovers take place, in more than 5% of the situations, the compensation of fund managers declines by more than 65.7%. When managers switch jobs in year t, in more than 5% of the instances, their compensation drops by over 80.9% from year $t-1$ to year $t+1$. These income risks are noteworthy.

We further decompose compensation into base pay and bonus using the quarterly compensation information available in LEHD. Specifically, to estimate a fund manager's annual bonus, we identify the highest paid quarter of the year as the "bonus quarter" if the pay during that quarter is at least 20% higher than the average pay of its two neighboring quarters. A fund manager's bonus pay for year t is calculated as the difference between the pay during the bonus quarter in year t and the average pay of the same manager over the two adjacent quarters. The base pay for year t is defined as the total annual pay of the fund manager minus that manager's bonus pay for the same year. The vast majority of bonuses are identified as being issued in the first quarter of the year. The summary statistics presented in Table 1 are based on observations of bonuses issued in the first quarter. The median of $\ln(Base_{m,t})$ is 12.61, corresponding to approximately \$300 thousand. The median of $\ln(Bonus_{m,t})$ is 12.00, corresponding to approximately \$163 thousand. The growth rate of the base pay shows a distribution very similar to that of the total pay, while the growth rate of bonuses is much more volatile. The summary statistics discussed above are similar when the filter for first quarter bonuses is not applied.

Manager-Level Fee Revenue. Funds can be managed by multiple managers, and a single manager might oversee several funds. Following Ibert et al. (2018), we allocate a fund's assets equally among all its managers. The total net asset for manager m in month t is:

$$TNA_{m,t} = \sum_{i \in \Omega_{m,t}} \frac{TNA_{i,t}}{M_{i,t}}, \tag{2.1}$$

where $\Omega_{m,t}$ represents the set of funds managed by manager m in month t and $M_{i,t}$ denotes the number of managers overseeing fund i in month t. Panel A of Table 1 displays the summary statistics for the natural log of the $TNA_{m,t}$ for each December. The median value of $\ln(TNA_{m,t})$ is 19.69, indicating that a typical fund manager manages around \$355.8 million in our dataset.

We calculate the fee revenue earned by manager m in month t using the following formula:

$$Rev_{m,t} = \sum_{i \in \Omega_{m,t-1}} \frac{TNA_{i,t-1}}{M_{i,t-1}} \times TER_{i,t}, \tag{2.2}$$

where $TER_{i,t}$ denotes the total expense ratio of fund i in month t. To determine the annual fee revenue earned by manager m, we sum up the monthly fee revenues for each year. The median of the log annual fee revenue stands at 15.21, equivalent to approximately

Table 1: Summary statistics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Manage-year panel data						
	Mean	SD	5^{th} pct	25^{th} pct	Median	75^{th} pct	95^{th} pct
$\ln(Pay_{m,t})$	13.08	1.34	10.78	12.50	12.90	13.93	15.28
$\ln(Base_{m,t})$	12.70	0.899	10.60	12.28	12.61	13.02	14.28
$\ln(Bonus_{m,t})$	12.02	1.923	9.14	10.52	12.00	13.64	15.02
$\ln(TNA_{m,t})$	19.66	1.85	16.50	18.29	19.69	21.05	22.68
$\ln(Rev_{m,t})$	15.17	1.762	12.27	13.83	15.21	16.57	18.01
$\ln(Rev_{m,t}/Rev_{m,t-1})$	0.075	0.704	−0.782	−0.138	0.069	0.309	0.972
$\ln(1+Flow_{m,t})$	−0.008	0.327	−0.414	−0.139	−0.030	0.110	0.512
$\ln(1+Systematic\ Flow_{m,t})$	−0.008	0.125	−0.042	−0.001	0.000	0.001	0.017
$\ln(1+Idiosyncratic\ Flow_{m,t})$	−0.033	0.295	−0.439	−0.155	−0.051	0.092	0.467
$\ln(1+Family\ Flow_{m,t})$	−0.009	0.214	−0.288	−0.089	−0.019	0.063	0.363
$\ln(1+R^{gross}_{m,t})$	0.076	0.221	−0.397	0.012	0.116	0.200	0.315
$\ln(1+R^{abn,CAPM}_{m,t})$	0.018	0.057	−0.058	−0.014	0.010	0.043	0.125
$\ln(1+R^{abn,Vanguard}_{m,t})$	0.010	0.046	−0.053	−0.013	0.007	0.027	0.082
	Panel B: Compensation growth						
	Mean	SD	5^{th} pct	25^{th} pct	Median	75^{th} pct	95^{th} pct
$\ln(Pay_{m,t}/Pay_{m,t-1})$ (without job turnovers)	0.038	0.661	−1.071	−0.151	0.045	0.205	0.790
$\ln(Base_{m,t}/Base_{m,t-1})$ (without job turnovers)	0.026	0.718	−1.084	−0.156	0.049	0.158	0.841
$\ln(Bonus_{m,t}/Bonus_{m,t-1})$ (without job turnovers)	0.128	2.746	−1.878	−0.093	0.032	0.222	3.495
$\ln(Pay_{m,t+1}/Pay_{m,t-1})$ (job turnovers in year t)	−0.065	1.289	−1.657	−0.408	0.072	0.493	1.203
$\ln(\overline{Pay}_{m,t+1\to t+3}/Pay_{m,t-1})$ (job turnovers in year t)	−0.156	1.467	−2.396	−0.479	0.039	0.484	1.497
	Panel C: Income risk (cross-manager distribution of time-series SD)						
	Mean	SD	5^{th} pct	25^{th} pct	Median	75^{th} pct	95^{th} pct
SD of $\ln(Pay_{m,t}/Pay_{m,t-1})$ (without job turnovers)	0.484	0.378	0.078	0.218	0.390	0.598	1.054
SD of $\ln(Base_{m,t}/Base_{m,t-1})$ (without job turnovers)	0.561	0.540	0.064	0.202	0.400	0.730	1.302
SD of $\ln(Bonus_{m,t}/Bonus_{m,t-1})$ (without job turnovers)	2.465	2.158	0.000	0.318	2.219	4.142	6.244
SD of $\ln(Rev_{m,t}/Rev_{m,t-1})$	0.552	0.441	0.108	0.255	0.426	0.681	1.547
SD of $\ln(1+Flow_{m,t})$	0.302	0.278	0.056	0.145	0.245	0.345	0.723
SD of $\ln(1+Systematic\ Flow_{m,t})$	0.046	0.106	0.001	0.002	0.004	0.047	0.195
SD of $\ln(1+Idiosyncratic\ Flow_{m,t})$	0.220	0.168	0.041	0.092	0.173	0.302	0.580
SD of $\ln(1+Family\ Flow_{m,t})$	0.185	0.218	0.035	0.067	0.113	0.233	0.545
SD of $\ln(1+R^{gross}_{m,t})$	0.223	0.103	0.090	0.147	0.220	0.274	0.378
	Panel D: Self-disclosed compensation contracts						
	Mean	SD	5^{th} pct	25^{th} pct	Median	75^{th} pct	95^{th} pct
$D^{NonPerf}_{m,t}$	0.149	0.356	0	0	1	1	1
$D^{AUM}_{m,t}$	0.096	0.294	0	0	0	0	1

Notes. This table reports the summary statistics of the main variables. In columns (1) and (2) we report the mean and standard deviation of each variable. In columns (3)–(7) we report the 5th, 25th, 50th, 75th, and 95th percentiles, respectively. The sample period of the data in Panels A to C is from 2000 to 2014, while the sample period of the data in Panel D is from 2005 to 2014.

$4.0 million.

Manager-Level Flows. We first compute the monthly fund-level flows as:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + Ret_{i,t})}{TNA_{i,t-1}}, \tag{2.3}$$

where $TNA_{i,t}$ and $Ret_{i,t}$ denote the total net assets (TNA) and the net return for fund i in month t, respectively. Following Elton, Gruber and Blake (2001), we require that the lagged TNA (i.e., $TNA_{i,t-1}$) exceed \$15 million. If it doesn't, the flow observation for fund i in month t is excluded. Additionally, we account for the incubation bias following Evans (2010).

We proceed to compute the monthly manager-level flows by aggregating the monthly fund-level flows across all funds overseen by manager m. The average is weighted based on the one-month lagged fund asset, divided by the number of managers.

$$Flow_{m,t} = \frac{1}{TNA_{m,t-1}} \sum_{i \in \Omega_{m,t-1}} \frac{TNA_{i,t-1}}{M_{i,t-1}} \times Flow_{i,t}. \tag{2.4}$$

To determine the flow of manager m on an annual basis, we aggregate the monthly manager-level flows for each year. As depicted in Panel A of Table 1, the yearly manager-level flow exhibits considerable volatility. The mean value stands at -0.8%, with a standard deviation of 32.7%.

Dou, Kogan and Wu (2023) demonstrate that the fund flows of active mutual funds exhibit a pronounced factor structure, with the common component reacting to macroeconomic shocks. Theoretically, the manager-level fund flows should comprise two components. The first component aligns with the common fund flows as described by Dou, Kogan and Wu (2023). In contrast, the second component captures the residual flows orthogonal to the common fund flows.

To decompose these manager-level flows, we regress the monthly manager-level flows against the common fund flows, utilizing a 3-year rolling window. This is done provided there are at least 12 monthly observations within the rolling window:

$$Flow_{m,t-\tau} = a_{m,t} + \beta^{flow}_{m,t} \times common\ flow_{t-\tau} + \varepsilon_{m,t-\tau}, \quad \text{with } \tau = 0, 1, \cdots, 35, \tag{2.5}$$

where $common\ flow_{t-\tau}$ represents the common fund flow in month $t-\tau$ and $\beta^{flow}_{m,t}$

denotes manager m's common flow beta in month t.

The systematic flow for each manager on a monthly basis is defined as:

$$Systematic\ Flow_{m,t} = \beta^{flow}_{m,t,avg} \times common\ flow_t, \tag{2.6}$$

where $\beta^{flow}_{m,t,avg}$ represents the average common flow beta for manager m as of the preceding year. The results of our analysis remain similar when we use the common flow betas from the final month, instead of the average across all months, of the preceding year. We utilize lagged common flow betas to deliberately avoid reliance on contemporaneous information when estimating exposure to common flows, viewing this as a persistent trait.

The residual, or the difference between the manager-level flow and its systematic component, is termed the idiosyncratic flow:

$$Idiosyncratic\ Flow_{m,t} = Flow_{m,t} - Systematic\ Flow_{m,t}. \tag{2.7}$$

To calculate the systematic and idiosyncratic flows of manager m on an annual basis, we aggregate the corresponding monthly flows for each manager throughout the year.

