Production Complementarities in Asset Management*

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October 2021

Abstract

Incentive provision is expected to be a key driver of asset managers' compensation, yet empirical evidence on performance-based pay has been limited and mixed. This paper delivers a novel perspective on managerial incentives by examining the role of production complementarities between managers and firms, and quantifying to what extent such complementarities are internalized into compensation. Production complementarities naturally arise in asset management because a firm can influence a manager's expected productivity by teaming her up with the right skill set and by advertising her performance to investors. Different managers benefit from firm externalities differently and hence face different trade-offs between their current monetary compensation and firm support. Using a unique registry-based dataset on the production and compensation of Israeli mutual fund managers, we find that managers working with more skilled teammates and receiving more advertising receive lower salaries today in return for higher expected productivity. Such effects are stronger for more skilled and less visible managers. The results are consistent with the incentive provision theory for forward-looking agents in the presence of production complementarities.

*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.

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1 Introduction

Asset management has always been a key topic in finance because professional investment funds play a major role in the management of global savings and pricing of financial assets. Over the last decades, investors have consistently shown an increasing preference for delegated management leading to rapid industry growth, resulting in \$103 trillion in the assets managed globally by the end of 2020.[1] The central theme in the study of asset management relates fund incentives to generating superior performance. The benchmark theories suggest that such incentives are provided by fund investors since they can add or withdraw capital based on fund returns (Berk and Green (2004)). As a result, skilled funds grow larger and earn higher fee revenue, consistent with the well-documented positive relation between fund size and its past performance (Sirri and Tufano (1998)).

However, the actual asset management is conducted by portfolio managers whose incentives are shaped by their contract with the firm and the overall labor market, rather than directly by investor flows (Kaniel and Orlov (2021)). Despite the vast theoretical literature that relates compensation to performance, the empirical evidence on compensation in asset management has been limited and mixed. On the one hand, using the hand-collected information on portfolio manager compensation structures, Ma, Tang and Gómez (2018) show that many employment contacts of portfolio managers include bonuses tied closely to performance. On the other hand, using the actual compensation that managers received, Ibert, Kaniel, Van Nieuwerburgh and Vestman (2017) find that manager performance accounts for only a minor fraction of the variation in pay and firm characteristics are equally important in explaining compensation. The seemingly conflicting evidence highlights the need to study "the complementarities between fund managers and fund complexes" (Ibert et al. (2017)) and inspires us to take a more holistic perspective on managerial incentives. To this end, in this paper we explore the role of production complementarities between managers and firms in a joint fund management process and quantify to what extent such complementarities explain variations in manager compensation. Doing so allows us to provide a richer understanding of professionals' actual incentives not only for asset management, but also more

[1] The Global Asset Management 2021 Report by Boston Consulting Group.

broadly, labor economics given the prevalence of joint production in all sorts of economic activities today.[2] Such understanding is crucial for academics, regulators, professionals and investors.

While a large and important economics literature has documented the impact of production complementarities on individual productivity, little is known about how such complementarities are internalized in compensation.[3] A major challenge is a lack of readily available and high-quality individual level data on not only productivity but also compensation, and the latter is particularly rare. We overcome this challenge by assembling a large employment compensation dataset from the mutual fund industry in Israel. Spanning across almost the entire population of mutual fund portfolio managers in Israel managing 1,446 mutual funds from 2006 to 2014, our data combine proprietary compensation data from administrative tax records (an analog of the U.S. W-2 form) with publicly available data on their portfolio characteristics (an analog of the CRSP Mutual Fund Database). To the best of our knowledge, this is the most comprehensive dataset that includes detailed joint production from which we observe not only who works with whom on which fund, the affiliation of each manager, but also the revenue that each manager generates, the split of revenue between managers and firms, the skill composition within each team, and the sales support provided by each firm.

The mutual fund industry provides an excellent laboratory for studying the role of production complementarities in incentive provision. First, the industry is highly labor intensive and nearly 70% of funds are co-managed (Patel and Sarkissian (2017b)). This implies that an individual manager's productivity depends not only on her own human capital, but also her team capital – teams that are often assigned by firms. Second, the industry is characterized by information asymmetry in that firms have more information than investors about managerial ability (Berk, Van Binsbergen and Liu (2017), Kaniel and Orlov (2021)), and search frictions in that investors have limited resources to conduct fund search (Hortaçsu and Syverson (2004), Roussanov,

[2]Joint production has become prevalent in many economic activities, such as asset management (Patel and Sarkissian (2017a)), academic research (Azoulay, Graff Zivin and Wang (2010)), department sales (Chan, Li and Pierce (2014)), steel mills (Boning, Ichniowski and Shaw (2007)), sports industry (Ichniowski and Preston (2014)), and garment production (Hamilton, Nickerson and Owan (2003)).

[3]For example, the literature has examined the impact of high-ability agents on their peers' productivity through free riding (Hölmstrom (1979)), learning (Hamilton, Nickerson and Owan (2003)), and peer pressure or preferences (Bandiera, Barankay and Rasul (2005, 2009, 2010); Mas and Moretti (2009))

Ruan and Wei (2021)). This makes advertising and marketing a necessary channel to boost fund size (Solomon, Soltes and Sosyura (2014), Gallaher, Kaniel and Starks (2015), Kaniel and Parham (2016)). As a consequence of both features, production complementarities naturally arise in this industry, because a firm can influence a manager's expected productivity by teaming her up with the right skill set and by advertising her performance to investors. In addition, we can measure manager productivity as a market value of her output - a total fee revenue that a manager generates. This measure is well-defined in asset management and consistent with commonly used productivity measures that are based on revenue per employee (Foster, Haltiwanger and Syverson (2008), Hsieh and Klenow (2009), Syverson (2011)).

A preliminary investigation of the data reveals interesting patterns. First, while there is substantial variation in manager compensation and revenue across firms, there is even more variation within firms. Standard manager characteristics and fund attributes, together with firm and manager fixed effects can explain only 54% of the variation in compensation and 63% in revenue. This suggests that manager characteristics and firm attributes, when evaluated in isolation, are not sufficient to explain the dispersion in managerial compensation. Second, adding interactions between manager and firm fixed effects boosts the amount of explained variations by an additional 33% for compensation and 30% for revenue, consistent with the presence of production complementarities between managers and the firms in this industry.

We interpret these patterns through the lens of an employment compensation model built upon Han and Miller (2015). The key idea is that an agent's output depends not only on the agent's characteristics and the affiliated firm's characteristics, but also on how well the agent integrates with the rest of the firm. For a forward-looking agent, the compensation consists of today's salary and the continuation value that she derives from staying with the current firm. The latter is shaped by the within-firm capital that the firm employs to influence the opportunity that an agent receives to use her human capital to produce. In equilibrium, an agent faces a trade-off between current monetary compensation and the level of firm support that enhances future productivity. Firms differ in the level of support they can provide, and agents differ in how much they benefit from such support, making the compensation contract specific to each agent-firm match.

Applying this framework to the mutual fund industry, team externalities improve managers' investment performance through knowledge spillover; firm advertising contributes to the rate at which managers attract new investment. These two sources of production complementarities reflect a non-wage amenity owing to preference of managers to work with firms where they are particularly likely to generate more revenues. An immediate implication is that managers that are assigned to more skilled teams generate higher expected revenue, but earn lower compensation today. With skill complementarity, these effects are stronger for more skilled managers. A second implication is that managers that receive larger marketing support from the firm generate higher expected revenue, but earn lower compensation today. Such effects are weaker for more established and visible managers, given the substitutability between firm marketing and managers' own visibility.

Ultimately, the importance of production externalities is an empirical question. In our main analysis, we take the model's implications to the data and find strong support for the role of such externalities in asset management. First, managers assigned to work with skilled teams generate 32% higher expected revenue but earn 10% lower current compensation. These effects are almost twice as large for skilled managers. Second, skilled managers who work for firms with larger sales teams, generate 41% higher expected revenue but earn 19% lower current compensation. The effects of advertising are stronger for managers with low own visibility, suggesting that firm advertising is particularly helpful for more competent but less known portfolio managers. These estimates are robust even after we control for a comprehensive set of time-varying manager, firm, fund attributes, as well as rich interactions of firm, year, manager and experience fixed effects. Taken together, we find that firm externalities, such as team assignment and firm advertising, affect manager revenue and compensation in opposite directions and that such effects vary across managers depending on the value they drive from firm support. This evidence is hard to reconcile with a static performance-based compensation structure but fully consistent with the incentive provision for forward-looking agents in the presence of production complementarities.

Even with the very rich set of controls and fixed effects at our disposal, two concerns remain. The first concern is the selection of managers into teams or firms based on their time-varying unobserved attributes. For example, more capable managers are more likely to be teamed up with more skilled peers and work for firms with better advertising resources. At the same time, if such capability varies over time in an unobserved way, it is likely to confound the positive team and advertising effects on manager revenue. We note that this is unlikely a concern in our setting. If it was indeed the case, we should observe the firm support variables affect the expected revenue and manager compensation in the same direction. But the estimates show the opposite. Nevertheless, to mitigate this concern, we further restrict the sample to managers who switch firms or teams within a firm. Comparing manager compensation and revenue right before and after she switches firms helps address the possible selection on time-varying unobserved manager characteristics. Performing the same analysis when a manager switches teams within a firm further helps to control the unobserved time-varying conditions that are specific to firm-manager-year level other than changes in team composition. Overall, the results are highly robust across all these specifications, suggesting that sorting on unobservables is unlikely to bias our main findings.

Another legitimate concern is the potential endogeneity associated with firm investment in advertising. To address this, we instrument the size of the sales team in a given firm by the average size of sales teams of other firms in the previous year. The underlying assumption is that a firm increases its investment in its sales force in response to an increase in sales investment of its competitors. The exclusion restriction is satisfied if the industry-level sales investment, excluding the firm itself, does not directly affect compensation of the firm's individual managers, conditional on a rich set of controls. We provide evidence in favor of these assumptions and find that the IV estimates are highly comparable to those from the baseline specifications.

Our study contributes to the literature on compensation and incentives in asset management. A large and increasing body of the literature has focused on the demand side of this industry – how investors compensate asset managers and how they pay for the services of the fund (Fama and French (2010)), Berk and Green (2004) and Berk and Van Binsbergen (2015)). The prior work emphasized the role of implicit incentives embedded in the convex relationship between fund flows and performance (Sirri and Tufano (1998), Chevalier and Ellison (1997)).[4] However, com-

[4]The explicit performance-based incentives rarely exist in advisory contracts between asset managers and their investors (Elton, Gruber and Blake (2003)).

pensation of portfolio managers by firms has received little attention despite its importance for better understanding managerial incentives. A notable exception is the recent theoretical advancement by Kaniel and Orlov (2021) who show skilled managers are willing to accept below-reservation wages today in exchange for building reputation faster. Our focus on the tradeoff managers face between the salary today and the production complementaries that the firm provides is consistent with this spirit. On the empirical front, two pioneering papers on compensation contracts between fund families (firms) and managers are Ma, Tang and Gómez (2018) and Ibert, Kaniel, Van Nieuwerburgh and Vestman (2017).

Using U.S. data on compensation structure from the SEC filings, Ma, Tang and Gómez (2018) find that 79% of funds offer a bonus contingent on performance, hence providing strong evidence for the prevalence of performance-based incentives in the mutual fund industry. They document novel and rich variations in compensation structure, shedding new light on understanding managerial incentives in the asset management industry. Our work shares a similar spirit in that both are broadly consistent with an optimal contracting equilibrium in the mutual fund industry (Almazan, Brown, Carlson and Chapman (2004), Chen, Goldstein and Jiang (2008)). At the same time, we provide a new insight that incentives depend not only on monetary compensation but also on idiosyncratic matches between managers and firms. The latter helps explain how and why the relationship between manager performance and compensation varies across firms and managers.

Using the actual compensation data from the Swedish mutual fund industry, Ibert, Kaniel, Van Nieuwerburgh and Vestman (2017) do not find strong evidence for sensitivity of pay to performance. Instead, they emphasize the role of the firm, showing that firm-level revenue, profits and performance are important determinants of manager compensation. Inspired by this, our work takes an equilibrium approach that examines manager input and firm input jointly rather than separately. Doing so allows us to rationalize the seemingly conflicting evidence about sensitivity of pay to performance. In particular, in a world where managers and the firm work together to produce, the pay-performance sensitivity would be mitigated by the firm-level input if such input contributes positively to a manager's productivity. We test this explanation by incorporating two firm inputs – team assignment and firm advertising, both of which complement an individual manager's skill in the joint production. The results reveal that small average pay-performance sensitivities mask substantial heterogeneity in compensation incentives, depending on how much managers benefit from complementary team skills and sales investment that firms provide. In this sense, our findings add a new layer to the understanding of the managerial incentives, revealing a rich picture about the interplay between the firm, the managers and the fund's investors.

More broadly, our work adds to the labor economics literature on within-firm network capital such as the peer effects on productivity through cooperation or helping (Kandel and Lazear (1992)). We confirm the importance of worker coordination design in labor markets (Holmström and Milgrom (1990)). One important missing piece in the literature is the within-firm network effects on labor compensation. While Han and Miller (2015) develop and test the employment network theory on compensation and turnover in the context of the real estate brokerage industry, they investigate a different source of production complementarity. In addition, they do not observe the actual compensation and rely on a structural model to infer its distribution. Our advantage is that we precisely observe how firms compensate each individual manager. This allows us to provide direct evidence about how an employee is integrated into the rest of the firm and how this employee-firm-specific integration is internalized in her lifetime productivity and compensation.

2 Institutional Background and Dataset

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

2.1 The Israeli Mutual Fund Market

In 2014, the Israeli mutual market included roughly 1,446 funds that managed \$80B. 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 into 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. In Appendix, Table B1 shows the distribution of fund across asset classes.

2.2 Dataset Construction

We construct our dataset from several data sources. We start with public disclosures of mutual fund companies (Part B of 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.[5] We hand-collect the information on portfolio managers including age, job tenure, the list of funds that they manage in given year as well as the date when they started to manage a particular fund.[6] This data allows us to track almost the entire population of mutual fund portfolio managers in Israel from 2010 to 2014.[7] As we observe the dates when managers became responsible for particular funds, we extend the dataset 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 her 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.[8] This survivorship bias-free database covers the entire universe of Israeli mutual funds, and it includes detailed fund characteristics such as fees, commissions, assets under management, returns, fund's style and asset allocation across broadly defined sets of securities. The overall matched sample covers the 87% of Israeli mutual fund industry's assets under management between 2010 and 2014 and 49% of this industry between 2006 and 2009 (see Figure B1 in the Appendix). We exclude index funds and money market funds from this sample.

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

[6] The firms are not obliged to disclose 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.

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

[8] This data set has been previously used in Shaton (2017).

We then construct portfolios of funds for each manager on an annual basis to later 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 (1999) and Ibert, Kaniel, Van Nieuwerburgh and Vestman (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 portfolio's characteristics such as fees and fund age as an AUM-weighted sum of characteristics of individual funds.

