JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS pp. 1–31

doi:10.1017/S0022109025101713

Winning Teams or Winning Pay? The Impact of Team Allocation on Fund Manager Compensation and Careers

Lu Han
University of Wisconsin-Madison Wisconsin School of Business
lu.han@wisc.edu

Galit Ben Naim
Ministry of Finance, Israel Economics and Research Department
galitbe@mof.gov.il

Stanislav Sokolinski
Michigan State University Broad College of Business
sokolins@msu.edu (corresponding author)

Abstract

We examine how team allocation shapes mutual fund managers' compensation as well as their future productivity and careers. Assignment to a high-quality team lowers immediate compensation but accelerates career development—sharpening investment skill, boosting media visibility, deepening industry and style specialization, and raising future revenue. Team quality also raises promotion odds and explains the steep, tenure-based earnings profile common in asset management. Team allocation therefore acts as a career-steering mechanism embedded in fund-family compensation contracts.

I. Introduction

Incentive provision is a central theme in asset-management research. While investor demand and fund flows shape fund-family incentives (Berk and Green (2004), Sirri and Tufano (1998)), the supply-side channel—managerial compensation—has only recently come into focus. Because portfolio managers make day-to-day investment decisions, the effectiveness of demand-side incentives, and the career signals they send, ultimately depends on how compensation is structured.

Recent work pinpoints key determinants of manager pay. Ma, Tang, and Gomez (2019) and Bai, Ma, Mullally, and Tang (2023) document performance-

We are grateful for helpful comments to Ran Duchin (the editor), an anonymous referee, and Claire Celerier, Briana Chang, Dean Corbae, Jesse Davis, Rich Evans, Paolo Fulghieri, Yunzhi Hu, Ron Kaniel, Dmitry Orlov, Jon Reuter, Timothy Riddiough, Jacob Sagi, Donghwa Shin, Erwan Quintin, Clemens Sialm, Boris Vallee, Stijn Van Nieuwerburgh, Randall Wright, Dayin Zhang and seminar participants at Rutgers University, University of North Carolina at Chapel Hill and University of Wisconsin at Madison, Financial Management Association Annual Conference 2022 and China International Conference in Finance 2022. All errors are our own. Dina Dizengoff and Ethan Fried provided excellent research assistance. Sokolinski thanks the Lab for Economic Applications and Policy (LEAP) at Harvard University for the financial support.

based bonuses, while Ibert, Kaniel, Van Nieuwerburgh, and Vestman (2017) and Cen, Dou, Kogan, and Wu (2023) show that fund size and revenues also feed into compensation. Yet a large share of pay variation—and the associated career rewards—remains unexplained, inviting a closer look inside the fund family. As Ibert et al. (2017) note, compensation differences driven by fund-family pay policies persist even after accounting for individual performance, underscoring that intra-family dynamics may matter as much as external fund flows.

We examine one salient intra-family channel: the way managers are allocated across investment teams. Roughly 70% of funds are comanaged, making teamwork a defining feature of the industry (Patel and Sarkissian (2017)). Labor-economics research shows that teaming with high-quality peers can raise individual productivity and shape careers through knowledge spillovers, learning opportunities, and social incentives such as peer pressure.[1] We bring this insight to asset management, asking whether team placement shapes not only productivity but also compensation and long-run career paths.

We address these questions with a novel panel of Israeli mutual fund managers' tax records matched to detailed team assignments. Tracking how team placement shapes compensation—and the incentives that guide career-building behavior—opens a window onto the supply-side forces in an industry built on collaboration. Although we focus on asset management and portfolio managers, our setting speaks broadly to any occupation where teamwork propels career advancement.[2]

We start by measuring how team allocation affects both compensation and productivity—proxied by total fee revenue—of mutual fund managers.[3] A baseline model with standard pay drivers plus firm-year and manager-firm fixed effects explains 74% of the variation in compensation and 79% in revenue. Adding team-by-year fixed effects raises explanatory power by another 16% for compensation and 15% for revenue, underscoring the importance of team placement.

We explain the strong association between team placement, compensation, and career growth with a stylized model in which firms optimally assign managers to teams and set wages. In the model, *team quality*—the aggregate human capital of a manager's teammates—enters intertemporal utility, so forward-looking managers willingly trade lower current pay for faster human-capital accumulation and higher future earnings when they join superior teams. A forward-looking manager may accept lower current pay to join a high-quality

[1]For example, prior work shows that working with high-quality teams improves productivity through knowledge spillovers (Mas and Moretti (2009)), learning (Hamilton, Nickerson, and Owan (2003)), or social incentives and peer pressure (Bandiera, Barankay and Rasul (2005), (2009), (2010)). Theoretical studies emphasize peer pressure (Kandel and Lazear (1992)) and moral hazard in teams (Hölmstrom (1979)).

[2]Some previously studied examples of such occupations include academic research (Azoulay et al. (2010)), sales (Chan et al. (2014)), steel mills (Boning et al. (2007)), sports (Ichniowski and Preston (2014)), and garment production (Hamilton et al. (2003)).

[3]Our approach follows Ibert et al. (2017). In mutual funds, fee revenue is a natural productivity metric because it captures the market value of the asset-management service a manager produces, consistent with standard revenue-per-employee measures (Foster, Haltiwanger, and Syverson (2008), Hsieh and Klenow (2009), and Syverson (2011)).

team that accelerates skill accumulation, boosts future productivity, and ultimately lifts career earnings. The model thus predicts a negative contemporaneous link between team quality and pay, but a positive link with subsequent productivity growth and compensation. Contracts differ across manager–firm pairs, reflecting heterogeneity in how much managers value team quality and how much team capital firms allocate.

To test these predictions, we focus on two forms of team capital that shape a manager's long-term productivity—and thus both compensation and long-run career momentum. First is investment skill: Teaming with highly skilled colleagues fosters on-the-job learning and amplifies fund flows, a core driver of profitability (Sirri and Tufano (1998)). Second is media visibility: In a market where investors face information gaps and search frictions, team-level visibility boosts individual recognition, draws capital, and lifts future revenues.[4] Working alongside more visible teammates can elevate a manager's own profile, channel greater investor attention, and translate into higher revenue and, eventually, higher pay. We define manager skills using Berk and Van Binsbergen's (2015) "value added" approach and measure visibility by counting the number of newspaper articles in Israel's leading business outlets.[5]

Our evidence is consistent with the model's predictions. Managers on higher-quality teams tend to earn less today, and the magnitudes are economically meaningful. A 1-standard-deviation increase in teammates' average skill is associated with a 4.03% lower current salary, and a comparable rise in teammates' media visibility correlates with a 3.09% pay reduction. By contrast, the same increase in a manager's own skill relates to a 6.06% pay premium, while higher personal visibility is linked to a 1% gain. Team capital and individual capital, therefore, have similar magnitudes but opposite signs, suggesting that short-run pay concessions may align with steeper long-run earnings. These associations hold after controlling for a rich set of manager, team, and firm characteristics and are robust to alternative measures of skill and team quality.

To address potential selection in team assignments, we use a difference-in-differences (DiD) design contrasting *switchers*—managers who change teams within a firm–year—with *stayers.* After accounting for an extensive set of confounders, we find no pre-trends in pay or skill, supporting parallel trends. The DiD estimates show that only moves from high-quality to low-quality teams materially affect compensation: Switching from high-skill to low-skill teammates lifts pay by 12% and moving from high-visibility to low-visibility teammates raises pay by 14%. These jumps appear immediately after the move, suggesting firms offset the loss of team capital, whereas moves in the opposite direction are muted—consistent with wage stickiness that hinders downward adjustment. As we cannot fully rule out the influence of unobserved time-varying factors, we view our DiD evidence as

[4]For example, Berk, Van Binsbergen, and Liu (2017) and Kaniel and Orlov (2021) highlight uncertainty about manager skill; Hortaçsu and Syverson (2004) and Roussanov, Ruan, and Wei (2021) underscore search frictions; and Solomon, Soltes, and Sosyura (2014), Gallaher, Kaniel, and Starks (2015), and Kaniel and Parham (2016) document how media coverage attracts flows.

[5]Unlike prior studies on fund-level marketing, we focus on the visibility of individual managers rather than of their firms or funds.

supportive rather than conclusive. To further assess potential bias, we apply the statistical test from Cinelli and Hazlett (2020), which provides an upper bound on the impact of unobserved confounders.

Why do managers value team quality? Our framework posits that team capital accelerates human-capital formation and, in turn, future productivity. Empirically, managers paired with higher-skill teammates experience faster gains in their own investment skill, while those working with more visible teammates see their personal media visibility rise. These effects appear immediately after joining a high-quality team in our DiD tests and persist over time; managers from high-skill teams also outperform when later running "solo" funds, confirming genuine skill acquisition.

We next link team quality to specialization—industry and style concentration that signal expertise (Kacperczyk et al. (2005)). DiD estimates show that moving to a high-skill team containing at least one specialist markedly increases both forms of concentration, whereas moves to low-skill teams leave specialization unchanged. Finally, collaboration with superior teams translates into tangible career gains: higher future revenue and faster compensation growth, consistent with team-driven human-capital accumulation fueling long-run earning power.

In our final test, we study whether a manager's first comanaged assignment shapes future outcomes. Younger and less experienced managers disproportionately land on high-quality first teams, and that single match delivers lasting gains: Compensation growth accelerates and promotion odds rise, even after controlling for all later team moves. Subsequent reallocations matter far less—the second team has modest, short-lived effects, and the third none at all. The first team thus leaves a unique, durable imprint on a manager's pay and career trajectory.

Taken together, our evidence offers a fresh explanation for the well-documented increasing pay–experience profile in finance (Philippon and Reshef (2012), Ellul et al. (2022)). High-quality teams act as incubators of human capital: Junior managers learn investment techniques and ride visibility spillovers that attract flows, thereby raising their future revenue base. These long-horizon benefits encourage early-career managers to accept lower initial pay, much as workers in other human-capital–intensive professions accept apprenticeship wages. As experience accumulates, managers progressively internalize the know-how and networks once provided by the team, so the incremental value of team capital—and the pay discount it justifies—shrinks. This dynamic naturally steepens the earnings curve with tenure: compensation growth accelerates as managers harvest returns on their early human-capital investment. Consistent with this mechanism, we estimate that the effects of team quality on compensation are two to three times stronger for less experienced junior managers compared to their more senior colleagues.

Recent research underscores that teamwork boosts fund performance by increasing diversity (Evans, Prado, Rizzo, and Zambrana (2021)), curbing uninformed trading (Fedyk et al. (2020)), limiting return inflation (Patel and Sarkissian (2021)), and dampening behavioral biases such as extrapolation (Barahona et al. (2022)) and opinion extremity (Bär, Kempf, and Ruenzi (2011)). We contribute a complementary angle: The benefits of teaming are not free. Managers on higher-quality teams accept lower contemporaneous pay, revealing that team capital is partly priced through compensation trade-offs. This insight dovetails with labor-economics evidence that peer interactions lift productivity (Kandel and Lazear (1992), Bandiera et al. (2005), (2009), (2010), and Mas and Moretti (2009)) yet rarely considers how those gains feed into individual earnings. By tracking actual wages, we show that within-firm team composition shapes long-run pay and human-capital accumulation, spotlighting the firm as a platform that matches heterogeneous talent and helps monetize complementarities.[6]

Overall, our study enriches the literature on fund-family incentives and finance careers in three ways. First, we establish that a manager's compensation depends not only on their own skills but also on the human capital embedded in their team, unveiling a new team-based incentive channel. Second, this interdependence has clear career consequences: managers who trade lower immediate pay for stronger teammates progress faster and ultimately earn more. Third, we show that within-firm team assignments actively sculpt career trajectories, linking short-run pay policies to long-run talent outcomes. Taken together, these findings clarify how fund families leverage team composition to align incentives and advance managerial careers in an industry where comanagement is increasingly pivotal.

II. Institutional Background and Dataset

In this section, we describe the construction of the data set. We also discuss the summary statistics and the definitions of the key variables.