Fund Family Flows. We compute the fund family flows by aggregating the fund-level flows across all funds belonging to the same fund family. These flows are averaged, with weights derived from the one-month lagged fund asset size.

$$Family\ Flow_{m,t} = \frac{\sum_{i \in \Omega_{m,f,t-1}} TNA_{i,t-1} \times Flow_{i,t}}{\sum_{i \in \Omega_{m,f,t-1}} TNA_{i,t-1}}. \tag{2.8}$$

where $\Omega_{m,f,t}$ represents the set of funds overseen by fund family f where manager m is employed during month t. To calculate the annual fund family flows, we aggregate the monthly fund family flows for each year.

Manager-Level Returns. To measure monthly manager-level returns, we aggregate the monthly fund-level gross returns across all funds supervised by manager m. This aggregation is weighted according to the one-month lagged fund asset, scaled by the number of managers overseeing the fund.

$$R_{m,t}^{gross} = \frac{1}{TNA_{m,t-1}} \sum_{i \in \Omega_{m,t-1}} \frac{TNA_{i,t-1}}{M_{i,t-1}} \times R_{i,t}^{gross} \tag{2.9}$$

To calculate the annual returns of manager m, we sum up the monthly manager-level returns for the year. As delineated in Panel A of Table 1, the yearly manager-level returns have a standard deviation of 22.1%. Consequently, even though the yearly manager-level returns exhibit substantial fluctuations, they are less pronounced than the variations observed in the yearly manager-level flows.

Income Risk of Fund Managers. To further illustrate the income risk faced by fund managers, we first compute the time-series standard deviation of their income growth rate for each manager and then tabulate the cross-manager distribution of this income risk. As shown in Panel C of Table 1, the average standard deviation of the income growth rate is 0.484, suggesting that fund managers face substantial income risk. Unsurprisingly, the growth rate of bonuses is much more volatile than that of base pay. The growth rate of manager-level fund revenue has an average standard deviation of 0.552, which is very similar to the average standard deviation of the income growth rate. The volatility of fund revenue growth is influenced by both fund flows' growth, with an average standard deviation of 0.302, and returns' growth, with an average standard deviation of 0.223.

Self-Disclosed Compensation Contracts. Based on the compensation contract disclosures in the SAI, we define two indicator variables. It's important to note that these variables are not mutually exclusive. The variable $D_{m,t}^{NonPerf}$ equals one if a manager's compensation is not tied to the fund's investment performance, and zero otherwise. In our sample, the average value of this indicator variable across manager-years is 0.149. Similarly, $D^{AUM}_{m,t}$ equals one if the manager's compensation is linked to the fund's AUM, and zero otherwise. The average value of this variable across fund manager-years in our sample is 0.096.

3 Empirical Analysis

In this section, we explore the determinants of fund managers' compensation. First, in Section 3.1, we examine the relation between a manager's compensation and the fee revenue, flow, and performance. Subsequently, in Section 3.2, we investigate the compensation of managers after they transition to new jobs and analyze how flows and performance from their previous funds shape their compensation at the new firms. Finally, in Section 3.3, we present causal evidence of the impact of fund revenue on manager compensation.

3.1 Compensation of Fund Managers

In this section, we examine the compensation of fund managers, specifically focusing on scenarios without job turnovers. We begin by exploring the relationship between compensation levels and fund revenue in Section 3.1.1. Subsequently, we delve into compensation growth, examining its correlation with flow and performance in Section 3.1.2. In Section 3.1.3, we analyze heterogeneity among managers working in funds that have varying types of self-disclosed compensation contracts. Lastly, in Section 3.1.4, we decompose manager-level fund flows into systematic and idiosyncratic flows, assessing their influence on the growth of manager compensation.

3.1.1 Relation Between Compensation Level and Fund Revenue

We begin by examining whether the compensation of fund managers is influenced by the fee revenue of the funds they oversee and the performance of those funds. Specifically, we regress the compensation of fund managers on the one-year lagged fee revenue generated by the manager and the one-year lagged fund returns at the manager level. The compensation of managers for a given year is the sum of their quarterly labor income throughout that year. We require all four quarterly incomes to be positive to ensure yearly income is comparable across manager-years. The analysis is based on a sample of around 2,200 manager-year observations. To account for aggregate time-series fluctuations in compensation common to all managers, we include year fixed effects. As depicted in Column (1) of Table 2, the coefficient for fee revenue is positive and statistically significant. The magnitude of the pay-revenue sensitivity stands at roughly 0.230, noticeably less than 1. This indicates that the pass-through of fund revenues to compensation is not complete, suggesting a concave relation between compensation and revenue. While the coefficient for fund performance is positive, it is not statistically significant, suggesting that fund performance doesn't have a strong influence on manager compensation beyond fee revenues. In Column (2) of Table 2, when introducing manager fixed effects, the results remain largely unchanged although the magnitude of the pay-revenue sensitivity further reduces to 0.119.

In Columns (5) through (6) of Table 2, we incorporate one-year lagged flows at the manager-level as an independent variable. We observe that the one-year lagged flows are positively correlated with compensation after accounting for one-year lagged fee revenue. This result holds marginal statistical significance when manager fixed effects are included. Meanwhile, the coefficient for the one-year lagged performance continues to be statistically insignificant. This suggests that fund flows and performance mainly influence compensation through AUM although fund flows might have additional explanatory roles for compensation beyond fee revenues. Our results are consistent with those of

Table 2: Relation of fund manager compensation with revenue and performance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\ln(Pay_{m,t})$									
$\ln(Rev_{m,t-1})$	0.230***	0.119***	0.230***	0.122***	0.231***	0.123***				
	[5.85]	[2.88]	[5.83]	[3.00]	[5.83]	[3.01]				
$\ln(1 + R^{gross}_{m,t-1})$	0.392	0.052			0.386	0.023			0.071	0.021
	[1.27]	[0.53]			[1.28]	[0.21]			[0.22]	[0.14]
$\ln(1 + Flow_{m,t-1})$			0.033	0.102*	0.018	0.102*	0.149**	0.137**	0.147**	0.137**
			[0.25]	[1.86]	[0.14]	[1.75]	[2.10]	[2.29]	[2.12]	[2.27]
$\ln(Rev_{m,t-2})$							0.214***	0.083**	0.214***	0.082**
							[5.86]	[2.24]	[5.71]	[2.19]
Adjusted R-squared	0.137	0.797	0.136	0.797	0.137	0.797	0.148	0.766	0.148	0.766
Manager FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table examines the relation of fund manager compensation with revenue and performance. The dependent variable is the natural log of the fund manager's labor income in year t. The independent variables include the natural log of the revenue generated by the manager in years $t-1$ and $t-2$, the natural log of the annual fund returns at the manager level in year $t-1$, and the natural log of the annual fund flows at the manager level in year $t-1$. Standard errors are double-clustered at both the manager and year levels. The sample period of the data is from 2000 to 2014. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Ibert et al. (2018), who find that the compensation of Swedish mutual fund managers is primarily based on manager-level revenue, with performance-sensitive compensation playing a minimal role. In combination with the findings of Ibert et al. (2018), our results strongly contradict the predictions of the contract theory literature. This literature posits that a significant portion of a fund manager's compensation should be directly tied to fund return performance, distinct from the fund's AUM, especially in cases where there is uncertainty about the manager's capabilities.

To further differentiate between flow and performance, we control for two-year lagged fee revenue in Columns (7) through (10). Conceptually, with these regression specifications, we normalize the conditions for managers in terms of their fee revenue in year $t-2$ and then assess the impact of flows and returns from year $t-1$ on the compensation at year t. The coefficients for flows prove to be positive and statistically significant, but those for returns continue to lack significance. The insights gleaned from Columns (7) to (10) underscore the pivotal role of flow in influencing fund managers' compensation. One potential concern is that mutual funds may compensate their managers based on the risk-adjusted returns instead of gross returns. To address this concern, we further use

Table 3: Relation of compensation growth with flow and performance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$\ln(Pay_{m,t}/Pay_{m,t-1})$											
$\ln(1+Flow_{m,t})$	0.019	0.068							0.014	0.059		
	[0.47]	[1.28]							[0.34]	[1.11]		
$\ln(1+Flow_{m,t-1})$	0.073**	0.145**	0.167***	0.199**					0.071**	0.140**	0.154***	0.184**
	[2.51]	[2.60]	[5.21]	[2.52]					[2.57]	[2.61]	[5.85]	[2.48]
$\ln(1+Flow_{m,t-2})$			−0.080	−0.074							−0.078	−0.076
			[−1.41]	[−1.18]							[−1.33]	[−1.15]
$\ln(1+R^{gross}_{m,t})$					−0.016	0.093			−0.007	0.117		
					[−0.11]	[0.58]			[−0.05]	[0.68]		
$\ln(1+R^{gross}_{m,t-1})$					0.271***	0.386***	0.286*	0.402**	0.251***	0.338**	0.211	0.331*
					[3.37]	[3.11]	[1.95]	[2.44]	[3.43]	[2.79]	[1.41]	[2.07]
$\ln(1+R^{gross}_{m,t-2})$							0.209*	0.366**			0.194	0.358**
							[1.80]	[2.58]			[1.45]	[2.51]
Adjusted R-squared	0.044	0.149	0.098	0.183	0.043	0.144	0.094	0.180	0.046	0.152	0.100	0.187
Manager FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table examines the relation of compensation growth with flow and performance. The dependent variable is the compensation growth of fund managers in year t, which is the difference in the natural log of the fund manager's labor income in year t compared to year $t-1$. The independent variables include the natural log of the annual fund flows at the manager level in years t, $t-1$, and $t-2$, and log annual fund returns at the manager level in years t, $t-1$, and $t-2$. Standard errors are double-clustered at both the manager and year levels. The sample period of the data is from 2000 to 2014. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

alphas estimated by the CAPM model and the excess returns over the Vanguard index fund benchmark portfolio as the alternative measures for performance in Appendix B. We find similar patterns. As shown in Table A.1, the coefficients for flows are positive and statistically significant after controlling for the two-year lagged fee revenue, while the coefficients for the risk-adjusted returns are statistically insignificant.

3.1.2 Relation of Compensation Growth with Flow and Performance

After examining compensation levels, we now turn our attention to the compensation growth rate. This metric is arguably more informative. While various unobserved characteristics of fund managers can influence compensation levels, the compensation growth rate should more directly correlate with measures indicative of managers' actions, such as the fund flow they attract and the return performance they generate.