Table 1 presents the summary statistics of our sample. Panel A shows the manager-level data where the unit of observation is manager-year. The average manager is 39 years old, manages the average fund in her portfolio for 2.5 years, has 6.1 years of experience in mutual fund management and 8.5 years of experience in the asset management industry. In terms of education, 49% of managers hold an MBA degree, and 56% of them have a master's degree in another area. The average portfolio manager is responsible for managing 4.6 funds.

Panel B presents characteristics of individual funds which we use to obtain manager-level portfolio characteristics. The average fund has 110 million shekels under management, has been operating for 8 years, and charges an percentage fee of 0.95%. The average fund's risk-adjusted performance equals -1%, but it is not statistically distinguishable from zero.

Panel C presents the data at the firm level. The average firm employs 2.8 managers and operates 24 mutual funds. These characteristics vary significantly across firms.

2.3 Compensation and Productivity

The key outcome variables in our analysis are compensation and productivity. We measure a manager's compensation in two ways, by the dollar amount that she receives in a given year and by a split ratio measured by the fraction of the compensation the manager receives out of the total revenue that her funds generate. The latter is consistent with the notion that fund managers capture only a share of the additional fund revenues (Ibert, Kaniel, Van Nieuwerburgh and Vestman (2017)), which is agreed upon between the firm and manager. To start, we match portfolios of individual managers with their compensation data using administrative tax records from the Israel

Tax Authority. We use Form 106 (the equivalent of the U.S. W-2) which is an annual statement of wage and taxes. We directly observe the annual compensation from each employer and can exactly infer how much each manager earned from a particular asset management firm. We exclude a small number of cases where managers worked less than nine months in the company. The final dataset includes 255 managers and 1,264 manager-year observations.

As shown in Table 1, the average mutual fund portfolio manager in Israel earns 426,000 shekels per year which equals to approximately $121,000 during that time period. This statistic puts the average manager into the top 2% of labor income distribution in Israel. At the same time, there is significant variation in compensation in our sample, with the 10th percentile being equal to 97,000 shekels and the 90th percentile being equal to 742,000 shekels. The average split ratio equals 12.13%, with the 10th percentile being equal to 2.31% and the 90th percentile being equal to 42.40%. Overall, the patterns here are consistent with the recent literature that compensation in the finance industry is higher and more skewed than in other sectors (Célérier and Vallée (2019)).

Turning to productivity, we consider total fee revenue generated by a manager's portfolio funds as a proxy. Fee revenue measures the total market value of the asset management services provided by the manager. In this sense, it fits well with the recent literature that measures productivity with revenue per employee (Foster, Haltiwanger and Syverson (2008), Hsieh and Klenow (2009), Syverson (2011)). Unlike manager skill that measures the quality of one particular input, manager productivity in the form of fee revenue relates to the value of the total output. 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 a 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 (1999), Berk, Van Binsbergen and Liu (2017) and Ibert, Kaniel, Van Nieuwerburgh and Vestman (2017). Panel A of Table 1 shows that the average manager generates 4.8 million shekels in fee revenue. There is substantial dispersion in manager productivity since the 10th percentile equals 0.1 million shekels, and the 90th percentile equals nearly 12 million shekels.

An attractive feature of our dataset is that it provides within-firm and between-firm variation in compensation and productivity. In Figure 1, we decompose the manager-year-level variations into within-firm and between-firm variation by regressing compensation and revenue against a set of manager and firm characteristics, year fixed effects and firm fixed effects. For an intuitive comparison, we center the distribution of between-firm fixed effects and within-firm residuals on the mean compensation and revenue in the data. Figure 1 shows significant variation both within and between firms. Even after accounting for manager and portfolio characteristics, the between-firm standard deviation of $Log(Compensation)$ equals 0.73, while the within-firm standard deviation is larger, being equal to 0.88. Revenues and split ratio exhibit similar patterns. A growing literature relates the distribution of pay in finance to heterogeneous levels of manager performance (Ma, Tang and Gómez (2018)) and firm revenues and profits (Ibert, Kaniel, Van Nieuwerburgh and Vestman (2017)). We explore the role of production complementarities between managers and firms that create variations within and between firms.

2.4 Sources of Production Complementarities

We distinguish between two sources of production complementarities in the mutual fund industry: team work and advertising. First, the financial industry is highly labor intensive, and team work has been particularly prevalent (Patel and Sarkissian (2017a), Patel and Sarkissian (2017b)). This implies that an individual manager's productivity depends not only on her human capital, but also her team's capital – teams that are often assigned by firms. Second, the industry is characterized by information asymmetry in that firms have more information than investors about managerial ability (Berk, Van Binsbergen and Liu (2017)). Hence through advertising, firms can significantly boost fund size (Solomon, Soltes and Sosyura (2014), Gallaher, Kaniel and Starks (2015), Kaniel and Parham (2016), Roussanov, Ruan and Wei (2021)). Since managers differ in their own skills and visibility, the benefits they derive from the same level of team and advertising support may vary. To capture these idiosyncratic match values, we construct measures of manager skill, team skill, manager visibility and firm advertising support in turn. The variations in these measures provide the key sources of production complementarities that we explore in this paper.

Manager Skill and Team 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 manager alpha represents returns 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 for details).

We define manager m's value added as a total value added of all the funds under her 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 manager history up to year t:

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

where T_{mt} is the number of years manager m appears in the data prior to year t. For easier interpretation of our regression results, we create an indicator variable $1_{Skilled_{mt}}$ which equals one if $S_{mt} > 0$. In other words, we call a portfolio manager "skilled" if she is expected to extract positive value from capital markets given her history, as opposed to destroying value.

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

$$S_{mt}^{team} = \frac{1}{N-1} \sum_{n \neq m} S_{nt}, \tag{6}$$

where N is a number of team members, and S_{nt} is a skill of manager n in year t. If a manager works on multiple teams, we calculate S_{mt}^{team} across all the co-workers in all the teams. We also map S_{mt}^{team} variable into the indicator variable $1_{Skilled\ Team_{mt}}$ which equals one if $S_{mt}^{team} > 0$.

Panel A of Table 1 shows that the fraction of managers on teams over the sample years equals 75% which is comparable to the U.S. estimates from Patel and Sarkissian (2017b). Excluding the manager herself, an average manager is on 1.55 teams and has 0.7 teammates. In addition, about 37% of portfolio managers work with skilled teams. Figure 2 shows that the fraction of managers working on teams increased from less than 60% to around 80% between 2006 and 2014. The fraction of co-managed funds increased from less than 40% to around 60%. The prevalence of teamwork highlights the increasing importance of peer effects in the mutual fund industry.

Manager Visibility and Sales Team Size We next construct a measure of manager m's own visibility in time t, $Visibility_{mt}$, based on the total number of media mentions in the popular financial media. We go through the websites of the three major Israeli financial newspapers and one popular financial website.[9] We perform searches of each manager's name and count the number of articles that mention the manager in each year across all the websites from 2006 to 2014. We read all the articles to verify that the name mentioned in the article belongs to the portfolio manager. Most of the articles left describe managers' performance, their opinions on financial markets, securities recommendations, and their career moves.

As shown in Panel A of Table 1, the visibility of the average manager equals 8, meaning that 8 articles mentioning the average manager were published in the major financial media outlets in a given year. Nearly 25% of portfolio managers have zero visibility. Roussanov, Ruan and

[9]The four sources are The Marker, Globes, Calcalist and Bizportal.

Wei (2021) show that marketing is nearly as important as performance and fees for determining fund size in the mutual fund industry. The substantial variation in managers' own visibility thus highlights another important source of production externality that firms provide: marketing and advertising.

We measure the firm's ability to market and advertise its funds by evaluating how much labor is allocated to sales, marketing and advertising. We call this measure the relative sales team size. To calculate it, we go through Part B of the Prospectus where each mutual fund company provides a disclosure about the firm's structure and the number of employees in different departments. We define the relative sales team size as:

$$Sales\ Team_{ft} = \frac{Salespeople_{ft}}{K_{ft}} \tag{7}$$

where $Salespeople_{ft}$ is a number of employees who are involved in sales, marketing, business development or financial adviser relations in firm f in year t, and K_{ft} is a total number of funds in firm f in year t. This measure is consistent with the observation in Roussanov, Ruan and Wei (2021) that the bulk of the marketing costs is related to compensation paid to brokers and financial advisers.

Using $Salespeople_{ft}$ limits our sample in a number of ways. First, some firms do not report the number of salespeople. Second, these disclosures are available only after 2010 so we can use this measure only for a subsample of managers. Overall, we are able to collect and match sales team data with 943 manager-year observations, representing 74% of our sample. Panel C of Table 1 shows that the mean sales team is 0.42, indicating an average fund receives 0.42 staff support in marketing and advertising. There is substantial dispersion in sales team across firms over years, with the 90th percentile nearly four times than the 10th percentile.

The prior work evaluates marketing efforts at the fund-level. It is done by examining the distribution commissions (for example, 12b-1 fees in the U.S.) charged by the firms (Roussanov, Ruan and Wei (2021)) or by directly observing the media coverage, for example, in newspapers (Solomon et al. (2014), Kaniel and Parham (2016)). Since commissions represent the compensation to brokers for fund distribution, they are a good measure of marketing resources devoted to this specific sales channel. Media coverage of individual funds and their holdings a represent the amount of the advertising output. It is less informative about the amount of inputs allocated to marketing, especially at the firm level. Unlike these measures, our measure focuses on the relative amount of labor inputs allocated to sales and marketing at the firm-level. This allows to take into account a variety of potential sales activities such as advertising across multiple media sources and broker relations. Our measure thus represents a proxy for the aggregate amount of "marketing support" that the firm is able to provide to its portfolio managers.

In our empirical work below, we map $Sales\ Team_{ft}$ and $Visibility_{mt}$ into two indicator variables: $1_{Large\ Sales\ Team_{ft}}$ and $1_{High\ Visibility_{mt}}$. Both indicator variables equal one if the value of the underlying continuous variable is above its median in year t.

2.5 Baseline Differences in Compensation and Productivity

Table 2 reports the differences in manager compensation and productivity for managers with different teams and different advertising support. Compared to those working with less skilled teams and those working for firms with small sales teams, managers working with skilled teams and in firms with large sales teams generate substantially higher revenue but earn lower monetary compensation, both in the total dollar amount and in the split of fee revenue. Since team skills and firm marketing efforts help boost fund size, the positive association between team skills, firm advertising and the corresponding managers' revenue is expected. However, these variables are negatively associated with the current monetary compensation that manager receives. This is hard to reconcile with standard incentive-based theories where the observed revenue or observed revenue-enhancing factors are used as contractable measures to form a basis for compensation contracts. In the subsequent theoretical framework, we interpret these patterns through the lens of a joint production model.

3 Conceptual Framework

In this section we present a simple framework to illustrate the nature of a compensation equilibrium in the presence of production complementarities. The framework is adapted from Han and Miller (2015)'s model of dynamic interactions within an employment network which includes a much more detailed setting.[10] We present the model and its equilibrium implications in a heuristic way, given our paper is empirical in its focus.

We start with a brief overview. The key idea of Han and Miller (2015) is that the value added by each agent to a project depends not only on the agent's characteristics but also on how well the agent integrates with the rest of the firm. Positive externalities within the firm increase human capital by facilitating future production. The revenue from each project is divided between agent salary and firm profits. Firms set compensation packages for their agents and are responsible for hiring. The equilibrium outcomes are defined by the compensation of agents, the profits of firms, and the entry, mobility and retirement choices of the agents.

Consider an agent i who works on her sth project for firm j. The agent's characteristics are denoted by a vector x_{is}. The characteristics of the firm are denoted by a vector y_{ijs}. Both vectors are dynamically updated when i completes a project or when she moves across firms. The agent's characteristics follow the deterministic law of motion $x_{i,s+1} \equiv g\left(x_{is}, y_{ijs}\right)$. We denote the production output of the sth project (i.e. revenue) as $m_{is}(x_{is})$. Revenue increases with x_{is} ($\frac{\partial m_{is}}{\partial x_{is}} > 0$), in line with the idea that more skilled agents are more productive.

It is convenient to cast the jth firm's offer to agent i as an expected lifetime compensation package – the sum of the current salary $b_j(m_{is})$ plus the agent's future expected compensation from being with the firm j at least until the next project is completed, $f_j(m_{i,s+1})$. Specifically, $b_j(m_{is}) = \alpha_{js} + \beta_{ijs} m_{ijs}(x_{is})$ where α_{js} captures a firm-wide bonus and $\beta_{ijs} m_{ijs}(x_{is})$ captures a bonus component that is contingent on the agent's production output.[11] Similarly, $f_j(m_{i,s+1}) = E_s\left[\alpha_{js} + \beta_{ij,s+1} m_{ijs}(x_{is})\right]$. In equilibrium, the firm chooses the optimal split ratio, β_{ijs}, such that a

[10] There are several relevant issues such as entry and exit of individual agent from the network, the creation and dissolution of firms, and endogenous choice of compensation form, which we abstract from.

[11] In the case of the mutual fund industry, Ma et al. (2018) document that 79% of funds have compensation contracts with a bonus component.

manager is indifferent between staying with the current firm and switching to an alternative firm netting of switching cost ϵ_{is}. We assume that the second best compensation that manager i could earn in another firm is u_{is}, which is independent of the support by firm j, y_{ijs}. Thus the equilibrium is represented by

$$b_j(m_{is}) + f_j(m_{i,s+1}) \equiv \left[\alpha_{js} + \beta_{ijs} m_{ijs}(x_{is})\right] + E_s\left[\alpha_{j,s+1} + \beta_{ij,s+1} m_{ij,s+1}(x_{i,s+1})\right] = u_{is} - \epsilon_{is}. \quad (8)$$

Assumption 1: $\frac{\partial x_{i,s+1}}{\partial y_{ijs}} > 0$

Assumption 1 reflects a dynamic form of production complementarities in that firm support y_{ijs} facilitates the growth of agent i's human capital. This is consistent with the common observations that agents improve their skill by learning-and-working with higher-ability peers and enhance their reputation by working with well-established firms.

Proposition 1 *Under Assumption 1, a higher level of firm j's support matched to agent i, y_{ijs}, leads to*

a. an increase in future productivity of the agent ($E_s\left[m_{i,s+1}\right]$), and

b. a reduction in current compensation (b_{ijs}) and split ratio (β_{ijs}).[12]

Proposition 1 shows that in equilibrium, an agent is willing to trade current salary ($b_j(m_{is})$) for receiving positive within-firm externalities (y_{ijs}), as the latter enhances her future profile and hence expected lifetime earnings.