A. The Israeli Mutual Fund Market

As of 2016, our sample from the Israeli mutual market includes 1446 funds that managed approximately 250 billion shekels. The market consists of different types of funds, starting from pure equity funds and ending with government bond funds. Many funds are hybrid and invest in a number of different asset classes simultaneously. As a group, Israeli mutual funds allocate roughly 25% of assets to equities, 30% to corporate bonds, and another 25% to government bonds. Table B1 in the Supplementary Material shows the distribution of funds across asset classes.

B. Data set Construction

We construct our data set from five data sources. We start with public disclosures of mutual fund companies (Part B of the Fund Prospectus) to identify individual mutual fund portfolio managers. Since 2010, mutual fund companies in Israel have to disclose the identity of their portfolio managers through public reports submitted to the Israel Securities Authority and the Tel-Aviv Stock Exchange on an annual basis.[7] We hand-collect the information on portfolio

[6]Relatedly, Han and Miller (2015) study employment networks in real-estate brokerage and infer compensation structurally, but they do not observe actual pay.

[7]This information is publicly available both on http://maya.tase.co.il and on https://www.magna.isa.gov.il.

managers, including age, job tenure, the list of funds they manage every year, as well as the date when they started to manage a particular fund.[8] This data allows us to track almost the entire population of mutual fund portfolio managers in Israel from 2010 to 2016.[9] As we observe the dates when managers became responsible for particular funds, we extend the data set back to 2006 for a subset of managers and funds. For example, if we know that the manager started managing the fund in February 2006, we include this fund in their portfolio since the given date.

Next, we match this data using unique fund identifiers with a database on monthly characteristics of funds purchased from Praedicta—a large private Israeli data vendor.[10] This survivorship bias-free database covers the entire universe of Israeli mutual funds; it includes detailed fund characteristics such as fees, assets under management, returns, fund style, and asset allocation across broadly defined sets of securities. The overall matched sample covers 89% of the Israeli mutual fund industry's assets under management between 2010 and 2016 and 49% of this industry between 2006 and 2009 (see Figure B1 in the Supplementary Material). We exclude index funds and money market funds from our sample.

We construct portfolios of funds for each manager on an annual basis to fit the compensation data, which is reported annually. Fund managers can be listed as managers of multiple funds, and funds can have multiple managers. If the fund is managed by N managers, we follow Chevalier and Ellison (1999a), Ibert et al. (2017), and Berk et al. (2017), attributing $1/N$ assets to every manager, assuming that all the managers listed contribute equally to the management of the fund. We construct annualized manager portfolios' characteristics, such as fees and fund age, as an assets under management (AUM)-weighted sum of characteristics of individual funds. In our robustness checks, we also assume that senior managers play a larger role in managing funds, with assets allocated based on a manager's experience rather than equally among all managers.

Table 1 summarizes the sample. Panel A (manager-year) shows an average age of 39 and 6.1 years of mutual fund experience; Israeli equities account for 42% of portfolio assets, 12% of managers hold senior roles (e.g., CEO or chief strategist), and each oversees 4.4 funds on average. Panel B (fund-year) reports mean AUM of 112 million shekels, fund age of 8 years, and a fee of 0.82%. Panel C (firm-year) indicates that the typical firm employs 3 managers and runs 28 funds, but most manager-year observations come from the largest quartile of firms, which average 12 managers.

[8]The firms are not obliged to disclose the names of fund managers but they have to disclose their license numbers. All portfolio managers in Israel have to pass the Israel Securities Authority qualification exam to obtain a license to be able to work as portfolio managers. In cases when we had only a license number, we used it to find the individual manager's name on the Israel Securities Authority website.

[9]Very small mutual fund companies are not subject to this disclosure, so the data set does not cover the whole population of fund managers.

[10]This data set has been previously used in Shaton (2017) and Sokolinski (2023).

TABLE 1

Summary Statistics

Table 1 presents the summary statistics of our sample. Panel A presents the information at the manager-year level. *Compensation* is the manager's compensation in shekels. *Skill* is the Berk and Van Binsbergen (2015) measure of the manager's investment skill. *Visibility* is the number of newspaper articles about the manager in the four major business outlets in Israel. *Manager Age* is the manager's age in years. *Industry Experience* is the number of years that the manager has been working in the mutual fund industry. *Equity Share* is the fraction of equity funds in the manager's portfolio. $1_{Additional\ Role}$ indicator equals 1 if the manager has an extra role in the company (such as CEO or head of the investment committee). *Revenue* is the manager's fee revenue. *AUM* is the assets under management. *Fee* is the percentage fee. *Number of Funds* is the number of funds in the manager's portfolio. 1_{Team} indicator equals 1 if the manager is working with the team. *Number of Teams* is the number of teams that the manager is working with. *Team Skill* is the average skill of the manager's team members. *Team Visibility* is the average number of articles about the manager's team members in the four major business outlets in Israel. *Team Industry Experience* is the average number of years that the manager's team members have been working in the mutual fund industry. *Team Equity Share* is the average fraction of equity funds in the portfolios of the manager's team members. *Team Size* is the number of managers on the team, being equal to 0 for independent managers. *Number of Teams* is the number of teams that the manager is working with. Table 1 presents the descriptive statistics of our sample. Panel B presents the information at the fund-year level. Panel C presents the information at the firm-year level. *AUM* is the assets under management. *Fee* is the percentage fee. α is the estimate of the manager's performance from the multi-benchmark model for fund returns (see Section II.D for details). *Fund Age* is the number of years since the fund's inception. *Number of Managers* is the number of portfolio managers that the firm employs. *Number of Funds* is the number of funds that the firm operates.

Panel A. Manager-Year Level	*N*	Mean	SD	10%	25%	50%	75%	90%
Manager Characteristics								
Compensation (MM, Shekels)	1,786	0.438	0.52	0.10	0.18	0.29	0.44	0.69
Skill (MM, Shekels)	1,786	3.35	21.62	−22.58	−7.83	−0.89	1.34	11.61
Visibility (number of articles)	1,786	7.87	11.42	0	0	5	12	19
Manager Age (years)	1,786	39.60	8.37	31	34	38	44	51
Industry Experience (years)	1,786	6.18	6.31	1	2	4	8	14
Equity Share (fraction)	1,786	0.42	0.58	0	0	0.25	0.84	1
$1_{Additional\ Role}$ *(indicator)*	1,786	0.12	0.33	0	0	0	0	1
Portfolio Characteristics								
Revenue (MM, Shekels)	1,786	4.68	6.63	0.11	0.55	2.19	6.35	11.70
AUM (MM, Shekels)	1,786	743.96	1143.06	66.09	314.72	313.07	960.82	2007.65
Fee (%)	1,786	0.92	0.68	0.31	0.53	0.88	1.25	1.92
Number of Funds	1,786	4.4	5.8	1	3	7	11	15
Team Characteristics								
1_{Team} *(indicator)*	1,786	0.75	0.43	0	0	1	1	1
Team Skill (MM, Shekels)	1,786	4.85	28.81	−45.42	−19.84	−0.47	11.78	33.58
Team Visibility (number of articles)	1,786	13.39	22.08	0	1.07	7.07	25.34	46.33
Team Industry Experience (years)	1,786	3.17	5.44	0.97	1.56	2.98	4.26	8.22
Team Equity Share (fraction)	1,786	0.52	0.68	0	0	0.31	0.73	1
Team Size	1,786	0.70	0.94	0	0	0.29	1	2
Number of Teams	1,786	1.55	1.96	0	0	1	1	2
Panel B. Fund-Year Level								
AUM (MM, Shekels)	15,227	111.87	187.98	3.93	12.51	41.35	120.30	296.2
Fee (%)	15,227	0.82	0.79	0.11	0.27	0.71	1.39	2.08
α (%)	15,227	−1.52	5.23	−7.94	−3.23	−0.78	0.73	3.65
Fund Age (years)	15,227	8.08	7.76	1	2.58	5.75	10.75	19.33
Panel C. Firm-Year Level								
AUM (MM, Shekels)	521	2,252.22	4,250.18	16.70	64.85	371.05	2,356.40	7,613.40
Number of Managers	521	3.02	3.22	1	1	2	4	8
Number of Funds	521	27.86	40.51	2	4	10	32	76

C. Variable Construction

1. Compensation

Using Form 106—the Israeli equivalent of a U.S. W-2—we link each manager's annual pay to their portfolio records, producing 302 managers and 1,786 manager-years after excluding cases with fewer than 9 months of employment. Panel A of Table 1 shows that the mean compensation is 438,000 shekels ($\approx$\$125,000), placing the average manager in the top 2% of Israel's income distribution. Pay is highly dispersed: The 10th percentile earns 100,000 shekels and the 90th percentile 690,000 shekels, consistent with evidence that finance compensation is both high and skewed (Célérier and Vallée (2019)).

2. Revenue

We define the manager's fee revenue as

$$Revenue_{mt} = \sum_{i \in \Omega_{mt}} \left(\frac{AUM_{it}}{N_{it}} \times f_{it} \right), \tag{1}$$

where Ω_{mt} is the set of all the funds managed by manager m in year t, AUM_{it} are assets under management in fund i, f_{it} is a fund i's fee (expense ratio), and N_{it} is the number of managers who manage fund i. We attribute equal $(1/N_{it})$ fraction of revenue to each manager m as in Chevalier and Ellison (1999b), Berk et al. (2017) and Ibert et al. (2017). Panel A of Table 1 shows that the average manager generates 4.68 million shekels in fee revenue. There is substantial dispersion in manager revenue since the 10th percentile equals 0.11 million shekels, and the 90th percentile equals nearly 12 million shekels.

D. Manager, Human Capital, and Team Quality

Our sample contains 360 distinct teams across all years. Panel A of Table 1 shows that 75% of manager-years involve teamwork—a share similar to the U.S. estimates in Patel and Sarkissian (2017). Excluding herself, the average manager belongs to 1.55 teams and works with 0.7 teammates. Figure 1 illustrates the rising trend: From 2006 to 2016, the fraction of managers on teams climbed from under 60% to roughly 80%, while the share of comanaged funds grew from below 40% to about 60%. This expansion underscores the growing role of peer effects in mutual fund management.

We next construct our measures of manager human capital and team quality. We distinguish between two dimensions of human capital: investment skill and media visibility.

1. Investment Skill

We follow Berk and Van Binsbergen (2015) and construct a measure of manager skill based on the value that the manager extracts from capital markets. Since the manager's risk-adjusted performance ("alpha") represents return to investors and depends on fund size, the fund i's value added over year t is defined as:

$$V_{it} = AUM_{i,t-1}\alpha_{it}, \tag{2}$$

where $AUM_{i,t-1}$ are assets under management in fund i at the end of year $t-1$, and the fund's annual alpha is calculated as the difference between the fund's annual return R_{it} and its benchmark return R_{it}^B:

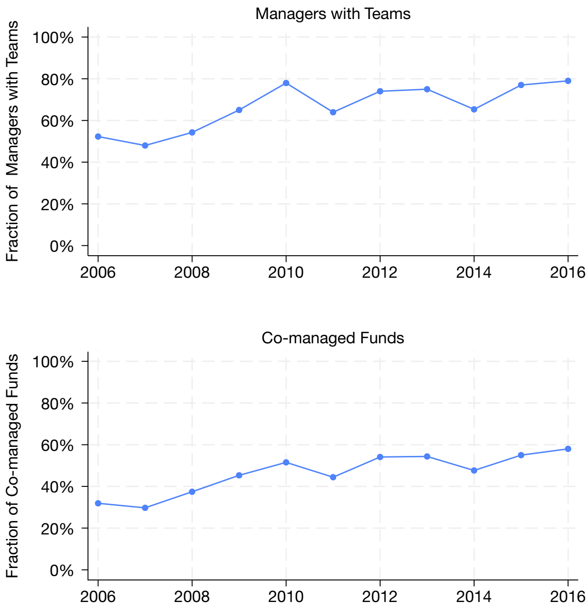
$$\alpha_{it} = R_{it} - R_{it}^B. \tag{3}$$

We estimate the benchmark return R_{it}^B using a procedure similar to the one from Berk and Van Binsbergen (2015) (see Appendix A in the Supplementary Material for details). Panel B of Table 1 shows that the average fund's risk-adjusted performance

FIGURE 1

Prevalence of Teamwork in the Israeli Mutual Fund Industry

Figure 1 presents the time series of the fraction of managers with teams and the fraction of funds that are comanaged. The fund is defined as comanaged if it is managed by more than one manager.