In Table 3, we examines the relation of compensation growth with both flow and performance. The dependent variable is the compensation growth of fund managers in year t, represented by the difference in the natural log of the fund manager's labor income between year t and year $t-1$. As in Table 2, the compensation of managers for a given year is the sum of their quarterly labor income throughout that year. We mandate that all quarterly incomes be positive to prevent scenarios where managers work only part of the year, ensuring a meaningful comparison of the compensation growth rate. Consistent with Table 2, the analysis is based on a sample of around 2,200 manager-year observations. The independent variables comprise the natural log of the annual fund flows at the manager level in years t, $t-1$, and $t-2$, and the log of annual fund returns at the manager level in years t, $t-1$, and $t-2$. We include year fixed effects in the regressions to account for aggregate changes in the compensation growth rate common to all managers. As depicted in Table 3, both the flow and performance in year $t-1$ are positively correlated with compensation growth in year t. These findings are statistically and economically significant. For instance, as per Column (12), a one standard deviation increase in flow (i.e., 0.327) correlates with a 6.02% rise in compensation (calculated as 0.327×0.184). Similarly, a one standard deviation increase in performance (i.e., 0.221) corresponds to a 7.32% surge in compensation (calculated as 0.221×0.331).

We measure manager performance using gross returns in the analysis of Table 3. However, the best performance measure to explain pay changes remains an empirical question. To address this, we conduct a horse race comparison among gross returns, CAPM alphas, and the excess returns over the Vanguard index fund benchmark portfolio. Since we require non-missing observations for risk-adjusted return measures, the analysis is based on a sample of around 2,000 manager-year observations. The results are presented in Table 4. In Columns (1) and (2), we regress pay changes from year $t-1$ to year t on gross returns for year $t-1$. We find that the coefficient is positive and statistically significant. In Columns (3) and (4), we use the abnormal returns estimated by the CAPM model as the performance measure. Interestingly, the coefficient becomes statistically insignificant. In Columns (5) and (6), we use the Vanguard excess returns as the performance measure. We

Table 4: Relation of compensation growth with different performance measures.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\ln(Pay_{m,t}/Pay_{m,t-1})$									
$\ln(1+Flow_{m,t-1})$									0.147***	0.263**
									[2.81]	[2.36]
$\ln(1+Flow_{m,t-2})$									−0.044	−0.036
									[−0.71]	[−0.56]
$\ln(1+R^{gross}_{m,t-1})$	0.277**	0.359**					0.281**	0.391**	0.253*	0.307**
	[2.64]	[2.29]					[2.72]	[2.51]	[1.94]	[2.22]
$\ln(1+R^{gross}_{m,t-2})$									0.217*	0.209*
									[1.86]	[1.78]
$\ln(1+R^{abn,CAPM}_{m,t-1})$			0.169	0.366			−0.062	−0.078	−0.137	−0.234
			[0.71]	[1.54]			[−0.16]	[−0.18]	[−0.49]	[−0.62]
$\ln(1+R^{abn,CAPM}_{m,t-2})$									−0.182	−0.259
									[−0.71]	[−0.87]
$\ln(1+R^{abn,Vanguard}_{m,t-1})$					0.198	0.490**	0.258	0.387	0.262	0.489*
					[0.52]	[2.15]	[0.60]	[1.42]	[0.61]	[1.77]
$\ln(1+R^{abn,Vanguard}_{m,t-2})$									0.017	0.196
									[0.04]	[0.53]
Adjusted R-squared	0.244	0.315	0.242	0.314	0.242	0.314	0.245	0.316	0.311	0.429
Manager FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table examines the relation of compensation growth with flow and different performance measures. The dependent variable is the compensation growth of fund managers in year t, calculated as the difference in the natural log of the fund manager's labor income between year t and year $t-1$. The independent variables include the natural log of the annual fund flows at the manager level in years $t-1$ and $t-2$, and log annual fund returns (gross returns, CAPM alphas, and the Vanguard excess returns) at the manager level in years $t-1$ and $t-2$. Standard errors are double-clustered at both the manager and year levels. The sample period of the data is from 2000 to 2014. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

find that the coefficient is statistically significant only when both manager and year fixed effects are included. We then include all three performance measures as independent variables in Columns (7) and (8) to conduct a horse race comparison. We find that the coefficient for the gross returns remains positive and statistically significant, while the coefficients for the two risk-adjusted returns become statistically insignificant. In Columns (9) and (10), we further add flows for years $t-1$ and year $t-2$, as well as gross returns and risk-adjusted returns for year $t-2$, to the list of independent variables. We again find that the coefficients for the gross returns are the most significant among the three performance measures. Taken together, the findings in Table 4 suggest that mutual funds seem to compensate managers based on gross returns rather than risk-adjusted returns. This result is intuitively sound because gross returns are directly related to changes in AUM, which in turn affects the fee revenues of the mutual funds. In contrast, risk-adjusted

Table 5: Growth of base pay and bonus.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$\ln(Base_{m,t}/Base_{m,t-1})$						$\ln(Bonus_{m,t}/Bonus_{m,t-1})$					
$\ln(1+Flow_{m,t-1})$	0.137**	0.259***			0.128**	0.256***	0.308**	0.528***			0.257**	0.470***
	[2.45]	[2.80]			[2.28]	[2.70]	[2.40]	[2.84]			[2.36]	[2.70]
$\ln(1+R^{gross}_{m,t-1})$			0.305	0.188	0.246	0.098			0.768*	0.942*	0.649*	0.777*
			[1.40]	[0.91]	[1.12]	[0.44]			[1.86]	[1.69]	[1.71]	[1.75]
Adjusted R-squared	0.032	0.206	0.029	0.192	0.034	0.207	0.036	0.170	0.044	0.172	0.050	0.185
Manager FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table examines the relation of base pay and bonus growth with flow and performance. The dependent variable in columns (1) – (6) is the base pay growth of fund managers in year t, which is the difference in the natural log of the fund manager's base pay in year t compared to year $t-1$. The dependent variable in columns (7) – (12) is the bonus growth of fund managers in year t, which is the difference in the natural log of the fund manager's bonus in year t compared to year $t-1$. To estimate a fund manager's bonus in a year, we first identify the highest paid quarter during a year as the "bonus quarter" if the pay during the highest paid quarter is at least 20% higher than the average pay during its two neighboring quarters. A fund manager's bonus pay in year t is defined as the pay in a bonus quarter in year t minus the average pay of the same fund manager in the two neighboring quarters. The base pay during year t is defined as the annual pay of a fund manager minus the bonus pay of the same manager during year t. In this set of analyses, we focus on the subsample where bonus is paid during the first quarter of the year for consistency. The independent variables include the natural log of the annual fund flows at the manager level in year $t-1$ and log annual fund returns at the manager level in year $t-1$. Standard errors are double-clustered at both the manager and year levels. The sample period of the data is from 2000 to 2014. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

returns are not directly associated with changes in AUM.

Table 5 examines the relation between base pay and bonus growth with respect to flow and performance. We concentrate on the subsample where bonuses are paid during the first quarter of the year in this table. This subsample comprises approximately 1,400 manager-year observations. The results are similar if we do not apply this filter. We find that lagged flow is positively and significantly correlated with both base pay and bonus growth. However, the relation between compensation growth and lagged performance is only statistically significant for bonuses. The literature has long debated the persistence of mutual fund managers' performance (e.g., Carhart, 1997; Bollen and Busse, 2005; Kaniel et al., 2023). Our empirical findings suggest that mutual fund firms might be reluctant to increase base pay based on performance due to uncertainties surrounding its persistence. Conversely, since flows can exhibit persistence and thus represent a more predictable future revenue stream, mutual fund firms might be more inclined to adjust base pay based on flow. In line with these conjectures, the one-year autocorrelation of yearly manager-level flow in our dataset is 0.30 and statistically significant, while the one-year autocorrelation of the yearly manager-level gross return stands at -0.10, also statistically

Table 6: Nonlinearity in the relation of compensation growth with flow and performance.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(Pay_{m,t}/Pay_{m,t-1})$					
$\ln(1+Flow_{m,t-1}) \times 1^{st}$ *Flow Tertile*$_{m,t-1}(Low)$	0.087	0.024			0.065	−0.012
	[0.64]	[0.14]			[0.49]	[−0.07]
$\ln(1+Flow_{m,t-1}) \times 2^{nd}$ *Flow Tertile*$_{m,t-1}$	−0.040	−0.044			−0.041	−0.044
	[−0.19]	[−0.21]			[−0.22]	[−0.25]
$\ln(1+Flow_{m,t-1}) \times 3^{rd}$ *Flow Tertile*$_{m,t-1}(High)$	0.066**	0.177***			0.067**	0.180***
	[2.38]	[2.86]			[2.36]	[2.93]
$\ln(1+R^{gross}_{m,t-1}) \times 1^{st}$ *Return Tertile*$_{m,t-1}(Low)$			0.359***	0.533***	0.428***	0.728***
			[3.34]	[3.22]	[2.58]	[3.02]
$\ln(1+R^{gross}_{m,t-1}) \times 2^{nd}$ *Return Tertile*$_{m,t-1}$			0.279	0.515*	0.287	0.535*
			[1.25]	[1.82]	[1.36]	[1.94]
$\ln(1+R^{gross}_{m,t-1}) \times 3^{rd}$ *Return Tertile*$_{m,t-1}(High)$			0.441**	0.735***	0.428**	0.728***
			[2.62]	[2.98]	[2.58]	[3.02]
1^{st} *Flow Tertile*$_{m,t-1}(Low)$	−0.019	−0.031			−0.021	−0.040
	[−0.39]	[−0.47]			[−0.44]	[−0.62]
3^{rd} *Flow Tertile*$_{m,t-1}(High)$	−0.001	−0.011			−0.001	−0.030
	[−0.02]	[−0.22]			[−0.29]	[−0.62]
1^{st} *Return Tertile*$_{m,t-1}(Low)$			0.052	0.082	0.049	0.077
			[1.28]	[1.50]	[1.28]	[1.50]
3^{rd} *Return Tertile*$_{m,t-1}(High)$			0.001	−0.017	−0.005	−0.028
			[0.01]	[−0.32]	[−0.11]	[−0.51]
Adjusted R-squared	0.045	0.150	0.045	0.147	0.156	0.049
Manager FE	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table examines the nonlinearity in the relation of compensation growth with flow and performance. The dependent variable is the compensation growth of fund managers in year t, which is the difference in the natural log of the fund manager's labor income in year t compared to year $t-1$. We sort managers into tertiles based on the natural log of the annual fund flows at the manager level in year $t-1$ and log annual fund returns at the manager level in year $t-1$. The main independent variables include the interaction between the indicators for manager tertile sorted on lagged flows and the lagged flows, the interaction between the indicators for manager tertile sorted on lagged returns and the lagged returns, and also the tertile indicators. Standard errors are double-clustered at both the manager and year levels. The sample period of the data is from 2000 to 2014. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

significant.