Assumption 2: $\frac{\partial^2 m_{ijs}}{\partial x_{is} \partial y_{ijs}} > 0$

Assumption 2 reflects another form of production complementarity in that higher y_{ijs} enhances the marginal productivity $\frac{\partial m_{i,s}}{\partial x_{i,s}}$. This is intuitive as an agent's output depends on not only what she knows but also who she works with and other support she receives from the firm.[13]

Proposition 2. *Under Assumption 2, $\frac{\partial b_{ij,s}}{\partial x_{i,s}}$ decreases with firm support $y_{ij,s}$.*[14]

Take $x_{i,s}$ as an agent's skill, then Proposition 2 implies that, while always being positive, the

[12] Proof of Proposition 1: Following Assumption 1, higher y_{ijs} leads to higher $x_{i,s+1}$, which further increases $E_s\left[m_{i,s+1}\right]$ given $\frac{\partial m_{i,s}}{\partial x_{i,s}} > 0$. Given that the right-hand-side of equation (8) is independent of y_{ijs}, this further leads to a decline in current compensation b_{ijs} and split ratio (β_{ijs}).

[13] Previous literature has extensively documented the impact of high-ability agents on their peers' productivity through free riding (Hölmstrom (1979)), learning (Hamilton, Nickerson and Owan (2003)), and peer pressure or preferences (Bandiera, Barankay and Rasul (2005, 2009, 2010); Mas and Moretti (2009)) and shared network and reputation.

[14] Proof of Proposition 2: This follows directly from Assumption 2 and the equilibrium condition (8).

level of skill premium decreases with the firm-level input if such input complements the agent's skill in the joint production. Together, Propositions 1 and 2 offer an equilibrium link between a agent's compensation and production complementarities that a firm provides. In the absence of production complementarities between a firm and an agent, $\frac{\partial x_{i,s+1}}{\partial y_{ij,s}} = 0$ and $\frac{\partial m_{i,s}}{\partial y_{ij,s} \partial x_{i,s}} = 0$. In this case, the marginal productivity and future characteristics of agent i are independent of the support she receives from the firm. As a result, $x_{i,s}$ should have the same effect on agent i' productivity (m_i) and salary (b_i), and the wage premium to $x_{i,s}$ ($\frac{\partial b_{ij,s}}{\partial x_{i,s}}$) does not vary across managers or firms. In this sense, our model nests the standard performance-based pay model as a special case. On the other hand, if a firm can use its capital to enhance an agent's opportunity to use her human capital to produce ($\frac{\partial m_{i,s}}{\partial y_{ijs} \partial x_{i,s}} > 0$) and facilitate the growth of the agent's human capital ($\frac{\partial x_{i,s+1}}{\partial y_{ijs}} > 0$), then better matched firm capital raises the expected productivity of agent i and reduces her current salary in equilibrium. With heterogeneous agents and firms, the degree of production complementary varies across firms and agents, making the compensation contract specific for each agent-firm match.

We apply this model to the mutual fund industry. Motivated by the data patterns documented in Section 2, we measure $y_{ij,s}$ by the average skill in the team (excluding the manager herself) and the size of the sales team. We start our discussion with team capital. Since fund management by teams of portfolio managers has become prevalent in the mutual fund industry (Patel and Sarkissian (2017b)), firms differ in the composition of managers. Else equal, manager i benefits from working with a highly skilled team through knowledge spillover, accumulated experience and shared reputation and network. In equilibrium, forward-looking managers would be willing to accept a lower reward for her skill today in order to be matched with more skillful peers. If skilled managers benefit more from working with skilled teams, their current compensation is further reduced.

Implication 1. *Conditional on manager and firm characteristics, an increase in the average team skill leads to an increase in manager expected productivity and a reduction in the current salary. With skill complementarities, these effects are stronger for more skilled managers.*

The mutual fund industry is also featured by asymmetric information in that firms know more about managers' skill than investors (Berk, Van Binsbergen and Liu (2017)). As a result, marketing is nearly as important as skill for determining fund size (Roussanov, Ruan and Wei (2021)). Since managers attract investment through the observation of their performance by investors, highly-performing but less visible managers would benefit more from firms' investment in advertising, which is in turn internalized into the compensation package.

Implication 2. *Conditional on manager and firm characteristics, an increase in the size of the sales team leads to an increase in manager i' expected productivity and a reduction in the current salary. With complementarities between investment skill and marketing support, and substitutability between a manager's own visibility and the firm's marketing, these effects are stronger for more skilled but less visible managers.*

To summarize, the key crux of the model is that the compensation consists not only of today's salary but also the continuation value. The latter is shaped by the within-firm capital that firms employ to influence the opportunity that a manager receives to use her human capital to produce. In the mutual fund industry, peer externalities improve managers' investment performance through knowledge spillover; firm advertising contributes to the rate at which managers attract new investment. These two sources of production complementarities reflect a non-wage amenity owing to the preference of managers to work with firms that they are particularly likely to generate more revenues. While the within-firm labor composition and marketing resources can be fixed for each firm, their benefits vary across managers, placing a firm on uneven footing with respect to the salary split they offer to different managers. Ultimately, the existence and magnitude of these compensation externalities are an empirical question. In the next section, we take the model's implications to the data.

4 Empirical Analysis

In this section, we first present motivating evidence that highlights the importance of production complementarities for explaining variations in manager pay and revenue. We then estimate the effects of two sources of production complementarities assigned by the firm: team capital and marketing support.

4.1 Motivating Evidence

We start with the following econometric specification:

$$y_{mft} = \lambda_f + \lambda_t + \gamma X_{mft} + \epsilon_{mft}, \tag{9}$$

where y_{mft} takes one of the two outcome variables (compensation and expected productivity) for manager m of firm f in year t and λ_f and λ_t are firm and year fixed effects, respectively. X_{mft} is a set of time-varying manager and portfolio characteristics such as: the manager's skill ($1_{Skilled_{mt}}$), the age of the portfolio funds, the number of funds under management, the manager's fund and industry experience as well as her age and education. In all the specifications, the standard errors are double-clustered by manager and year. As motivating evidence, we exploit the role of time-invariant production complementarities on compensation and revenue by examining the changes in R-squared with and without the interactions between manager and firm fixed effects. Thus, although all models include the time-varying characteristics of managers and firms as well as various fixed effects, we do not include interactions between manager characteristics and firm characteristics in the baseline specification.

We present the results in Table 3. For brevity, we only report the R-squared, and the full set of results appears in Tables B2 - B4 in the Appendix. To start, column (1) confirms common findings from the previous literature. In particular, observed manager characteristics such as manager experience, visibility and abnormal returns, together with observed portfolio characteristics such as fund age and size, explain 25% of the variation in compensation and 38% of the variation in revenue. In column (2), adding firm fixed effects raises the R-squared to 47% for compensation and 57% for revenue. This captures time-invariant firm-level characteristics such as advertising, marketing, research and distribution network, which plays an important role in a manager's output and compensation (Ibert, Kaniel, Van Nieuwerburgh and Vestman (2017)). In column (3), adding manager fixed effects allows us to further control for unobserved time-invariant manager characteristics that are related to investment skills or reputation. Doing so delivers additional explanatory power, yet a large fraction of variation compensation and revenues still remains unexplained, leaving room for other determinants.

In column (4), we add the interaction between manager and firm fixed effects, which captures the unobserved time-invariant complementarities specific to the particular firm-manager match. The R-squared increases to 73% for compensation and 87% for revenue, consistent with our framework where the productivity of a manager depends not only on her own skills and the level of firm support, but also on how well she integrates with the rest of the firm. The latter creates an idiosyncratic match between managers and firms, which adds substantial explanatory power for manager output and compensation. In column (5), we further look into the role of matching at a more granular level and include an interaction between manager and team fixed effects to capture unobserved complementarities between portfolio managers and specific portfolio management teams within firms. The R-squared further increases to 87% for compensation and 93% for revenues, indicating that the production complementarity at the team level matters even more than that at the firm level.

The significant increase in R-squared with the inclusion of the interaction of fixed effects reveals two key facts. First, a substantial dispersion in portfolio manager compensation cannot be fully explained by portfolio and manager characteristics, or by systematic differences across managers and firms. Second, matching between managers and firms, especially between managers and teams within the firm, explain a significant part of the variation in both compensation and revenue. The evidence points to the existence of production complementarities modeled in Section 3. In the next section, we distinguish between two sources of production complementarities and estimate their effects on revenue and compensation.

4.2 Estimation Strategy

To start, we extend the baseline specification in the following way:

$$y_{mft} = \lambda_f + \lambda_t + \beta C_{mft} + \gamma X_{mft} + \epsilon_{mft}, \tag{10}$$

where

$$C_{mft} = \left[1_{Team_{mft}}, 1_{Skilled\ Team_{mft}}, 1_{Skilled_{mt}} \times 1_{Team_{mft}}, 1_{Skilled_{mt}} \times 1_{Skilled\ Team_{mft}} \right].$$

C_{mft} includes the main set of variables that capture the team effects – an important source of production complementarities that firms offer since teams are often assigned by firms. We start with the teamwork variables, $1_{Team_{mft}}$ and $1_{Skilled\ Team_{mft}}$, to separately evaluate the team effect both along the extensive margin (being on a team) and along the intensive margin (being on a highly skilled team). We further include their interactions with $1_{Skilled_{mt}}$ to examine how the team effects vary across managers with different skill levels.

The main identifying assumption behind the specification in Equation 10 is that the variables in C_{mft} are uncorrelated with unobserved time-varying factors ϵ_{mft}, conditional on the set of control variables X_{mft}, and fixed effects λ_f and λ_t. However, this assumption is subject to a number of selection concerns. First, more capable managers are more likely to work in teams with other capable managers. Controlling for manager skill helps alleviate this problem, but manager ability and potential are ultimately unobserved and can be correlated with both team-related variables and outcome variables. Second, the decisions regarding team composition and hiring can be affected by unobserved time-varying policies at the firm-level. The same unobserved time-varying firm effects can influence compensation and revenues of individual portfolio managers, being a confounding factor for the production complementarity effects.

We take several steps to address these concerns. First, we estimate specifications of the form:

$$y_{mft} = \lambda_f \times \lambda_t + \lambda_m + \beta C_{mft} + \gamma X_{mft} + \epsilon_{mft}, \tag{11}$$

where we augment our baseline specification with two additional sets of control variables: 1) manager fixed effects, λ_m; and 2) the interaction between firm and time fixed effects, $\lambda_f \times \lambda_t$. Introducing manager fixed effects allows us to control for unobserved time-invariant heterogeneity across managers including manager background and ability. Incorporating the interaction between firm and time fixed effects fully controls for any time-varying firm-specific unobservables such as compensation policy or any policies related to teamwork. In these specifications, the effects of team variables are identified from time-series variation for a given manager controlling for time-varying observed and unobserved firm characteristics, time-varying observed manager characteristics and time-invariant unobserved manager characteristics.

Second, we introduce the additional interactions between manager fixed effects and an indicator variable $1_{Experienced_{mft}}$ which equals one if the manager m's mutual fund industry experience is above the median in year t. This specification allows us to further control for a more obscured source of selection bias: while junior managers are more likely to join a team as a learner, senior managers are more likely to lead a team or work independently. In this specification, the team effects are identified from time-series variation for a given manager *within a specific career stage*. This approach further helps alleviate the concern about selection on the manager's career-stage-specific characteristics.

Despite our inclusion of a comprehensive set of observed characteristics and rich interactions of fixed effects, one may still be concerned about the sorting of managers to teams due to unobserved time-varying factors across managers and firms. To address this, we further restrict the sample to managers who switch firms or teams within a firm. Comparing the same manager's compensation and revenue right before and after she switches firms helps to address the possible selection on time-varying unobserved manager characteristics. Performing the same analysis when the manager switches teams within a firm further helps to control for the unobserved time-varying conditions that are specific to firm-manager-year level other than changes in team composition. We discuss this approach in detail in Section 5.1.

Turning to the effects of sales and advertising, we augment C_{mft} with additional interaction variables. In particular, we are interested in the effect of sales team size, as measured by the indicator variable $1_{Large\,Sales\,Team_{ft}}$, and how it varies across managers with different skill and visibility, as measured by $1_{Skilled_{mt}}$ and $1_{High\,Visibility_{mt}}$. Since $1_{Large\,Sales\,Team_{ft}}$ varies at the firm-year level and $1_{High\,Visibility_{mt}}$ varies at the manager-year level, their direct effects will be captured by the interaction of firm and year fixed effects, and manager fixed effects in Equation 11. Therefore, we interact $1_{Large\,Sales\,Team_{ft}}$ with $1_{Skilled_{mt}}$ to estimate the effect of marketing support for skilled managers as predicted by Implication 1. We also introduce a triple interaction between $1_{High\,Visibility_{mt}}$,

$1_{Large\ Sales\ Team_{ft}}$ and $1_{Skilled_{mt}}$ to capture the differential effects for skilled managers with different levels of their own visibility. For completeness, we further add two additional interactions, $1_{Skilled_{mt}} \times 1_{High\ Visibility_{mt}}$ and $1_{High\ Visibility_{mt}} \times 1_{Large\ Sales\ Team_{ft}}$, to fully capture the effects of complementarities between manager skill, visibility, and the firm's marketing support. As a result, we have:

$$C_{mft} = C_{mft}^{team} + C_{mft}^{sales},$$

where

$$C_{mft}^{team} = \left[1_{Team_{mft}}, 1_{Skilled\ Team_{mft}}, 1_{Skilled_{mt}} \times 1_{Team_{mft}}, 1_{Skilled_{mt}} \times 1_{Skilled\ Team_{mft}}\right],$$

$$\begin{aligned} C_{mft}^{sales} = \Big[& 1_{Skilled_{mt}} \times 1_{Large\ Sales\ Team_{ft}}, 1_{Skilled_{mt}} \times 1_{High\ Visibility_{mt}}, \\ & 1_{High\ Visibility_{mt}} \times 1_{Large\ Sales\ Team_{ft}}, 1_{Skilled_{mt}} \times 1_{High\ Visibility_{mt}} \times 1_{Large\ Sales\ Team_{ft}}\Big]. \end{aligned}$$

One threat to the identification of the sales effect is that firms with more productive managers may choose to invest more in marketing and advertising. We alleviate this concern by instrumenting the size of the sales team with the average size of sales teams of other firms in the previous year. The underlying assumption is that the investments in sales teams are driven by the investments of competitor firms, but the latter does not directly affect revenue or compensation of individual managers, conditional on a rich set of control variables. In Section 5.1, we discuss this approach in detail, followed by supporting evidence for the identification assumption and the resulting IV estimates.

4.3 The Effects of Team Capital and Firm Advertising

Tables 4 presents the estimation results for manager compensation and expected fee revenue.[15] The unit of observation is a manager in a given year. Since our set of control variables (described

[15] With rational expectation, the actual revenue in period $t+1$ is used to proxy the expected revenue.

in Section 4.1) includes manager skill, we account for the manager-level performance-based component of compensation (Ma, Tang and Gómez (2018)). Further, the interaction of firm and year fixed effects allows us to capture time-varying firm profits, revenue and performance, which have been shown to be important determinants of manager compensation in Ibert et al. (2017).

Column (1) of Panel A shows that, else equal, skilled managers generate 7% higher fee revenues and receive 8% higher compensation in a given year. The revenue and compensation effects are in the same direction, consistent with the standard principal-agent contracts where the principal rewards an agent's input that increases total output.