(α) equals -1.5%, and it is statistically indistinguishable from zero. This result is consistent with Fama and French (2010) who show that the average U.S. mutual fund does not outperform. We later show that our results are robust to different ways of estimating risk-adjusted performance.

We define manager m's value added as a total value added of all the funds under their management. If fund i is managed by N_{it} managers in year t, we attribute equal $(1/N_{it})$ fraction of value added to each manager. Then manager m's value added is defined:

$$V_{mt} = \sum_{i \in \Omega_{mt}} \frac{V_{it}}{N_{it}}, \tag{4}$$

where Ω_{mt} is the set of all the funds managed by manager m in year t. We next define manager m's skill as an expected value added given the manager history up to year t:

$$Skill_{mt} = \sum_{w=1}^{T_{mt}} \frac{V_{mw}}{T_{mt}}, \tag{5}$$

where T_{mt} is the number of years manager m appears in the data prior to year t.[11]

[11]Ma, Tang, and Gomez (2019) show that the average performance evaluation period is 3 years, based on the data from the U.S. compensation contracts. While we follow Berk and Van Binsbergen (2015) and take into account the entire history of the manager prior to year t, the average T_{mt} equals 3.5 years which is close to the estimate from Ma, Tang, and Gomez (2019).

We define $1_{Team_{mt}}$ as an indicator variable that equals 1 if at least one of the funds in the manager's portfolio is comanaged. If manager *i* works on team in year *t*, we measure the manager team's skill by calculating the average skill of her coworkers given by

$$TeamSkill_{mt} = \frac{1}{N-1}\sum_{n \neq m} Skill_{nt}, \tag{6}$$

where N is a number of team members, and $Skill_{nt}$ is a skill of manager n in year t. If a manager works on multiple teams, we calculate $TeamSkill_{mt}$ across all the coworkers in all the teams.

Panel A of Table 1 reports the distribution of investment skill. Mean skill is 3.55 million shekels per manager and 4.85 million shekels per team, but dispersion is wide: The median manager and median team show negative skill, echoing the U.S. evidence in Berk and Van Binsbergen (2015) that many funds destroy value. Yet managers of larger funds tend to post positive skill, so—because they command most capital—the average manager still adds value overall.

2. Media Visibility

We measure a manager's personal visibility, $Visibility_{mt}$, as the yearly count of media mentions in Israel's principal financial outlets, following Solomon, Soltes, and Sosyura (2014) and Kaniel and Parham (2016). For each year from 2006 to 2016, we search the manager's name across The Marker, Globes, Calcalist, and Bizportal, manually verifying that each hit refers to the portfolio manager.[12]

Panel A of Table 1 shows that the average manager appears in 7.87 media articles per year, yet nearly 25% receive no coverage at all. Because marketing can matter almost as much as performance and fees for fund size (Roussanov, Ruan, and Wei (2021)), this dispersion underscores visibility as a critical dimension of managerial human capital.

In line with the definition of the team's investment skill, we measure the team's media visibility as

$$TeamVisibility_{mt} = \frac{1}{N-1}\sum_{n \neq m} Visibility_{nt}, \tag{7}$$

where N is a number of team members, and $Visibility_{nt}$ is a visibility of manager n in year t. If a manager works on multiple teams, we calculate $TeamVisibility_{mt}$ across all the coworkers in all the teams.

III. Does Team Allocation Matter for Compensation and Revenue?

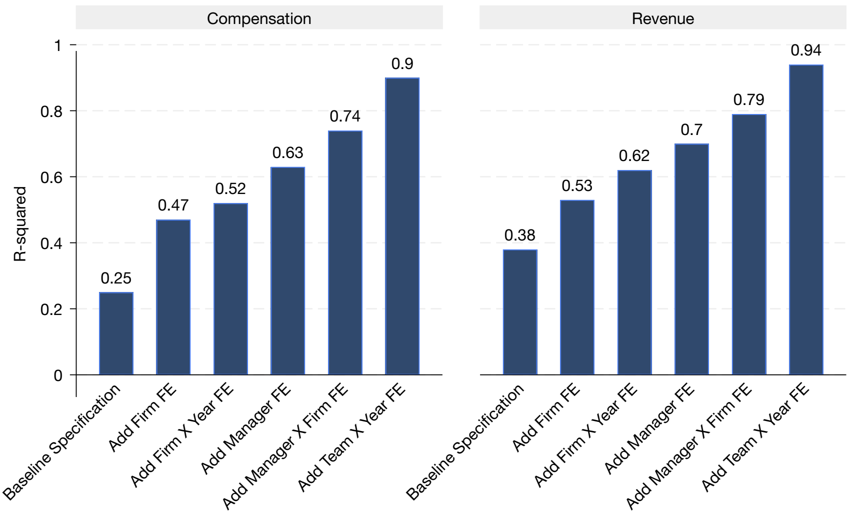
We first test whether team placement explains variation in pay and revenue beyond known drivers using

[12]These four outlets dominate Israeli financial journalism over the sample period. Articles typically discuss performance, market views, security recommendations, or career moves.

FIGURE 2

Variation in Compensation and Revenues

Figure 2 displays the R^2 values from regressions of portfolio manager compensation and revenues on manager characteristics and various fixed effects. The first bar of each graph reports the R^2 from the baseline model, which includes a range of time-varying characteristics of managers and their portfolio, along with time fixed effects. We include the following characteristics: manager's skill and visibility, portfolio revenues, manager's age and industry experience, number of funds under management, share of equity funds in the manager's portfolio, and an indicator variable for having additional responsibilities outside of portfolio management. These characteristics are detailed and explained in Table 1. The additional bars represent R^2 values from models that include extra fixed effects. This progression of models with increasing complexity helps in understanding how different variables and fixed effects contribute to explaining the variation in portfolio managers' compensation and revenues.



$$y_{mft} = \lambda_t + \gamma X_{mft} + \epsilon_{mft}, \tag{8}$$

where y_{mft} is manager m's compensation or revenue in firm f and year t, and λ_t are year effects. The control vector X_{mft} includes skill, visibility, portfolio revenue, age, industry tenure, number of funds, equity share,[13] and an indicator for executive duties (e.g., head of the investment committee or chief investment strategist). These covariates follow Ibert et al. (2017) and Ma et al. (2019).

We gauge how different forces shape compensation and productivity by adding fixed effects to the baseline model and observing the jump in explanatory power (R^2); results appear in Figure 2. Observable manager and portfolio characteristics alone account for 25% of pay and 38% of revenue. Introducing firm fixed effects—capturing corporate culture, shared research, and distribution networks—raises R^2 to 47% and 53%, respectively. Firm-by-year effects push these shares to 52% and 62%, reflecting time-varying firm resources.

Next, we layer on manager fixed effects to absorb unchanging personal traits and manager-by-firm effects to capture match quality. Combined, these factors propel R^2 to 74% for compensation and 79% for revenue, underscoring that who the manager is—and where they work—matters greatly. Yet a sizeable residual remains.

[13]Because advisor fees are fixed within asset classes in Israel (Sokolinski (2023)), the equity share absorbs distribution-related variation.

The final step adds team-by-year fixed effects, isolating variation among managers working side-by-side in the same period. R^2 jumps to 90% for pay and 94% for revenue, an extra 16 percentage points (pps) and 15 pps, respectively. Thus, even after controlling for firm environment and individual attributes, team allocation explains a large slice of both compensation and performance.[14]

While the aggregate test cannot pinpoint *which* team attributes drive these gains, labor-economics studies emphasize peer skill and overall team quality (Hamilton et al. (2003), Mas and Moretti (2009)). Guided by those insights, the next section sets out a framework and testable predictions on how specific facets of team quality affect pay, productivity, and career progression.

IV. Conceptual Framework and Testable Hypotheses

Forward-looking managers weigh not only today's salary but also the continuation value of landing on a high-quality team—an investment in their future careers. Appendix C in the Supplementary Material formalizes this idea in a stylized employment model that underpins our empirical tests.

The model rests on two industry facts. First, teaming with strong peers builds human capital. Knowledge spillovers, peer pressure, and social preferences raise individual performance (Hamilton, Nickerson, and Owan (2003), Mas and Moretti (2009), and Bandiera, Barankay, and Rasul (2005), (2009), (2010)). In funds, the key dimensions are investment skill and media visibility: managers can learn from skilled colleagues and gain exposure by working alongside highly visible ones—the *human-capital channel.* Second, richer human capital boosts productivity and, ultimately, pay. Skilled managers attract larger future revenues (Berk and Van Binsbergen (2015)), while media coverage draws inflows that expand fee income (Solomon et al. (2014), Kaniel and Parham (2016)). Our framework, therefore, links team quality to long-run compensation through its impact on skill, visibility, and revenue.

In equilibrium, forward-looking managers accept lower current pay to join higher-quality teams because the resulting human-capital gains raise future productivity and earnings. From the model in Supplementary Material Appendix C, we derive the following testable hypotheses:

Hypothesis 1 (Team Quality and Compensation). A manager's contemporaneous compensation decreases with team quality.

This hypothesis reflects the core trade-off in our model: Managers accept a near-term pay discount in exchange for longer-term gains from skill development and visibility spillovers.

Hypothesis 2 (Team Quality and Human Capital Channel).

a. A manager's future investment skill increases with the team's current investment skill.
b. A manager's future media visibility rises with the team's current media visibility.

[14]Since we use team-by-year fixed effects to gauge the marginal contribution of team allocation, we exclude 21 single-fund solo managers and 15 multi-fund solo managers from these tests.

This hypothesis directly tests the human capital channel, examining whether managers build skills and visibility by working with more capable or prominent teammates.

Hypothesis 3 (Team Quality, Revenue Growth, and Compensation Growth). A manager's future compensation growth and revenue growth increase with current team quality.

This hypothesis links team quality to long-term outcomes: better team affiliations, despite their cost in contemporaneous pay, lead to stronger future performance and compensation growth.

The model also permits heterogeneity: Managers differ in how much they gain from team-based learning, so contracts feature manager–firm-specific trade-offs. Those expecting larger benefits from top teams accept steeper initial pay cuts. Section VII tests this by contrasting junior and senior managers, extending evidence on career-cycle pay dynamics in Ellul et al. (2022).

V. Effects of Team Quality on Compensation

A. Methodology

We estimate

$$(9)\quad y_{mft} = \lambda_m + \lambda_{ft} + \beta_1 TeamSkill_{mft} + \beta_2 TeamVisibility_{mft} + \gamma X_{mft} + \lambda Y_{mft} + \epsilon_{mft},$$

where y_{mft} is the log of manager m's annual compensation at firm f in year t.[15]

The main challenge is that more able managers may sort into better teams, confounding the link between team quality and pay. We mitigate this concern in several layers. First, manager fixed effects λ_m absorb all time-invariant ability and reputation differences. Second, the rich vector X_{mft} controls for time-varying determinants of pay—skill, visibility, portfolio revenue, age, tenure, fund count, equity share, and any executive duties. Third, firm-by-year effects λ_{ft} net out contemporaneous firm-level shocks such as changes in compensation policy, advertising, or research support. Finally, Y_{mft} adds team size and averaged teammate characteristics so that β_1 and β_2 are not merely proxying for other team traits. Standard errors are double-clustered by manager and year.

The residual threat is sorting on *time-varying* unobservables, represented by ε_{mft}. To address this, Section V.C turns to DiD event studies around managers who switch teams within the same firm, offering an additional check on our estimates.