Next, we explore potential nonlinearity in the relation between compensation growth and both flow and performance. Specifically, we categorize managers into tertiles based on the natural log of annual fund flows at the manager level for year $t-1$ and the log of annual fund returns at the same level for year $t-1$. We then regress the compensation growth rate on the interaction between the indicators for manager tertile sorted on lagged flows and the lagged flows, the interaction between the indicators for manager tertile sorted on lagged returns and the lagged returns, and also the tertile indicators. As in Table 2, this set of analyses is based on a sample of around 2,200 manager-year observations. The outcomes of these regressions are detailed in Table 6.

Table 7: Heterogeneity across funds with varying self-disclosed compensation contracts.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(Pay_{m,t}/Pay_{m,t-1})$					
$\ln(1+Flow_{m,t-1})$	0.136***	0.081**	0.145***			
	[4.50]	[2.31]	[5.41]			
$D_{m,t-1}^{NonPerf} \times \ln(1+Flow_{m,t-1})$		0.171				
		[1.11]				
$D_{m,t-1}^{AUM} \times \ln(1+Flow_{m,t-1})$			−0.131			
			[−0.90]			
$\ln(1+R_{m,t-1}^{gross})$				0.518***	0.480***	0.518***
				[3.58]	[2.86]	[3.08]
$D_{m,t-1}^{NonPerf} \times \ln(1+R_{m,t-1}^{gross})$					0.091	
					[0.52]	
$D_{m,t-1}^{AUM} \times \ln(1+R_{m,t-1}^{gross})$						−0.002
						[−0.00]
Adjusted R-squared	0.373	0.375	0.374	0.373	0.374	0.373
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table examines the heterogeneity across funds with different self-disclosed compensation contracts. The dependent variable is the compensation growth of fund managers in year t, which is the difference in the natural log of the fund manager's labor income in year t compared to year $t-1$. We construct two indicator variables for compensation contracts based on the SAIs in year $t-1$. The first indicator variable, $D_{m,t-1}^{NonPerf}$, equals one for managers who work in funds that do not mention performance-based pay in their SAIs. The second indicator variable, $D_{m,t-1}^{AUM}$, equals one for managers who work in funds that mention AUM-based pay in their SAIs. The independent variables include the natural log of the annual fund flows at the manager level in year $t-1$, the interaction terms between flow and the two indicator variables for compensation contracts, the natural log of the annual fund returns at the manager level in year $t-1$, and the interaction terms between returns and the two indicator variables for compensation contracts. Standard errors are double-clustered at both the manager and year levels. The sample period of the data is from 2005 to 2014. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

We observe that the positive correlation between compensation growth and flow is mainly evident in the top tertile of flows, implying that mutual fund firms likely employ fund flows as a criterion for determining pay increases rather than pay reductions. In contrast, the positive association between compensation growth and performance is significant in both the bottom and top tertiles. This suggests that mutual fund firms take performance into account when deciding on both pay hikes and reductions. These findings align with the results in Table 5, as flows coincide with the growth of base pay, which is less susceptible to downward adjustments compared to bonuses.

3.1.3 Heterogeneity Across Self-Disclosed Compensation Contracts

We explore the heterogeneity across funds based on their self-disclosed compensation contracts. Specifically, we create two indicator variables related to compensation contracts from the SAIs in year $t-1$. The first indicator variable, $D_{m,t-1}^{NonPerf}$, is set to one for managers working in funds that do not specify performance-based pay in their SAIs. The second indicator variable, $D^{AUM}_{m,t-1}$, is set to one for managers working in funds that mention AUM-based pay in their SAIs. Similar to Ma, Tang and Gómez (2019), we also find that a large majority of managers (85.1% in the merged sample) work in mutual funds that report investment performance-based pay in their SAIs, whereas only a small fraction of managers (9.6% in the merged sample) work in funds that explicitly report AUM-based pay.

We consider the interaction of these indicators with both flow and performance and incorporate them into the list of independent variables. Due to data availability of SAIs, the analysis is based on a sample spanning from 2005 to 2014 and containing around 1,100 manager-year observations. As shown in Table 7, the coefficients for these interaction terms are statistically insignificant. This suggests that, regardless of their self-disclosed compensation contracts, funds appear to reward their managers in a similar manner based on flow and performance. For example, according to Columns (3) of Table 7, flow comoves significantly and positively with compensation growth for funds that do not explicitly mention AUM-based pay. Similarly, for funds that report investment performance-based pay in their SAIs, flow also comoves significantly and positively with compensation growth (see Column (2) of Table 7). These findings cast doubt on the credibility and clarity of the compensation structures disclosed in SAIs.

One likely factor driving this discrepancy is the strategic marketing considerations of fund companies. It's plausible that funds would be highly motivated to portray their managers' incentives as perfectly aligned with the performance outcomes that potential investors seek. Our findings suggest that investors should interpret the wording in the disclosures with a grain of salt. Instead of equating the word "performance" in the SAIs to returns, we should recognize that it might also encompass fund asset growth (i.e., flows). More generally, our findings are related to studies on the strategic disclosures of mutual funds. For example, it has been shown that there are substantial mismatches

Table 8: Relation of compensation growth with common fund flows.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(Pay_{m,t}/Pay_{m,t-1})$		$\ln(Base_{m,t}/Base_{m,t-1})$		$\ln(Bonus_{m,t}/Bonus_{m,t-1})$	
Common Flow$_t$	0.080***	0.087**	0.089**	0.101*	0.065	0.016
	[3.50]	[2.24]	[2.20]	[1.80]	[1.01]	[0.28]
Common Flow$_{t-1}$	−0.039	−0.055	−0.039	−0.039	−0.030	−0.075
	[−1.49]	[−0.80]	[−0.96]	[−0.69]	[−0.74]	[−1.36]
Adjusted R-squared	0.032	0.239	0.028	0.191	0.023	0.202
Manager FE	No	Yes	No	Yes	No	Yes

Notes. This table examines the relation of compensation growth with common fund flow. The dependent variable in columns (1) – (2) is the compensation growth of fund managers in year t, which is the difference in the natural log of the fund manager's labor income in year t compared to year $t-1$. The dependent variable in columns (3) – (4) is the base pay growth of fund managers in year t, which is the difference in the natural log of the fund manager's base pay in year t compared to year $t-1$. The dependent variable in columns (5) – (6) is the bonus growth of fund managers in year t, which is the difference in the natural log of the fund manager's bonus in year t compared to year $t-1$. Base pay and bonus are defined in Table 5. The independent variables include the common fund flow of mutual funds in years t and $t-1$ as in Dou, Kogan and Wu (2023). The common fund flows are standardized to have a mean of zero and a standard deviation of one during the sample period presented in this table, which spans from 2000 to 2014. Standard errors are double-clustered at both the manager and year levels. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

between the stated investment objectives and actual styles of mutual funds (e.g., Brown and Goetzmann, 1997; DiBartolomeo and Witkowski, 1997) and between the stated risk classifications of fund holdings and the actual risk levels (e.g., Chen, Cohen and Gurun, 2021).

3.1.4 The Roles of Systematic and Idiosyncratic Flows

Dou, Kogan and Wu (2023) demonstrate that the fund flows of active mutual funds contain a common component that responds to macroeconomic shocks. Therefore, an important question arises: does the compensation of fund managers respond to these common fund flows? To answer this question, we regress the compensation growth on both the contemporaneous and one-year lagged common fund flows. This analysis is conducted using a sample of around 1,400 manager-year observations, consistent with Table 5. To ease the interpretation of the coefficient, we standardize the common fund flows to have a mean of zero and a standard deviation of one. Note that since common fund flows are a time series, we do not control for year fixed effects in our regressions. Table 8 presents the results. We find that common fund flows correlate with compensation growth contemporaneously. This result is economically significant. A one standard

Table 9: Relation of compensation growth with systematic and idiosyncratic flows.

	Panel A: Baseline regressions					
	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(Pay_{m,t}/Pay_{m,t-1})$		$\ln(Base_{m,t}/Base_{m,t-1})$		$\ln(Bonus_{m,t}/Bonus_{m,t-1})$	
$\ln(1+Systematic\ Flow_{m,t})$	0.698**	0.718**	0.718*	0.737**	0.604	0.589
	[2.53]	[2.54]	[1.87]	[2.60]	[1.21]	[1.33]
$\ln(1+Idiosyncratic\ Flow_{m,t})$	0.167*	0.195	−0.020	−0.014	0.197	0.243
	[1.75]	[1.48]	[−0.23]	[−0.12]	[1.60]	[1.66]
$\ln(1+Systematic\ Flow_{m,t-1})$	−0.090	−0.052	−0.058	0.108	−0.123	−0.088
	[−1.27]	[−1.22]	[−0.77]	[0.41]	[−0.60]	[−0.33]
$\ln(1+Idiosyncratic\ Flow_{m,t-1})$	0.256**	0.150**	0.220	−0.048	0.276**	0.163**
	[2.81]	[2.15]	[1.71]	[−0.32]	[2.47]	[2.29]
Adjusted R-squared	0.027	0.083	0.022	0.105	0.016	0.055
Year FE	No	Yes	No	Yes	No	Yes
	Panel B: Controlling for fund family flows					
	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(Pay_{m,t}/Pay_{m,t-1})$		$\ln(Base_{m,t}/Base_{m,t-1})$		$\ln(Bonus_{m,t}/Bonus_{m,t-1})$	
$\ln(1+Systematic\ Flow_{m,t})$	0.634**	0.689**	0.688*	0.689*	0.601	0.680
	[2.28]	[2.24]	[1.76]	[2.05]	[1.10]	[1.17]
$\ln(1+Idiosyncratic\ Flow_{m,t})$	0.056	0.082	−0.030	−0.021	0.194	0.243
	[0.79]	[1.20]	[−0.30]	[−0.21]	[1.27]	[1.64]
$\ln(1+Systematic\ Flow_{m,t-1})$	−0.098	−0.062	−0.056	0.099	−0.123	−0.089
	[−1.38]	[−1.35]	[−0.72]	[0.42]	[−0.61]	[−0.34]
$\ln(1+Idiosyncratic\ Flow_{m,t-1})$	0.244**	0.137**	0.215	−0.050	0.276**	0.163**
	[2.84]	[2.21]	[1.59]	[−0.39]	[2.47]	[2.30]
$\ln(1+Family\ Flow_{m,t})$	0.247**	0.254**	0.306*	0.307*	0.006	0.020
	[2.25]	[2.33]	[1.74]	[1.92]	[0.02]	[0.08]
Adjusted R-squared	0.029	0.085	0.023	0.109	0.016	0.055
Year FE	No	Yes	No	Yes	No	Yes

Notes. This table examines the relation of compensation growth with both systematic and idiosyncratic fund flows. The dependent variable in columns (1) – (2) is the compensation growth of fund managers in year t, which is the difference in the natural log of the fund manager's labor income in year t compared to year $t-1$. The dependent variable in columns (3) – (4) is the base pay growth of fund managers in year t, which is the difference in the natural log of the fund manager's base pay in year t compared to year $t-1$. The dependent variable in columns (5) – (6) is the bonus growth of fund managers in year t, which is the difference in the natural log of the fund manager's bonus in year t compared to year $t-1$. Base pay and bonus are defined in Table 5. The independent variables include the natural log of the annual systematic and idiosyncratic flows at the manager level in years t and $t-1$. We further control for the natural log of the annual fund family flows in year t in Panel B. Standard errors are double-clustered at both the manager and year levels. The sample period of the data is from 2000 to 2014. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

deviation increase in common flows correlates with a more than 8% rise in compensation. The comovement between common flows and compensation growth is more pronounced in base pay than in bonuses. Our findings indicate that common flows indeed influence managers' compensation, lending strong empirical support to Dou, Kogan and Wu (2023), who posit that fund managers have strong incentives to hedge against common flow risks.