However, not all the inputs have the same effects on revenue and compensation. As shown in Section 3, when the firm's inputs are complementary to a manager's inputs, such inputs, while revenue-enhancing, can reduce the compensation that the manager receives. We focus on two such complementarities: team assignment and firm advertising.

Team Capital As shown in Column (1) of Panel A, for less skilled managers, being on a team is associated with an increase of 29 log points (34 percentage points) in revenue. Being on a skilled team leads to an additional 41 log points (50 percentage points) increase in revenue. Moreover, the team effects are stronger for skilled managers. Skilled managers on teams generate an additional 19 log points (21 percentage points) in revenue, relative to less skilled managers. If a skilled manager works with a skilled team, fee revenue increases by an additional 25 log points (28 percentage points). The combined economic effect of the team variables on skilled managers is quite large, being equal to 49 percentage points. The large positive effects of $\left[1_{Skilled_{mt}} \times 1_{Team_{mft}}, 1_{Skilled_{mt}} \times 1_{Skilled\,Team_{mft}}\right]$ indicate the degree of complementarity between a manager's own skill and the skill of her teammates.

Despite that team capital has substantial positive effects on managers' production output, it generates opposite effects on the current compensation of managers. Column (2) shows that for more skilled managers, being on a team is associated with a 4 percentage points decline in compensation, while being on a skilled team further reduces the compensation by 15 log points (16 percentage points). The magnitude of the combined effect of team skill on compensation is large (20 percentage points) and statistically significant.

With the inclusion of manager fixed effects, the findings above are unlikely to be driven by manager-specific time-invariant omitted factors that could induce positive assortative matching between skilled managers and skilled teams. If it was indeed the case, we should observe the firm support variables affect the expected revenue and manager compensation in the same direction. But the estimates show the opposite. These patterns are also unlikely to be driven by the average skill within the firm (as opposed to team-specific skill) or by other time-varying factors at the firm level (i.e. the total number of portfolio managers) since we are comparing managers working with the same firm in a given year. It is thus the skill of the specific team rather than the aggregate level of skill within the firm that matters the most.

A legitimate concern is that the same manager might take different roles in teams at different career stages. If the change in roles is correlated with not only her propensity to be matched with a team and team skill, but also with her compensation, this could introduce another bias into our key estimates. To address this concern, we further control for the interaction between manager fixed effects and the experience indicator. Thus, we are comparing the same manager in a given career period associated with the same firm but switching between two different teams. Columns (3)-(4) show that the estimated coefficients remain stable and comparable to those from columns (1)-(2). Appendix Table B5 further repeats the specifications using the split ratio to measure compensation instead. The patterns are similar to what we find here.

Taken together, we find that strong support for Implication 1 from Section 3. Working with a skilled team enhances a manager's future productivity but lowers her current compensation. Since teams are assigned by the firm, the evidence is consistent with our theoretical framework of joint production whereby managers face a trade-off between higher monetary compensation received in the current period and positive externalities from fund family that enhance future productivity.

Marketing Support Panel B repeats the specifications from Panel A, but with the addition of interactions between manager visibility, manager skill, and the size of the firm's sales team. Again, columns (1)-(2) control for manager fixed effects and the interaction between firm and year fixed effects, while columns (3)-(4) further control for the interaction between manager fixed effects and the experience indicator. The results are highly consistent across different specifications and we focus our discussion below on the last two columns.

Column (3) shows that a skilled manager in a given career stage generates 4 percentage points higher total revenue when she is more known to investors via media coverage. The estimated manager visibility effect is comparable to the corresponding manager skill effect, suggesting that visibility plays a nearly as important role as investment skill for determining fund revenue, consistent with the sizable information frictions faced by mutual fund investors found in Roussanov, Ruan and Wei (2021). In addition, conditional on being known to investors, a highly-skilled manager is more likely to be chosen, indicating the complementarity between skill and visibility.

As shown in Table 1, managers differ substantially in their own visibility. As a result, firms' investment in marketing and sales provides an important source of production complementarity that benefits different managers differently. Column (3) shows that, for skilled managers with low visibility, working for a firm with a large sales team increases revenues 41 log points (51 percentage points). Such effect is reduced by 7 log points to 34 log points (40 percentage points) for skilled managers with high visibility. This is again intuitive as managers with high visibility have developed their own reputation and hence benefit less from the firm-level marketing effort to increase investors' awareness.

Turning to compensation, column (4) reveals that managers' visibility and firms' investment in sales team, although both revenue-enhancing, have opposite effects on manager compensation. For a skilled manager, being highly visible increases her pay by 3 percentage points. Similar to investment skill, visibility is an important manager-level determinant of revenue. Its positive effect on manager pay is consistent with the common wisdom on performance-based contracts where the revenue is used to form a basis for compensation contracts. On the other hand, working for a firm with a large sales team reduces compensation by 19 log points (21 percentage points) for skilled managers. Such effect is reduced by 7 percentage points to 12 log points (13 percentage points) for managers who are highly visible. The fact that firm's marketing support weakens the relationship between pay and investment skill is fully consistent with Implication 2. It highlights the strong demand from "average" managers, particularly those with low visibility, for firm support in advertising and marketing. Such need gives rise to compensation externalities within the fund family, which is crucial for understanding the role of incentive-based contracts in the mutual fund industry.

Overall, Table 4 shows that asset management teams and sales teams, both assembled by the firms, provide important production complementarity to an individual manager's own skills.[16] Consistent with the model, we find that managers are willing to trade their current monetary compensation for higher expected future productivity, enhanced by either the firm's team assignment or marketing support or both.

5 Robustness Checks

In this section, we discuss several robustness checks. The rich interactions of fixed effects in our baseline specifications help address sorting of managers based on time-invariant unobserved characteristics. However, one might still be concerned about unobserved time-varying *manager-firm specific* characteristics. For example, a firm could decide to change its distribution network or expand its research division. Managers can also gain fundraising ability or investment skill over time. If these changes occur independently, they would have been captured by the inclusion of the interaction of firm and year fixed effects, as well as the interaction between manager and experience fixed effects. However, if these changes are correlated, our estimates of production complementarity effects can be biased. For example, this can happen when managers with improving skill or other unobserved abilities are more likely to join firms that invest more in research or advertising infrastructure (and hence have skilled teams to partner the manager with or larger sales teams).

We address this additional selection bias by using two approaches: (i) exploiting variation within a sample of managers who switch firms or teams within a firm, and (ii) the instrumental variables. The former helps address the endogeneity of both team-related and firm-related

[16] The effects of firm support remain large when interpreted in standard deviations of an outcome variable. Being on a skilled team increases log revenue by 0.34 standard deviations and reduces log compensation by 0.25 standard deviations. Working for a firm with a large sales team increases log revenue of skilled managers by 0.52 standard deviations and reduces their log compensation by 0.44 standard deviations.

variables. The latter has a specific focus on addressing the endogeneity of the firm's sales team size.

5.1 Robustness Checks using Switcher Samples

We construct samples of managers who switch between firms or between teams within firms. Using the samples of switchers allows us to compare the outcomes immediately before and immediately after the transition event. If manager-specific and firm-specific unobservables do not change simultaneously and dramatically over this short time period, this comparison helps mitigate the sorting bias.

Figure 3 shows the likelihood of switching firms by experience and age. Portfolio managers are most likely to switch firms in the middle of their careers. The probability of switching is the highest for managers with 10-15 years of industry experience, being equal to 14%. It is lower for managers with less than 10 years or more than 15 years of experience. We find a similar pattern across age groups where the likelihood of switching peaks at 14.8% for managers who are 40-50 years old.

Table 5 presents the information on a number of variables a year before and immediately after the transition for 98 transitions across firms that we identify. On average, portfolio managers experience a large increase in both compensation and productivity around the transition event. For the average transition, the compensation increases by 50 log points (65 percentage points) and the revenue unconditionally increases by 38 log points (46 percentage points).

At the same time, the average likelihood of being on a team declines by 22 percentage points, and the average likelihood of working for a firm with large sales teams declines by 29 percentage points. After the transition, the managers are also less likely to work with skilled teams, conditional on staying on a team, but this difference is not statistically significant. This result is consistent with the transitions occurring later in the manager's career. Mid-career managers may have already accumulated the benefits of teamwork and marketing support, and now they move to firms that offer higher compensation but less support.

We next present a series of regression tests, examining how transitions across firms affect compensation and revenue, conditional on transition characteristics. To provide a granular description of transitions, we create a set of indicator variables to account for a variety of transition characteristics. The indicator variables with $0 \to 1$ superscript equal one if the manager becomes a team member ($1^{0\to1}_{Team}$), moves to a skilled team ($1^{0\to1}_{Skilled\ Team}$), or moves to a firm with large sales team ($1^{0\to1}_{Large\ Sales\ Team}$). We also create set of indicator variables with $1 \to 0$ superscript to characterize the "reverse" transitions: the manager becomes independent ($1^{1\to0}_{Team}$), moves to a less skilled team ($1^{1\to0}_{Skilled\ Team}$), or to a firm with small sales team ($1^{1\to0}_{Large\ Sales\ Team}$). Our outcome variables are the log-changes in compensation and revenue within one year around the transition. All the specifications include new firm, previous firm, and year fixed effects.

The results in Table 6 are highly consistent with our baseline results from Table 4. Columns (1) and (3) show that transition from being independent to being on a team is associated with a 10 percentage points increase in revenue and a 27 log points (31 percentage points) reduction in compensation. If a manager becomes a member of a skilled team, the revenue increases by 92 log points (150 percentage points) and the compensation declines by 39 percentage points. On the other hand, becoming independent is associated with increased compensation but not necessarily a change in revenue. This is consistent with the fact that the switchers are typically mid-career managers, as shown in Figure 3. These managers have already accumulated the network capital and reputation from their prior work experience and need less firm-level support from the new firm. As a result, the new firm need to pay higher compensation in order to attract them. Taken together, these results provide additional support for Implication 1. The estimates on the sales team are also consistent with the framework's predictions. Moving from a firm with a small sales team to a firm with a large sales team is associated with an increase in revenue and a decline in compensation, while a reverse transition leads to an increase in compensation.

Columns (2) and (4) further show that the effects of being on team and transitioning to skilled teams are larger for skilled managers, and the effect of transitions to firms with larger sales teams is larger for less visible managers, consistent with our main results.

In sum, our results from the sample of transitions across firms are highly consistent with our baseline results. In Appendix Table B6, we additionally examine transitions across teams within the same firms. We only focus on the effects of teamwork since the immediate variation in sales team size is small. The results are quantitatively and qualitatively similar. As expected, the changes in compensation associated with transition within firms are smaller relative to the transitions across firms.

5.2 Instrumental Variables Approach

Marketing and advertising are one of the important competition dimensions in the mutual fund industry and therefore may generate potential endogeneity concerns in our main empirical specifications. For example, unobserved firm history, corporate culture and market trends could drive up a firm's revenue, compensation, and marketing spending simultaneously and hence induce an upward bias in an OLS estimation of the sales team effect. As long as these unobserved factors vary at the firm-year level, they are less of an issue given the inclusion of the interaction of firm and year fixed effects. However, one may still be concerned that for a given firm in a given year, the need for advertising depends on the expected productivity of individual managers. To address this, we propose to instrument the size of the sales team by the average size of the sales team across other firms in the previous year.

Our instrument is the lagged cross-sectional average of $1_{Large\,Sales\,Team_{ft}}$ indicator for all other firms, excluding firm f. The underlying identification assumption is that the firm's investment in marketing and advertising depends on the investment of its competitors. If the competitors invest more in a given year, then the firm can respond by increasing its own sales team over the next year. The exclusion restriction is that the competitors' sales team size does not directly affect current compensation and productivity of portfolio managers in the firm other than through its effect on the firm's current sales team, conditional on a rich set of control variables and combinations of fixed effects that account for the unobserved history of firms and unobserved talents of managers.

We first examine the power of the instrument. Panel A of Table 7 presents the results from regressing $1_{Large\,Sales\,Team_{ft}}$ indicator on $1_{\widehat{Large\,Sales\,Team}_{t-1}}$, the average industry sales team size in the previous year, excluding the firm itself. The relation between the variables is significantly positive and robust across a number of specifications with a variety of control variables and fixed effects.

Intuitively, firm i's marketing investment could decrease firm j's probability of being known to the investors and force firm j to also invest more in marketing, resulting in a wasteful "arms race" competition as shown in Roussanov et al. (2021). This provides the necessary variation underlying our identification of the sale team effects.

Recall that our main specifications in Table 4 do not directly include $1_{Large\,Sales\,Team_{ft}}$ indicator since we control for the interaction of firm and year fixed effects. Instead, it includes the three interactions of $1_{Large\,Sales\,Team_{ft}}$ with other variables: 1) the interaction with $1_{Skilled_{mt}}$; 2) the interaction with $1_{High\,Visibility_{mt}}$; and 3) the triple interaction between all the variables. Therefore, we treat these three interactions variables as endogenous and instrument them using the corresponding interactions with$1_{\widehat{Large\,Sales\,Team}_{t-1}}$. We follow a standard 2SLS procedure as described below.

In the first stage, we run three separate regressions, regressing each of the three endogenous variables separately on all the three instruments and control variables from the main specification. We next calculate fitted values for each endogenous variable. Our first-stage regression specification is given by

$$z_{mft} = \lambda_f \times \lambda_t + \lambda_m \times 1_{Experienced_{mft}} + \beta {C^{team}}_{mft} + \psi I_{mft} + \gamma X_{mft} + \epsilon_{mft}. \tag{12}$$

In this specification, z_{mft} is an endogenous interaction variable: $1_{Skilled_{mt}} \times 1_{Large\,Sales\,Team_{ft}}$, $1_{High\,Visibility_{mt}} \times 1_{Large\,Sales\,Team_{ft}}$ or $1_{Skilled_{mt}} \times 1_{High\,Visibility_{mt}} \times 1_{Large\,Sales\,Team_{ft}}$. C^{team} is the set of exogenous interaction variables that capture asset management team complementarities.[17] I_{mft} is the vector of three instruments:

$$I_{mft} = \left[1_{Skilled_{mt}} \times 1_{\widehat{Large\,Sales\,Team}_{t-1}}, 1_{High\,Visibility_{mt}} \times 1_{\widehat{Large\,Sales\,Team}_{t-1}}, 1_{Skilled_{mt}} \times 1_{High\,Visibility_{mt}} \times 1_{\widehat{Large\,Sales\,Team}_{t-1}}\right].$$

Table 8 shows that Stock-Yogo F-statistics from the first stage are above 13 across all the endogenous variables, suggesting that the first stage power of our instruments is very strong. Hence the estimates are unlikely to be affected by a weak-instrument issue.

[17] X_{mft} is our standard set of control variables from Equation 11, with the addition of $1_{Skilled_{mt}} \times 1_{High\,Visibility_{mt}}$. This interaction variable does not include the sales team size and therefore is not instrumented.