B. Does Team Quality Decrease the Short-term Compensation of Portfolio Managers?

Table 2 reports our main results from testing Hypothesis 1. Column 1 shows that the manager's own investment skill and the investment skill of their teammates

[15]Because skill and visibility can take nonpositive values, we retain them in levels and adopt a log-level specification.

TABLE 2

Effects of Team Quality on Compensation

Table 2 presents the results from regressing manager compensation on team and manager characteristics. *Compensation* is the manager's compensation in shekels. *Skill* is the Berk and Van Binsbergen (2015) measure of the manager's investment skill in columns 1–7, and it is the manager's α from the Five-Benchmark Model (see Section II.D) in column 8. *Visibility* is the number of newspaper articles about the manager in the four major business outlets in Israel. 1_{Team} indicator equals 1 if the manager is working with the team. *Team Skill* is the average skill of the manager's team members. *Team Visibility* is the average number of articles about the manager's team members in the four major business outlets in Israel. The remaining variables are defined in Table 1. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors double-clustered by manager and year are in parentheses.

$y =$	$Log(Compensation_{m,t})$							
	1	2	3	4	5	6	7	8
$Skill =$	BvB	BvB	BvB	BvB	BvB	BvB	BvB	Alpha
$1_{Team_{m,t}}$	0.046	0.049	0.047	0.039	0.035	0.045	0.072	0.075
	(0.094)	(0.118)	(0.127)	(0.094)	(0.088)	(0.077)	(0.097)	(0.070)
$Skill_{m,t}$	0.0028***		0.0025**	0.0028***	0.0027**	0.0021**	0.0024***	0.44**
	(0.0009)		(0.0009)	(0.0009)	(0.00105)	(0.0010)	(0.0008)	(0.17)
$Team\,Skill_{m,t}$	−0.0022**		−0.0018**	−0.0017**	−0.0017**	−0.0013**	−0.0014**	−0.59**
	(0.0011)		(0.0007)	(0.0007)	(0.0007)	(0.0005)	(0.0005)	(0.24)
$Visibility_{m,t}$		0.0010**	0.0010**	0.0012***	0.0012***	0.0012***	0.0012***	0.0010***
		(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$Team\,Visibility_{m,t}$		−0.0017***	−0.0017***	−0.0013***	−0.0012***	−0.0011***	−0.0011***	−0.0011***
		(0.0005)	(0.0005)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Manager Characteristics								
$Log(Revenue_{m,t})$				0.096***	0.079***	0.082***	0.071**	0.075**
				(0.017)	(0.020)	(0.020)	(0.034	(0.032)
$Log(Manager\,Age_{m,t})$				0.658**	0.603**	0.784***	0.799**	0.702**
				(0.266)	(0.247)	(0.216)	(0.219	(0.257)
$Log(Industry\,Experience_{m,t})$				0.336***	0.359***	0.310***	0.286**	0.217**
				(0.067)	(0.066)	(0.074)	(0.092)	(0.104)
$1_{Additional\,Role_{m,t}}$				0.389***	0.374***	0.340***	0.315***	0.321***
				(0.076)	(0.076)	(0.082)	(0.079)	(0.094)
$Log(Number\ of\,Funds_{m,t})$				0.052	0.078	0.074	0.054	0.051
				(0.047)	(0.053)	(0.043)	(0.081)	(0.093)
$Equity\,Share_{m,t}$				0.051	0.058	0.034	0.054	0.040
				(0.079)	(0.077)	(0.087)	(0.058)	(0.054)
Team Characteristics								
$Log(Team\ Industry\,Experience_{m,t})$					0.028	0.014	0.014	0.013
					(0.014)	(0.015)	(0.018)	(0.017)
$Log(Team\,Size_{m,t})$					−0.382*	−0.385	−0.430	−0.398
					(0.179)	(0.255)	(0.299)	(0.375)
$Log(Team\,Age_{m,t})$					0.057*	0.039	0.048	0.041
					(0.030)	(0.044)	(0.045)	(0.051)
$Team\ Equity\,Share_{m,t}$					0.262	0.315*	0.244	0.291
					(0.156)	(0.152)	(0.190)	(0.192)
Observations	1,749	1,749	1,749	1,710	1,710	1,510	1,476	1,476
R^2	0.342	0.341	0.346	0.553	0.559	0.611	0.873	0.782
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Firm × Year FE	No	No	No	No	No	Yes	Yes	Yes
Manager FE	No	No	No	No	No	No	Yes	Yes

have opposing effects on their current pay. An increase of 1 standard deviation in the manager's own skill (21.62 million shekels) leads to an increase of 6.05% $(21.62 \times 0.0028 \times 100\%)$ in the manager's compensation, while an increase of 1 standard deviation in the team's skill (28.81 million shekels) reduces the compensation by 6.34% $(28.81 \times (-0.0022) \times 100\%)$.[16]

Column 2 shows that the manager's media visibility and the team's media visibility also generate opposing effects on compensation. The estimated coefficients, as well as their economic magnitudes, are smaller than the effects of investment skill. An increase of 1 standard deviation in the manager's visibility (11.42 media

[16]Since we use log-level specifications with respect to skill and visibility measures, the estimated coefficient (β) implies that a one-unit increase in skill or visibility is associated with a $100 \times \beta\%$ increase in compensation.

mentions) increases their compensation by 1.14% ($11.42 \times 0.0010 \times 100\%$), while an increase of 1 standard deviation in the team's visibility (22.08 media mentions) reduces the compensation by 3.75% ($22.08 \times (-0.0017) \times 100\%$). In column 3, we simultaneously control for investment skill and media visibility. The results show that the effects of different measures of team quality are not subsumed by each other, indicating that they represent different dimensions of the manager's human capital.

Adding manager controls in column 4 leaves the main coefficients largely intact. Consistent with Ibert et al. (2017), fee revenue, age, experience, and executive duties all boost pay. Column 5 further adjusts for team characteristics: managers on smaller, older teams earn more, yet the opposing impacts of team skill and visibility remain economically and statistically strong.

In column 6, we add firm-by-year fixed effects, which slightly reduces the effects of both team investment skill and media visibility. Adding manager fixed effects in column 7 does not significantly affect the estimates. In this most restrictive version of our regression specifications, we find that the increase of 1 standard deviation in the team skill reduces compensation by 4.03% ($28.81 \times (-0.0014) \times 100\%$), and a similar increase in the team's visibility reduces compensation by 3.09% ($22.08 \times (-0.0011) \times 100\%$).

Column 8 replaces the Berk and Van Binsbergen (2015) skill metric with the manager's risk-adjusted return, α. A 1-standard-deviation increase in team α (6.29 pp) is linked to a 3.71% drop in pay ($6.29\% \times (-0.59)$). Because the Berk and Van Binsbergen (2015) metric adjusts for decreasing returns to scale, finding similar results with α confirms that our conclusions do not depend on any specific scale assumption.[17] Section B.1 in the Supplementary Material presents additional robustness checks—including richer manager and team controls (experience, education, within-team variance, lagged skill/visibility, and compensation histories), experience-weighted team contributions, a large-firm subsample, an alternative style-adjusted skill measure, and alternative clustering—all of which leave our main results unchanged.

One concern is that team quality could be highly collinear with individual characteristics, inflating standard errors. We test this in column 7 specification by computing variance-inflation factors (VIFs). The VIFs for *Skill*, *Team Skill*, *Visibility*, and *Team Visibility* are 1.34, 1.78, 2.34, and 1.09, respectively—well below conventional danger thresholds. Multicollinearity is limited because teammates often run other funds solo or in different groups and may join the team at different times. Supplementary Material Table B3 confirms only moderate correlations (0.299–0.456) between individual and team measures, consistent with the low VIFs.

C. Event Studies Based on Team Switching

1. Methodology

Our final identification concern is that unobserved, time-varying traits could drive both team moves and pay. We address this with a DiD event study that tracks

[17]Table B2 in the Supplementary Material demonstrates that our results are robust across different potential performance evaluation periods, specifically using 3-year and 5-year estimates of both fund alpha and the Berk and Van Binsbergen (2015) skill measure.

managers who switch teams within the same firm, limiting the sample to larger firms (at least 4 managers and 2 teams) to ensure sufficient transitions. Teams are sorted into terciles by skill (and separately by visibility), with moves classified as low-to-high or high-to-low. This yields 201 within-firm switches: 71 up- and 35 down-moves in skill, and 67 up- and 26 down-moves in visibility.

For each switch, we compare the "switcher" to all same-firm colleagues who do not change teams that year ("stayers"). Because a manager can be a switcher in one event and a stayer in another, the cohorts are event-specific; 89% of events involve a single switcher. We follow both groups from 3 years before the move ($i=-3,-2,-1$) through the transition year ($i=0$) and 2 years after ($i=1,2$). This window lets us verify parallel pre-trends and observe post-move dynamics.

Although team reassignment is not random—skill growth, career ambitions, or firm policies may influence both switching and pay—the within-firm, switcher-versus-stayer framework, combined with pre-trend tests, helps mitigate bias from such time-varying unobservables. We estimate two distinct regression specifications:

$$(10)\qquad y_{\text{mfte}} = \lambda_m + \lambda_{\text{ft}} + \lambda_e + \sum_{i=-3, i\neq -1}^{2} \left(\beta_i \times \mathbb{1}_{\text{me}}^{L\to H} \times \mathbb{1}_i\right) + \gamma X_{\text{mt}} + \lambda Y_{\text{mt}} + \epsilon_{\text{mfte}}.$$

$$(11)\qquad y_{\text{mfte}} = \lambda_m + \lambda_{\text{ft}} + \lambda_e + \sum_{i=-3, i\neq -1}^{2} \left(\beta_i \times \mathbb{1}_{\text{me}}^{H\to L} \times \mathbb{1}_i\right) + \gamma X_{\text{mt}} + \lambda Y_{\text{mt}} + \epsilon_{\text{mfte}},$$

Equations (10) and (11) are estimated separately for "low-to-high" ($L \to H$) and "high-to-low" ($H \to L$) moves. The treatment indicators $\mathbb{1}_{me}^{L\to H}$ and $\mathbb{1}_{me}^{H\to L}$ equal to 1 when manager m is the switcher in event e, 0 for stayers. Interaction terms with year dummies $\mathbb{1}_i (i=-3,-2,0,1,2)$ yield the coefficients of interest, β_i, which measure the switcher–stayer gap in year i relative to the omitted pre-transition year $i=-1$. A detailed vector of controls, used in equation (9), completes the specification.

Our DiD design seeks to isolate changes in compensation specifically connected with transitioning between teams. However, this approach depends on the assumption that any unobserved factors remain uncorrelated with an individual's team-switching status, conditional on our controls. We do not claim that the DiD design definitively establishes causality; rather, we view it as a tool to help reduce, though not fully eliminate, selection concerns.

An essential element of the DiD methodology is the parallel trends assumption: Absent a team switch, switchers and stayers would follow comparable trajectories in compensation. To assess this, we plot and examine time-series patterns of compensation for both groups in the years before switching occurs. If the trends appear similar, it supports the parallel trends assumption. Any divergence would signal the possibility of time-varying confounders. We present these results in the next subsection and interpret them cautiously in light of the usual caveats about nonexperimental data.