Because manager-level fund flows can have heterogeneous exposure to common fund flows, we further decompose fund flows into systematic and idiosyncratic components.

Systematic flows capture the portion of fund flows that comove with the common fund flows, while idiosyncratic flows are the residual component. We investigate the relation between compensation growth and both the contemporaneous and one-year lagged systematic and idiosyncratic flows. Because we use a three-year rolling window to construct the systematic and idiosyncratic flow measures, the sample size for this analysis is reduced to approximately 900 manager-year observations. The findings are presented in Panel A of Table 9. We find that while systematic and idiosyncratic flows both comove positively with compensation growth, they differ in two main ways. First, systematic flows comove contemporaneously with compensation growth, whereas idiosyncratic flows comove with the compensation growth in the subsequent year. Second, the comovement between systematic flows and compensation growth is more pronounced in base pay, while the comovement between idiosyncratic flows and compensation growth is notably evidence in bonuses.

A plausible explanation is that common fund flows react to macroeconomic conditions. Consequently, mutual fund firms may be nimble in adjusting compensation upon detecting macroeconomic signals informative of future revenues. In contrast, modifying manager pay based on their idiosyncratic flows might necessitate a longer duration, given that firms must meticulously assess each manager's contribution. In Panel B of Table 9, we incorporate the contemporaneous family fund flows as an additional independent variable. Our observations indicate that, akin to the systematic flows, family fund flows comove with compensation growth contemporaneously, with this comovement primarily evident in base pay. This pattern in family fund flows is consistent with the aforementioned explanation. Because family-level flows, compared with manager-level flows, are more likely to reflect overarching economic conditions than the individual performance of managers. When accounting for family fund flows, the magnitude of the coefficient for the systematic flows decreases, yet it remains statistically significant. This result suggests that the relation between systematic flows and compensation growth is only partly influenced by fund family flows.

The positive comovement between fund family flows and compensation growth that we document aligns with the findings of Ibert et al. (2018) from Swedish data. Our results suggest that, akin to Swedish fund managers, the compensation of U.S. fund managers also includes a component sourced from a fund-family-wide bonus pool. This compensation structure helps explain the cross-fund subsidization phenomena highlighted in previous studies (e.g., Gaspar, Massa and Matos, 2006; Bhattacharya, Lee and Pool, 2013) and reconciles observed patterns of competition and cooperation within mutual fund families (e.g., Evans, Prado and Zambrana, 2020).

3.2 Career Outcomes of Fund Managers

In Section 3.1, we have examined how the compensation of fund managers is related to fund revenue, flow, and performance. These analyses are conditional on there being no job turnovers. In other words, the compensation and the determinants we study (i.e., fund revenue, flow, and performance) are from the same employers. In this section, we further study how the flow and performance of fund managers are related to their compensation in new firms after they change jobs.

3.2.1 Compensation Growth Following Job Turnovers

We examine the relation of fund managers' career outcomes with flows and performance by tracking the compensation of these managers after they depart from mutual fund firms. The LEHD data provide a unique identifier for individuals, allowing us to determine the compensation of individuals once they leave their respective firms.

In Table 10, we regress compensation growth around job changes on the flows and returns preceding the the job turnovers. In Panel A of Table 10, we regress pay changes surrounding manager turnovers on the flows and returns prior to these turnovers. The analysis is conditional on job turnovers of managers and is based on a sample of around

Table 10: Compensation growth following job turnovers.

	Panel A: Total flows			
	(1)	(2)	(3)	(4)
	$\log(Pay_{m,t+1}/Pay_{m,t-1})$		$\log(\overline{Pay}_{m,t+1\to t+3}/Pay_{m,t-1})$	
$\ln(1+Flow_{m,t-1})$	0.256**	0.263**	0.317**	0.258**
	[2.35]	[2.36]	[2.64]	[2.30]
$\ln(1+R^{gross}_{m,t-1})$	0.574	0.252	0.354	0.026
	[1.56]	[0.54]	[1.18]	[0.07]
Adjusted R-squared	0.014	0.088	0.013	0.101
Year FE	No	Yes	No	Yes

	Panel B: Systematic and idiosyncratic flows			
	(1)	(2)	(3)	(4)
	$\log(Pay_{m,t+1}/Pay_{m,t-1})$		$\log(\overline{Pay}_{m,t+1\to t+3}/Pay_{m,t-1})$	
$\ln(1+Systematic\ Flow_{m,t-1})$	0.298**	0.300**	0.340**	0.297**
	[2.26]	[2.11]	[2.18]	[2.15]
$\ln(1+Idiosyncratic\ Flow_{m,t-1})$	0.552*	0.570*	0.508*	0.545*
	[1.88]	[1.78]	[1.80]	[1.82]
$\ln(1+R^{gross}_{m,t-1})$	0.641	0.309	0.424	0.081
	[1.61]	[0.67]	[1.49]	[0.21]
Adjusted R-squared	0.019	0.092	0.016	0.105
Year FE	No	Yes	No	Yes

Notes. This table examines the relation of compensation growth with flow and performance, conditional on fund managers changing their employers in year t. The dependent variable in columns (1) and (2) is the compensation growth of fund managers from year $t-1$ to year $t+1$, which is the difference in the natural log of the fund manager's labor income in year $t+1$ compared to year $t-1$. The compensation of year $t+1$ is sourced from the new employers, whereas the compensation of year $t-1$ comes from the original employers. The dependent variable in columns (3) and (4) represents the difference in the natural log of the fund manager's average labor income from year $t+1$ up to $t+3$ compared to the labor income from year $t-1$. Compensation for the period from year $t+1$ to $t+3$ is provided by the new employers, while the compensation for year $t-1$ is from the original employers. The independent variables in Panel A include the natural log of the annual fund flows at the manager level in year $t-1$ and the natural log of the annual fund returns at the manager level in year $t-1$. The independent variables in Panel B include the natural log of the annual systematic and idiosyncratic flows at the manager level in year $t-1$ and the natural log of the annual fund returns at the manager level in year $t-1$. Standard errors are clustered at the year level. The sample period of the data is from 2000 to 2014. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

400 unique manager turnover events. We do not control for manager fixed effects because the majority of managers in our data sample do not change jobs more than once. We observe that fund flows are positively correlated with pay changes around manager turnover events. However, fund performance does not significantly correlate with these pay changes. These findings suggest that fund flows continue to influence managers' compensation after they switch jobs, whereas performance does not. In Panel B of Table 10, we further decompose flows into systematic and idiosyncratic components. Our analysis indicates that both types of flows influence compensation following job turnovers.

Table 11: Job turnovers with large compensation changes.

	Panel A: Total flows							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$D^{Demotion}_{m,t}$				$D^{Promotion}_{m,t}$			
$D^{Large\ Outflow}_{m,t-3\to t-1}$	0.041**	0.037**	0.040**	0.036**			−0.005	−0.006
	[2.36]	[2.35]	[2.26]	[2.25]			[−0.36]	[−0.34]
$D^{Large\ Inflow}_{m,t-3\to t-1}$			−0.006	−0.015	0.032*	0.039*	0.031*	0.039*
			[−0.37]	[−1.07]	[1.80]	[1.85]	[1.83]	[1.81]
$D^{Large\ Negative\ Return}_{m,t-3\to t-1}$	0.011	0.003	0.009	0.003			−0.013	−0.032
	[0.42]	[0.11]	[0.33]	[0.11]			[−0.66]	[−1.28]
$D^{Large\ Positive\ Return}_{m,t-3\to t-1}$			−0.012	−0.003	0.020**	0.026**	0.019**	0.022**
			[−1.28]	[−0.38]	[2.47]	[2.50]	[2.50]	[2.28]
Adjusted R-squared	0.018	0.226	0.019	0.227	0.028	0.205	0.028	0.207
Manager FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	Panel B: Systematic and idiosyncratic flows			
	(1)	(2)	(3)	(4)
	$D^{Demotion}_{m,t}$		$D^{Promotion}_{m,t}$	
$D^{Large\ Systematic\ Outflow}_{m,t-3\to t-1}$	0.037**	0.035**		
	[2.27]	[2.18]		
$D^{Large\ Idiosyncratic\ Outflow}_{m,t-3\to t-1}$	0.029*	0.030*		
	[1.86]	[1.88]		
$D^{Large\ Systematic\ Inflow}_{m,t-3\to t-1}$			0.040**	0.044**
			[2.19]	[2.18]
$D^{Large\ Idiosyncratic\ Inflow}_{m,t-3\to t-1}$			0.028*	0.028*
			[1.87]	[1.89]
$D^{Large\ Negative\ Return}_{m,t-3\to t-1}$	0.013	0.008		
	[0.77]	[0.47]		
$D^{Large\ Positive\ Return}_{m,t-3\to t-1}$			0.016*	0.019*
			[1.77]	[1.87]
Adjusted R-squared	0.020	0.235	0.031	0.214
Manager FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes

Notes. This table examines how job turnovers with large compensation changes are related to flows and performance in the years preceding the turnovers. The dependent variable in columns (1) – (4), $D^{Demotion}_{m,t}$, is an indicator variable that equals one if the labor income of manager m in year $t+1$ is at least 20% lower than the labor income in year $t-1$ and the manager experiences a job turnover in year t. The dependent variable in columns (5) – (8), $D^{Promotion}_{m,t}$, is an indicator variable that equals one if the labor income of manager m in year $t+1$ is at least 20% higher than the labor income in year $t-1$ and the manager experiences a job turnover in year t. The independent variables include a set of indicator variables that represent large inflows and outflow and large positive and negative returns. $D^{Large\ Outflow}_{m,t-3\to t-1}$ is an indicator variable that equals one if the average fund flow of the manager from year $t-3$ to year $t-1$ is ranked in the bottom decile. $D^{Large\ Inflow}_{m,t-3\to t-1}$ is an indicator variable that equals one if the average fund flow of the manager from year $t-3$ to year $t-1$ is ranked in the top decile. $D^{Large\ Systematic\ Outflow}_{m,t-3\to t-1}$ and $D^{Large\ Idiosyncratic\ Outflow}_{m,t-3\to t-1}$ are indicator variables that equal one if the average systematic and idiosyncratic flows of the manager from year $t-3$ to year $t-1$ are ranked in the bottom decile, respectively $D^{Large\ Systematic\ Inflow}_{m,t-3\to t-1}$ and $D^{Large\ Idiosyncratic\ Inflow}_{m,t-3\to t-1}$ are indicator variables that equal one if the average systematic and idiosyncratic flows of the manager from year $t-3$ to year $t-1$ are ranked in the top decile, respectively. $D^{Large\ Negative\ Return}_{m,t-3\to t-1}$ is an indicator variable that equals one if the average fund returns of the manager from year $t-3$ to year $t-1$ is ranked in the bottom decile. $D^{Large\ Positive\ Return}_{m,t-3\to t-1}$ is an indicator variable that equals one if the average fund returns of the manager from year $t-3$ to year $t-1$ is ranked in the top decile. Standard errors are double-clustered at both the manager and year levels. The sample period of the data is from 2000 to 2014. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

3.2.2 Job Turnovers With Large Compensation Changes

Furthermore, we investigate the relation between job turnovers accompanied by significant compensation changes and flows and performance that precede these turnovers. We define $D_{m,t}^{Demotion}$ and $D_{m,t}^{Promotion}$) as indicator variables for significant income demotions and promotions, respectively. $D_{m,t}^{Demotion}$ takes a value of one if the labor income of manager m in year $t+1$ is at least 20% lower than the labor income in year $t-1$, and the manager undergoes a job turnover in year t. Conversely, $D_{m,t}^{Promotion}$ takes a value of one if the labor income of manager m in year $t+1$ is at least 20% higher. The mean values of the $D_{m,t}^{Demotion}$ and $D_{m,t}^{Promotion}$ are 4.2% and 3.3%, respectively. We regress $D_{m,t}^{Demotion}$ and $D_{m,t}^{Promotion}$ on a set of indicator variables that represent large inflows and outflow and large positive and negative returns in the years leading up to the turnovers. Note that the data sample in this analysis is a manager-year panel. The sample contains around 2,400 manager-year observations. Unlike the analysis in Table 10, the sample is not limited to job turnover events. We control for year fixed effects to account for aggregate changes in the income demotions and promotions common to all managers. As illustrated in Panel A of Table 11, large outflows (i.e., those in the bottom decile) increase the probability of demotions by a significant 4 percentage points. This change is of substantial economic importance. On the other hand, large inflows and positive returns (i.e., those in the top decile) are associated with a greater probability of promotions. These results are both statistically and economically significant. In Panel B of Table 11, we incorporate indicator variables that represent large systematic and idiosyncratic flows. [5] Our analysis indicates that both flow types are associated with both income demotions and promotions.

[5] Similar to Table 9, the sample size for this analysis is reduced to 1,500 after incorporating systematic and idiosyncratic flows.

3.3 Causal Effects of Fund AUM and Revenue on Compensation

In Table 2, we present a body of evidence demonstrating a positive correlation between fund manager compensation and the lagged AUM and revenue of the funds under their management. Nevertheless, it is important to note that this evidence alone falls short of establishing a definitive causal relationship, indicating that fund manager compensation is determined by the AUM or revenue of the funds under the manager's supervision. This limitation arises due to an endogeneity issue. Specifically, the observed positive correlation between fund manager compensation and the lagged AUM and revenue of the funds under their management may be influenced by unaccounted-for variables. For instance, both manager compensation and fund AUM (and revenue) can be simultaneously influenced by the skill level of fund managers, irrespective of whether these skills are reflected in the fund returns. On the one hand, manager compensation is at least partly determined by the skill level of fund managers, and on the other hand, fund AUM grows faster with a higher level of fund manager skills, not only due to potentially higher fund returns, but also due to money inflows from fund clients who recognize fund manager skills (e.g., Berk and Green, 2004).

To establish a conclusive causal relationship, suggesting that mutual funds compensate their managers primarily based on fund AUM (or revenue), even though this pass-through from fund revenue to manager compensation is incomplete, we rely on variations in a fund's AUM (or revenue) that goes beyond the inherent skill level and the influence of its fund managers. These variations in fund AUM (or revenue) are commonly attributed to luck, whether it be favorable or unfavorable. If mutual funds actively adjust manager compensation based on variations in fund AUM (or revenue) that are independent of perceived skill levels of fund managers, which are referred to as "non-fundamental" variations in fund AUM (or revenue), the positive correlation between fund manager compensation and the lagged AUM and revenue of the funds under their management, as documented in Table 2, is likely to reflect a causal relationship.

To capture non-fundamental fluctuations in fund AUM and revenue, we employ an instrumental variable approach inspired by the idea of heterogeneous demand-driven price impacts, as introduced by Koijen and Yogo (2019).[6] This instrumental variable is crafted to capture the changes in a fund's AUM and revenue resulting from exogenous changes in demand by other institutions, beyond the control of the fund family.

Particularly, in accordance with Koijen and Yogo (2019), we begin by creating an instrumental variable to capture variations in the market equity of asset n, which are outside the control of fund i. This instrumental variable, denoted by $\widehat{me}_{i,t}(n)$, is defined as follows:

$$\widehat{me}_{i,t}(n) = \ln\left(\sum_{j\neq i} A_{j,t}\frac{\mathbb{1}_{j,t}(n)}{1+\sum_{n'=1}^{N}\mathbb{1}_{j,t}(n')}\right), \tag{3.1}$$

where $A_{j,t}$ represents the total investment made by institution j in all stocks indexed by $n = 1, \cdots, N_t$ during quarter t, and $\mathbb{1}_{j,t}(n) \equiv \mathbb{1}\{n \in \mathcal{N}_{j,t}\}$ indicates whether stock n lies within institution j's investment scope during quarter t, which is denoted by $\mathcal{N}_{j,t}$. The investment scope of institution j in a given quarter is approximated by the set of stocks it has held within the past 3 years, which includes the set of all stocks it currently holds or has held in any of the past 11 quarters. The integer N_t is a large number representing the total count of stocks traded in public equity markets during quarter t. It's important to note that this instrumental variable, $\widehat{me}_{i,t}(n)$, relies solely on the investment scope of other institutions and the distribution of public equity ownership among all institutions over time. Neither of these factors is under the control of the manager for fund i. To put it simply, this instrumental variable, $\widehat{me}_{i,t}(n)$, can be thought of as the counterfactual market equity, determined by the market-clearing price, assuming that other investors, $j \neq i$, hold

[6] In Appendix D, we investigate whether fund manager compensation is primarily determined by the perceived skill level of the managers, as opposed to the realized fund AUM or revenue. Specifically, we explore whether fund manager compensation is reflective of managerial skills that go beyond what can be inferred from actual fund revenue. To assess this, we utilize the value-added measure developed by Berk and van Binsbergen (2015) as a proxy for the skill level of fund managers. Our findings reveal that the relationship between compensation and these value-added measures becomes statistically insignificant when we account for manager fixed effect, fund revenues, or fund AUM. These results cast doubt on the alternative hypothesis that fund compensation primarily mirrors managerial skills rather than the realized fund revenues.

an equally weighted portfolio within their own investment scopes. The construction of the instrumental variable intentionally removes the influence of fund manager actions from the equation.

Now that we have the instrumental variable, $\widehat{me}_{i,t}(n)$, available at the stock-fund-quarter level, along with the portfolio weights of fund i, we can construct an instrumental variable designed to capture variations in fund i's AUM and revenue that are uncorrelated with the skill level of managers within fund i. In particular, we aggregate $\widehat{me}_{i,t}(n)$ across the stocks held by fund i based on its portfolio holdings in quarter $t-4$ using the following equation:

$$\widehat{me}_{i,t} = \sum_{n=1}^{N} w_{i,t-4}(n) \times \widehat{me}_{i,t}(n), \tag{3.2}$$

where $w_{i,t-4}(n)$ represents the portfolio weights of stock n within fund i during quarter $t-4$. We opt for using weights with a one-year lag, $w_{i,t-4}(n)$, to address concerns that portfolio weights formed in quarters very close to t might reflect the skills of fund managers in selecting stocks with short-term mispricing.

Finally, we further aggregate the fund-level instrumental variables, denoted as $\widehat{me}_{i,t}$, to the level of fund managers. This addresses situations where a single fund manager oversees multiple funds. The aggregation is done as follows:

$$\widehat{me}_{m,t} = \frac{1}{TNA_{m,t-4}} \sum_{i \in \Omega_{m,t-4}} \frac{TNA_{i,t-4}}{M_{i,t-4}} \times \widehat{me}_{i,t}. \tag{3.3}$$

where $\Omega_{m,t-4}$ represents the set of funds managed by fund manager m in quarter $t-4$, $M_{i,t-4}$ denotes the number of fund managers overseeing fund i in quarter $t-4$, and $TNA_{m,t-4}$ indicates the total net assets under the supervision of fund manager m in quarter $t-4$ as defined by equation (2.1). These quarterly variables are recorded at the quarter-end month. Since our regression analysis is conducted annually, we aggregate the quarterly $\widehat{me}_{m,t}$ into yearly averages to obtain the instrumental variable at the manager-year level.

Table 12: Causal effects of fund AUM and revenue on compensation.

Panel A: First-stage IV regressions

	(1)	(2)	(3)	(4)	(5)	(6)
		$\ln(AUM_{m,t})$			$\ln(Rev_{m,t})$	
$\widehat{me}_{m,t}$	0.469***	0.636***	0.675***	0.380***	0.640***	0.615***
	[2.82]	[11.68]	[3.83]	[2.82]	[11.01]	[3.83]
F-test statistics	14.01	125.8	18.12	14.05	121.3	18.17
Manager FE	No	Yes	No	No	Yes	No
Year FE	No	No	Yes	No	No	Yes

Panel B: Second-stage IV regressions

	(1)	(2)	(3)	(4)	(5)	(6)
		$\ln(Pay_{m,t})$			$\ln(Pay_{m,t})$	
$\ln(\widehat{AUM}_{m,t-1})$	0.640**	0.487***	0.496**			
	[2.41]	[4.12]	[2.49]			
$\ln(\widehat{Rev}_{m,t-1})$				0.790**	0.484***	0.544**
				[2.44]	[3.94]	[2.51]
Manager FE	No	Yes	No	No	Yes	No
Year FE	No	No	Yes	No	No	Yes

Panel C: Reduced-form regressions

	(1)	(2)	(3)
		$\ln(Pay_{m,t})$	
$\widehat{me}_{m,t-1}$	0.304***	0.308***	0.337**
	[4.48]	[4.03]	[2.67]
Adjusted R-squared	0.012	0.625	0.064
Manager FE	No	Yes	No
Year FE	No	No	Yes

Notes. This table provides causal evidence for the roles of fund revenues in affecting manager compensation. Panel A presents results from the first stage of the IV regressions. In Columns (1) to (3), the dependent variable is the natural log of the AUM managed by the manager in year t. In Columns (4) to (6), the dependent variable is the natural log of the revenue generated by the manager in year t. The independent variable is the instrumental variable $\widehat{me}_{m,t}$. F-test statistics are provided. Panel B presents results from the second stage of the IV regressions. The dependent variable is the natural log of the fund manager's labor income in year t. In Columns (1) to (3), the independent variable is the natural log of the AUM managed by the manager in year $t-1$ predicted by the first-stage regressions. In Columns (4) to (6), the independent variable is the natural log of the revenue generated by the manager in year $t-1$ predicted by the first-stage regressions. Panel C presents results from the reduced form regressions. The dependent variable is the natural log of the fund manager's labor income in year t. The independent variable is the instrumental variable $\widehat{me}_{m,t-1}$. Standard errors are double-clustered at both the manager and year levels. The sample period of the data is from 2000 to 2014. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

After we have established the instrumental variable at the manager-year level to account for variations in fund AUM and revenue, we proceed to conduct a series of IV regression tests. The sample used for these tests comprises approximately $1,500$ manager-year observations. The variation in the instrumental variable, $\widehat{me}_{i,t}$, for fund i arises from changes in the investment scopes of other institutions, namely, changes in $\mathcal{N}_{j,t}$ for $j \neq i$. Similar to Koijen and Yogo (2019), our identifying strategy is motivated by an observation that most financial institutions hold a small set of stocks and that the set of stocks that they have held in the recent past (e.g., over the past 3 years) hardly changes over time. Many institutions operate within the confines of an investment mandate, which comprises predefined, rigid rules that remain unaffected by contemporary shifts in asset demand driven by informational or other fundamental factors. These investment mandates serve as the primary constraints that determine the boundaries of institutions' investment scopes.

The rationale behind the instrumental variable and the associated IV regression tests can be explained as follows. Suppose a stock is included in the investment scopes of multiple institutions, particularly larger ones. This inclusion generates a greater exogenous component of demand for the stock. Given the downward-sloping nature of demand, this heightened exogenous demand component leads to higher stock prices that are not linked to contemporaneous shifts in asset demand driven by informational or other fundamental factors. Mutual funds whose portfolios are heavily weighted towards such stocks are likely to see a substantial increase in their AUM and, consequently, their revenue. However, this gain is evidently unrelated to the skills of fund managers; instead, it is purely a matter of luck from the perspective of the funds. Our IV regression tests essentially aim to investigate whether these fund managers are compensated with a significantly higher amount corresponding to this luck-driven increase in AUM and revenue.

Panel A of Table 12 displays the results from the first-stage IV regressions. Columns (1) and (4) show that $\widehat{me}_{i,t}$ is highly correlated with contemporaneous AUM and fee revenue, respectively. The F-test scores all exceed 4.05, the Stock-Yogo critical value for rejecting the null of weak instruments (Stock and Yogo, 2005, table 5.2), demonstrating that the relevance condition of the instrumental variable is satisfied. To further illustrate the economic channel through which the instrumental variable $\widehat{me}_{i,t}$ affects AUM, we examine the relation between the instrumental variable and fund flows and returns in Appendix C. Specifically, we regress fund flows and returns in year t on changes in the instrumental variable from year $t-1$ to t (i.e., $\Delta\widehat{me}_{m,t}$). As presented in Table A.2 in the

Appendix, $\widehat{me}_{i,t}$ primarily influences contemporaneous fund returns while it does not move in tandem with flows. This finding is intuitive: an increase in demand from other investors drives up the prices of the underlying stocks, which, in turn, generates positive fund returns for the focal investor due to spillover effects.

Panel B of Table 12 presents the results from the second-stage IV regressions, wherein we regress compensation on predicted values of AUM and fund revenues. We have adjusted the standard errors to account for the fact that the independent variables are predicted values obtained from the first-stage regressions. Columns (1) and (4) indicate that the predicted AUM and fee revenue are positively correlated with compensation of fund managers in the subsequent year. The coefficient for the predicted values are statistically significant. In addition to the baseline regressions in Columns (1) and (4), we incorporate manager fixed effects or year fixed effects in both stages of the IV regression to isolate time-series or cross-sectional variations in the instrumental variable, respectively. As shown in Panels A and B of Table 12, our findings remain robust. Collectively, the results from the IV regression tests provide strong evidence supporting a causal relationship between compensation and both AUM and fee revenues.

Beyond the IV regressions, we conduct a reduced-form regression, directly regressing compensation on the one-year lagged instrumental variable. As indicated in Panel C of Table 12, the coefficient for the instrumental variable is positive and statistically significant, offering additional corroborative evidence in support of the identification tests.

4 Conclusion

In this research, we assemble a comprehensive dataset on the compensation and career trajectory of mutual fund managers, merging CRSP and Morningstar mutual fund data with the LEHD data from the U.S. Census.

Our study illustrates the significant influence of fee revenues on fund managers' compensation levels. Moreover, there's a positive correlation between compensation growth and both flows and performance. Notably, positive fund flows enhance both the base pay and bonus, while it's predominantly the positive fund returns that augment the bonus. Upon decomposing fund flows, we show that systematic flows align contemporaneously with base pay growth, and idiosyncratic flows correspond with bonus growth in the ensuing year.

In scenarios where managers transition to new positions, their compensation in these new roles is positively influenced by previous fund flows, though not by their performance preceding the job change. Finally, our analysis of job turnovers reveals a clear link between significant compensation shifts and preceding flows and performance. Specifically, large outflows substantially elevate the risk of demotions, whereas large inflows and large positive returns lean towards a higher probability of promotions. Our findings underscore the integral roles of both systematic and idiosyncratic flows in molding compensation changes during job transitions, as well as influencing career progression outcomes.

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Appendix

A Using Mutual Fund Prospectuses, LinkedIn Profiles, and Company Websites to Fill Out Incomplete Manager Names

We first use the fund managers' last names and the fund names to retrieve related mutual fund prospectuses (i.e., Form 485BPOS) from the SEC website. This method allows us to obtain the full names, including suffixes and middle initials, of most of the remaining managers. When these prospectuses do not provide complete names, we turn to LinkedIn profiles for additional details. The names and geographical information of the employers (i.e., mutual funds) help verify the accuracy of the LinkedIn results. For managers still lacking full names, we consult other sources, including official company websites, obituaries, and the CFA member directory. In cases of discrepancies, such as name abbreviations, we perform manual checks across all resources, prioritizing fund prospectuses when they provide the necessary details. This rigorous approach ensures the accuracy and completeness of the collected names, and our dataset includes full names for over 98% of the fund-year observations.

B Using Risk-Adjusted Returns as Alternative Performance Measures

In Table 2 of the main text, we have examined the relation between the compensation of fund managers and their performance, measured by gross returns. In this section, we employ alphas estimated by the CAPM model and the excess returns over the Vanguard index fund benchmark portfolio as alternative measures of performance.

To estimate the CAPM alphas of a fund, we regress the excess fund returns over the risk-free rates against the market excess returns, utilizing a 3-year rolling window. This is done provided there are at least 12 monthly observations within the rolling window:

$$Ret_{i,t-\tau} - Rf_{t-\tau} = R_{i,t}^{abn,CAPM} + \beta_{i,t}^{mkt} \times (Ret_{t-\tau}^{mkt} - Rf_{t-\tau}) + \varepsilon_{i,t-\tau}, \quad \text{with } \tau = 0, 1, \cdots, 35, \tag{B.1}$$

where $R_{i,t}^{abn,CAPM}$ denotes fund i's CAPM alphas in month t.

We proceed to compute the monthly manager-level CAPM alphas by aggregating the

Table A.1: Relation of fund manager compensation with revenue and risk-adjusted returns.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Relation of fund manager compensation with revenue and CAPM alphas						
	$\ln(Pay_{m,t})$					
$\ln(Rev_{m,t-1})$	0.238***	0.143***	0.238***	0.44***		
	[5.61]	[2.98]	[5.60]	[3.01]		
$\ln(1+R^{abn,CAPM}_{m,t-1})$	0.390	0.175	0.336	0.064	0.324	0.141
	[0.88]	[0.35]	[0.81]	[0.14]	[0.80]	[0.35]
$\ln(1+Flow_{m,t-1})$			0.071	0.057	0.102*	0.186**
			[0.46]	[0.75]	[1.93]	[2.23]
$\ln(Rev_{m,t-2})$					0.227***	0.101**
					[5.11]	[2.39]
Adjusted R-squared	0.140	0.836	0.140	0.836	0.142	0.805
Manager FE	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Relation of fund manager compensation with revenue and the Vanguard excess returns						
	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(Pay_{m,t})$					
$\ln(Rev_{m,t-1})$	0.238***	0.144***	0.238***	0.145***		
	[5.62]	[3.06]	[5.62]	[3.07]		
$\ln(1+R^{abn,Vanguard}_{m,t-1})$	0.391	−0.044	0.400	−0.172	0.455	0.260
	[0.96]	[−0.07]	[1.04]	[−0.30]	[0.98]	[0.76]
$\ln(1+Flow_{m,t-1})$			0.061	0.708	0.103*	0.180**
			[0.40]	[0.95]	[1.89]	[2.23]
$\ln(Rev_{m,t-2})$					0.226***	0.101**
					[5.12]	[2.37]
Adjusted R-squared	0.140	0.836	0.140	0.836	0.141	0.805
Manager FE	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table examines the relation of fund manager compensation with revenue and performance. The dependent variable is the natural log of the fund manager's labor income in year t. The independent variables include the natural log of the revenue generated by the manager in years $t-1$ and $t-2$, the natural log of the annual fund performance at the manager level in year $t-1$, and the natural log of the annual fund flows at the manager level in year $t-1$. We measure performance with CAPM alphas in Panel A and Vanguard excess returns in Panel B. Standard errors are double-clustered at both the manager and year levels. The sample period of the data is from 2000 to 2014. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

monthly fund-level CAPM alphas across all funds overseen by manager m. The average is weighted based on the one-month lagged fund asset, divided by the number of managers.

$$R^{abn,CAPM}_{m,t} = \frac{1}{TNA_{m,t-1}} \sum_{i \in \Omega_{m,t-1}} \frac{TNA_{i,t-1}}{M_{i,t-1}} R^{abn,CAPM}_{i,t}. \tag{B.2}$$

To determine the CAPM alphas of manager m on an annual basis, we aggregate the monthly manager-level CAPM alphas for each year.

To estimate the excess returns over the Vanguard index fund benchmark portfolio, we follow Berk and van Binsbergen (2015) to project the excess fund returns onto the

the excess returns of a set of Vanguard index funds, which include S&P 500 Index Fund (VFINX), Extended Market Index Fund (VEXMX), Small-Cap Index Fund (NAESX), European Stock Index Fund (VEURX), Pacific Stock Index Fund (VPACX), Value Index Fund (VVIAX), Balanced Index Fund (VBINX), Emerging Markets Stock Index Fund (VEIEX), Mid-Cap Index Fund (VIMSX), Small-Cap Growth Index Fund (VISGX), and Small-Cap Value Index Fund (VISVX). We determine the date to include the above index funds to the benchmark set based on their inception dates as illustrated in Table 1 of Berk and van Binsbergen (2015). Specifically, for each fund i, we run the following regression with a 3-year rolling window. This is done provided there are at least 12 monthly observations within the rolling window:

$$Ret_{i,t-\tau} - Rf_{t-\tau} = R_{i,t}^{abn,Vanguard} + \sum_{j=1}^{n(t)} \beta_{i,t}^{Vanguard,j} \times (Ret_{t-\tau}^{Vanguard,j} - Rf_{t-\tau}) + \varepsilon_{i,t-\tau}, \quad \text{(B.3)}$$

where $\tau = 0, 1, \cdots, 35$. Here, $R_{i,t}^{abn,Vanguard}$ denotes fund i's excess returns over the Vanguard index fund benchmark portfolio in month t, and $n(t)$ represents the number of Vanguard index funds included in the benchmark set in month t.

We proceed to compute the monthly manager-level Vanguard excess returns by aggregating the monthly fund-level excess returns across all funds overseen by manager m. The average is weighted based on the one-month lagged fund asset, divided by the number of managers.

$$R_{m,t}^{abn,Vanguard} = \frac{1}{TNA_{m,t-1}} \sum_{i \in \Omega_{m,t-1}} \frac{TNA_{i,t-1}}{M_{i,t-1}} R_{i,t}^{abn,Vanguard}. \quad \text{(B.4)}$$

To determine the Vanguard excess returns of manager m on an annual basis, we aggregate the monthly manager-level excess returns for each year.

We then use CAPM alpha and Vanguard excess returns as alternative performance measures to examine their relation with fund managers' compensation. Consistent with the findings in the main text, as illustrated in Table A.1, these performance measures are insignificantly related to compensation after we control for fund revenues. Since we require non-missing observations for risk-adjusted return measures, the analysis is based on a sample of around 2,000 manager-year observations.

Table A.2: Relation of the instrumental variable for AUM with flows and returns.

	(1)	(2)	(3)	(4)
	$\ln(1+R^{gross}_{m,t})$		$\ln(1+Flow_{m,t})$	
$\Delta\widehat{me}_{m,t}$	0.540***	0.582***	−0.018	−0.026
	[16.35]	[14.93]	[−0.38]	[−0.52]
Adjusted R-squared	0.155	0.255	0.000	0.312
Manager FE	No	Yes	No	Yes

Notes. This table examines the relation of the instrumental variable for AUM with flows and returns. The dependent variable in Columns (1) and (2) is the natural log of the annual fund returns at the manager level in year t, while the dependent variable in Columns (3) and (4) is the natural log of the annual fund flows at the manager level in year t. The independent variables is the changes of the instrumental variable for AUM from year $t-1$ to t (i.e., $\Delta\widehat{me}_{m,t} = \widehat{me}_{m,t} - \widehat{me}_{m,t-1}$). Standard errors are double-clustered at both the manager and year levels. The sample period of the data is from 2000 to 2014. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

C Relation Between the Instrumental Variable for AUM and Flows and Returns

In the main text, we present results from the IV regressions to provide causal evidence for the relation between AUM and compensation. To further illustrate the economic channel through which the instrumental variable $\widehat{me}_{i,t}$ affects AUM, we examine the relation between the instrumental variable and fund flows and returns in this section.

Specifically, we regress fund flows and returns in year t on changes in the instrumental variable from year $t-1$ to t (i.e., $\Delta\widehat{me}_{m,t} = \widehat{me}_{m,t} - \widehat{me}_{m,t-1}$). Consistent with Table 12, the analysis is based on a sample of around 1,500 manager-year observations. As presented in Table A.2, the instrument primarily influences contemporaneous fund returns while it does not move in tandem with flows. This finding is intuitive: an increase in demand from other investors drives up the prices of the underlying stocks, which, in turn, generates positive fund returns for the focal investor due to spillover effects.

D Relation Between Pay and Value Added

As discussed in the main text, one alternative explanation for the correlation between manager compensation and fee revenue is that both are influenced by management skills. According to this alternative explanation, fund investors recognize these skills and consequently allocate their money to these funds, as modeled by Berk and Green (2004). Concurrently, mutual funds set their managers' compensation based on these skills, which leads to the observed correlation between AUM and compensation. In Section 3.3, we employ an instrumental variable that captures the exogenous components of investor demand unrelated to the fund managers' families. This approach is used to provide causal evidence of the impact of fund revenue on compensation. In this section, we test the alternative explanation directly, utilizing the value-added measure developed by Berk and van Binsbergen (2015) as a proxy for fund managers' skills.

Specifically, we investigate whether fund manager compensation reflects management skills that extend beyond what is indicated by realized fund revenue. To explore this, we regress the value-added measure against compensation. Value added is defined as the product of before-fee alphas and AUM. We calculate alphas based on the CAPM alphas and the excess returns over the Vanguard index fund benchmark. Due to the distribution of the value-added measures having heavy tails at both the positive and negative sides, we apply the inverse hyperbolic sine transformation (e.g., Burbidge, Magee and Robb, 1988) to the value-added measures in our regressions.

In Panel A of Table A.3, we regress the value-added measure against one-year lagged compensation. The analysis is based on a sample of around 2,000 manager-year observations. Although compensation can predict subsequent year's value added, this relation becomes statistically insignificant when we focus on the within-manager time-series variations by including manager fixed effects (see Columns (2) and (8)). This result holds true regardless of the gross alpha measures used. Furthermore, the relation between compensation and value added also loses statistical significance after controlling for either fund revenues or AUM. This finding is consistent across different measures of gross alphas and remains the same whether or not manager fixed effects are included. These results challenge the view that mutual funds compensate their managers based on skills beyond those reflected in realized fund revenues.

One potential concern with our analysis in Panel A of Table A.3 is that the value-added measure, particularly when measured on a one-year basis, may be noisy. To address this concern, we average the value-added measures from year t to year $t+2$ and use this three-year average as the outcome variable. As shown in Panel B of Table A.3, we observe a very similar pattern. These findings further undermine the alternative hypothesis that fund compensation reflects management skills rather than realized fund revenues.

Table A.3: Relation between pay and value added.

	Panel A: Relation between pay and value added of next year											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$arcsinh(VA^{CAPM}_{m,t})$						$arcsinh(VA^{Vanguard}_{m,t})$					
$\ln(Pay_{m,t-1})$	0.152*	0.130	0.052	0.087	0.034	0.064	0.193**	0.055	0.105	0.023	0.098	0.028
	[2.06]	[1.40]	[0.90]	[1.08]	[0.58]	[0.84]	[2.55]	[0.76]	[1.28]	[0.49]	[1.39]	[0.52]
$\ln(Rev_{m,t-1})$			0.324***	0.209***					0.284***	0.194***		
			[4.24]	[2.84]					[3.44]	[2.78]		
$\ln(AUM_{m,t-1})$					0.370***	0.222***					0.331***	0.192***
					[4.81]	[2.98]					[4.87]	[2.76]
Adjusted R-squared	0.115	0.379	0.140	0.382	0.151	0.389	0.042	0.377	0.064	0.380	0.074	0.380
Manager FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Panel B: Relation between pay and the average value added of next three years											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$arcsinh(\overline{VA}^{CAPM}_{m,t\to t+2})$						$arcsinh(\overline{VA}^{Vanguard}_{m,t\to t+2})$					
$\ln(Pay_{m,t-1})$	0.095	0.132	0.021	0.081	0.002	0.078	0.238**	0.115	0.136	0.078	0.120	0.066
	[1.11]	[1.21]	[0.28]	[0.82]	[0.03]	[0.78]	[2.45]	[1.43]	[1.47]	[0.80]	[1.46]	[0.72]
$\ln(Rev_{m,t-1})$			0.234***	0.151**					0.320***	0.134***		
			[3.12]	[2.53]					[3.24]	[2.49]		
$\ln(AUM_{m,t-1})$					0.283***	0.197***					0.361***	0.164***
					[3.68]	[2.73]					[4.52]	[2.55]
Adjusted R-squared	0.108	0.482	0.121	0.485	0.129	0.485	0.045	0.572	0.073	0.534	0.085	0.534
Manager FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table examines the relation between pay and value added. Panel A investigates the relation between pay and value added of next year, while Panel B investigates the relation between pay and the average value added of next three years. The dependent variable in Columns (1) to (6) is the inverse hyperbolic sine transformation (e.g., Burbidge, Magee and Robb, 1988) of value added computed as the product between AUM and gross CAPM alphas. The dependent variable in Columns (7) to (12) is the inverse hyperbolic sine transformation of value added computed as the product between AUM and the Vanguard excess returns. The independent variables include the natural log of the fund manager's labor income in year $t-1$, the natural log of the revenue generated by the manager in years $t-1$, and the natural log of the AUM managed by manages in year $t-1$. Standard errors are double-clustered at both the manager and year levels. The sample period of the data is from 2000 to 2014. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.