While the exclusion restriction cannot be tested directly, we provide indirect evidence by checking whether our proposed instruments are correlated with variation in the outcome variables which is left unexplained by our main independent variables. In particular, we first compute the residuals from our main regressions in Table 4. These residuals capture the variation unexplained by $1_{Skilled_{mt}} \times 1_{Large\ Sales\ Team_{ft}}$, $1_{High\ Visibility_{mt}} \times 1_{Large\ Sales\ Team_{ft}}$ and $1_{Skilled_{mt}} \times 1_{High\ Visibility_{mt}} \times 1_{Large\ Sales\ Team_{ft}}$ indicators and the full set of control variables. We next regress the residuals on I_{mft} and report the results in Panel B of Table 7. Across all the outcome variables, we find that our proposed instrument interactions are uncorrelated with the residuals, providing additional support for our identification strategy.

In the second stage, we regress each of our dependent variables on the fitted values from the first stage and all the control variables. Our second-stage regression specification is given by:

$$y_{mft} = \lambda_f \times \lambda_t + \lambda_m \times 1_{Experienced_{mft}} + \beta {C^{team}}_{mft} + \psi \hat{z}_{mft} + \gamma X_{mft} + \epsilon_{mft}. \tag{13}$$

In this specification, y_{mft} is our independent variable (compensation or revenue), and $\hat{z}_{mft}$ is the set of the three fitted values from the first-stage regressions.

Table 8 reports the results. Across all the dependent variables, most of the 2SLS coefficients show magnitudes comparable to their OLS counterparts from Panel B of Table 4. They also exhibit similar levels of statistical significance, suggesting that our main results appear to be robust to the instrumental variables estimation. This is not surprising, as marketing is a firm-level decision that varies over time. Most of the omitted factors related to this decision are already controlled for in the main specifications with the inclusion of the interaction between firm and year fixed effects.

6 Implication for Pay-Performance Sensitivity

In their analysis of compensation of Swedish portfolio managers, Ibert et al. (2017) (IKVV) find that a manager's compensation responds weakly to her own performance or revenue but strongly to firm-level revenue, profits and performance. Using the Israeli portfolio manager data, we repeat the baseline specifications in IKVV and find similar evidence. The consistently small observed pay-performance sensitivity presents a quantitative puzzle for the standard incentive-based contracts that link managers' pay to their performance. In this section, we address this by exploring the role of production complementarities between managers and firms in a joint production process. We follow the IKVV's specifications as close as possible, and therefore, include fund performance as measured by its alpha, instead of the measure of skill from Berk and Van Binsbergen (2015) which we use throughout the rest of the paper. While the specifications are similar to those from the main analysis, the focus now is on the magnitude of pay-performance sensitivity, and as a result, the key variable of interest is the fund's risk-adjusted performance (alpha) instead of firm externalities.

Our baseline results confirm IKVV's findings on economically modest effects of manager-level revenue and performance on pay. Column (1) of Table 9 shows that a 1% increase in fund revenues is associated with a 0.22% increase in manager compensation. Column (2) shows that a 1% increase in fund performance increases manager compensation by 0.16%. Both are comparable to IKVV's estimates.[18] One key contribution of IKVV is to show that firm level variables, such as firm profits and revenues, are important determinants of manager compensation. In column (3), we capture these firm-level variables by including the interaction of firm and year fixed effects. In addition, we include time-varying manager and portfolio characteristics. The estimates of pay-performance and pay-revenue elasticities shrink slightly, and the R^2 increases to 0.60, again consistent with IKVV.

The evidence from IKVV and the replicated specifications above points to weak observed pay-performance sensitivity, inconsistent with the standard incentive-based contracts that link managers' pay to their performance. The conceptual framework that we developed in Section 3 provides a testable explanation. In particular, since IKVV measure skill by the fund's risk-adjusted performance, the pay-performance sensitivity can be interpreted as a manager's skill premium. Proposition 2 states that in a world where managers and the firm work together to produce, we expect that the pay-performance sensitivity would be mitigated by the firm-level input if such

[18]The effects are also comparable in terms of economic magnitudes. An increase of one standard deviation in log revenue increases compensation by 38.4% (28.1% in IKVV). An increase of one standard deviation in log abnormal return increases compensation by 1.8% (2.98% in IKVV)

input contributes positively to a manager's productivity. Given that both team skills and firm marketing support are complementary to an individual manager's performance, a manager will be willing to receive lower compensation for her performance in exchange for being matched with more skilled team or receiving more marketing support from the firm. Moreover, to the extent that managers differ in how much they benefit from such firm support, their pay-performance sensitivities also vary.

In column (4), we test this explanation by including two firm-level inputs: team allocation and marketing support. Consistent with the above, we find that the pay-performance sensitivity depends crucially on how well managers are supported by the firm. For example, while being matched to a random team has no significant impact on the pay-performance sensitivity, being matched to a skilled portfolio management team almost completely washes away the positive pay-performance sensitivity. Similarly, being matched to a large sales team eliminates most of the pay-performance sensitivity. In contrast, for managers who have high visibility and hence less need for firm marketing, their pay-performance sensitively almost doubles. These estimates remain robust when we further control for manager fixed effects in column (5).

Taken together, our results reveal that small average pay-performance sensitivities may mask substantial heterogeneities in incentives underlying the compensation contract. The established and skilled managers benefit less from team skill or firm marketing, hence their pay is more sensitive to their own performance. On the other hand, managers who rely heavily on team skills and firm marketing would willingly accept less reward for their own performance in order to receive better firm support that enhances their expected productivity. Our findings are highly consistent with IKVV's message that "managers' compensation cannot, and should not, be evaluated in isolation." In particular, by explicitly accounting for the complementaries between fund managers and fund families (firms), we show that the manager compensation depends not only on their own performance (as in Ma, Tang and Gómez (2018)), the firm's overall performance (as in Ibert, Kaniel, Van Nieuwerburgh and Vestman (2017)), but more importantly on the idiosyncratic match between firm-level resources and individual talents. Evidence for the latter is novel to the literature.

7 Conclusion

This paper studies the importance of production complementarities in explaining variations in productivity and compensation in asset management. We examine a framework that specifies how production complementarities between managers and firms affect manager expected productivity and hence compensation. We apply this framework to the asset management industry and provide novel evidence that a manager's productivity and compensation are shaped not only by their own performance and overall firm profitability, but more importantly by how they integrate with the rest of the firm. Production complementarities naturally arise in the mutual fund industry because most managers work in teams and firms know more than investors about managerial ability. The former implies that skilled managers benefit from working with other skilled ones, the latter implies that skilled but less visible managers benefit from being advertised. Using a unique dataset from a registry-based dataset on the production and compensation of Israeli mutual fund managers, we find that managers working with more skilled teammates and receiving more advertising receive lower salaries today in return for higher expected productivity. Such effects are stronger for more skilled and less visible managers. The results are consistent with the incentive provision theory for forward-looking agents in the presence of production complementarities.

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Figure 1: Variance Decomposition

This figure presents the results of variance decomposition for compensation, split ratio and productivity of portfolio managers. Each variable is regressed on firm fixed effects. We refer to the distribution the estimates of firm fixed effects as "between-firm" variation, and to the distribution of the residuals as "within-firm variation". *Log(Compensation)* is the natural logarithm of the manager's dollar compensation. *Log(Revenue)* is the natural logarithm of the manager's fee revenue. *Split Ratio* is the ratio of the manager's compensation to her fee revenues.

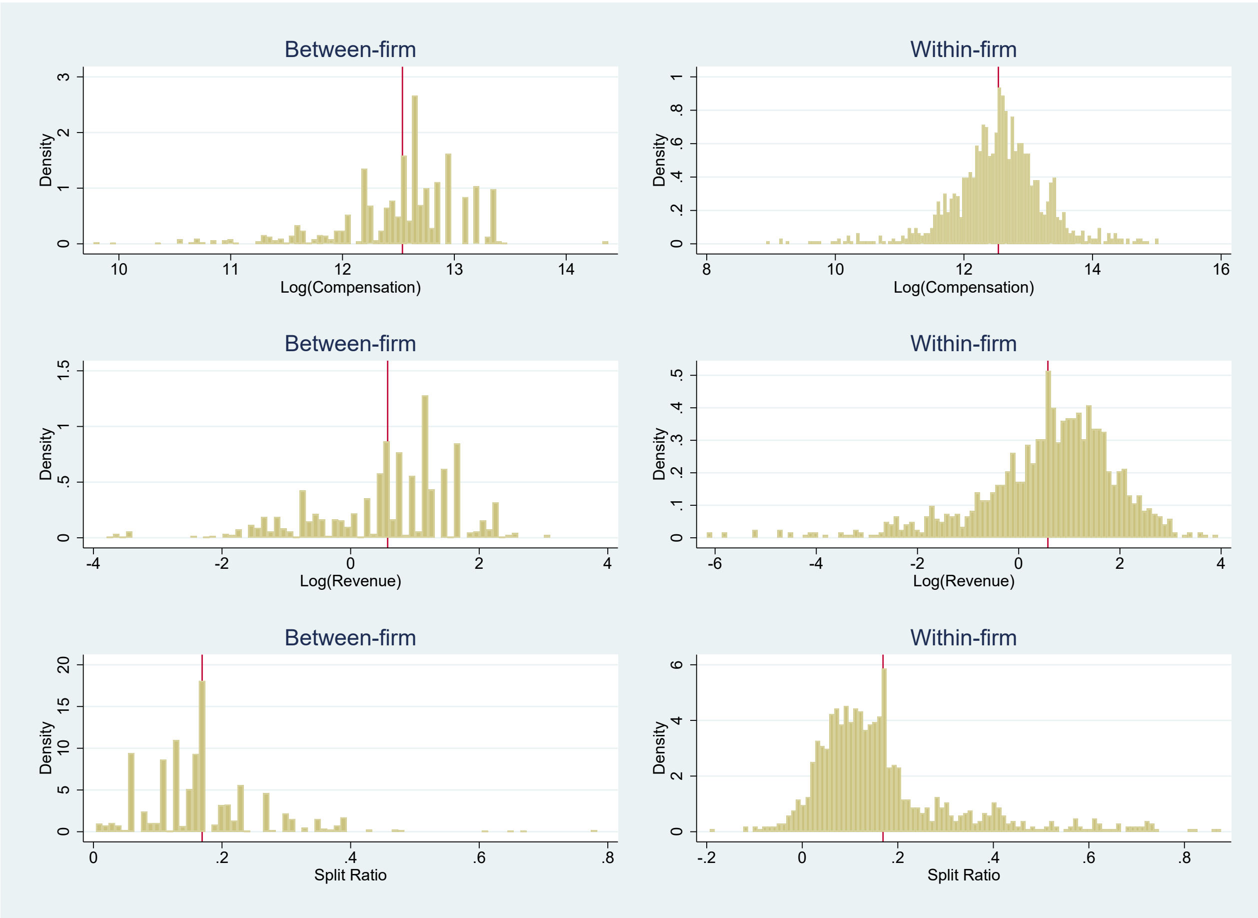

Figure 2: Co-managed Funds and Managers on Teams

This figure presents the times series of the fraction of managers with teams and the fraction of funds which are co-managed. The fund is defined as co-managed if it is managed by more than one manager.

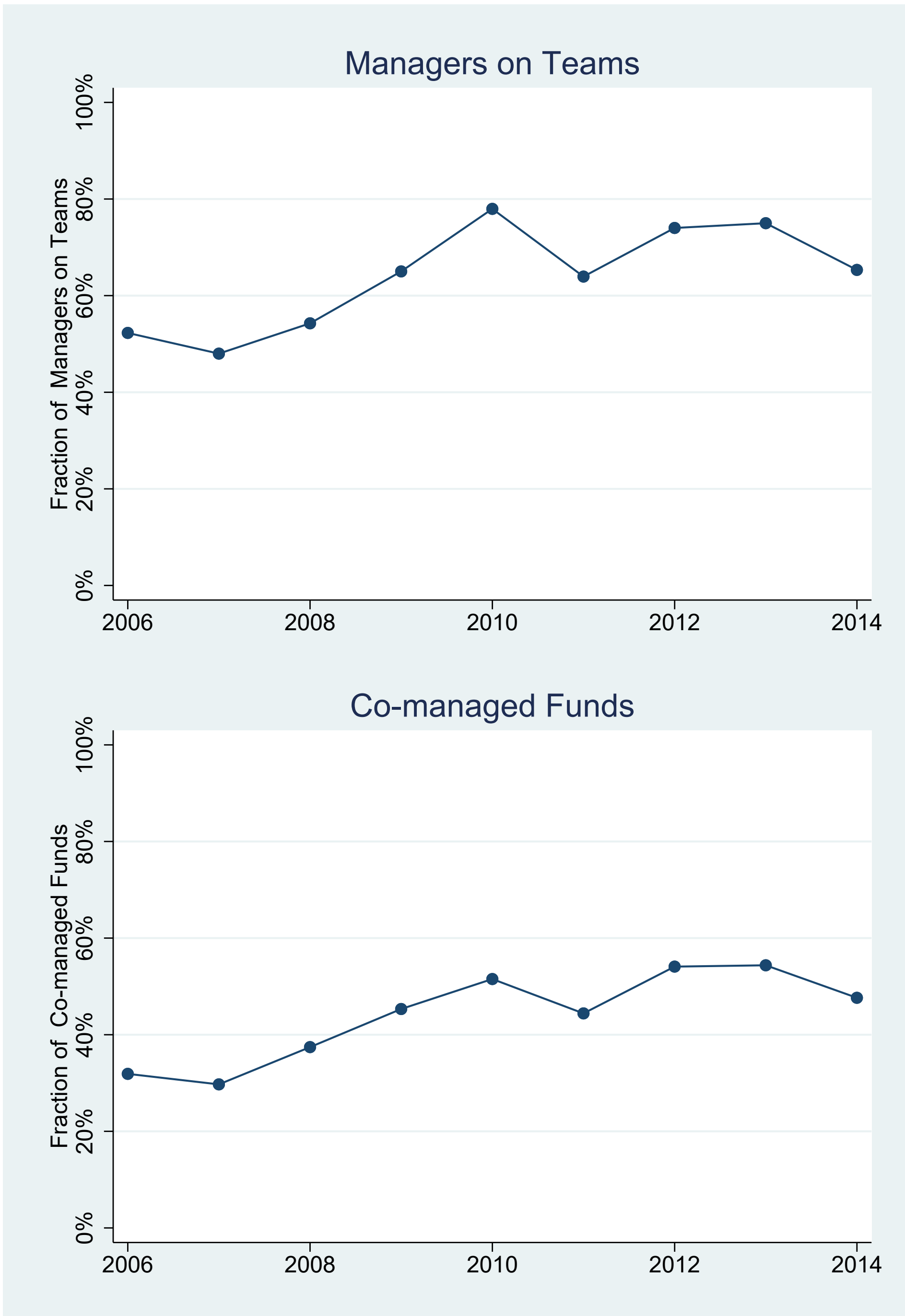

Figure 3: Job Switching Rates, Experience and Age

This figure presents the likelihood of switching firms across experience and age groups. *Job Switching Rate* is the fraction of managers which switch firms within their respective group.