2. DiD Results

Figure 3 presents DiD test results for team skill transitions. The capped spikes show the 95% confidence intervals. Graph A examines low- to high-skill transitions. Before the transition, compensation trends for those switching teams and

FIGURE 3

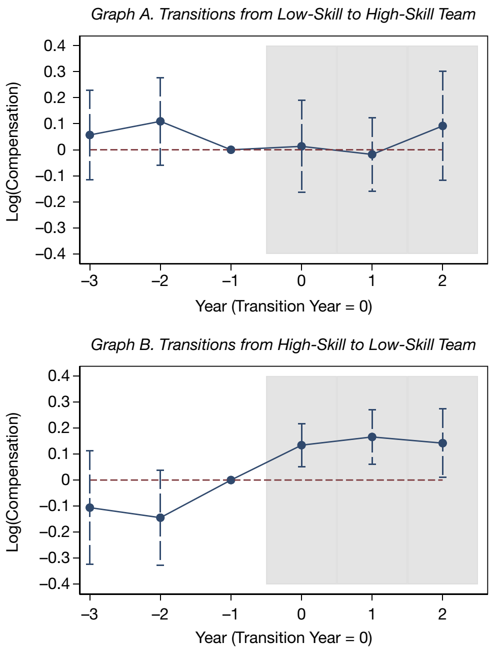
Effects of Team Investment Skill on Compensation: Event Study from Transitions Across Teams

Figure 3 assesses the effect of the transition across teams on compensation of portfolio managers by estimating the following two specifications separately for the transitions from low-skill teams to high-skill teams and vice versa:

$$Log(Compensation_{mfte}) = \lambda_m + \lambda_{ft} + \lambda_e + \sum_{i=-3, i \neq -1}^{2} \left(\beta_i \times \mathbb{1}_{me}^{L \to H} \times \mathbb{1}_i \right) + \gamma X_{mt} + \lambda Y_{mt} + \epsilon_{mfte},$$

$$Log(Compensation_{mfte}) = \lambda_m + \lambda_{ft} + \lambda_e + \sum_{i=-3, i \neq -1}^{2} \left(\beta_i \times \mathbb{1}_{me}^{H \to L} \times \mathbb{1}_i \right) + \gamma X_{mt} + \lambda Y_{mt} + \epsilon_{mfte}.$$

The details are in Section V.C. The figure shows the estimated coefficients $\beta_i^{L \to H}$ in Graph A and $\beta_i^{L \to H}$ in Graph B. These estimates are interpreted as the average difference in compensation between the managers who switch teams and the managers who stay on the same team within the same firm, relative to the reference period. Brackets are 95% confidence intervals with standard errors double-clustered by manager and year. The shaded region corresponds to the period after the transition. Time 0 is the transition year. Time − 1 is the one year before the transition event, which we use as the reference period.



those staying are similar, supporting the parallel trend assumption. However, post-transition, there is no notable impact on compensation.

Graph B investigates high- to low-skill transitions. Here too, the compensation trends prior to the transition show no significant differences between the groups, indicating adherence to the parallel trend assumption. However, post-transition, a notable change occurs: The compensation of those who switch to lower-skill teams increases significantly. These managers experience an immediate 12% increase in compensation, with a further incremental rise of about 3% the following year, ultimately stabilizing at a 13% increase in the second year after the transition.

Team moves matter mainly when managers exit high-skill groups: pay rises, likely because firms replace lost team capital with higher wages. No effect appears for low-to-high moves, consistent with wage stickiness that blocks pay cuts. This asymmetry complements Table 2. The DiD tracks within-manager shifts over the career, whereas the cross-section captures between-manager sorting (e.g., juniors choosing stronger teams), so the two designs offer complementary views of how team quality shapes compensation and career paths.

The 13% increase in compensation for managers transitioning to low-skill teams quantitatively aligns with findings from our initial analysis in Table 2. The difference in team skill levels, classified into high and low (upper and lower terciles), is approximately 71.75 million shekels or 2.5 standard deviations. According to estimates in Table 2, this magnitude of skill discrepancy corresponds to a 15% decrease in compensation, closely matching the DiD estimate. This comparison reinforces the internal consistency and robustness of our methodologies.

Figure 4 depicts outcomes of similar analyses, but using team visibility as a measure of quality. In Graph A, transitions from low-to-high visibility teams show

FIGURE 4

Effects of Team Media Visibility on Compensation: Event Study from Transitions Across Teams

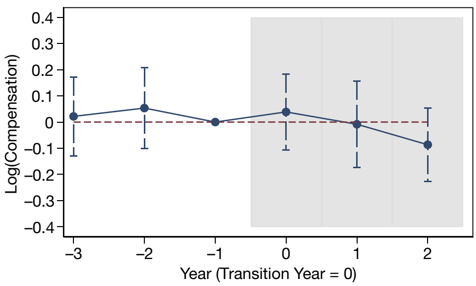
Figure 4 assesses the effect of the transition across teams on compensation of portfolio managers by estimating the following two specifications separately for the transitions from low-visibility teams to high-visibility teams and vice versa:

$$Log(Compensation_{mfte}) = \lambda_m + \lambda_{ft} + \lambda_e + \sum_{i=-3,\, i\neq -1}^{2} \left(\beta_i \times \mathbb{1}_{me}^{L\to H} \times \mathbb{1}_i\right) + \gamma X_{mt} + \lambda Y_{mt} + \epsilon_{mfte},$$

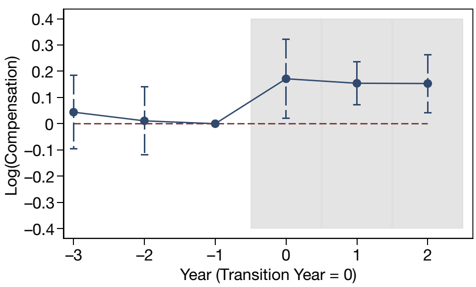
$$Log(Compensation_{mfte}) = \lambda_m + \lambda_{ft} + \lambda_e + \sum_{i=-3,\, i\neq -1}^{2} \left(\beta_i \times \mathbb{1}_{me}^{H\to L} \times \mathbb{1}_i\right) + \gamma X_{mt} + \lambda Y_{mt} + \epsilon_{mfte}.$$

The details are in Section V.C. The figure shows the estimated coefficients $\beta_i^{L\to H}$ in Graph A and $\beta_i^{L\to H}$ in Graph B. These estimates are interpreted as the average difference in compensation between the managers who switch teams and the managers who stay on the same team within the same firm, relative to the reference period. Brackets are 95% confidence intervals with standard errors double-clustered by manager and year. The shaded region corresponds to the period after the transition. Time 0 is the transition year. Time − 1 is the one year before the transition event, which we use as the reference period.

Graph A. Transitions from Low-Visibility to High-Visibility Team



Graph B. Transitions from High-Visibility to Low-Visibility Team



no impact on compensation, with no significant trends observed prior to the transition. Graph B, examining high-to-low visibility transitions, again reveals a compensation versus team quality trade-off. Here, switchers see an immediate moderate increase in compensation of around 14%, within a confidence interval of [−26%; −4%].

Just as we did with the effects of team investment skill, we can compare these findings to the baseline results presented in Table 2. The average difference in visibility between high- and low-visibility teams is about 1.8 standard deviations. Using data from Table 2, we calculate the economic effect size of our initial model to be approximately −7%. This finding aligns closely with the DiD estimate's confidence interval, further affirming the consistency and reliability of our results across different methodologies.

The DiD tests reinforce our baseline results and uncover a clear asymmetry: Compensation mainly adjusts when managers move from high- to low-quality teams. A complementary first-difference analysis that benchmarks each switcher against their own prior pay, rather than against stayers, reaches the same conclusion (Supplementary Material Table B10) and yields similar magnitudes, further validating the pattern. Although these event-study estimates exhibit no discernible pre-trends, the design cannot fully eliminate time-varying confounders that might influence both switching decisions and pay. Accordingly, we interpret the evidence as supportive rather than conclusive, while emphasizing that team transitions coincide with meaningful shifts in individual managers' compensation trajectories. Section B.2 in the Supplementary Material reports further robustness checks, including DiD tests that control for managers' career stage and sensitivity analyses for potential omitted-variable bias following Cinelli and Hazlett (2020).

VI. Examining the Mechanisms Behind the Effects of Team Quality

A. Does Team Affiliation Improve Manager Investment Skill and Visibility?

We turn to Hypothesis 2, which posits that managers sacrifice current pay because strong teams accelerate their own skill and visibility. Re-estimating equation (9) with the 3-year growth in those traits as the dependent variable, Table 3 confirms the prediction. A 1-standard-deviation rise in team skill raises the manager's skill growth by 11.52 pps (28.81 × 0.004; column 3); a comparable rise in team visibility boosts the manager's visibility growth by 4.41 pps (22.08 × 0.002; column 6). Personal and team skills also feed into visibility gains, suggesting spillovers across human-capital dimensions.

We probe Hypothesis 2 further with a DiD event-study, replacing the dependent variable in equations (10)–(11) by a 3-year growth in skill or visibility. Figures 5 and 6 mirror the asymmetric pattern seen for pay. In Figure 5, Graph A shows that a low-to-high team-skill move raises the manager's own skill growth by about 9 pps in the first year, edging up to 11 pps by the third year, with no pre-trend. Graph B finds no effect when skill moves high-to-low. In Figure 6, Graph A reveals that a low-to-high visibility move boosts personal visibility by 11 pps in the first

TABLE 3

Effects of Team Quality on Manager Skill Growth and Visibility Growth

Table 3 presents the results from regressing the manager's 3-year skill growth rate and 3-year visibility growth rate on team and manager characteristics. *Compensation* is the manager's compensation in shekels. *Skill* is the Berk and Van Binsbergen (2015) measure of the manager's investment skill. *Visibility* is the number of newspaper articles about the manager in the four major business outlets in Israel. 1_{Team} indicator equals 1 if the manager is working with the team. *Team Skill* is the average skill of the manager's team members. *Team Visibility* is the average number of articles about the manager's team members in the four major business outlet in Israel. All the specifications include the full set of manager and team characteristics from Table 2. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors double-clustered by manager and year are in parentheses.

$y =$	$\frac{\Delta Skill_{m,t\to t+3}}{Skill_{m,t}}$			$\frac{\Delta Visibility_{m,t\to t+3}}{Visibility_{m,t}}$		
	1	2	3	4	5	6
$1_{Team_{m,t}}$	0.021	0.026	0.022	0.287	0.290	0.205
	(0.088)	(0.095)	(0.088)	(0.213)	(0.205)	(0.288)
$Skill_{m,t}$	0.0018***		0.0018***	0.0006**		0.0006*
	(0.0004)		(0.0004)	(0.002)		(0.003)
$TeamSkill_{m,t}$	0.004**		0.004*	0.005**		0.005*
	(0.002)		(0.002)	(0.002)		(0.002)
$Visibility_{m,t}$		0.0022	0.0021		0.0010	0.0012
		(0.0061)	(0.0073)		(0.0031)	(0.0039)
$TeamVisibility_{m,t}$		0.0011	0.0011		0.002**	0.002**
		(0.0012)	(0.0018)		(0.001)	(0.001)
Observations	1,040	1,040	1,040	1,035	1,035	1,035
R^2	0.772	0.787	0.789	0.531	0.527	0.555
Manager characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Team characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes

year, peaks at 14 pps in the second year, and holds at 11 pps in the third year; Graph B shows no change for high-to-low moves.

Taken with the pay results (Figures 3–4), a clear trade-off emerges: Managers who climb to higher-quality teams gain skill and visibility but forego immediate pay increases, whereas those who step down enjoy higher current compensation yet forfeit human-capital growth—exactly the pattern predicted by our framework.