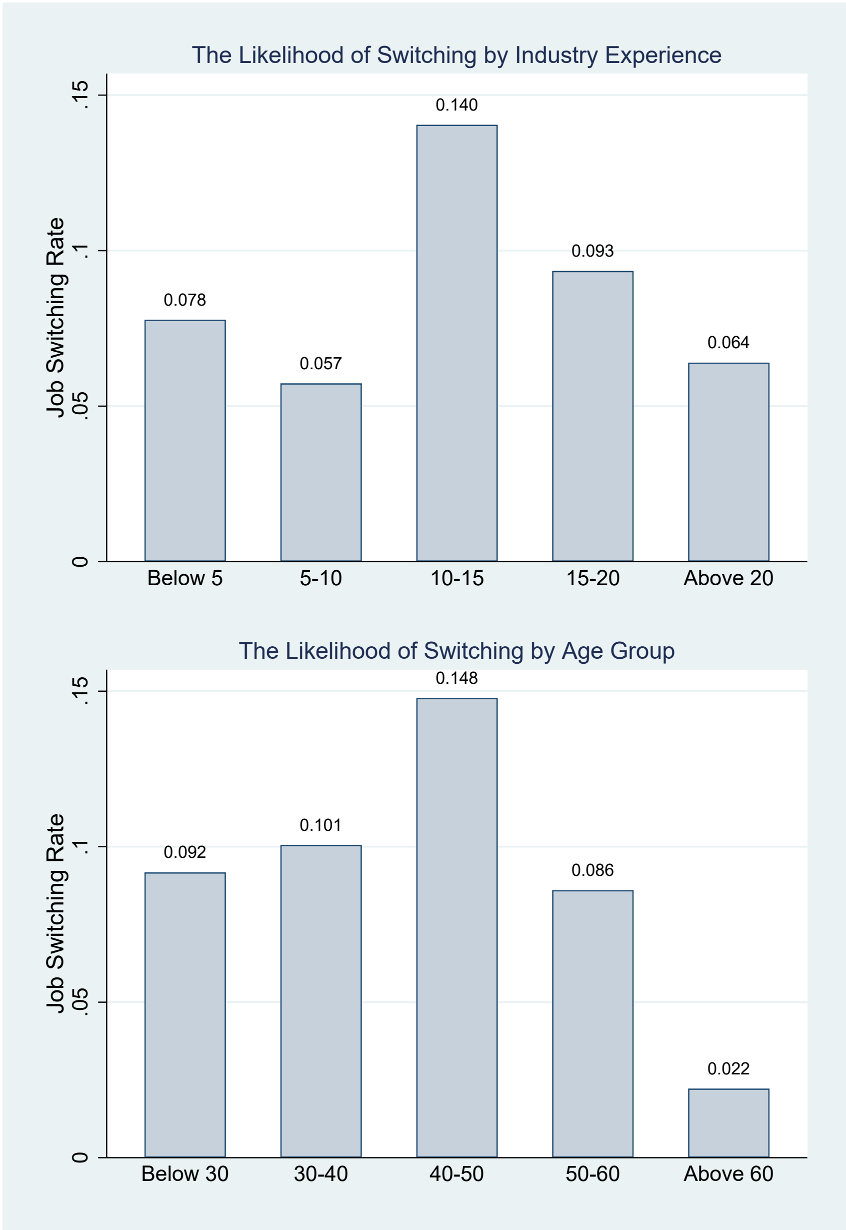

Table 1: Summary Statistics

This table presents the descriptive statistics of our sample. Panel A presents the information at the manager-year level. *Compensation* is the manager's dollar compensation. *Revenue* is the manager's fee revenue. *Split Ratio* is the ratio of the manager's compensation to her fee revenues. $1_{Skilled}$ indicator equals one if the manager's skill is positive. *Manager Age* is the manager's age in years. *Fund Experience* is the number of years that the manager has been responsible for the fund's management. *MF Industry Experience* is the number of years that the manager has been working in the mutual fund industry. *AM Industry Experience* is the number of years that the manager has been working in the asset management industry. *Visibility* is the number of newspaper articles about the manager in the four major business outlets in Israel. 1_{MBA} indicator equals one if the manager has an MBA degree. 1_{MA} indicator equals one if the manager has a non-MBA Master's degree. *AUM* is the assets under management. *Fee* is the percentage fee. *Fund Age* is the number of years since the fund's inception. *Number of Funds* is the number of funds in the manager's portfolio. 1_{Team} indicator equals one if the manager is working with the team. *Team Size* is the number of managers on the team, being equal zero for independent managers. *Number of Teams* is the number of teams that the manager is working with. $1_{Skilled\ Team}$ indicator equals one if the average skill of the manager's teams is positive.

Panel A: Manager-year Level	N	Mean	SD	10%	25%	50%	75%	90%
Manager Characteristics								
Compensation (MM, Shekels)	1,264	0.42	0.59	0.09	0.17	0.29	0.46	0.74
Split Ratio (%)	1,264	12.31	18.22	2.31	4.38	9/.90	23.62	42.40
$1_{Skilled}$ (MM, Shekels)	1,264	0.35	0.47	0	0	0	1	1
Manager Age (years)	1,264	39.56	8.54	31	33	38	44	51
Fund Experience (years)	1,264	2.58	2.87	0	0.78	1.88	3.66	5.82
MF Industry Experience (years)	1,264	6.14	6.40	0	2	4	8	14
AM Industry Experience (years)	1,264	8.54	7.55	1	3	6	12	19
Visibility (number of articles)	1,264	7.93	11.71	0	0	5.15	12.73	19.09
1_{MBA}	1,264	0.49	0.50	0	0	0	1	1
1_{MA}	1,264	0.56	0.49	0	0	1	1	1
Portfolio Characteristics								
Revenue (MM, Shekels)	1,264	4.86	6.96	0.10	0.54	2.23	6.57	12.07
AUM (MM, Shekels)	1,264	722.35	1113.57	17.7	61.76	313.07	927.07	1920.1
Fee (%)	1,264	1.01	0.63	0.34	0.57	0.91	1.38	1.97
Fund Age (years)	1,264	8.62	5.80	2.41	4.75	7.46	10.84	16.04
Number of Funds	1,264	4.6	5.04	1	2	4	9	14
Team Characteristics								
1_{Team}	1,264	0.75	0.43	0	0	1	1	1
Team Size	1,264	0.70	0.94	0	0	0.29	1	2
Number of Teams	1,264	1.55	1.96	0	0	1	1	2
$1_{Skilled\ Team}$	1,264	0.37	0.48	0	0	0	1	1

Table 1 - *Continued*

This table 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. *Fund Age* is the number of years since the fund's inception. $Log(1+\alpha_{it-1})$ is the estimate of fund past performance where α_{it-1} is the annualized intercept of the multi-benchmark model for fund returns (see Section 2.4 for details). *Sales Team* is the ratio of sales and marketing employees to the total number of funds for the given firm. *Number of Managers* is the number of portfolio managers that the firm employs. *Number of Funds* is the number of funds that the firm or the manager operates.

Panel B: Fund-year Level	N	Mean	SD	10%	25%	50%	75%	90%
AUM (MM, Shekels)	13,481	110.01	186.13	3.9	12.2	40	117.7	292.2
Fee (%)	13,481	0.95	0.76	0.11	0.33	0.88	1.57	2.12
$Log(1+\alpha_{it-1})$	13,481	-0.01	0.05	-0.08	-0.03	-0.01	0.006	0.035
Fund Age (years)	13,481	7.94	7.77	0.91	2.41	5.50	10.75	19.08
Panel C: Firm-year Level	**N**	**Mean**	**SD**	**10%**	**25%**	**50%**	**75%**	**90%**
AUM (MM, Shekels)	440	2075.12	3998.30	14.95	59.8	353.6	2257.96	6547.78
Fee (%)	440	1.13	0.67	0.48	0.76	1.15	1.42	1.93
Sales Team	261	0.42	0.32	0.19	0.27	0.36	0.55	0.74
Number of Managers	440	2.87	3.04	1	1	1	4	7.5
Number of Funds	440	24.71	37.88	2	3	8	29	64

Table 2: Differences in Revenue and Compensation Across Managers

This table presents the differences in manager characteristics across subsamples. Panel A shows the differences between managers who work for skilled and less skilled teams. Panel B shows the differences between managers who work for firms with large sales teams and small sales teams. *Compensation* is the manager's dollar compensation. *Revenue* is the manager's fee revenue. *Split Ratio* is the ratio of the manager's compensation to her fee revenues. $1_{Skilled\ Team}$ indicator equals one if the average skill of the manager's teams is positive. $1_{Large\ Sales\ Team}$ indicator equals one if the ratio of sales and marketing employees to the total number of funds for the given firm is above the median.

Panel A: Effects of Portfolio Management Team Skill

Manager Characteristics	$1_{Skilled\ Team} = 1$	$1_{Skilled\ Team} = 0$	Difference
Log(Compensation)	10.70	12.78	-2.08***
	(0.86)	(1.31)	
Log(Revenue)	1.51	-0.38	1.89**
	(0.76)	(0.46)	
Split Ratio	0.14	0.20	-0.06***
	(0.03)	(0.03)	

Panel B: Effects of Sales Team Size

Manager Characteristics	$1_{Large\ Sales\ Team} = 1$	$1_{Large\ Sales\ Team} = 0$	Difference
Log(Compensation)	9.61	12.98	-3.37***
	(0.70)	(0.95)	
Log(Revenue)	0.61	0.38	0.23**
	(0.26)	(0.16)	
Split Ratio	0.15	0.22	-0.07**
	(0.03)	(0.04)	

Table 3: Role of Matching in Explaining Compensation and Revenues

This table presents the R-squared from regressing portfolio manager compensation on manager and portfolio characteristics, and combinations of fixed effects. *Compensation* is the manager's dollar compensation. *Revenue* is the manager's fee revenue. *Split Ratio* is the ratio of the manager's compensation to her fee revenue. All the specifications include control variables such as $1_{Skilled}$, *Manager Age*, *Fund Experience*, *MF Industry Experience*, *AM Industry Experience*, 1_{MBA}, 1_{MA}, *Fund Age*, *Number of Funds*, and $1_{High\ Visibility}$. The detailed results are reported in Tables B2-B4 in the Appendix.

	R-squared				
	(1)	(2)	(3)	(4)	(5)
y=$Log(Compensation_t)$	25%	47%	54%	73%	87%
y=$Log(Revenue_{t+1})$	38%	57%	63%	87%	93%
y=$Split\ Ratio_t$	22%	38%	54%	66%	86%
Control variables	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Manager FE	No	No	Yes	No	No
Manager×Firm FE	No	No	No	Yes	No
Manager×Team FE	No	No	No	No	Yes

Table 4: Production Complementarity Effects on Manager Productivity and Compensation

This table presents the results from regressing manager compensation on team and firm characteristics, and their interactions with manager characteristics. *Compensation* is the manager's dollar compensation. 1_{Team} indicator equals one if the manager is working with the team. $1_{Skilled\,Team}$ indicator equals one if the average skill of the manager's teams is positive. $1_{Large\,Sales\,Team}$ indicator equals one if the ratio of sales and marketing employees to the total number of funds for the given firm is above the median. $1_{Skilled}$ indicator equals one if the manager's skill is positive. $1_{High\,Visibility}$ equals one if the number of newspaper articles about the manager in the four major business outlets in Israel is above the median. $1_{Experienced}$ indicator equals one if the manager's mutual fund industry experience is above the median. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors double-clustered by manager and year are in parentheses.

Panel A: Effects of Team Capital	(1)	(2)	(3)	(4)
$y =$	$Log(Revenue_{t+1})$	$Log(Compensation_t)$	$Log(Revenue_{t+1})$	$Log(Compensation_t)$
$1_{Skilled}$	0.07**	0.08**	0.08**	0.08**
	(0.03)	(0.04)	(0.04)	(0.04)
1_{Team}	0.29**	0.02	0.28**	0.02
	(0.14)	(0.09)	(0.14)	(0.09)
$1_{Skilled\,Team}$	0.41**	-0.11**	0.32**	-0.10**
	(0.20)	(0.05)	(0.17)	(0.05)
$1_{Skilled} \times 1_{Team}$	0.19**	-0.04**	0.22***	-0.06***
	(0.08)	(0.02)	(0.07)	(0.02)
$1_{Skilled} \times 1_{Skilled\,Team}$	0.25**	-0.15**	0.26**	-0.19**
	(0.11)	(0.07)	(0.12)	(0.09)
Observations	1,108	1,108	1,108	1,108
R-squared	0.92	0.86	0.93	0.88
Firm×Year FE	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	No	No
Manager FE×$1_{Experienced}$	No	No	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Table 4 - *Continued*

Panel B: Effects of Marketing Support	(1)	(2)	(3)	(4)
y =	$Log(Revenue_{t+1})$	$Log(Compensation_t)$	$Log(Revenue_{t+1})$	$Log(Compensation_t)$
$1_{Skilled}$	0.06**	0.12**	0.06**	0.11**
	(0.02)	(0.05)	(0.02)	(0.05)
1_{Team}	0.16**	0.00	0.13**	0.05
	(0.07)	(0.10)	(0.06)	(0.14)
$1_{Skilled\ Team}$	0.33**	-0.14***	0.39*	-0.12**
	(0.15)	(0.04)	(0.20)	(0.05)
$1_{Skilled} \times 1_{Team}$	0.12**	-0.08	0.11**	-0.08**
	(0.05)	(0.05)	(0.05)	(0.04)
$1_{Skilled} \times 1_{Skilled\ Team}$	0.21**	-0.15**	0.11	-0.15**
	(0.09)	(0.06)	(0.07)	(0.07)
$1_{Skilled} \times 1_{High\ Visibility}$	0.04**	0.04**	0.04**	0.03*
	(0.02)	(0.01)	(0.02)	(0.01)
$1_{Skilled} \times 1_{Large\ Sales\ Team}$	0.51**	-0.21**	0.41**	-0.19*
	(0.24)	(0.10)	(0.19)	(0.10)
$1_{High\ Visibility} \times 1_{Large\ Sales\ Team}$	0.03	-0.15**	0.02	-0.14**
	(0.15)	(0.07)	(0.15)	(0.07)
$1_{Skilled} \times 1_{High\ Visibility} \times 1_{Large\ Sales\ Team}$	-0.07**	0.08**	-0.07*	0.07**
	(0.03)	(0.03)	(0.03)	(0.03)
Observations	938	938	938	938
R-squared	0.94	0.85	0.96	0.86
Firm×Year FE	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	No	No
Manager FE×$1_{Experienced}$	No	No	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Table 5: Transition Across Firms: Comparison of Manager Characteristics

This table compares the characteristics of managers who moved between firms. *Compensation* is the manager's dollar compensation. *Revenue* is the manager's fee revenue. *Split Ratio* is the ratio of the manager's compensation to her fee revenues. 1_{Team} indicator equals one if the manager is working with the team. $1_{Skilled\ Team}$ indicator equals one if the average skill of the manager's teams is positive. $1_{Large\ Sales\ Team}$ indicator equals one if the ratio of sales and marketing employees to the total number of funds for the given firm is above the median. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Transitions of Managers Across Firms (N = 98)		
	Year Before Transition	Year After Transition	After vs. Before
Log(Compensation)	-1.91	-1.41	0.50***
t-stat			3.29
Log(Revenue)	0.17	0.55	0.38**
t-stat			2.29
Split Ratio	0.08	0.22	0.14**
t-stat			2.37
1_{Team}	0.55	0.33	-0.22**
t-stat			2.11
$1_{Skilled\ Team}$	0.56	0.49	-0.07
t-stat			0.85
$1_{Large\ Sales\ Team}$	0.93	0.64	-0.29**
t-stat			2.08

Table 6: Transition Across Firms: Effects of Production Complementarities on Compensation and Revenue

This table presents the results from regressing one-year changes in manager compensation and productivity on team and firm characteristics, and their interactions with manager characteristics for the sample of managers who switched firms. The changes are calculated as the differences in the outcome variables between the last year at the old firm and the first year at the new firm. *Compensation* is the manager's dollar compensation. *Revenue* is the manager's fee revenue. $1_{Skilled}$ indicator equals one if the manager's skill is positive. $1_{High\,Visibility}$ indicator equals one if the number of newspaper articles about the manager in the four major business outlets in Israel is above the median. $1^{0\to 1}_{Team}$ indicator equals one if the manager starts working with the team at the new firm, after being independent at the old firm. $1^{0\to 1}_{Skilled\,Team}$ indicator equals one if the manager joins the team with positive average skill at the new firm, after working with the negative-average-skill team at the old firm. $1^{0\to 1}_{Large\,Sales\,Team}$ indicator equals one if the ratio of sales and marketing employees to the total number of funds at the new firm is above the median, and it is below the median at the old firm. All the variables with $1 \to 0$ superscript are indicator variables for the reverse transitions. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors double-clustered by manager and year are in parentheses.

	(1)	(2)	(3)	(4)
	y=Δ*Log(Compensation)*$_{t,t+1}$		y=Δ*Log(Revenue)*$_{t,t+1}$	
$1^{0\to 1}_{Team}$	-0.27**	-0.24**	0.10**	0.14**
	(0.13)	(0.12)	(0.05)	(0.06)
$1^{1\to 0}_{Team}$	0.30**	0.17**	0.73	0.45
	(0.13)	(0.07)	(0.46)	(0.63)
$1^{0\to 1}_{Skilled\,Team}$	-0.39***	-0.42**	0.92**	0.75*
	(0.12)	(0.20)	(0.45)	(0.40)
$1^{1\to 0}_{Skilled\,Team}$	0.64	0.30	0.52	0.21
	(0.89)	(1.01)	(0.39)	(0.64)
$1^{0\to 1}_{Large\,Sales\,Team}$	-0.28**	-0.20*	0.37**	0.32*
	(0.12)	(0.11)	(0.14)	(0.16)
$1^{1\to 0}_{Large\,Sales\,Team}$	0.29**	0.30**	0.34***	0.37***
	(0.12)	(0.14)	(0.11)	(0.14)
$1_{Skilled} \times 1^{0\to 1}_{Team}$		-0.22**		0.17**
		(0.10)		(0.08)
$1_{Skilled} \times 1^{1\to 0}_{Team}$		0.24		0.71
		(0.65)		(0.92)
$1_{Skilled} \times 1^{0\to 1}_{Skilled\,Team}$		-0.12**		0.23**
		(0.06)		(0.10)
$1_{Skilled} \times 1^{1\to 0}_{Skilled\,Team}$		0.89		0.54
		(0.72)		(0.51)
$1_{Skilled} \times 1^{0\to 1}_{Large\,Sales\,Team}$		-0.38***		0.49*
		(0.13)		(0.25)
$1_{Skilled} \times 1^{1\to 0}_{Large\,Sales\,Team}$		1.82		-1.00
		(1.18)		(0.74)

Table 6 - *Continued*

	(1)	(2)	(3)	(4)
$1_{High\ Visibility} \times 1^{0\to1}_{Large\ Sales\ Team}$		0.22		0.25
		(0.31)		(0.45)
$1_{High\ Visibility} \times 1^{1\to0}_{Large\ Sales\ Team}$		0.22**		0.19*
		(0.11)		(0.10)
$1_{Skilled} \times 1_{High\ Visibility} \times 1^{0\to1}_{Large\ Sales\ Team}$		0.67		0.34
		(0.78)		(0.45)
$1_{Skilled} \times 1_{High\ Visibility} \times 1^{1\to0}_{Large\ Sales\ Team}$		-1.54		1.98
		(1.02)		(1.45)
Observations	98	98	98	98
R-squared	0.50	0.58	0.46	0.47
New Firm FE	Yes	Yes	Yes	Yes
Previous Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Table 7: Validity Tests for Instrumental Variables Regressions

This table presents the validity tests for instrumental variables regressions in Table 8. Panel A shows the results from regressing $1_{Large\,Sales\,Team}$ on $1_{\widehat{Large\,Sales\,Team}_{t-1}}$. $1_{Large\,Sales\,Team}$ indicator equals one if the ratio of sales and marketing employees to the total number of funds for the given firm is above the median. $1_{\widehat{Large\,Sales\,Team}_{t-1}}$ equals the average of $1_{Large\,Sales\,Team}$ across all the other firms in the previous year. Panel B presents the results from regressing the residuals from the regressions in Table 4 on I_{mft}, the full set of instruments. *Revenue* is the manager's fee revenue. *Compensation* is the manager's dollar compensation. All the specifications include the control variables from Table 4. $1_{Experienced}$ indicator equals one if the manager's mutual fund industry experience is above the median. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors double-clustered by manager and year are in parentheses.

Panel A: Relation between $1_{Large\,Sales\,Team}$ and $1_{\widehat{Large\,Sales\,Team}_{t-1}}$				
$y = 1_{Large\,Sales\,Team}$	(1)	(2)	(3)	(4)
$1_{\widehat{Large\,Sales\,Team}}$	0.58***	0.58***	0.64***	0.72***
	(0.11)	(0.15)	(0.17)	(0.20)
Observations	943	943	938	938
R-squared	0.21	0.38	0.59	0.61
Control variables	No	No	Yes	Yes
Firm FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Manager FE	No	No	Yes	No
Manager FE$\times 1_{Experienced}$	No	No	No	Yes

Panel B: Relation between OLS Residuals and Instruments		
	(1)	(2)
y = Residual from Regression in Panel B of Table 4	*Column (3)*: $Log(Revenue_{t+1})$	*Column (4)*: $Log(Compensation_t)$
$1_{Skilled_{mt}} \times 1_{\widehat{Large\,Sales\,Team}_{t-1}}$	0.03	0.07
	(0.19)	(0.24)
$1_{High\,Visibility_{mt}} \times 1_{\widehat{Large\,Sales\,Team}_{t-1}}$	0.11	-0.12
	(0.22)	(0.30)
$1_{Skilled_{mt}} \times 1_{High\,Visibility_{mt}} \times 1_{\widehat{Large\,Sales\,Team}_{t-1}}$	-0.07	-0.21
	(0.28)	(0.29)
Observations	938	938
R-squared	0.01	0.01

Table 8: Production Complementarity Effects: Instrumental Variables Approach

This table presents the results from regressing manager compensation and revenue on team and firm characteristics, and their interactions with manager characteristics. $1_{Large\,Sales\,Team}$ indicator is instrumented by $1_{\widehat{Large\,Sales\,Team}_{t-1}}$, the average $1_{Large\,Sales\,Team}$ indicator across all the other firms in the previous year. *Revenue* is the manager's fee revenue. *Compensation* is the manager's dollar compensation.1_{Team} indicator equals one if the manager is working with the team. $1_{Skilled\,Team}$ indicator equals one if the average skill of the manager's teams is positive. $1_{Large\,Sales\,Team}$ indicator equals one if the ratio of sales and marketing employees to the total number of funds for the given firm is above the median. $1_{Skilled}$ indicator equals one if the manager's skill is positive. $1_{High\,Visibility}$ equals one if the number of newspaper articles about the manager in the four major business outlets in Israel is above the median. $1_{Experienced}$ indicator equals one if the manager's mutual fund industry experience is above the median. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors double-clustered by manager and year are in parentheses.

	(1)	(2)
$y =$	$Log(Compensation_t)$	$Log(Revenue_{t+1})$
$1_{Skilled}$	0.08**	0.04**
	(0.04)	(0.02)
1_{Team}	0.02	0.15**
	(0.03)	(0.07)
$1_{Skilled\,Team}$	-0.12**	0.34**
	(0.06)	(0.15)
$1_{Skilled} \times 1_{Team}$	-0.05*	0.19*
	(0.02)	(0.10)
$1_{Skilled} \times 1_{Skilled\,Team}$	-0.09**	0.05
	(0.04)	(0.14)
$1_{Skilled} \times 1_{High\,Visibility}$	0.05	0.12**
	(0.04)	(0.06)
$1_{Skilled} \times 1_{Large\,Sales\,Team}$	-0.17**	0.24**
	(0.07)	(0.11)
$1_{High\,Visibility} \times 1_{Large\,Sales\,Team}$	-0.11**	0.11
	(0.05)	(0.09)
$1_{Skilled} \times 1_{High\,Visibility} \times 1_{Large\,Sales\,Team}$	0.06**	-0.12**
	(0.03)	(0.05)
Stock-Yogo F-statistic from the first stage:		
$1_{Skilled} \times 1_{Large\,Sales\,Team}$	14.46	31.23
$1_{High\,Visibility} \times 1_{Large\,Sales\,Team}$	15.45	21.76
$1_{Skilled} \times 1_{High\,Visibility} \times 1_{Large\,Sales\,Team}$	18.98	19.09
Observations	938	938
R-squared	0.86	0.93
Firm$\times$Year FE	Yes	Yes
Manager FE$\times 1_{Experienced}$	Yes	Yes
Control variables	Yes	Yes

Table 9: Production Complementarity Effects on Pay-Performance Sensitivity

This table compares our estimates to the estimates from Ibert, Kaniel, Van Nieuwerburgh and Vestman (2017), presenting the results from regressing manager compensation on her productivity (fee revenues), team and firm characteristics, and their interactions with manager characteristics. *Compensation* is the manager's dollar compensation. *Revenue* is the manager's fee revenue. $Log(1{+}\alpha_{it-1})$ is the estimate of fund performance where α_{it-1} is the annualized intercept of the multi-benchmark model for fund returns (see Section 2.4 for details). 1_{Team} indicator equals one if the manager is working with the team. $1_{Skilled\,Team}$ indicator equals one if the average skill of the manager's teams is positive. $1_{Large\,Sales\,Team}$ indicator equals one if the ratio of sales and marketing employees to the total number of funds for the given firm is above the median. $1_{Skilled}$ indicator equals one if the manager's skill is positive. $1_{High\,Visibility}$ equals one if the number of newspaper articles about the manager in the four major business outlets in Israel is above the median. $1_{Experienced}$ indicator equals one if the manager's mutual fund industry experience is above the median. *,**, 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)	(1)	(2)	(3)	(4)	(5)
Log(Revenue)	0.22***		0.17**	0.16***	0.17***
	(0.01)		(0.04)	(0.06)	(0.06)
$Log(1{+}\alpha_{it-1})$		0.16**	0.15**	0.21***	0.22**
		(0.08)	(0.06)	(0.07)	(0.10)
1_{Team}			-0.08	-0.02	-0.11
			(0.07)	(0.12)	(0.11)
$1_{Skilled\,Team}$			-0.10**	-0.24**	-0.15**
			(0.05)	(0.11)	(0.06)
$Log(1{+}\alpha_{it-1}){\times}1_{Team}$				1.86	3.21
				(1.44)	(3.55)
$Log(1{+}\alpha_{it-1}){\times}1_{Skilled\,Team}$				-0.21***	-0.23**
				(0.06)	(0.09)
$Log(1{+}\alpha_{it-1}){\times}1_{High\,Visibility}$				0.16**	0.12**
				(0.07)	(0.06)
$Log(1{+}\alpha_{it-1}){\times}1_{Large\,Sales\,Team}$				-0.19**	-0.11*
				(0.09)	(0.06)
$Log(1{+}\alpha_{it-1}){\times}1_{High\,Visibility} \times 1_{Large\,Sales\,Team}$				0.92	0.54
				(1.19)	(1.78)
$1_{High\,Visibility} \times 1_{Large\,Sales\,Team}$				-0.11**	-0.14**
				(0.05)	(0.07)
Observations	1,108	1,105	1,105	938	938
R-squared	0.19	0.01	0.60	0.69	0.84
Control Variables	No	No	Yes	Yes	Yes
Firm FE	No	No	No	No	No
Year FE	Yes	Yes	No	No	No
Firm×Year FE	No	No	Yes	Yes	Yes
Manager FE	No	No	No	No	Yes

Online Appendix

A Constructing Benchmark Return

We use a five-benchmark model to evaluate the fund performance, deriving the fund's alpha and its passive benchmark return. This model was developed for the Israeli Ministry of Finance to compare long-term investment instruments such as pension funds and provident funds. The model uses five benchmarks as proxies for risk factors: two equity market indices, Tel Aviv 100 Index and the MSCI World Index, as well as the three bond indices: inflation-indexed corporate bonds, inflation-indexed government bonds and non-indexed government bonds (Hamdani, Kandel, Mugerman and Yafeh (2017)). We apply the same model for estimating the performance of mutual funds because their holdings are very similar to the holdings of the provident funds (Shaton (2017)).

In the main analysis, we estimate fund betas using fund-level monthly data in the following specification:

$$R_{ik} - R_k^{RF} = \alpha_i + \sum_{f=1}^{F} \beta_{if} \left(R_{fk} - R_k^{RF} \right) + \epsilon_{ik}, \tag{14}$$

where $R_{ik} - R_k^{RF}$ is an excess return of fund i in month k above the risk free rate R_k^{RF} and $R_{fk} - R_k^{RF}$ is an excess return of factor f in month k. The risk-free rate R_k^{RF} is defined as monthly return on Israeli short-term (one year maturity) government bonds.

We follow Berk and Van Binsbergen (2015) and generate the fund's benchmark return multiplying the estimated fund betas by the annual excess returns on the indices in year t:

$$R_{it}^{B} = \sum_{f=1}^{F} \hat{\beta}_{if} \left(R_{ft} - R_t^{RF} \right). \tag{15}$$

Intuitively, benchmark return represents a return on the portfolio of passive assets that is the "closest" to the fund's asset holdings. This is the return that investors can achieve on their own purely relying on passive benchmarks that represent the alternative investment opportunity set.

B Additional Results

Figure B1: Sample Coverage

This figure presents the assets under management (AUM) of the entire Israeli mutual fund industry and the aggregated AUM of our sample.