B. Does Team Affiliation Improve Manager Specialization?

We next examine whether team affiliation improves manager specialization. To capture industry specialization, we use a standard measure of industry concentration from the mutual fund literature, popularized by Kacperczyk et al. (2005). This measure is commonly used to assess the extent of private information managers acquire within certain industries, leading to more focused investment strategies and reflecting enhanced expertise in those areas. We define the industry concentration measure for manager i in year t as

$$\text{ICI}_{i,t} = \sum_{j=1}^{J} \left(w_{m,j,t} - \bar{w}_{j,t}\right)^2, \tag{12}$$

where $w_{m,j,t}$ is the fraction of the manager's AUM invested in industry j, and $\overline{w}_{j,t}$ is the average fraction of AUM invested in industry j across all managers. We use the

FIGURE 5

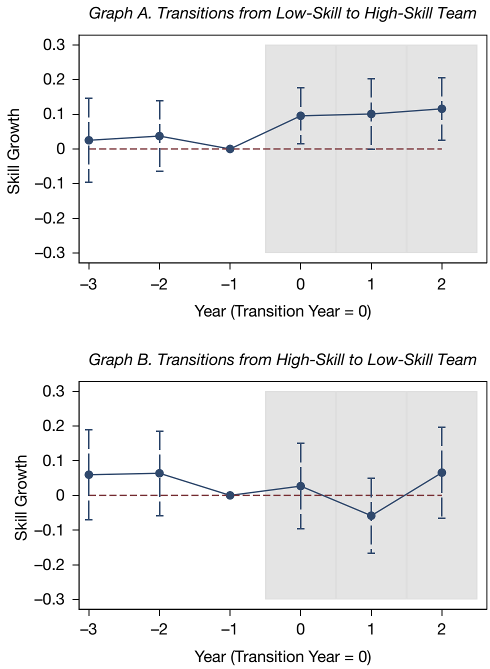
Effects of Team Investment Skill on Manager Skill Growth: Event Study from Transitions Across Teams

Figure 5 assesses the effect of the transition across teams on the skill growth rate of portfolio managers by estimating the following two specifications separately for the transitions from low-skill teams to high-skill teams and vice versa:

$$\frac{\Delta Skill_{mfe,t\to t+3}}{Skill_{mfe,t}} = \lambda_m + \lambda_{ft} + \lambda_e + \sum_{i=-3, i\neq -1}^{2} \left(\beta_i \times \mathbb{1}_{me}^{L\to H} \times \mathbb{1}_i\right) + \gamma X_{mt} + \lambda Y_{mt} + \epsilon_{mfte},$$

$$\frac{\Delta Skill_{mfe,t\to t+3}}{Skill_{mfe,t}} = \lambda_m + \lambda_{ft} + \lambda_e + \sum_{i=-3, i\neq -1}^{2} \left(\beta_i \times \mathbb{1}_{me}^{H\to L} \times \mathbb{1}_i\right) + \gamma X_{mt} + \lambda Y_{mt} + \epsilon_{mfte}.$$

The details are in Section V.C. The figure shows the estimated coefficients $\beta_i^{L\to H}$ in Graph A and $\beta_i^{L\to H}$ in Graph B. These estimates are interpreted as the average difference in investment skill growth between the managers who switch teams and the managers who stay on the same team within the same firm, relative to the reference period. Brackets are 95% confidence intervals with standard errors double-clustered by manager and year. The shaded region corresponds to the period after the transition. Time 0 is the transition year. Time -1 is the one year before the transition event, which we use as the reference period.



standard list of 20 industries in Israeli mutual fund filings, as shown in Supplementary Material Table B15.

Our second measure captures concentration within specific investment styles and asset classes rather than industries. While some mutual fund managers specialize within particular asset classes, others may oversee funds across multiple asset classes. For example, a manager might handle both equity and balanced funds. We define the style concentration measure for manager i in year t as

$$\mathrm{SC}_{i,t} = \sum_{s=1}^{S} \left(w_{m,s,t} - \bar{w}_{s,t}\right)^2, \tag{13}$$

FIGURE 6

Effects of Team Media Visibility on Manager Visibility Growth: Event Study from Transitions Across Teams

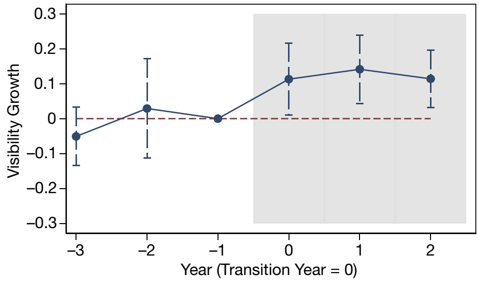
Figure 6 assesses the effect of the transition across teams on the visibility growth rate of portfolio managers by estimating the following two specifications separately for the transitions from low-visibility teams to high-visibility teams and vice versa:

$$\frac{\Delta Visibility_{mfe,t\rightarrow t+3}}{Visibility_{mfe,t}} = \lambda_m + \lambda_{ft} + \lambda_e + \sum_{i=-3, i\neq -1}^{2} \left(\beta_i \times \mathbb{1}_{me}^{L\rightarrow H} \times \mathbb{1}_i\right) + \gamma X_{mt} + \lambda Y_{mt} + \epsilon_{mfte},$$

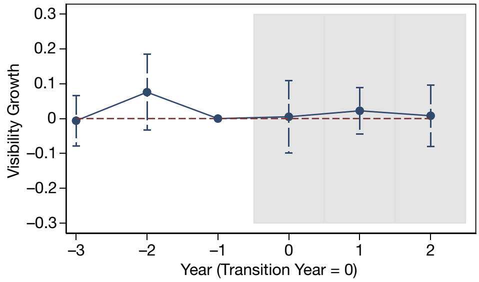
$$\frac{\Delta Visibility_{mfe,t\rightarrow t+3}}{Visibility_{mfe,t}} = \lambda_m + \lambda_{ft} + \lambda_e + \sum_{i=-3, i\neq -1}^{2} \left(\beta_i \times \mathbb{1}_{me}^{H\rightarrow L} \times \mathbb{1}_i\right) + \gamma X_{mt} + \lambda Y_{mt} + \epsilon_{mfte}.$$

The details are in Section V.C. The figure shows the estimated coefficients $\beta_i^{L\rightarrow H}$ in Graph A and $\beta_i^{L\rightarrow H}$ in Graph B. These estimates are interpreted as the average difference in visibility growth between the managers who switch teams and the managers who stay on the same team within the same firm, relative to the reference period. Brackets are 95% confidence intervals with standard errors double-clustered by manager and year. The shaded region corresponds to the period after the transition. Time 0 is the transition year. Time −1 is the one year before the transition event, which we use as the reference period.

Graph A. Transitions from Low-Visibility to High-Visibility Team



Graph B. Transitions from High-Visibility to Low-Visibility Team



where $w_{m,s,t}$ is the manager's fraction of AUM invested in style s, and $\overline{w}_{s,t}$ is the average fraction of AUM invested in style s across all managers. We use a standard list of 11 asset classes as "styles," detailed in Supplementary Material Table B1.[18]

[18]There are several differences between the two concentration measures. The industry concentration measure is typically applied to equity funds in the literature, capturing a granular specialization of equity fund managers within industries. The style concentration measure, however, is less granular, as it captures specialization in broader asset classes rather than within specific types of securities within an asset class. This asset class specialization is an important aspect of the Israeli mutual fund industry, which is relatively small and where managers may be required to oversee investments across multiple asset classes. Consequently, style concentration represents a higher level of specialization compared to industry concentration. Similar to the interpretation of industry concentration from Kacperczyk et al. (2005), increased style concentration may reflect enhanced expertise in specific styles, indicating better private information on the manager's part. To maintain consistency with these interpretations, our analysis below examines the effects of industry concentration only within the sample of managers overseeing equity funds and the effects of style concentration across all managers.

We test whether moving to a high-skill team that includes at least one highly specialized member sharpens a manager's own focus. Using the DiD framework for team-skill transitions, we split events by whether the destination team contains a specialist (top 30% of the specialization distribution in the transition year). The outcome is the manager's standardized specialization index, measured 1 year after the move, so coefficients can be read as standard-deviation changes. Separate regressions for specialist and nonspecialist destinations reveal how peer expertise shapes individual specialization.

Table 4 shows sharper focus only when managers join a high-skill team *with* a specialist: industry specialization rises by 0.232 standard deviations (Panel A) and style by 0.189 standard deviations (Panel B). High-skill teams lacking a specialist add just 0.092 standard deviations to style and leave industry unchanged, while moves to low-skill teams do nothing. Exposure to a high-skill specialist, therefore, looks pivotal for deepening expertise—an edge that can speed promotions and widen future fund-leadership roles.

To ensure that a higher concentration index reflects genuine specialization—rather than a shift into unrelated industries or styles—we construct a distance

TABLE 4

Effects of Team Transitions on Manager Specialization

Table 4 presents the results of estimating the effects of team switching on manager specialization. Panel A reports results for industry specialization, while Panel B focuses on style specialization. The specialization measures, $ICI_{i,t}$ and $SF_{i,t}$, are defined in Section VI.B, and the estimation methodology is detailed in Section V.C. For each specialization type, the table provides separate results for switches into teams with and without a specialist member. A specialist member is defined as a team member whose specialization level is in the top 30% of the specialization distribution for the same year. All the specifications include the full set of manager and team characteristics from Table 2. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors double-clustered by manager and year are in parentheses.

Panel A. Industry Specialization

$y =$	$ICI_{i,t}$			
	With Specialist Member		Without Specialist Member	
	1	2	3	4
$\mathbb{1}_{me}^{L\to H} \times \mathbb{1}_0$	0.232**		0.182	
	(0.101)		(0.125)	
$\mathbb{1}_{me}^{H\to L} \times \mathbb{1}_0$		0.044		0.102
		(0.054)		(0.090)
Observations	885	675	787	692
R^2	0.610	0.701	0.615	0.590

Panel B. Style Specialization

$y =$	$SF_{i,t}$			
	With Specialist Member		Without Specialist Member	
	1	2	3	4
$\mathbb{1}_{me}^{L\to H} \times \mathbb{1}_0$	0.189**		0.092**	
	(0.087)		(0.041)	
$\mathbb{1}_{me}^{H\to L} \times \mathbb{1}_0$		0.101		0.065
		(0.093)		(0.048)
Observations	1,021	943	967	806
R^2	0.593	0.638	0.629	0.694
Manager characteristics	Yes	Yes	Yes	Yes
Team characteristics	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes

metric $D_{i,t}$ that gauges how closely a manager's portfolio weights match those of a specialist teammate, defined as a peer in the top 30% of the specialization distribution:

$$D_{i,t} = \sum_{k=1}^{K} \left(w_{i,k,t} - w_{\text{spec},k,t}\right)^2.$$

A lower $D_{i,t}$ signals that the manager is reallocating toward the specialist's industries or asset classes, consistent with learning. Supplementary Material Table B13 shows that $D_{i,t}$ declines after managers move to high-skill teams but is unchanged when they join low-skill teams. These patterns suggest that team affiliation encourages learning in the very domains where the specialist excels, reinforcing the link between team composition and skill development. This result parallels Cici et al. (2018) and Bai et al. (2022), (2024), who find that specialization can be shaped by a manager's background, and extends that literature by demonstrating how team composition also influences managers' specialized allocations.

C. Does Team Affiliation Improve Future Compensation and Revenue?

We turn to Hypothesis 3: Does team quality lift future fee revenue and, in turn, compensation? Our framework predicts that managers accept lower current pay only if better teams accelerate lifetime earnings. Prior work shows that higher skill and visibility boost revenue (Berk and Van Binsbergen (2015), Solomon et al. (2014), and Kaniel and Parham (2016)) and that revenue feeds directly into pay (Ibert et al. (2017)). Given Section VI.A's evidence that strong teams speed skill and visibility growth, we expect corresponding gains in revenue and compensation growth.

Using equation (9)), we link team quality to 3-year compensation growth. Columns 1–3 of Table 5 show that a 1-standard-deviation rise in team skill (visibility) lifts the growth rate by roughly 14.4 pps (15.1 pps). Columns 4–6 report a parallel pattern for revenue growth, and column 7 confirms that next-year revenue already responds, implying that the productivity gains from strong teams surface quickly.

These findings bridge supply-side and demand-side forces: Firms decide team assignments and set pay, while investors reward the investment skill and visibility that drive revenue. Team quality matters for compensation precisely because it develops the very attributes investors value; without that demand, team placement would not shift the labor-market equilibrium for portfolio managers. Empirically, high-quality teams are linked not only to higher near-term revenue but also to faster long-run pay growth, making team affiliation a springboard for upward career mobility in asset management. Supplementary Material Section B.3 provides supplemental evidence from managers who run both solo- and team-managed funds, showing that higher team skill predicts stronger future skill growth and revenue in their solo portfolios, thereby confirming that the observed effects are not driven by mechanical "free-riding" on team returns.

TABLE 5

Effects of Team Quality on Compensation Growth and Revenue Growth

Table 5 presents the results from regressing the manager's 3-year compensation growth rate, 3-year revenue growth rate, and the next year's revenues on team and manager characteristics. *Compensation* is the manager's compensation in shekels. *Skill* is the Berk and Van Binsbergen (2015) measure of the manager's investment skill. *Visibility* is the number of newspaper articles about the manager in the four major business outlets in Israel. 1_{Team} indicator equals 1 if the manager is working with the team. *Team Skill* is the average skill of the manager's team members. *Team Visibility* is the average number of articles about the manager's team members in the four major business outlets in Israel. All the specifications include the full set of manager and team characteristics from Table 2. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors double-clustered by manager and year are in parentheses.

$y=$	$\Delta Log(Compensation)_{m,t\to t+3}$			$\Delta Log(Revenue)_{m,t\to t+3}$			$Log(Revenue)_{m,t+1}$
	1	2	3	4	5	6	7
$1_{Team_{m,t}}$	0.096	0.153	0.197	−0.112	−0.084	−0.114	0.085**
	(0.142)	(0.180)	(0.178)	(0.151)	(0.206)	(0.199)	(0.040)
$Skill_{m,t}$	0.0012**		0.002*	0.008**		0.008**	0.0041***
	(0.0005)		(0.001)	(0.003)		(0.003)	(0.0015)
$TeamSkill_{m,t}$	0.013**		0.005**	0.002**		0.002**	0.0024**
	(0.001)		(0.002)	(0.0001)		(0.001)	(0.0011)
$Visibility_{m,t}$		0.003*	0.004		0.004*	0.005**	0.0020**
		(0.001)	(0.003)		(0.002)	(0.002)	(0.008)
$TeamVisibility_{m,t}$		0.008*	0.007**		0.003**	0.003*	0.0022**
		(0.004)	(0.003)		(0.001)	(0.001)	(0.0011)
Observations	1,043	1,043	1,043	1,011	1,011	1,011	1,472
R^2	0.513	0.511	0.516	0.676	0.664	0.676	0.901
Manager characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

VII. Implications for Team Allocation for Career Outcomes

A. The Role of First Team Allocation

We next explore how the first team assignment shapes careers. A manager's initial team is the first occasion on which she comanages a fund—typically at industry entry, though sometimes later. We begin by asking who lands on a high-quality debut team. Defining high quality as above-median team skill or visibility (H-type), we estimate a linear probability model where the dependent variable equals 1 if the manager's first team is H-type. Explanatory variables include age, prior visibility, and tenure in asset management and mutual funds; team controls match those in Table 2. We omit investment skill because most entrants lack a performance record before their first assignment.

Table 6 indicates that younger, less-experienced mutual fund managers are more likely to debut on high-quality teams. Firms thus appear to pair junior managers with skilled, visible colleagues from the outset. Mutual fund experience, not general asset-management tenure, drives this pattern, highlighting that first assignments target fund-specific skill building.

We relate first-team quality to 5-year career outcomes—pay growth and two promotion proxies. "Role promotion" flags a move into senior titles (e.g., head of investment committee, CIO, CEO), capturing within-firm advancement revealed privately to the fund family. "Fund promotion" records a more than 50% jump in the number of funds a manager runs—about two extra mandates for the average manager

TABLE 6

Determinants of First-Team Quality

Table 6 presents regression results where the indicator variables for the quality of the first team are regressed on manager and team characteristics. For investment skill (visibility) as the quality measure, the indicator equals 1 if the team's investment skill (visibility) is classified as High, meaning above the median. The specifications in columns 2 and 4 include the full set of team characteristics from Table 2. All the variables are defined in Table 2. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors double-clustered by manager and year are in parentheses.

$y =$	$\mathbb{1}_{\text{First Team Quality}=H}$			
	Team Skill		Team Visibility	
	1	2	3	4
$Log(ManagerAge_{m,t})$	−0.472***	−0.531***	−0.401***	−0.589***
	(0.101)	(0.130)	(0.134)	(0.149)
$Visibility_{m,t}$	0.012	0.018	0.027	0.024
	(0.091)	(0.172)	(0.105)	(0.080)
$Log(IndustryExperience_{m,t})$	−0.221**	−0.292***	−0.179**	−0.151***
	(0.111)	(0.103)	(0.073)	(0.054)
$Log(AssetManagementIndustryExperience_{m,t})$	−0.121	−0.222	−0.223	−0.301
	(0.091)	(0.175)	(0.183)	(0.193)
Observations	1,451	1,451	1,451	1,451
R^2	0.542	0.582	0.559	0.573
Team Characteristics	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

—signaling skill-based internal recognition. We repeat the exercise for the second and third assignments, restarting the 5-year clock at each switch. All models control for the variables in Table 2 plus the team-assignment covariates from Table 6.

Table 7 confirms that debuting on a high-skill team pays off: compensation grows 14 pps faster, the chance of a senior title ("role promotion") rises 7 pps, and the odds of managing more funds jump 12 pps. These advantages fade but remain significant after later reassignments; second-team skill still nudges pay and role promotion, whereas third-team skill is ineffectual.

Table 8 shows a parallel—though slightly weaker—pattern for team visibility. First-team visibility lifts 5-year pay growth by 16 pps and fund-promotion odds by 13 pps, with no clear effect on role promotion. Visibility on the second team continues to aid pay and fund promotion, but by the third assignment, its influence disappears.

In sum, first-team quality is pivotal. High initial team skill or visibility boosts 5-year pay growth and fund-promotion odds, and modestly raises the chance of a senior title. These advantages persist—though they fade—after later reassignments. Second-team effects are weaker and confined to pay and, for skill, role promotion; the third team's quality has no discernible influence on compensation or career progression.

B. Do the Effects of Team Quality Contribute to High Returns-to-Experience?

Compensation in finance rises faster with tenure than in almost any other field. Philippon and Reshef (2012) document a sector-wide "experience premium," while Ellul, Pagano, and Scognamiglio (2022) show that the slope is steepest in asset

TABLE 7

Effects of First Team Investment Skill on Compensation Growth and Promotions

Table 7 presents regression results where the manager's 5-year compensation growth and the probability of receiving a promotion within the next 5 years are regressed on the investment skill level of the first, second, and third teams. *Compensation* is the manager's compensation in shekels. $\mathbb{1}_{RolePromotion_{m,t\to t+5}}$ equals 1 if the manager assumes an additional role, such as head of the investment committee, chief investment strategist, chief investment officer, or CEO. $\mathbb{1}_{FundPromotion_{m,t\to t+5}}$ equals 1 if there is a 50% increase in the number of portfolio funds. The explanatory variables are indicators equal to 1 if the investment skill of the first, second, or third team is classified as High, meaning above the median. All the specifications include the full set of manager and team characteristics from Table 2. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors double-clustered by manager and year are in parentheses.

$y =$	$\Delta Log(Compensation)_{m,t\to t+5}$			$\mathbb{1}_{RolePromotion_{m,t\to t+5}}$			$\mathbb{1}_{FundPromotion_{m,t\to t+5}}$		
	1	2	3	4	5	6	7	8	9
$\mathbb{1}_{FirstTeamInvestmentSkill=H}$	0.145***	0.070***	0.051***	0.072**	0.042**	0.041**	0.123**	0.057**	0.032**
	(0.041)	(0.025)	(0.015)	(0.031)	(0.020)	(0.019)	(0.051)	(0.021)	(0.014)
$\mathbb{1}_{SecondTeamInvestmentSkill=H}$		0.018**	0.012		0.031**	0.035		0.025	0.024
		(0.008)	(0.016)		(0.013)	(0.027)		(0.021)	(0.015)
$\mathbb{1}_{ThirdTeamInvestmentSkill=H}$			0.033			0.041			0.042
			(0.031)			(0.052)			(0.037)
Observations	1,451	1,214	1,009	1,451	1,214	1,009	1,451	1,214	1,009
R^2	0.351	0.272	0.215	0.342	0.245	0.209	0.302	0.256	0.217
Manager Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 8

Effects of First Team Visibility on Compensation Growth and Promotions

Table 8 presents regression results where the manager's 5-year compensation growth and the probability of receiving a promotion within the next 5 years are regressed on the visibility level of the first, second, and third teams. *Compensation* is the manager's compensation in shekels. $\mathbb{1}_{RolePromotion_{m,t\to t+5}}$ equals 1 if the manager assumes an additional role, such as head of the investment committee, chief investment strategist, chief investment officer, or CEO. $\mathbb{1}_{FundPromotion_{m,t\to t+5}}$ equals 1 if there is a 50% increase in the number of portfolio funds. The explanatory variables are indicators equal to 1 if the visibility of the first, second, or third team is classified as High, meaning above the median. All the specifications include the full set of manager and team characteristics from Table 2. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors double-clustered by manager and year are in parentheses.

$y =$	$\Delta Log(Compensation)_{m,t\to t+5}$			$\mathbb{1}_{RolePromotion_{m,t\to t+5}}$			$\mathbb{1}_{FundPromotion_{m,t\to t+5}}$		
	1	2	3	4	5	6	7	8	9
$\mathbb{1}_{FirstTeamVisibility=H}$	0.161***	0.063**	0.068**	0.028	0.021	0.025	0.137***	0.054**	0.033
	(0.042)	(0.030)	(0.026)	(0.036)	(0.025)	(0.027)	(0.054)	(0.024)	(0.018)
$\mathbb{1}_{SecondTeamVisibility=H}$		0.052***	0.047***		0.018	0.020		0.041**	0.038*
		(0.010)	(0.015)		(0.015)	(0.024)		(0.020)	(0.020)
$\mathbb{1}_{ThirdTeamVisibility=H}$			0.034			0.048			0.039
			(0.029)			(0.058)			(0.039)
Observations	1,451	1,214	1,009	1,451	1,214	1,009	1,451	1,214	1,009
R^2	0.359	0.266	0.228	0.331	0.238	0.210	0.298	0.257	0.206
Manager Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

management, where pay accelerates sharply after just a few years on the job. Conventional explanations emphasize scarce skills, tournament incentives, and performance pay, yet these factors alone leave some of the sector's exceptional growth unexplained.

We contribute a fresh angle: Team quality magnifies returns to experience. High-skill, high-visibility teams serve as incubators of human capital, speeding the accumulation of both technical expertise and professional exposure. Junior managers who accept lower initial pay to join such teams effectively invest in a high-yield asset: the future wage gains that flow from faster skill and visibility growth. As they advance, the required discount dwindles, so their pay curve bends upward more sharply. This mechanism helps account for the especially pronounced compensation trajectories observed in team-oriented finance roles.

To test the idea formally, we let the effect of team quality vary with seniority. Defining "junior" managers as those with fewer than 4 years of mutual fund experience (the sample median) and "senior" managers as those with more, we interact standardized team skill and visibility with seniority indicators in our baseline regressions. Experience itself remains in the control set, but we drop the main seniority dummies to avoid multicollinearity. If our hypothesis is correct, the team-quality coefficients should be far larger (in absolute value) for juniors, indicating that early-career managers bear a steeper up-front pay discount that later translates into above-average earnings growth.

Table 9 shows that team quality discounts are concentrated among junior managers. In column 1, a 1-standard-deviation rise in team skill trims junior pay by 5.74%—— more than triple the 1.72% cut for seniors—implying that juniors give up a substantial share of current income to embed themselves in stronger teams.

TABLE 9

Effects of Team Quality on Compensation for Senior and Junior Managers

Table 9 presents the results from regressing manager compensation on team and manager characteristics and their interaction with the indicators for the manager's seniority. *Compensation* is the manager's compensation in shekels. *Skill* is the Berk and Van Binsbergen (2015) measure of the manager's investment skill. *Visibility* is the number of newspaper articles about the manager in the four major business outlets in Israel. 1_{Team} indicator equals 1 if the manager is working with the team. *Team Skill* is the average skill of the manager's team members. *Team Visibility* is the average number of articles about the manager's team members in the four major business outlets in Israel. Both *Team Skill* and *Team Visibility* are standardized such that their mean equals 0 and their standard deviation equals 1. 1_{Junior} indicator equals 1 if the manager's industry experience is below the median. 1_{Senior} indicator equals 1 if the manager's industry experience is above the median. All the specifications include the full set of manager and team characteristics from Table 2. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors double-clustered by manager and year are in parentheses.

y =	$Log(Compensation_{m,t})$					
	1	2	3	4	5	6
$1_{Team_{m,t}}$	0.051	0.055	0.045	0.033	0.037	0.020
	(0.088)	(0.047)	(0.098)	(0.067)	(0.051)	(0.058)
$Skill_{m,t}$	0.0021**	0.0022**	0.0019**	0.0019**	0.0019**	0.0020**
	(0.0008)	(0.0010)	(0.0009)	(0.0008)	(0.0009)	(0.0009)
$Visibility_{m,t}$	0.0010**	0.0011**	0.0010**	0.0010**	0.0010**	0.0009*
	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0005)
$1_{Junior_{m,t}} \times TeamSkill_{m,t}$	−0.0574***		−0.0516***	−0.0545***		−0.0488***
	(0.0081)		(0.0075)	(0.0095)		(0.0092)
$1_{Senior_{m,t}} \times TeamSkill_{m,t}$	−0.0172**		−0.0230**	−0.0145**		−0.0201*
	(0.0075)		(0.0104)	(0.0066)		(0.0107)
$1_{Junior_{m,t}} \times TeamVisibility_{m,t}$		−0.0309***	−0.0242***		−0.0252***	−0.0220***
		(0.0087)	(0.0091)		(0.0093)	(0.0082)
$1_{Senior_{m,t}} \times TeamVisibility_{m,t}$		−0.0132**	−0.0132**		−0.0110*	−0.0110*
		(0.0063)	(0.0062)		(0.0060)	(0.0061)
Observations	1,476	1,476	1,476	1,476	1,476	1,476
R^2	0.515	0.572	0.577	0.861	0.878	0.880
Manager characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Team characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	No	No	No	Yes	Yes	Yes

Column 2 yields a similar, though smaller, gap for visibility: a 1-standard-deviation boost in team visibility lowers junior compensation by 3.09%, versus 1.32% for seniors. Column 3 confirms both channels remain significant when entered jointly, and columns 4–6 show that the patterns survive manager fixed effects and the full suite of controls. These sizable, age-dependent discounts suggest that early-career managers invest heavily in team capital, which later translates into the accelerated pay growth documented in Figure 3 and Table 5, helping account for the steep returns to experience observed in asset management.

VIII. Conclusions

Our evidence reframes compensation as a strategic lever for developing talent, not merely rewarding past performance. Fund families appear to price "team capital" into pay, asking junior managers to invest upfront by accepting lower salaries in exchange for faster skill formation and heightened visibility. This practice aligns individual incentives with the firm's need to cultivate future star performers, suggesting that asset managers manage career trajectories as deliberately as they manage portfolios.

These findings broaden the lens on performance evaluation. Traditional metrics focus on individual track records, yet our results indicate that a manager's formative team environment is a powerful predictor of both subsequent productivity and compensation. Investors, recruiters, and boards may therefore gain forecasting power by tracking a manager's team history—much as baseball analysts follow minor-league systems to project major-league success. Incorporating team-quality adjustments into manager rankings could sharpen capital allocation across funds and talent alike.

Finally, the study contributes to labor economics by quantifying how peer spillovers translate into lifetime earnings. The steep experience premium in finance, long viewed as a puzzle, becomes more comprehensible once team dynamics are considered: High-quality teams serve as accelerators that steepen the wage–experience curve. Similar mechanisms may operate in other knowledge industries—consulting, tech, academia—where collaborative work dominates. Policies and contracts that recognize and harness these spillovers could boost both firm performance and worker welfare.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109025101713.

References

Azoulay, P.; J. S. Graff Zivin; and J. Wang. "Superstar Extinction." *Quarterly Journal of Economics*, 125 (2010),549–589.

Bai, J.; L. Ma; K. A. Mullally; and Y. Tang. "Are Mutual Fund Managers Paid for Performance? Evidence from U.S. Administrative Earnings Data." Working Paper (2023).

Bai, J. J.; Y. Tang; C. Wan; and H. Z. Yüksel. "Fund Manager Skill in an Era of Globalization: Offshore Concentration and Fund Performance." *Journal of Financial Economics*, 145 (2022),18–40.

Bai, J. J.; Y. Tang; C. Wan; and H. Zafer Yüksel. "Thematic Concentration and Mutual Fund Performance." Northeastern University Research Paper No. 4164823 (2024).
Bandiera, O.; I. Barankay; and I. Rasul. "Social Preferences and the Response to Incentives: Evidence from Personnel Data." *Quarterly Journal of Economics*, 120 (2005), 917–962.
Bandiera, O.; I. Barankay; and I. Rasul. "Social Connections and Incentives in the Workplace: Evidence from Personnel Data." *Econometrica*, 77 (2009), 1047–1094.
Bandiera, O.; I. Barankay; and I. Rasul. "Social Incentives in the Workplace." *Review of Economic Studies*, 77 (2010), 417–458.
Bär, M.; A. Kempf; and S. Ruenzi. "Is a Team Different from the Sum of its Parts? Evidence from Mutual Fund Managers." *Review of Finance*, 15 (2011), 359–396.
Barahona, R.; S. Casella; and K. A. E. Jansen. "Do Teams Alleviate or Exacerbate Biased Beliefs? Evidence from Extrapolation Bias in Mutual Funds." Working Paper, available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3783421 (2022).
Berk, J. B., and R. C. Green. "Mutual Fund Flows and Performance in Rational Markets." *Journal of Political Economy*, 112 (2004), 1269–1295.
Berk, J. B., and J. H. Van Binsbergen. "Measuring Skill in the Mutual Fund Industry." *Journal of Financial Economics*, 118 (2015), 1–20.
Berk, J. B.; J. H. Van Binsbergen; and B. Liu. "Matching Capital and Labor." *Journal of Finance*, 72 (2017), 2467–2504.
Boning, B.; C. Ichniowski; and K. Shaw. "Opportunity Counts: Teams and the Effectiveness of Production Incentives." *Journal of Labor Economics*, 25 (2007), 613–650.
Célérier, C., and B. Vallée. "Returns to Talent and the Finance Wage Premium." *Review of Financial Studies*, 32 (2019), 4005–4040.
Cen, X.; W. W. Dou; L. Kogan; and W. Wu. "Fund Flows and Income Risk of Fund Managers." NBER Working Paper No. 31986 (2023).
Chan, T. Y.; J. Li; and L. Pierce. "Compensation and Peer Effects in Competing Sales Teams." *Management Science*, 60 (2014), 1965–1984.
Chevalier, J., and G. Ellison. "Are Some Mutual Fund Managers Better than Others? Cross-Sectional Patterns in Behavior and Performance."*Journal of Finance*, 54 (1999a), 875–899.
Chevalier, J., and G. Ellison. "Career Concerns of Mutual Fund Managers." *Quarterly Journal of Economics*, 111 (1999b), 389–432.
Cici, G.; M. Gehde-Trapp; M.-A. Göricke; and A. Kempf. "The Investment Value of Fund Managers' Experience outside the Financial Sector." *Review of Financial Studies*, 31 (2018), 3821–3853.
Cinelli, C., and C. Hazlett. "Making Sense of Sensitivity: Extending Omitted Variable Bias." *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 82 (2020), 39–67.
Ellul, A.; M. Pagano; and A. Scognamiglio. "Careers in Finance." Working Paper, available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3983617 (2022).
Evans, R. B.; M. Porras Prado; A. E. Rizzo; and R. Zambrana. "The Performance of Diverse Teams: Evidence from U.S. Mutual Funds." Working Paper (2021).
Fama, E. F., and K. R. French. "Luck Versus Skill in the Cross-Section of Mutual Fund Returns." *Journal of Finance*, 65 (2010), 1915–1947.
Fedyk, A.; S. Patel; and S. Sarkissian. "Managerial Structure and Performance-Induced Trading." Working Paper, available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2978811 (2020).
Foster, L.; J. Haltiwanger; and C. Syverson. "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *American Economic Review*, 98 (2008), 394–425.
Gallaher, S.; R. Kaniel; and L. T. Starks. "Advertising and Mutual Funds: From Families to Individual Funds." Working Paper, available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1362535 (2015).
Hamilton, B. H.; J. A. Nickerson; and H. Owan. "Team Incentives and Worker Heterogeneity: An Empirical Analysis of the Impact of Teams on Productivity and Participation." *Journal of Political Economy*, 111 (2003), 465–497.
Han, L., and R. Miller. "Employment Networks in the Professions." Working Paper, available at https://events.bse.eu/live/files/1243-unifieddoclu-han-18416.pdf (2015).
Hölmstrom, B. "Moral Hazard and Observability." *Bell Journal of Economics* (1979), 74–91.
Hortaçsu, A., and C. Syverson. "Product Differentiation, Search Costs, and Competition in the Mutual Fund Industry: A Case Study of S&P 500 Index Funds." *Quarterly Journal of Economics*, 119 (2004), 403–456.
Hsieh, C.-T., and P. J. Klenow. "Misallocation and Manufacturing TFP in China and India." *Quarterly Journal of Economics*, 124 (2009), 1403–1448.
Ibert, M.; R. Kaniel; S. Van Nieuwerburgh; and R. Vestman. "Are Mutual Fund Managers Paid for Investment Skill?" *Review of Financial Studies*, 31 (2017), 715–772.

Ichniowski, C., and A. Preston. "Do Star Performers Produce More Stars? Peer Effects and Learning in Elite Teams." NBER Working Paper No. 20478 (2014).
Kacperczyk, M.; C. Sialm; and L. Zheng. "On the Industry Concentration of Actively Managed Equity Mutual Funds." *Journal of Finance*, 60 (2005), 1983–2011.
Kandel, E., and E. P. Lazear. "Peer Pressure and Partnerships." *Journal of Political Economy*, 100 (1992), 801–817.
Kaniel, R., and D. Orlov. "Intermediated Asymmetric Information, Compensation and Career Prospects." Working Paper (2021).
Kaniel, R., and R. Parham. "WSJ Category Kings - the Impact of Media Attention on Consumer and Mutual Fund Investment Decisions." *Journal of Financial Economics* 123 (2016), 337–356.
Ma, L.; Y. Tang; and J.-P. Gomez. "Portfolio Manager Compensation in the U.S. Mutual Fund Industry." *Journal of Finance*, 74 (2019), 587–638.
Mas, A., and E. Moretti. "Peers at Work." *American Economic Review*, 99 (2009), 112–145.
Patel, S., and S. Sarkissian. "To Group or Not to Group? Evidence from Mutual Fund Databases." *Journal of Financial and Quantitative Analysis*, 52 (2017), 1989–2021.
Patel, S., and S. Sarkissian. "Portfolio Pumping and Managerial Structure." *Review of Financial Studies*, 34 (2021), 194–226.
Philippon, T., and A. Reshef. "Wages and Human Capital in the U.S. Finance Industry: 1909–2006." *Quarterly Journal of Economics*, 127 (2012), 1551–1609.
Roussanov, N.; H. Ruan; and Y. Wei. "Marketing Mutual Funds." *Review of Financial Studies*, 34 (2021), 3045–3094.
Shaton, M. O. "The Display of Information and Household Investment Behavior." Working Paper, available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2662694 (2017).
Sirri, E. R., and P. Tufano. "Costly Search and Mutual Fund Flows." *Journal of Finance*, 53 (1998), 1589–1622.
Sokolinski, S. "Regulating Commission-Based Financial Advice: Evidence from a Natural Experiment." *Journal of Financial and Quantitative Analysis*, 58 (2023), 1359–1389.
Solomon, D. H.; E. Soltes; and D. Sosyura. "Winners in the Spotlight: Media Coverage of Fund Holdings as a Driver of Flows." *Journal of Financial Economics*, 113 (2014), 53–72.
Syverson, C. "What Determines Productivity?" *Journal of Economic Literature*, 49 (2011), 326–365.