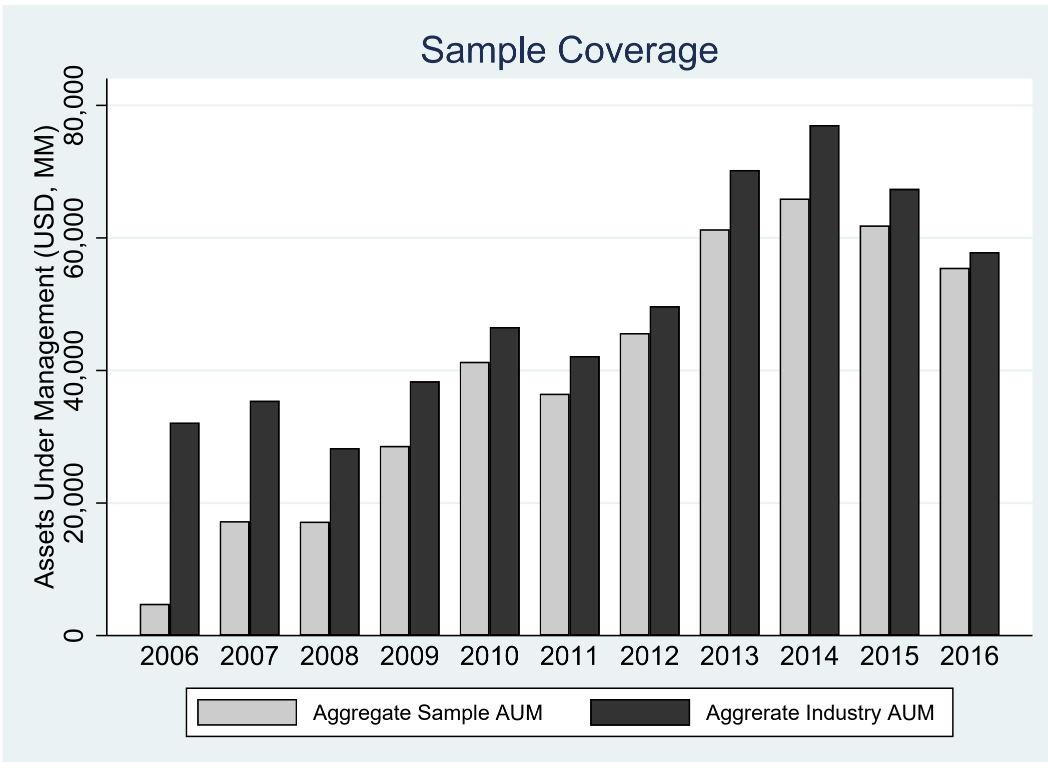

Table B1: Sample Composition

This tables presents the distribution of the sample mutual funds across asset classes.

Primary Asset Class	Number of Funds	Percentage by Count
Israeli Fixed Income - Broad Market	294	21%
Israeli Fixed Income - Sheqels	272	18%
Israeli Fixed Income - Corporate and Convertibles	206	15%
Israeli Fixed Income - Government	191	12%
Israeli Equity	159	11%
Global Equity	136	10%
Global Fixed Income	74	5%
Flexible	35	3%
Fund of Israeli Funds	34	2%
Leverage & Strategic	27	2%
Israeli Fixed Income - Foreign Currency	18	1%
Total	1446	

Table B2: Role of Matching in Explaining Portfolio Manager Compensation

This table presents the results from regressing portfolio manager compensation on manager and portfolio characteristics and combinations of fixed effects. *Compensation* is the manager's dollar compensation. $1_{Skilled}$ indicator equals one if the manager's skill is positive. *Manager Age* is the manager's age in years. *Fund Experience* is the number of years that the manager has been responsible for the fund's management. *MF Industry Experience* is the number of years that the manager has been working in the mutual fund industry. *AM Industry Experience* is the number of years that the manager has been working in the asset management industry. 1_{MBA} indicator equals one if the manager has an MBA degree. 1_{MA} indicator equals one if the manager has a non-MBA Master's degree. *Fund Age* is the number of years since the fund's inception. *Number of Funds* is the number of funds in the manager's portfolio. $1_{High\ Visibility}$ equals one if the number of newspaper articles about the manager in the four major business outlets in Israel is above the median. *,**, 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)	(1)	(2)	(3)	(4)	(5)
$1_{Skilled}$	0.07**	0.08**	0.09***	0.09**	0.09**
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
Fund Age	0.02***	0.02***	0.00	0.01	0.01
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Number of Funds	0.02***	0.02***	0.01***	0.01***	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Manager Age	0.02**	0.02***	0.03***	0.02***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Fund Experience	0.10***	0.08***	0.08***	0.06***	0.11***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
MF Industry Experience	0.01	0.02	0.02	0.02	0.04
	(0.01)	(0.03)	(0.02)	(0.03)	(0.05)
AM Industry Experience	0.02***	0.03***	0.03**	0.02**	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$1_{High\ Visibility}$	0.13**	0.11*	0.12**	0.11**	0.13***
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)
1_{MBA}	0.32***	0.32***			
	(0.09)	(0.10)			
1_{MA}	-0.21**	-0.29***			
	(0.09)	(0.10)			
Observations	1,242	1,222	1,221	1,132	1,175
R-squared	0.25	0.47	0.54	0.73	0.87
Firm FE	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Manager FE	No	No	Yes	No	No
Manager×Firm FE	No	No	No	Yes	No
Manager×Team FE	No	No	No	No	Yes

Table B3: Role of Matching in Explaining Portfolio Manager Revenue

This table presents the results from regressing portfolio manager revenue on manager and portfolio characteristics and the combinations of fixed effects. *Revenue* is the manager's fee revenues. $1_{Skilled}$ indicator equals one if the manager's skill is positive. *Manager Age* is the manager's age in years. *Fund Experience* is the number of years that the manager has been responsible for the fund's management. *MF Industry Experience* is the number of years that the manager has been working in the mutual fund industry. *AM Industry Experience* is the number of years that the manager has been working in the asset management industry. 1_{MBA} indicator equals one if the manager has an MBA degree. 1_{MA} indicator equals one if the manager has a non-MBA Master's degree. *Fund Age* is the number of years since the fund's inception. *Number of Funds* is the number of funds in the manager's portfolio. $1_{High\ Visibility}$ equals one if the number of newspaper articles about the manager in the four major business outlets in Israel is above the median. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors double-clustered by manager and year are in parentheses.

y=Log(Revenue)	(1)	(2)	(3)	(4)	(5)
$1_{Skilled}$	0.10**	0.11**	0.13**	0.13***	0.12***
	(0.05)	(0.05)	(0.06)	(0.04)	(0.04)
Fund Age	0.08***	0.08***	0.04***	0.03***	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of Funds	0.09***	0.07***	0.06***	0.05***	0.02***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
Manager Age	-0.01	-0.01	0.01	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Fund Experience	0.04**	0.03**	0.09***	0.08***	0.08***
	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)
MF Industry Experience	0.06***	0.07***	0.06***	0.06***	0.07**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
AM Industry Experience	0.03***	0.03***	0.04**	0.03***	0.04**
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
$1_{High\ Visibility}$	0.09**	0.08**	0.08**	0.09*	0.08**
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
1_{MBA}	0.15	0.03			
	(0.16)	(0.18)			
1_{MA}	-0.29*	-0.21			
	(0.16)	(0.17)			
Observations	1,216	1,195	1,194	1,107	1,137
R-squared	0.38	0.57	0.63	0.87	0.93
Firm FE	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Manager FE	No	No	Yes	No	No
Manager×Firm FE	No	No	No	Yes	No
Manager×Team FE	No	No	No	No	Yes

Table B4: Role of Matching in Explaining Portfolio Manager Split Ratio

This table presents the results from regressing portfolio manager split ratio on manager and portfolio characteristics and combinations of fixed effects. *Split Ratio* is the ratio of the manager's compensation to her fee revenues. $1_{Skilled}$ indicator equals one if the manager's skill is positive. *Manager Age* is the manager's age in years. *Fund Experience* is the number of years that the manager has been responsible for the fund's management. *MF Industry Experience* is the number of years that the manager has been working in the mutual fund industry. *AM Industry Experience* is the number of years that the manager has been working in the asset management industry. 1_{MBA} indicator equals one if the manager has an MBA degree. 1_{MA} indicator equals one if the manager has a non-MBA Master's degree. *Fund Age* is the number of years since the fund's inception. *Number of Funds* is the number of funds in the manager's portfolio. $1_{High\,Visibility}$ equals one if the number of newspaper articles about the manager in the four major business outlets in Israel is above the median. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors double-clustered by manager and year are in parentheses.

y=Split Ratio	(1)	(2)	(3)	(4)	(5)
$1_{Skilled}$	0.12**	0.12**	0.13***	0.12**	0.14**
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
Fund Age	-0.16***	-0.18***	-0.37***	-0.15***	-0.14***
	(0.06)	(0.07)	(0.11)	(0.05)	(0.04)
Number of Funds	0.02**	0.02**	0.03**	0.03**	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Manager Age	0.12	0.08	0.11	0.11	0.10
	(0.08)	(0.08)	(0.09)	(0.08)	(0.09)
Fund Experience	0.16**	0.21**	0.25***	0.22**	0.23*
	(0.07)	(0.10)	(0.08)	(0.11)	(0.12)
MF Industry Experience	0.12	0.11	0.13	0.12	0.12
	(0.09)	(0.10)	(0.11)	(0.10)	(0.11)
AM Industry Experience	0.21**	0.26**	0.22**	0.22**	0.24***
	(0.10)	(0.11)	(0.10)	(0.11)	(0.09)
$1_{High\,Visibility}$	0.04**	0.02**	0.05**	0.04**	0.03**
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
1_{MBA}	0.26**	0.23*			
	(0.12)	(0.12)			
1_{MA}	0.14**	0.15			
	(0.07)	(0.09)			
Observations	1,242	1,222	1,221	1,132	1,175
R-squared	0.22	0.38	0.54	0.66	0.84
Firm FE	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Manager FE	No	No	Yes	No	No
Manager×Firm FE	No	No	No	Yes	No
Manager×Team FE	No	No	No	No	Yes

Table B5: Production Complementarity Effects on Manager Split Ratio

This table presents the results from regressing manager split ratio on team and firm characteristics, and their interactions with manager characteristics. *Split Ratio* is the ratio of the manager's compensation to her fee revenues. 1_{Team} indicator equals one if the manager is working with the team. $1_{Skilled\ Team}$ indicator equals one if the average skill of the manager's teams is positive. $1_{Large\ Sales\ Team}$ indicator equals one if the ratio of sales and marketing employees to the total number of funds for the given firm is above the median. $1_{Skilled}$ indicator equals one if the manager's skill is positive. $1_{High\ Visibility}$ equals one if the number of newspaper articles about the manager in the four major business outlets in Israel is above the median. $1_{Experienced}$ indicator equals one if the manager's mutual fund industry experience is above the median. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors double-clustered by manager and year are in parentheses.

y = *Split Ratio*$_t$	(1)	(2)	(3)	(4)
$1_{Skilled}$	0.37***	0.42***	2.31**	2.22**
	(0.12)	(0.15)	(1.08)	(0.90)
1_{Team}	-0.78	-0.83	-2.44	-2.70
	(0.63)	(0.68)	(2.03)	(2.33)
$1_{Skilled\ Team}$	-0.42**	-0.41**	-0.34**	-0.44*
	(0.20)	(0.20)	(0.15)	(0.23)
$1_{Skilled} \times 1_{Team}$	-0.49***	-0.48**	-2.09***	-3.24**
	(0.19)	(0.21)	(0.72)	(1.50)
$1_{Skilled} \times 1_{Skilled\ Team}$	-0.26**	-0.25**	-0.78**	-0.70**
	(0.13)	(0.12)	(0.33)	(0.35)
$1_{Skilled} \times 1_{High\ Visibility}$			0.03**	0.03**
			(0.02)	(0.02)
$1_{Skilled} \times 1_{Large\ Sales\ Team}$			-0.19**	-0.19**
			(0.08)	(0.08)
$1_{High\ Visibility} \times 1_{Large\ Sales\ Team}$			-0.64**	-0.60**
			(0.31)	(0.30)
$1_{Skilled} \times 1_{High\ Visibility} \times 1_{Large\ Sales\ Team}$			0.38**	0.19*
			(0.19)	(0.10)
Observations	1,108	1,108	938	938
R-squared	0.67	0.69	0.72	0.73
Firm×Year FE	Yes	Yes	Yes	Yes
Manager FE	Yes	No	Yes	No
Manager FE×$1_{Experienced}$	No	Yes	No	Yes
Control variables	Yes	Yes	Yes	Yes

Table B6: Transitions Across Teams Within Firms

This table presents the results from regressing one-year changes in manager compensation and productivity on team characteristics, and their interactions with manager characteristics for the sample of managers who switched teams within firms. The changes are calculated as the differences in the outcome variables between the last year in the old team and the first year in the new team. *Compensation* is the manager's dollar compensation. *Revenue* is the manager's fee revenue. $1_{Skilled}$ indicator equals one if the manager's skill is positive. $1^{0\to1}_{Team}$ indicator equals one if the manager starts working with the team at the new firm, after being independent at the old firm. $1^{0\to1}_{Skilled\ Team}$indicator equals one if the manager joins the team with positive average skill at the new firm, after working with the negative-average-skill team at the old firm. All the variables with $1\to0$ superscript are indicator variables for the reverse transitions. *,**, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors double-clustered by manager and year are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
	y=Δ*Log(Compensation)*$_{t,t+1}$			y=Δ*Log(Productivity)*$_{t,t+1}$		
$1^{0\to1}_{Team}$	0.02	0.04	0.13	0.21**	0.18**	0.17*
	(0.12)	(0.12)	(0.18)	(0.09)	(0.08)	(0.10)
$1^{1\to0}_{Team}$	-0.21	0.09**	0.07	0.06**	-0.10	-0.08
	(0.04)	(0.06)	(0.04)	(0.13)	(0.13)	(0.22)
$1^{0\to1}_{Skilled\ Team}$	0.16	0.12	0.04	0.34**	0.21**	0.31*
	(0.13)	(0.11)	(0.18)	(0.16)	(0.10)	(0.16)
$1^{1\to0}_{Skilled\ Team}$	0.13*	0.13*	0.19**	0.21	0.15	0.30
	(0.07)	(0.07)	(0.08)	(0.14)	(0.17)	(0.21)
$1_{Skilled}\times1^{0\to1}_{Team}$		0.08	0.04		0.38	0.61*
		(0.10)	(0.19)		(0.26)	(0.28)
$1_{Skilled}\times1^{1\to0}_{Team}$		0.07**	0.08**		0.09	0.09
		(0.03)	(0.03)		(0.28)	(0.48)
$1_{Skilled}\times1^{0\to1}_{Skilled\ Team}$		0.19	0.22		0.14**	0.15**
		(0.22)	(0.31)		(0.06)	(0.06)
$1_{Skilled}\times1^{1\to0}_{Skilled\ Team}$		0.14**	0.13**		0.25	0.44
		(0.06)	(0.06)		(0.38)	(0.56)
Observations	263	263	161	252	252	159
R-squared	0.26	0.26	0.38	0.41	0.42	0.56
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	No	No	Yes	No	No	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes