Aggregated Compensation Peer Group Disclosure and Managerial Labor Market Competition: A Network Analysis

Ray Rui Gao
University of Southern California
ray.gao@marshall.usc.edu

Yifei Lu
University of Illinois Urbana-Champaign
yifeilu@illinois.edu

October 2025

Aggregated Compensation Peer Group Disclosure and Managerial Labor Market Competition: A Network Analysis

ABSTRACT

In this paper, we develop novel measures of managerial labor market classification and competition by constructing networks of compensation benchmarking peers disclosed in proxy statements. These networks represent firms' relative positions within the managerial labor market. Our classifications strongly predict executive moves across firms, outperforming a comprehensive set of predictors in the literature. Subsequent tests further demonstrate the strength of our methodology in capturing the multidimensional and dynamic features of the managerial labor market. We also validate our competition measures by showing that they are associated with retention tools, such as higher equity pay and longer pay duration. Finally, we apply our measures to test two theoretical predictions. First, we find that labor market competition could explain controversial pay practices. Second, we demonstrate that the labor market provides managers with tournament incentives to deliver superior future performance.

Show me who your friends are, and I will tell you who you are. — a proverb

1. Introduction

Understanding the boundaries and competitiveness of the managerial labor market is important to studies of executive compensation. Although numerous studies have refined product industry classifications (Bhojraj et al., 2003; Hoberg and Phillips, 2016) and competition measures (Ali et al., 2008; Bushman et al., 2016; Li et al., 2013), there has been limited research on the measurement of managerial labor market classifications and competition measures.[1] In this paper, we systematically investigate managerial labor market competition based on a framework of competition adapted from Phillips (2013). Using compensation benchmarking peer group disclosure, we develop network-based managerial labor market classifications and competition measures and apply them to test theoretical predictions related to the managerial labor market.

Empirically characterizing competition in the managerial labor market is challenging because a firm's demand for managerial talent is usually *multidimensional* (Hansen et al., 2021; Kaplan and Sorensen, 2021; Lazear, 2009) and *dynamic* (Brochet et al., 2021; Guay et al., 2015). Despite the complexity of the labor market, existing literature commonly uses product market industries to approximate managerial labor classifications, an approach that only captures a single and static aspect of managerial talent. This approach runs counter to the fact that external hires are more often from outside the same product industry (Cadman and Carter, 2014; Fee and Hadlock, 2003), thus calling for methods to better characterize managerial labor market competition.

We overcome this challenge by conducting network analysis on aggregated compensation benchmarking peer group disclosure. Unlike peers used for relative performance evaluation

---

[1] Throughout the paper, we use "labor" to refer to top corporate executives (i.e., top-five executive officers named in proxy statements) unless otherwise noted (e.g., in a few tests, we only examine CEOs). To distinguish the labor market from the product market, we use the term "classifications" to refer to managerial labor market classifications and the term "industries" to refer to product market industries.

(hereafter RPE peers), which are typically selected from the same industry to filter out noise in firm performance driven by common shocks (Holmström, 1982), compensation benchmarking peers (hereafter compensation peers) are usually drawn from both within and outside the same industry to identify labor competitors with common talent demand to gauge the reservation wage (Holmström and Kaplan, 2003).[2,3] As a result, compensation peer group disclosure contains rich information about firms' dynamic demand for multidimensional talent. Compared to current methods, relying on compensation peers allows researchers to characterize labor market competition without the need to specify numerous factors (e.g., industry, size, location) that reflect similarities in talent demands, as boards have already incorporated these factors into peer choices. In addition, compensation peers selected by boards contain their superior private information about competitors, which is otherwise unobservable to academics (Brickley and Zimmerman, 2010).

We use network analysis to aggregate and extract information about managerial labor market competition from compensation peer group disclosure. Prior work, such as Jaffe (1986) and Hoberg and Phillips (2016), demonstrates the strength of network-based measures in characterizing technological and product markets, respectively. Building on this foundation, our paper extends the network approach to the managerial labor market. Specifically, we construct the compensation benchmarking network by linking firms if one cites the other as its compensation peer. The network assigns each firm to a spatial location based on aggregated benchmarking patterns (e.g., connectedness to other firms), creating a Hotelling-like talent space where nearby firms demand a similar mix of executive skills.[4] Network analysis offers two major advantages in

---

[2] For example, Delta Air Lines mentioned that "our peer group is composed of three major U.S. airlines and eighteen other companies in the hotel/leisure, transportation/distribution/machinery/aerospace/defense, and retail industries," and that "in order to retain and attract the talent we need, Delta must compete with these types of companies".

[3] On average, compensation peers and RPE peers overlap by 44% in our sample.

[4] Hotelling (1929) uses spatial representation to describe the product market where the distance between products reflects the extent of product differentiation.

our research context. First, it helps us extract more information about managerial labor market competition from network features, such as the links beyond direct ones, the density of links, and the spatial location of a firm in the network. Second, it reduces noise in peer choices and is less likely to be affected by opportunistic peer selections because a firm's relative position in the entire network is *jointly* determined by all firms.

With the network representation, we first examine "who are the competitors" and construct managerial labor classifications (hereafter, MLCs) with different granularities. Our first and narrowest classification, Direct Peer, defines firms within the same classification as those who either benchmark against or are benchmarked by a focal firm. Our second classification, Indirect Peer, consists of direct peers of a focal firm's direct peers, following the transitive property of connections. Our final and broadest classification, Louvain Peer, includes all peers in the same cluster (hereafter, Louvain group) identified by the Louvain method. This heuristic optimization algorithm is commonly used to detect communities in large networks by maximizing intra-cluster and minimizing inter-cluster links (Blondel et al., 2008). Intuitively, in our research context, managers of firms from the same (different) Louvain group have similar (different) skills.

We validate and demonstrate the strength of our MLCs by examining to what extent they predict talent flows (i.e., job-hopping), a natural manifestation of talent competition. We show that MLCs not only strongly predict future talent flows but also outperform a comprehensive set of factors used in the literature to identify labor market competitors (e.g., industry, size, location). The explanatory power of MLCs *alone* is comparable to that of all existing predictors *combined*, suggesting that MLCs identify labor market competitors more effectively than conventional methods. Moreover, we show that executives are likely to move to both selected peers (i.e., compensation peers selected by the focal firm) and potential peers (i.e., peers *not* selected by the

focal firm but belonging to the same MLCs), indicating that using MLCs based on aggregated peer group disclosure helps identify additional labor competitors beyond self-identified ones.

We conduct two additional tests to further demonstrate the appealing features of our MLCs — multidimensional and dynamic. First, we distinguish our labor classifications from product industries, which are commonly used in previous research to identify labor market competitors, by dividing labor market peers into two sub-groups: peers within versus outside the same product industry as the focal firm. We find that both sub-groups have strong predictive power for future talent flows, suggesting that MLCs capture firms' demands for multidimensional skills beyond industry-related knowledge. Second, we examine the dynamic feature of MLCs and show that current peers (i.e., firms that are currently in MLCs) have greater predictive power for talent flows than past or future peers (i.e., firms that were in or will join MLCs). This evidence demonstrates MLCs' dynamic feature and highlights the evolving nature of managerial labor market competition.

Next, we examine "how fierce is the competition" and construct competition measures to quantify the magnitude of managerial labor market competition faced by each firm. Our measures build on two constructs in contracting theories, namely outside opportunities (Oyer, 2004) and talent transferability (Murphy and Zábojník, 2004, 2007). Firms face greater managerial labor market competition when their executives have more outside opportunities and when the executives' talents are more suitable for potential employers. Using network analysis, we construct five competition measures at different granularity levels. The most local measure only considers competition from the closest competitors, whereas the most global measure considers competition from all the firms in the compensation benchmarking network.

While our competition measures primarily reflect labor demand, they may also capture aspects of labor supply, such as the size or quality of the available talent pool. Therefore, we

validate our measures by examining how they shape compensation contracts. We find that CEOs of firms facing more competition, as proxied by our measures, receive higher compensation. Moreover, the increase in compensation is in the form of equity pay with longer vesting periods instead of cash pay, consistent with the talent retention motive of equity pay (Balsam and Miharjo, 2007; Jochem et al., 2018). These results suggest that our measures are associated with talent retention strategies, thus providing support for the interpretation that they predominantly capture labor demand, as more supply would reduce the need for such efforts.

Finally, we apply our labor classifications and competition measures to examine two theories. First, Oyer's (2004) theoretical model demonstrates that outside opportunities in the managerial labor market could explain seemingly problematic compensation practices, such as pay for luck (Bertrand and Mullainathan, 2001) and the relative performance evaluation (RPE) puzzle (Murphy, 1999). The literature so far, however, has mixed evidence on this question partially because of the lack of direct measures on labor competition. We revisit this question by applying our competition measures that are intended to capture competition directly. Consistent with the theory, we find that firms pay more for luck and use less RPE when they face greater competition.

Second, Fama (1980) theoretically shows that the labor market can serve as an incentive device to discipline managers. According to the tournament theory (e.g., Lazear and Rosen, 1981), a CEO strives to outperform her labor market competitors to get better-paid jobs (i.e., win the tournament). In this case, outside employment opportunities incentivize managers to deliver superior performance, and such incentive increases with the tournament prize. One challenge to empirically test this theory is to identify a manager's potential employers, which are then used to measure the tournament prize. We overcome this challenge by applying MLCs to identify potential employers. Consistent with external tournament incentives, we find that a CEO incentivized by a

larger tournament prize, proxied by the pay gap between her current pay and the second highest pay among her potential employers in the same MLC, is associated with superior firm performance. In contrast, we fail to find tournament incentives using product industry peers as potential employers. These findings suggest that MLCs better capture the theoretical notion of rivals in a tournament, thereby allowing for more powerful tests of the theory. In addition, if the labor market is efficient in the sense that firms scout for managers with higher marginal productivity, the compensation used to retain managerial talent should induce better performance. We employ a similar research design as Core et al. (1999) and find that the component of compensation explained by our competition measures is associated with better future accounting and stock performance, indicating that managers who are more sought after deliver superior performance.

Our study contributes to the literature on the managerial labor market. First, we develop novel network-based managerial labor classifications and competition measures. Our method captures the multidimensional and dynamic nature of firms' competition for managerial talent. In this way, our paper directly speaks to two understudied components in the framework of managerial labor market competition, namely, the identification of competitors and the measurement of competition. Filling this gap is important because these two components often set the stage for examining other aspects of labor market competition. Moreover, our results convey an important message to the literature by showing that labor market competitors are related to but different from product market competitors, casting doubt on the common practice of using the product market to approximate the managerial labor market.

Second, our paper provides empirical evidence of several labor theories (e.g., Fama, 1980; Oyer, 2004). Our measures better capture the underlying theoretical constructs and thus allow for more powerful tests. Inaccurately identifying the labor market for executives can prevent

6

researchers from drawing appropriate inferences about contracting theory (e.g., Cadman and Carter, 2014). Our findings on the use of RPE and external tournament incentives deepen our understanding of the interplay among the managerial labor market, manager incentives, and compensation contract design.

Finally, our paper also contributes to the compensation disclosure literature. Recent studies document that the expanded compensation disclosure mandated in 2006 provides useful information about managerial incentives and firms' prospects (e.g., Bloomfield, 2021; Ferri et al., 2018; Packard, 2018). Our paper complements these studies and shows that the compensation peer group section in Compensation Discussion and Analysis (CD&A) provides useful information about managerial labor market competition. Moreover, the compensation benchmarking literature is still unsettled on whether peer groups are selected to retain managerial talent (e.g., Albuquerque et al., 2013) or to opportunistically inflate CEO compensation (e.g., Faulkender and Yang, 2010). Our paper offers a fresh perspective by revisiting this question at the aggregate level and suggests that aggregated peer selection reflects an efficient response to managerial labor market competition.

2. Framework and institutional background

2.1 Managerial labor market competition framework

We propose a comprehensive managerial labor market competition framework to guide our analyses. The framework is adapted from Phillips' (2013) discussion on the important aspects of a typical examination of competition and tailored to the job market for executives. It includes five components, starting with the labor market definition, which determines the market or location where firms compete for managerial talent. We focus on the labor market for top executives at U.S. public firms. The second component is the identification of labor market competitors, corresponding to our first research question (i.e., who are the competitors). In subsequent analyses,

we construct labor classifications and demonstrate that they help identify potential competitors for a firm's talent. The third component is the measurement of labor market competition, corresponding to our second research question (i.e., how fierce is the competition). This component aims to quantify the extent of competition faced by a firm. We construct competition measures at the firm-year level and apply them to investigate other components in the framework.

The fourth component of the framework is the type of labor market competition; it considers how firms compete for managers. For example, do they offer higher pay, more attractive forms of pay (e.g., more equity pay, preferable vesting criteria), other preferential treatments (e.g., pay for luck), perks, and non-pecuniary rewards to compete for talent? Recent papers, such as Cadman et al. (2021) and Na (2020), study how labor competition shapes compensation contracts. The last component of the framework is the consequences of labor market competition. For example, losing managerial talent to other firms is a direct consequence of competition. Recent studies document the effect of labor market competition on risk-taking (e.g., Chen et al., 2021), voluntary disclosure (e.g., Ali et al., 2019), and management incentives (e.g., Ma et al., 2020).

Most previous studies on the managerial labor market focus on the last two components of the framework (i.e., how firms compete and the consequences of labor competition). In contrast, few papers study the identification of competitors and the measurement of competition, which usually set the stage for analyses surrounding the last two components in the framework. In this regard, our paper bridges an important gap in the literature.

2.2 Institutional background on compensation peer group disclosure

We focus on the compensation peer group disclosure in proxy statements because it provides valuable information about the job market for executives. As noted in Holmström and Kaplan (2003), the practice of pay benchmarking—comparing the salary of executives at other

firms—enables firms to gauge the market wage for managers and set compensation at a competitive level to retain and motivate top executives.

In practice, talent is one of the top considerations in a firm's peer group selection process. In a recent report on how companies select peers for executive compensation benchmarking purposes, Equilar (2023) collects the peer selection criteria disclosed by firms as part of SEC rules and shows that talent (71.6%), together with industry (88.2%) and revenue (76.6%), are among the top three most mentioned peer group criteria. To further examine how firms select compensation peers, we analyze 200 randomly selected proxy statements of firms with compensation peer changes and find that most firms explicitly disclose their peer selection criteria. Based on these disclosures, we generate a word cloud in Figure 1, where the font size of each keyword reflects word frequency. The analysis highlights common criteria such as revenue, market capitalization, industry, business, operations, and global presence. Notably, many firms also emphasize broader talent competition considerations, frequently using terms such as "compete," "comparable," "peer," "skill," "executive talent," and "competitor" to justify their peer selection.

The compensation benchmarking literature also provides empirical evidence that the competition for talent is one key determinant of compensation peer selection. For example, Faulkender and Yang (2010) find that the competition for talent, proxied by talent flows in the past between the disclosing firm and companies in the four-digit SIC industry, leads to a higher likelihood of being chosen as a peer. In addition, they find other factors, such as whether the candidate company is from the same industry, of similar size, of similar visibility and operational complexity (proxied by market index membership such as S&P 500), and with chairman CEOs are more likely to be compensation peers. This evidence suggests that peer selection reflects the similarity of firms in many dimensions, which demonstrates the benefit of using peer selection in

our research context. Otherwise, it is very challenging to specify a comprehensive list of factors to identify labor competitors.[5]

To further illustrate the advantage of using the compensation peer group to capture labor competition, consider Delta Air Lines' disclosure below in its 2019 DEF 14A filing to justify its peer selection:

> Our peer group is composed of three major U.S. airlines and eighteen other companies in the hotel/leisure, transportation/distribution, machinery/aerospace/defense, and retail industries. *We selected these industries because we believe it is important that our peer group have business characteristics that are similar to Delta's*, including revenue size, market capitalization, number of employees, operating margin, and global presence. *In order to retain and attract the talent we need, Delta must compete with these types of companies*, and if the peer group was limited to the airline industry, we would have to include companies that are a fraction of the size and scope of Delta.[6] *(Emphasis added)*

Note that Delta's peer group is composed of not only other airlines but also non-airline companies, such as Marriott, Coca-Cola, FedEx, Honeywell, and Best Buy. These compensation peers likely contain valuable information about the demand for multidimensional talent beyond the usually focused product industry dimension. To the extent that Delta's operations are related to the hospitality and logistics industry, which complements Delta's main product offerings (e.g., flights), these compensation peers reflect firms' operational features that are informative about labor demand and competition yet difficult to capture using common proxies such as industry or size. Moreover, a firm's peer group is reviewed annually by the compensation committee to ensure appropriateness, allowing us to capture contemporary talent demand changes in the labor market.

---

[5] The literature also finds that firms tend to select peers with higher compensation, yet the explanation is still under debate. For example, Bizjak et al. (2011) and Faulkender and Yang (2010, 2013) argue that benchmarking against higher-paid peers reflects opportunism in peer selection. On the contrary, Albuquerque et al. (2013) argue that this behavior represents a reward for unobserved CEO talent. Schneider (2021) argues that benchmarking against larger firms provides aspirational motivation for CEOs and is consistent with an efficient response to labor market competition. Admittedly, a firm can opportunistically choose peers with higher pay to inflate compensation. Yet, such behavior is unlikely to systematically influence its position in the entire network as it is jointly determined by all firms, which highlights another benefit of our network method.

[6] See Appendix B for complete discussions on the compensation peer groups for Delta Air Lines and Target Corporation in their DEF 14A filings in 2019.

As a result of these reviews, the annual compensation peer turnover rate in our sample is 14 percent.[7] These unique features of compensation peer disclosure help us better capture the multidimensional and time-varying features of the competition in the labor market.

The disclosure also has several other appealing features, making it a natural starting point for constructing our labor classifications and competition measures. First, peer group disclosure is mandated by the SEC and thereby widely available among firms. Second, self-identified peer firms reflect the private information of board members and compensation consultants regarding the managerial labor market. This information is not otherwise available to researchers. Brickley and Zimmerman (2010) similarly note that boards of directors have an advantage in industry benchmarking compared to academics due to their private information about the management team and industry knowledge. Third, peer group disclosure is relatively reliable as it is reviewed by shareholders, proxy advisors, and regulators periodically.

3. Network Analysis

3.1 Data

Our sample period is from 2006, the first year when the compensation peer group disclosure becomes available, to 2018. We first obtain data on compensation peers selected by firms from the ISS Incentive Lab database. This gives us an initial sample consisting of 260,868 focal-peer pairs with non-missing central index keys (CIKs), covering 1,662 unique focal CIKs. Next, we merge focal-peer pairs with the Execucomp database. The matching process yields 1,247 unique focal firms and 177,010 focal-peer pairs. We finally obtain stock prices from CRSP and financial data from Compustat to construct the variables used in our study.

---

[7] For a recent example of firms changing compensation peers due to changes in labor competition, Ebay added Walmart Inc. and Etsy Inc. to its compensation peer group in 2021, citing "due to the retail ecommerce sector increasingly becoming a talent competitor" as the reason behind such change, according to Ebay's proxy statement.

Table 1 Panel A reports the number of focal-peer pairs, unique focal firms, and unique peer firms during our sample period.[8] Figure 2 shows the distribution of peer selections. Panel A shows the histogram of the number of peers disclosed (#Benchmarking). The distribution is bell-shaped, with a long tail to the right. Firms most commonly choose 15 to 19 peers. Panel B shows the histogram of the number of times a firm is selected as a peer (#Benchmarked). In contrast to the number of benchmarking peers, most firms are only benchmarked by a few firms. Finally, Panel C displays the heat map of #Benchmarking versus #Benchmarked. Most of the observations are around the diagonal of the matrix, indicating a positive correlation between #Benchmarking and #Benchmarked.

3.2 Characteristics of the compensation benchmarking network

We construct a compensation benchmarking network for each year using all focal-peer links disclosed in that fiscal year. A directed link from A to B is formed if firm A (i.e., the focal firm) selects firm B (i.e., the peer firm) as its compensation peer. Table 1 Panel B provides summary statistics on the compensation peer groups. On average, focal firms select 15.62 peers and are selected by 5.14 firms. 54 percent of compensation peers come from the same SIC2 industries, 53 percent come from the same TNIC2 industries, and 67 percent have sales within 50-200% of the focal firm.[9] These statistics indicate that product industry or size is important but not the only criterion for peer selection. Peer choices also change over the years. Among 9,888 focal firms that have data for the previous year, each firm, on average, chooses 2.65 new peers and keeps 12.85 old peers, indicating a turnover ratio of 14 percent. While there is a significant degree of persistence in peer selection, this turnover suggests that firms do update their compensation peers

---

[8] Incentive Lab covers the compensation benchmarking data of S&P 500 and most S&P 400 firms. Our sample is comparable to recent studies using the peer benchmarking data from Incentive Lab (e.g., Cadman et al., 2021).
[9] We use SIC2(3) to refer to two-(three-) digit SIC industries, FF12 (FF48) to refer to Fama-French 12 (48) industries, and TNIC2(3) to refer to TNICs from Hoberg and Phillips (2016) as granular as two-(three-) digit SIC industries.

annually to some extent.

3.3 Compensation benchmarking network graphs

Figure 3 presents the compensation benchmarking networks for the year 2018. Each node represents a firm, and the lines connecting nodes represent the benchmarking relations among firms. We use a multilevel layout algorithm developed by Hu (2005) to generate the network graph. This algorithm, which brings together the strengths of force-directed and multilevel algorithms, is especially suitable for displaying large networks because of its efficiency and accuracy. A firm's relative position in the network is representative of this firm's position in the managerial labor market space. Firms closer to (distant from) each other are more (less) likely to be competitors.

Panels A and B are the same except for the coloring of the nodes. In Panel A, we color the nodes based on firms' product industries (i.e., FF12). The figure illustrates that while firms within the same industries tend to cluster together, many firms from different industries are also adjacent, highlighting discrepancies between the managerial labor market and the product market. In Panel B, we color the nodes based on firms' labor groups (i.e., Louvain groups) identified using the Louvain method, a network-based clustering approach. Intuitively, clustering patterns reflect similarity in managerial talent.

Comparing Panel B to Panel A, we find that some adjacent firms from different product industries are assigned to the same Louvain group, whereas some firms from the same product industry are separated into different Louvain groups if they are far away from each other. Such difference further highlights the disparity between the managerial labor market and the product market. The comparison also visually demonstrates the advantage of our network method in capturing multidimensional competition for various executive skills beyond product-related ones.

4. Who are the competitors? Managerial labor classifications (MLCs)

4.1 Method

To illustrate our MLCs and the conceptual underpinning behind our network method, we consider a simplified managerial labor market where firms with heterogeneous demands for two skills compete for managerial talent. Figure 4 Panel A is the graphical representation of such a market, where the horizontal (vertical) axis represents the demand for Skill 1 (Skill 2).[10] Firms that are located more towards the right (top) are those with higher demand for executives with Skill 1 (Skill 2), and vice versa. For example, the focal firm, represented by a dark blue triangle, seeks executives with both high Skill 1 and high Skill 2. Similar to Figure 3, firms that are closer to each other on the graph demand more similar managerial talent, making them labor market competitors.

We define labor market peers in three different ways: Direct Peer, Indirect Peer, and Louvain Peer, with scopes from narrow to broad. Figure 5 graphically illustrates these MLCs. Our first and narrowest classification, Direct Peer, includes firms that are selected by the focal firm as compensation peers (*Selected Peer*, represented by circle B) and firms that are not selected by but select the focal firm as a compensation peer (*Direct Potential Peer*, represented by circle C). Because direct peers possess very similar executive talent as the focal firm, they represent the closest set of firms in the talent space. In Figure 4 Panel A, these peers appear as dark blue dots located within a gray-shaded circle, which represents the peer selection range of the focal firm.

Our second classification, Indirect Peer, is defined as the direct peers of the focal firm's direct peers. The idea is based on the transitive property of links: If firm A and firm B share similar talent demands and firm B and firm C share similar talent demands, firm A and firm C are likely to share similar talent demands, even if they are not direct peers. On the graph, one direct peer of the focal firm extends the range of labor competitors further to the blue-shaded circle (the peer

---

[10] We use "skill" as a catch-all term for executive characteristics, including expertise, ability, and knowledge.

selection range of the direct peer), leading to the inclusion of indirect peers shown as light-blue dots. In this regard, the method helps recover information that is otherwise truncated when relying only on direct linkages. Indirect peers also have the benefit of capturing the intersection of several firm characteristics that represent firms competing for similar managerial talent while excluding firms that are less likely to be selected as peers, potentially reducing the noise and bias introduced by opportunistic peer selection (Cadman and Carter, 2014). Online Appendix 1 (OA.1) shows Target Inc.'s direct peer and indirect peer networks.

Our third classification, Louvain Peer, is based on the Louvain method, a state-of-the-art technique to extract the community structures of large networks in network science. This method is an optimization algorithm that identifies clusters in large networks by optimizing modularity, which measures the extent to which nodes connect more with nodes within the communities than outside those communities (Blondel et al., 2008).[11] As illustrated in Figure 4 Panel A, the Louvain method divides firms into four groups based on the clustering patterns. Firms within the same group are Louvain peers with each other and have similar talent demands. For instance, firms in Louvain Group I demand executives with high Skill 1 and high Skill 2, whereas firms in Louvain Group IV demand executives with high Skill 1 but low Skill 2. The Louvain method has the benefit of aggregating information about the managerial labor market utilizing all peer selections, thereby providing additional information beyond direct and indirect peers.

Table 1 Panel C describes Louvain groups in 2007 and 2018 in terms of the top three main component industries, the average compensation, and the number of firms in each group. Two key observations emerge from this table. First, most Louvain Groups span multiple product industries, again highlighting the multidimensional nature of managerial talent. For instance, group #2 in

---

[11] Louvain method is commonly used to detect clusters in different networks, such as CEOs' personal connection networks (El-Khatib et al., 2015) and institutional investor cliques (Crane et al., 2019).

2018 contains 74 firms from 15 different industries. Second, the composition of Louvain groups changes significantly from 2007 to 2018, demonstrating the dynamic nature of managerial skills. For example, in 2007, "Food Products," "Restaurants, Hotels, Motels," and "Transportation" are clustered in group #6. By contrast, these three industries fall into different Louvain groups in 2018 (i.e., groups #2 and #7), which are likely driven by the changing competitive landscape and business environment. Such changes eventually shift managerial skill set demand.

4.2 Managerial labor classifications and talent flows

As our first set of tests, we investigate talent flows between firms because labor movement is a direct manifestation of labor competition. To acquire suitable managerial talent, firms may poach executives with the skills they need from competitors, resulting in talent flows between firms. If our MLCs indeed capture the competitors of a firm in the managerial labor market, talent flows should be more likely to happen between firms from the same MLC than across different MLCs. We construct a sample of talent flow events following Gao et al. (2015). Specifically, we track EXECID for each executive in the Execucomp database to locate each executive's positions across different firms over the sample period. A talent flow event happens if one of the named executives leaves her previous employer and joins a new firm within a one-year gap.

Table 2 Panel A describes the talent flow sample. Of the 595 top executive moves, 23 percent are to selected peers of the departure firm, 6 percent to direct potential peers, 45 percent to indirect potential peers, and 8 percent to Louvain potential peers.[12] Together, 82 percent of managerial talent flows happen between MLC peers. By contrast, executives move to firms within the same SIC2 product industry (with comparable market size) only 38 percent (36 percent) of the

---

[12] Figure 5 illustrates the relation between MLCs, selected peers, and potential peers. In short, Direct Peer include selected peers and potential direct peers. Indirect (Louvain) Peer is the same as potential indirect (Louvain) peers, as they are not selected by the focal firm as compensation peers by definition. In talent flow tests, selected peers, direct potential peers, indirect potential peers, and Louvain potential peers are mutually exclusive.

time, suggesting that many moves happen between firms from different industries and sizes.[13]

4.2.1 MLCs, selected peers, and potential peers

To compare the power of MLCs versus selected peers and other predictors in the literature in predicting talent flows, we estimate the following logistic model:

$$Talent\ Flow_{ijt+1} = \alpha + \boldsymbol{\beta}(Selected\ Peer)_{ijt} + \boldsymbol{\gamma}(Potential\ Peer)_{ijt} + \boldsymbol{\lambda}(Firm\ Similarity\ Controls)_{ijt}$$
$$+ \boldsymbol{\psi}(Departing\ Firm\ Controls)_{it} + \boldsymbol{\omega}(New\ Firm\ Controls)_{jt} + \varepsilon_{ijt} \qquad (1)$$

Talent Flow$_{ijt+1}$ is an indicator variable that takes the value of one if at least one of the top five executives of firm i moves to the top five executive positions of firm j within a one-year gap in year $t+1$, and zero otherwise. *Selected Peer$_{ijt}$* is an indicator that takes the value of one if firm j is selected by firm i as its compensation peer in year t, and zero otherwise. *Potential Peer$_{ijt}$* is a set of indicators that takes the value of one if firm j is *not* selected by firm i as its compensation peers in year t, but identified as firm i's labor market peers based on MLCs (i.e., *Direct Potential Peer*, *Indirect Potential Peer*, and *Louvain Potential Peer*); and zero otherwise. We also include a set of *Firm Similarity Controls* that determine peer selection (e.g., Faulkender and Yang, 2010; Albuquerque et al., 2013), such as *Product Market Peer Dummies* (e.g., *Same SIC2* and *Same TNIC2*), historical talent flows, size similarities, and geographical proximity. Finally, we control for firm characteristics that can potentially affect turnover, including firm size, growth opportunities, and past performance for both the focal firm i and the peer firm j.

Table 2 Panel B presents the results based on Eq. (1). Column (1) shows the result of regressing *Talent Flow* on *Selected Peer* along with the predictors specified in Faulkender and Yang (2010). The coefficient on *Selected Peer* is positive and significant at the 1 percent level, suggesting that compensation peers contain additional information about the managerial labor

---

[13] Online Appendix 2 (OA.2) provides examples of talent flow between firms not in the same industry but belong to the same MLC.

market. We subsequently add three indicators of potential peers in column (2). The coefficients on these indicators are also positive and significant at the 1 percent level, indicating additional information content uncovered using the network method. As for control variables, we find executives are more likely to move to a firm in the same industry, with a similar size, with a similar non-powerful CEO, and having historical talent flows with the focal firm.

In column (3), we include 18 additional controls that predict talent flows between firms, including similarity in profitability and complexity, geographical proximity, common compensation consultant, same TNIC industries, industry returns correlation, and characteristics of focal or peer firms. The coefficients on four MLC indicators remain positive and significant, indicating that MLCs uncover labor information beyond factors specified by researchers. In terms of economic magnitude, *Selected Peer*, *Direct Potential Peer*, *Indirect Potential Peer*, and *Louvain Potential Peer* rank first, second, third, and fifth among all predictors by relative margins.[14,15] The coefficient on *Selected Peer* (i.e., Direct Selected Peer) is statistically larger than all the 20 dummy control variables based on pairwise t-tests (p-value < 0.05). The coefficients on *Direct Potential Peer*, *Indirect Potential Peer*, and *Louvain Potential Peer* are statistically larger than 19, 19, and 18 of the 20 dummy control variables, respectively (p-value < 0.05).

To further demonstrate the strength of our MLCs, we run two additional regressions and show the results in columns (4)-(5). The pseudo-R^2 is 9.7% for the regression with only MLC

---

[14] Relative margins are defined as the predictive margins if the indicator equals one divided by the predictive margins if the indicator equals zero. For example, the relative margins of 11.578 for *Direct Potential Peer* means that the executive of a firm is 11.578 times more likely to move to a direct potential peer firm than a non-direct potential peer firm, after controlling for other variables.

[15] Analyst coverage-based peers can also be useful in identifying labor competitors because analysts commonly co-cover companies sharing similar fundamentals (Ali and Hirshleifer, 2020; Kaustia and Rantala, 2021; Lee et al., 2016). Conceivably, these firms need similar managerial talent to manage similar business activities. We add analyst peers to the talent flow prediction model and present the results in Online Appendix 3 (OA.3) Panel A. We find that analyst peers are strong predictors of talent moves. Analyst peers rank number 5 among all predictors by relative margin. Nevertheless, the coefficients on MLCs are still statistically and economically significant, suggesting that the information captured by MLCs is incremental to that captured by analyst coverage-based peers.

indicators included in column (4) and 7.5% in column (5) for the regression with all the predictors in Faulkender and Yang (2010) included. [16] Therefore, the MLC indicators predict talent flows better than the 11 predictors combined. Moreover, comparing column (2) with (5), the pseudo-R^2 increases by 58.7% (11.9/7.5 – 1) after including the MLC variables, indicating that MLCs contain significant competition-related information beyond predictors in the literature. Finally, we address the rare event bias in logistic regression documented in King and Zeng (2001) since job hopping is a rare event. We follow the suggestion from Allison (2012) and implement the penalized likelihood method by Firth (1993). As shown in OA.3 Panel C, our results remain robust after correcting for rare event bias using the Firth logit model.

The strength of our MLCs over researcher-determined factors is that they implicitly capture different facets of managerial skills in a condensed fashion. In contrast, it is hard to develop labor competitor groups based on numerous determinants because (1) managerial skills are many, and some of them are unobservable; (2) the list of managerial skills demanded by firms is often firm-specific; and (3) the intersection (union) of the determinants ends up with a too small (large) group.[17]

Collectively, the results in Table 2 demonstrate that MLCs significantly predict future talent flows, with a predictive power both comparable with and incremental to a comprehensive list of researcher-determined predictors. We also show that while firms identify some managerial

---

[16] The greater economic significance of MLCs is not driven by the larger size of these MLC groups. Instead, it is ultimately determined by the signal-to-noise ratio. To further alleviate this concern, we include FF12 industry, which has a size similar to the Louvain group, as well as smaller groups with industry-size matched peers. We find qualitatively similar results. See OA.3 Panel B for robustness tests after including these additional predictors.

[17] The definition of MLCs is based on the discrete geodesic distance measure, representing the minimum number of edges that need to be traversed to get from one node to another. Although geodesic distance is the most common distance measure in the network literature, a continuous distance measure may potentially capture more variation. Therefore, we construct Euclidean distance based on similarities in peer profiles (i.e., Direct Peer) as a continuous distance measure and test whether it predicts future talent flows. Online Appendix 4 (OA.4) provides detailed discussions on Euclidean distance construction. The result suggests that continuous Euclidean distance measures capture additional information about the managerial labor competition, though the incremental information is modest.

labor market competitors via peer benchmarking, they can also spot potential competitors by analyzing other firms' compensation peer disclosures. Therefore, we encourage firms to analyze aggregated compensation peer group disclosures to spot potential labor market competitors.

4.2.2 Multidimensional and time-varying features of MLCs

In this section, we demonstrate the multidimensional and time-varying features of MLCs. We illustrate the multidimensional feature by showing that MLCs are incremental to product industries, a commonly used approximation of the managerial labor market in the literature. To isolate the product industry component of MLCs, we decompose MLCs into peers from the same product industry (i.e., TNIC2 or SIC2) and peers from different product industries. We then regress *Talent Flow$_{ijt+1}$* on the decomposed MLCs to test whether the predictive power of MLCs comes from firms inside or outside the same product industry. If MLCs capture a single dimension of executive similarity (i.e., product market), the MLCs outside the same product industry should have little predictive power for *Talent Flow$_{ijt+1}$*. Our regression model is as follows:

$$Talent\ Flow_{ijt+1} = \alpha + \boldsymbol{\beta}(Same\ Industry\ MLC)_{ijt} + \boldsymbol{\gamma}(Diff\ Industry\ MLC)_{ijt}$$
$$+ \boldsymbol{\lambda}(Firm\ Similarity\ Controls)_{ijt} + \boldsymbol{\psi}(Departing\ Firm\ Controls)_{it} + \boldsymbol{\omega}(New\ Firm\ Controls)_{jt} + \varepsilon_{ijt}\ (2)$$

Same Industry MLC$_{ijt}$ is a vector of indicators that take the value of one if firm *i* and *j* belong to the same product industry and are within the same MLC in year *t*, and zero otherwise. *Diff Industry MLC$_{ijt}$* is a vector of indicators that take the value of one if firm *i* and *j* belong to different product industries but are within the same MLC in year *t*, and zero otherwise. The control variables are the same as those included in column (3) of Table 2 Panel B.

Table 3 Panel A presents the results. In column (1), we find that the coefficient on *Direct Peer Diff Product Industry* is positive and significant at the 1 percent level. Moreover, executives are even more likely to move to direct peers that are outside than inside the same product industry,

as the coefficient on *Direct Peer Diff Product Industry* is significantly larger than that on *Direct Peer Same Product Industry* (p-value < 0.01). In columns (2)-(3), we add decomposed indirect peers and Louvain peers to the regression and continue to find that different industry components are strong predictors for talent flows, though the economic magnitude is not larger than the same industry component. In column (4), we decompose combined MLC groups into *Same Product Industry* and *Diff Product Industry* and again find that they both strongly predict future talent flows.

Next, we investigate the time-varying feature of MLCs. The average turnover rates of direct peers, indirect peers, and Louvain peers are 17%, 25%, and 31%, respectively, suggesting that MLCs change substantially over time. The network methods amplify the change in peer selection, as indirect peers and Louvain peers change more often than direct peers. To formally test the time-varying benefit of MLCs, we employ a research design similar to Jayaraman et al. (2021) and examine the extent to which past, current, new, and future MLC peers predict future talent flows. Past peers are firms that were firm i's MLC peers in year t-1 but not in year t; New peers are firm i's MLC peers in year t but not in year t-1; Current peers are firm i's MLC peers in year t-1 and in year t; Future peers are firm i's MLC peers in year t+1 but not in year t. We include these peer indicators in Eq. (1) and re-estimate the talent prediction model. If our MLCs indeed capture the dynamics in talent demands and competition, we expect that current and new peers to have a stronger predictive power in predicting future talent flows than past and future peers.[18,19]

Table 3 Panel B reports the results. In columns (1)-(3), we decompose MLCs of different granularity into past, new, current, and future peers and find that the predictive power of *New Peer*

---

[18] Online appendix 5 (OA.5) shows that firms replace peers in a manner consistent with talent similarity rather than opportunism. New peers have lower pay and are slightly smaller than past peers but are more similar to focal firms in key dimensions such as industry, size, past talent movements, profitability, and global presence.
[19] We require that peers appear in the intersection of ISS, Compustat, and CRSP in year t-1, t, and t+1 in the regression analysis. Therefore, peer changes due to mechanical reasons such as acquisition, bankruptcy, or delisting are not included in our sample, and thus do not affect our results.

and *Current Peer* are generally larger than that of *Past Peer* and *Future Peer*, suggesting that firms that dropped out of the talent space or will enter the talent space in the future are less likely to compete for talent in year *t*. In column (4), we decompose the combined MLC groups and find similar results. The economic magnitude measured by relative margins also indicates that new and current MLC peers are more relevant labor market competitors than past and future MLC peers. The coefficient on *Current Peer* is significantly larger than that on *Past Peer* and *Future Peer* (p-value < 0.01).

Overall, the evidence highlights that MLCs capture the multidimensional and time-varying features of labor competition. Our findings question the common practice of approximating managerial labor competitors with product market classifications (usually static) in the literature.

5. How fierce is the competition? Managerial labor competition measures

5.1 Method

We construct measures of managerial labor market competition based on the information revealed in the compensation benchmarking network. Our competition measures are related to two theoretical constructs. The first construct is the number of outside opportunities. Compensation theories view outside opportunities as an important determinant of compensation contracts through participation constraints (Oyer, 2004; Giannetti, 2011). More outside opportunities increase the chance of executives being poached by rival firms and thus serve as a proxy for competitiveness in the managerial labor market. The second construct is the transferability of the executive talent to other firms. Executive talents increase a firm's productivity more when they fit into the talents required by the firm's tasks. Hence, firms face higher poaching risks when their executive skills are more transferrable (Murphy and Zábojník, 2004, 2007).

Figure 4 Panels B and C graphically illustrate the relation between these two constructs

and network-based competition measures in a two-skill managerial labor market. The notion of outside options is explained in Panel B, where firms falling in the shadowed area are suitable outside options for the CEO of firm A. Panel B(1) shows an example of a CEO with fewer outside opportunities, as only a couple of firms demand similar skills as the focal firm, whereas Panel B(2) shows an example of a CEO with more outside opportunities, as many firms demand similar skills as the focal firm. Panel C demonstrates the notion of the transferability of managerial talent. Panel C(1) provides an example of a CEO with low-transferability peers, as the focal firm's peers are further away (i.e., dissimilar talent demands). By comparison, Panel C(2) shows an example of a CEO with high-transferability peers, as the focal firm's peers are closer to each other.

We construct five measures based on these two constructs using the network method and describe our measures following the scope of the labor classifications, from local to global. The first measure is in-degree centrality (*InDegree*), measured as the number of firms citing the focal firm as a compensation peer. [20] *InDegree* captures the number of outside options for the executives in the most narrowly defined market. The second measure is the clustering coefficient (*Clustering*), which captures the degree to which neighboring firms in the network cluster with the focal firm (Hanneman and Riddle, 2005). Peer firms' talent demand is more similar to the focal firm's demand if peer firms are more closely clustered with the focal firm in the network. Hence, *Clustering* captures the transferability of the focal firm's talent with its direct peers.

Our third and fourth measures are constructed based on the Louvain groups. *Louvain Size* is the number of firms in each Louvain group. It captures the number of outside options for the firm within a broader definition of labor market competitors. *Louvain Density* is the density of

---

[20] We do not count the number of peer firms cited by a focal firm to alleviate biases in peer selection because the focal firm has direct control over the number of peers it chooses. In contrast, the focal firm does not have direct control over the competition measures we are using, which are jointly determined by other firms.

links within the same Louvain group. It calculates the extent to which the firms cluster in the same Louvain group and thus captures the transferability of talents in a broader group.

The fifth measure is eigenvector centrality (*Eigenvector*), which measures the average closeness with all the other firms in the network (Hanneman and Riddle, 2005). This measure captures the transferability of talent in the broadest sense by assuming that all the firms in the network are potential managerial labor competitors. Central firms face competition from all kinds of firms, while peripheral firms only compete with firms around them in the local market.

Table 4 Panel A provides summary statistics for our managerial labor competition measures. [21] On average, firms in our sample are chosen by 13.8 firms as compensation peers. The mean value of *Clustering* is 0.32, meaning that two direct peers of a firm are also direct peers with each other 32 percent of the time. The average *Louvain Size* and *Louvain Density* are 159.38 and 0.06, respectively, suggesting that the Louvain group has 159.38 members on average and that firms are direct peers of 6 percent of other firms within the same Louvain group. The mean of the network centrality measure *Eigenvector* is 0.02, with a median of 0.01 and a standard deviation of 0.09. These statistics suggest that most firms are at the periphery and scattered in the outskirts of the network, yet a small number of firms are at the center of the network (with larger Eigenvector centrality). This hub-and-spoke pattern is graphically illustrated in Figure 3.

We conduct principal component analysis on the five network measures to reduce dimensionality. We extract two principal components with eigenvalues greater than one, and they collectively explain 63.17 percent of the variation in the five network measures we use. Panel B shows the factor loading on competition measures. Based on the factor loading of each component, our two principal components capture the two theoretical constructs behind labor competition that

---

[21] Online Appendix 6 (OA.6) provides autocorrelations of our network measures in Panel A, firms with the highest and lowest competition measures in 2018 in Panel B, and the correlation matrix in Panel C.

we intend to capture. The first principal component mainly reflects the transferability construct. *Clustering* and *Louvain Density*, which are intended to capture similarity in talent demands, have the largest loading coefficients in this component (i.e., 0.523 and 0.524). The second principal component mostly captures the outside opportunities construct. *InDegree* and *Louvain Size*, which capture the number of similar firms, have the largest loading coefficients in this component (i.e., 0.531 and 0.537). The loading coefficient on *Eigenvector* is also larger on this component than Component 1, suggesting a higher association with the second principal component.

To understand the determinants of our competition measures, we estimate models regressing each competition measure on firm characteristics and corporate governance proxies. The results, presented in Online Appendix 7 (OA.7), show that our network measures are positively associated with pay level and firm size. We interpret this as evidence that our measures capture labor competition, as higher-quality CEOs tend to be assigned to larger firms and receive higher pay (Gabaix and Landier, 2008). However, an alternative interpretation is opportunism in peer selection—large and high-paying firms are central because peers use them to justify higher pay (Faulkender and Yang, 2010). Nevertheless, we find no significant correlations between our competition measures and corporate governance proxies, including the E-index (Bebchuk, Cohen, and Ferrell, 2009), board independence, and CEO tenure, which is inconsistent with opportunistic peer selection. We further investigate this issue in Section 6.2.2.

Another caveat is that our competition measures could also capture the supply of talent, such as the size and quality of available talent. Since this interpretation cannot be ruled out ex-ante, we rely on validation tests in the next section to determine whether the variation captured by our measures aligns more closely with competition or the supply of talent.

5.2 Managerial labor competition measures and executive compensation

5.2.1 Total compensation

We first investigate the relation between competition measures and total compensation. We expect competition measures to be positively associated with total compensation because firms increase the total compensation level to retain CEOs when managerial labor market competition is greater (e.g., Gabaix and Landier, 2008; Terviö, 2008).

We use the following specification to test the relation between our measures and total pay:

$$
\begin{aligned}
Ln(Total\ Pay)_{i,t} = \alpha &+ \boldsymbol{\beta}(Network\text{-}based\ Labor\ Competition\ Measures)_{i,t} \\
&+ \gamma_1 Ln(Product\ Mkt\ Peer\ Pay)_{i,t} + \gamma_2(Number\ of\ Product\ Peers)_{i,t} + \boldsymbol{\lambda}(Controls)_{i,t-1(t)} \\
&+ Fixed\ effects + \varepsilon_{i,t}
\end{aligned}
\tag{3}
$$

The dependent variable is the natural logarithm of total compensation to the CEO at firm *i* in year *t*. The variables of interest are the *Network-based Labor Competition Measures*, including *InDegree*, *Clustering*, *Louvain Density*, *Louvain Size*, and *Eigenvector*, or the two principal components (i.e., *PCOMP1* and *PCOMP2*) of these variables. We standardize these measures to have zero mean and unit variance in all the regressions to facilitate the interpretation of economic magnitude. Regarding control variables, we include the median total pay among similar-sized product market peers and the number of firms within the same product market to isolate labor market competition from product market competition. [22] In addition, we control for other determinants of CEO compensation documented in the literature, such as stock returns, return on

---

[22] In our baseline regression, we do not control for the median total compensation in the compensation peer group. Although prior studies (e.g., Faulkender and Yang, 2010; Bizjak et al., 2011) document a positive effect of median peer group pay on total CEO compensation, including it in our analysis might obscure the relationship between labor competition and executive pay. This is because median peer pay partly reflects competition from direct peers, which overlaps with our competition measures capturing competition from all potential competitors, including direct peers. Also, controlling for median peer pay may introduce collider variable issue, which complicates the interpretation of the coefficients on our competition measures. Given the close relation between our peer selection-based competition measures and median peer pay, it is not feasible to interpret the effect of our measures on total compensation holding median peer pay constant. Nevertheless, following suggestions from Whited et al. (2022), we estimate an alternative model including median peer pay in the Online Appendix 8 (OA.8) test (1). Our results remain robust, though the magnitude of the coefficients on our competition measures decreases slightly, confirming our intuition that median peer pay subsumes the labor competition from direct peers.

assets (ROA), firm size, market-to-book ratio, leverage, and volatility. Finally, we add industry and year fixed effects in Eq. (3).

Table 5 Panel A presents the results of the analysis. In columns (1)-(4), we find that all five measures are associated with higher CEO compensation. The coefficients of *InDegree*, *Clustering*, *Louvain Density*, *Louvain Size*, and *Eigenvector* are all positive and significant at the 1 percent level. When we include all five measures together in column (5), the coefficients of all the measures remain positive and significant, indicating that our competition measures capture distinct aspects of executive labor market competition. The most local measure, *InDegree*, has the largest economic significance, suggesting closest peers as a significant source of labor competition.[23] However, other more global measures also considerably increase CEO compensation, indicating that network methods help capture competition from a broader set of firms. Finally, we use the principal components based on the five measures. In column (6), we find that *PCOMP1* and *PCOMP2* are positively associated with compensation. In terms of magnitude, a one standard deviation increase in *PCOMP1 (PCOMP2)* is associated with a 6.9 percent (7.0 percent) increase in CEO compensation, respectively. In column (7), we include Industry×Year fixed effects to further control for the effect of the product market on executive compensation, and the results remain robust.

We conduct a battery of robustness tests in OA.8 using additional controls, such as the general ability index developed by Custodio et al. (2013), corporate governance proxies (e.g., E-index, board characteristics, etc.), and the competition proxy developed by Cadman et al. (2021). We also use different subsamples, alternative fixed effects, and alternative clustering schemes. Our

---

[23] The coefficient on *InDegree* is statistically larger than the coefficients on the other four network measures (p-value < 0.01). For comparisons between other pairs of network measures, the coefficient on *Louvain Size* is statistically larger than that on *Eigenvector* (p-value < 0.05). We caution that the economic magnitude only reflects the strength of association between our competition measures and CEO pay rather than the total causal effect of labor competition.

results remain similar in these robustness tests. In Online Appendix 9 (OA.9), we further show that the above results also extend to non-executive officers (NEOs), suggesting that our measures also capture the magnitude of labor market competition for NEOs.

5.2.2 Compensation components and pay duration

To further validate our competition measures, we test their association with different components of compensation. Balsam and Miharjo (2007) and Jochem et al. (2018) show that restricted equity grants provide CEOs with incentives to remain with the firm because the forfeited benefits upon leaving the firm increase the CEO's cost of taking outside opportunities. Hence, we expect firms facing greater labor competition to have higher equity pay and longer vesting periods.

To test our prediction, we replace the dependent variable in Eq. (3) with either total equity pay, total cash pay, or the percentage of equity pay. Table 5 Panel B reports the results on pay components. Consistent with our prediction, we find that higher labor market competition is significantly associated with higher equity pay (column 1) and equity pay percentage (column 3). By contrast, we find weaker results for cash pay (column 2). In terms of magnitude, a one standard deviation increase in *PCOMP1 (PCOMP2)* is associated with a 15.1 (23.6) percent increase in equity pay. In column (4), we use the pay duration measure developed by Gopalan et al. (2014) to capture the vesting period of different pay components. We find that *PCOMP1* is positively and significantly associated with pay duration, suggesting that boards lengthen vesting schedules to retain executives when facing more competition. Collectively, the results in Table 5 further support the validity of our competition measures.

Overall, the above findings demonstrate that our competition measures are closely linked to retention tools, such as higher total and equity-based compensation and longer pay duration. These results are more consistent with our measures capturing competition instead of talent supply,

as higher supply should reduce the need for retention-related contract design.

6. Applications to theoretical questions

6.1 Participation constraints and incentive contracts

Oyer (2004) argues that firms reward CEOs for luck to retain managerial talent because CEOs' outside opportunities vary with the luck component. However, the literature so far finds mixed evidence regarding this theory.[24] One challenge that researchers face in examining how labor market competition affects compensation contracts is the measurement of labor competition. Our direct competition measures allow us to revisit this question and offer a cleaner test.

First, we examine how labor market competition affects pay for luck following the approach in Daniel et al. (2020). We first decompose firm stock returns into components attributable to *Luck* and *Skill* by regressing a firm's monthly stock returns (*FirmReturn*) on monthly industry (*IndReturn*) and market returns (*MktReturn*) for each firm-year:

$$FirmReturn_{i,t} = \alpha_i + \beta_i IndReturn_{j,t} + \delta_i MktReturn_t + \varepsilon_{i,t} \qquad (4)$$

where *j* refers to the industry of firm *i*. *Luck* is measured as the annualized monthly fitted value of industry returns and market returns (i.e., $\hat{\beta}_i IndReturn_{j,t} + \hat{\delta}_i MktReturn_t$), whereas *Skill* is measured as the annualized monthly intercept plus residual (i.e., $\hat{\alpha}_i + \varepsilon_{i,t}$). We then estimate how pay for luck changes with labor market competition based on the following model:

$$\begin{aligned}
Ln(Total\ Pay)_{i,t} = {} & \alpha + \boldsymbol{\beta}_1 Skill_{i,t} + \boldsymbol{\beta}_2 Luck_{i,t} + \boldsymbol{\beta}_3 Skill_{i,t} \times PCOMP1_{i,t} \\
& + \boldsymbol{\beta}_4 Skill_{i,t} \times PCOMP2_{i,t} + \boldsymbol{\beta}_5 Luck_{i,t} \times PCOMP1_{i,t} + \boldsymbol{\beta}_6 Luck_{i,t} \times PCOMP2_{i,t} \\
& + \boldsymbol{\beta}_7 PCOMP1_{i,t} + \boldsymbol{\beta}_8 PCOMP2_{i,t} + \lambda(Controls)_{i,t-1(t)} + Fixed\ effects + \varepsilon_{i,t} \qquad (5)
\end{aligned}$$

---

[24] For example, Bizjak et al. (2008) provide evidence that the pay for luck practice can be driven by a firm's desire to adjust pay to retain talent. Rajgopal et al. (2006) and Na (2020) find that firms use less RPE when managers have more outside opportunities on the job market. In contrast, De Angelis and Grinstein (2020) document that firms refrain from using RPE when the market for CEO talent is less transferrable.

Table 6 Panel A presents the results. In column (1), the coefficient on *Luck* is positive and significant, suggesting the existence of pay for luck. In columns (2)-(3), we find that the coefficients on *Luck × PCOMP1* and *Luck × PCOMP2* are positive and significant, indicating that firms pay more for luck to retain their CEOs when facing more intensive labor market competition.

Next, we turn to the tests on the use of RPE. We follow the RPE specification in Albuquerque (2009) and Jayaraman et al. (2021) to examine the relation between labor market competition on RPE:

$$
\begin{aligned}
Ln(Total\ Pay)_{i,t} = {} & \alpha + \beta_1 Ln(ReturnOwn)_{i,t} + \beta_2 Ln(ReturnPeer)_{i,t} \\
& + \beta_3 Ln(ReturnOwn)_{i,t} \times PCOMP1_{i,t} + \beta_4 Ln(ReturnOwn)_{i,t} \times PCOMP2_{i,t} \\
& + \beta_5 Ln(ReturnPeer)_{i,t} \times PCOMP1_{i,t} + \beta_6 Ln(ReturnPeer)_{i,t} \times PCOMP2_{i,t} \\
& + \beta_7 PCOMP1_{i,t} + \beta_8 PCOMP2_{i,t} + \lambda(Controls)_{i,t-1(t)} + Fixed\ effects + \varepsilon_{i,t}
\end{aligned}
\tag{6}
$$

where *Ln(Total Pay)* is the total compensation in fiscal year *t*, focal firm return (*Return Own*) is the focal firm's stock returns throughout fiscal year *t*, and peer firm return (*Return Peer*) is the equal-weighted TNIC3-size matched peers throughout the focal firm's fiscal year *t*.[25]

In Table 6 Panel B column (1), we confirm the use of RPE in our sample. The coefficient on *Ln(Return Peer)* is negative and significant, suggesting that the CEO is punished (rewarded) when peers are performing better (worse). In terms of the magnitude of RPE, the RPE ratio is -0.654 (-0.125/0.191) and significantly different from negative one, suggesting weak-form RPE (i.e., not strong-form RPE).[26] In column (2), we find that the interaction terms between *Ln (Return Peer)* and *PCOMP1*(*PCOMP2*) are positive and significant, indicating that firms facing stronger labor market competition use less RPE because they now become less sensitive to peer stock

---

[25] Our RPE results remain robust using the alternative RPE specification in Antle and Smith (1986).
[26] The strong-form RPE test follows Aggarwal and Samwick (1999) and Jayaraman et al. (2021). If the common industry shock in performance is completely filtered out, then the RPE ratio should not be significantly different from -1.

returns. In terms of economic magnitude, a one standard deviation increase in *PCOMP1* (*PCOMP2*) increases the RPE ratio from -0.638 to -0.347 (-0.317), a 45.6% (50.3%) increase in percentage term.

Finally, we add additional controls that affect the use of RPE, including idiosyncratic variance (*Idio Var*), the number of peer firms within the same product industry (*FF Peer Num*), the return correlation with peer firms (*Ret Corr*), by interacting them with peer returns. This test helps rule out the possibility that our results on labor market competition and RPE use reflect systematic differences in other dimensions beyond the labor market. As shown in column (3), the coefficients on peer return and competition measures remain positive and significant with these additional controls. Furthermore, the interaction terms load in a way consistent with prior literature (e.g., Albuquerque, 2014). For example, the coefficient on *Ln(Return Peer) × Idio Var* is positive and significant, suggesting less RPE use when firms have more idiosyncratic returns. The coefficient on *Ln(Return Peer) × Ret Corr* is negative and significant, suggesting more RPE use when the firm's stock return is more correlated with peers. Finally, we find that the coefficient on *Ln(Return Peer) × FF Peer Num* is positive and significant, indicating that firms use less RPE when they have more peers with similar size within the same product industry.

Taken together, these findings on pay for luck and RPE use support Oyer's (2004) theory and provide direct evidence that some pay practices previously deemed questionable can be a natural response to labor market competition.

6.2 The incentive role of the managerial labor market

Fama (1980) theoretically shows that the managerial labor market sorts managers based on their abilities and hence can serve as a device to discipline managers. Therefore, we test how labor market competition affects firm performance in the following two settings.

6.2.1 External tournament incentive

According to the tournament theory by Lazear and Rosen (1981), pay gaps between hierarchy levels provide promotion-based incentives to employees, motivating them to compete to win the tournament prize by delivering superior performance. In the context of the external labor market for managers, a CEO exerts more effort to increase firm performance so that she can win in the tournament against other executives and move to a higher-paying company eventually.

To empirically test external tournament incentives, researchers need to identify who the potential employers of a firm's CEO are (i.e., managerial labor market competitors). Recent papers rely on product industry classifications (Coles et al., 2018) and geographical proximity (Ma et al., 2020) to generate a pool of potential employers. However, product market and geographical proximity each capture only one aspect of labor market competition. By contrast, our MLCs capture the multidimensional feature of labor competition. Therefore, MLCs allow for a more powerful test of external tournament incentives as they better capture tournament competitors (and thereby the tournament prize) depicted in theory.

We follow the specification of Coles et al. (2018) and Ma et al. (2020) to test external tournament incentives and measure them using MLCs or product industries:

$$Q_{it} = \alpha + \beta_1 Ln(Potential\ Employer\ Pay\ Gap)_{it} + \gamma_1 Ln(Delta)_{it} + \gamma_2 Ln(Firm\ Gap)_{it}$$
$$+\lambda(Firm,\ Industry,\ CEO\ Controls)_{it} + Fixed\ Effects + \varepsilon_{it} \qquad (7)$$

We use Tobin's Q as a proxy for firm performance (or value). The variable of interest *Ln(Potential Employer Pay Gap)*$_{it}$ proxies for tournament prize, which is defined as the natural logarithm of the pay gap between the total pay of the CEO at firm *i* and the second-highest-paid CEO among potential employers in year *t*. This pay gap reflects compensation growth opportunities. To test the source of tournament incentives, we horserace MLCs with product

industry peers (i.e., FF48 and TNIC2). If MLCs capture potential employers of the CEO, we expect the coefficient on *Ln(Potential Employer Pay Gap)* to be positive and significant, which suggests a positive relation between the tournament prize and the performance delivered by the CEO.

Table 7 Panel A shows the results of external tournament incentives from estimating Eq. (6). In columns (1)-(2), we follow prior studies and use product industries based on FF48 and TNIC2 to calculate the tournament prize. The coefficients on *Ln(FF48 Pay Gap)* and *Ln(TNIC2 Pay Gap)* are positive but insignificant, suggesting that product market peers are likely to be noisy approximations of a CEO's potential employers.[27] We then replace product industries with our labor classifications. In columns (3)-(5), we calculate the firm's pay gap using (1) direct peers, (2) direct peers and indirect peers, and (3) direct peers, indirect peers, and Louvain peers. The coefficients on *Ln(Direct Peer Pay Gap)*, *Ln(Indirect Peer Pay Gap)*, and *Ln(Louvain Peer Pay Gap)* are all positive and statistically significant at the 1 percent level, indicating that our labor classifications better capture the potential employers of CEOs.

6.2.2 Pay for competition and future performance

The competitive assignment model suggests that competition between firms lead to higher pay for managers with higher marginal productivity (e.g., Gabaix and Landier, 2008). Accordingly, we expect that CEOs receiving higher pay due to higher competition between hiring firms should perform better. However, competition can also foster rent-seeking behavior by CEOs, and in this case, higher pay does not necessarily translate into better performance. In the spirit of Core et al. (1999), we examine how future performance is associated with the proportion of compensation explained by our competition measures and estimate the following model:

---

[27] Another explanation for the lack of statistical significance is the endogeneity issue. Coles et al. (2018) do not find a significant relation between product industry pay gap and Tobin's Q in a simple OLS specification when using FF30 industries to calculate the pay gap. They find results consistent with the tournament theory when they use local pay characteristics as an instrument for the pay gap.

$$Future\ ROA\ or\ Return_{i,t+1/t+2/t+3} = \alpha + \beta_1(Fitted\ Pay)_{i,t} + \lambda(Controls)_{i,t} + Fixed\ effects + \varepsilon_{i,t}\ \ (8)$$

Future ROA$_{i,t+1/t+2/t+3}$ (*Future Return* $_{i,t+1/t+2/t+3}$) is the average ROA (return) for firm *i* in the subsequent one, two, and three years, respectively. *Fitted Pay*$_{it}$ is the fitted value of total pay explained by the five network measures based on the coefficients on them estimated in column (5) of Table 5 Panel A. Columns (1)-(3) of Table 7 Panel B show the results when using future ROA as the performance measure. In all three columns, the coefficient on fitted labor competition pay (*Fitted Pay*) is positive and statistically significant. We find similar results in columns (4)-(6) when using future stock returns as the performance measure. These results suggest that the higher pay to retain talent incentivizes managers to deliver superior performance.[28] The findings also rule out the possibility that our competition measures primarily capture managers' rent-seeking behaviors, such as opportunism in peer selection. If that is the case, we would otherwise observe a negative relation between fitted competition pay and future firm performance.

7. Conclusion

We use network analysis to extract information about managerial labor market competition from aggregated compensation peer group disclosure and construct managerial labor classifications and competition measures. We validate and apply them to gain additional insights into the effects of the managerial labor market. This paper has important implications for both firms and researchers. Our results suggest that firms can identify potential competitors using aggregated compensation peer group disclosures. For researchers, our findings caution against using product industries to approximate the managerial labor market.

---

[28] To reconcile with the previous results in Section 6.2.1 on labor competition and pay for luck, the two findings reflect an integrated compensation strategy: pay for luck helps secure CEOs with more outside options, while higher pay retains high-quality executives who can deliver superior future performance.

Future research could expand on our framework in several ways. One avenue is to apply our methodology to smaller U.S. firms or foreign firms whose labor market structures and competition environment may differ from large U.S. public firms. For instance, the managerial labor market competition among smaller public firms in the U.S. can be studied using the Equilar database which covers Russell 3000 firms. The European labor market can be examined using the ISS Incentive Lab Europe database with compensation benchmarking data of European firms. Additionally, researchers could apply our classifications and measures to identify and answer other questions about the managerial labor market. For example, does labor market competition shape other seemingly questionable pay practices, such as perks and severance pay? To compete for talent, do firms mimic or differentiate from pay practices at labor market competitors? How do other market participants (e.g., analysts) respond to labor competition?

REFERENCES

Aggarwal, R., and A. Samwick. 1999. The other side of the trade-off: The impact of risk on executive compensation. *Journal of Political Economy* 107 (1): 65-105.

Albuquerque, A. M. 2009. Peer firms in relative performance evaluation. *Journal of Accounting and Economics* 48(1): 69-89.

Albuquerque, A. M. 2014. Do growth-option firms use less relative performance evaluation? *The Accounting Review* 89(1): 27-60.

Albuquerque, A. M., G. De Franco, and R. S. Verdi. 2013. Peer choice in CEO compensation. *Journal of Financial Economics* 108 (1): 160–181.

Ali, U., and D. Hirshleifer. 2020. Shared analyst coverage: Unifying momentum spillover effects. *Journal of Financial Economics* 136(3): 649-675.

Ali, A., S. Klasa, and E. Yeung. 2008. The limitations of industry concentration measures constructed with Compustat data: Implications for finance research. *Review of Financial Studies* 22(10): 3839-3871.

Ali, A., N. Li, and W. Zhang. 2019. Restrictions on managers' outside employment opportunities and asymmetric disclosure of bad versus good news. *The Accounting Review* 94 (5): 1–25.

Allison, P. 2012. Logistic regression for rare events. https://statisticalhorizons.com/logistic-regression-for-rare-events.

Antle, R., and A. Smith. 1986. An empirical investigation of the relative performance evaluation of corporate executives. *Journal of Accounting Research* 24 (1): 1–39.

Balsam, S., and S. Miharjo. 2007. The effect of equity compensation on voluntary executive turnover. *Journal of Accounting and Economics* 43 (1): 95–119.

Bebchuk, L., Cohen, A., & Ferrell, A. (2009). What matters in corporate governance?. *The Review of financial studies*, *22*(2), 783-827.

Bertrand, M., and S. Mullainathan. 2001. Are CEOs rewarded for luck? The ones without principals are. *Quarterly Journal of Economics* 116(3): 901-932.

Bhojraj, S., C. M. Lee, and D. K. Oler. 2003. What's my line? A comparison of industry classification schemes for capital market research. *Journal of Accounting Research* 41(5): 745-774.

Bizjak, J., M. Lemmon, and L. Naveen. 2008. Does the use of peer groups contribute to higher pay and less efficient compensation?. *Journal of Financial Economics* 90 (2): 152–168.

Bizjak, J., M. Lemmon, and T. Nguyen. 2011. Are all CEOs above average? An empirical analysis of compensation peer groups and pay design. *Journal of Financial Economics* 100 (3): 538–555.

Blondel, V. D., J.-L. Guillaume, R. Lambiotte, and E. Lefebvre. 2008. Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment* 2008 (10): P10008.

Bloomfield, M. J. 2021. Compensation disclosures and strategic commitment: Evidence from revenue-based pay. *Journal of Financial Economics* 141(2), 620-643.

Brickley, J. A., and J. L. Zimmerman. 2010. Corporate governance myths: comments on Armstrong, Guay, and Weber. *Journal of Accounting and Economics* 50 (2–3): 235–245.

Brochet, F., P. Limbach, M. Schmid, and M. Scholz-Daneshgari. 2021. CEO tenure and firm value. *The Accounting Review* 86(6): 47-71.

Bushman, R. M., B. E. Hendricks, and C. D. Williams. 2016. Bank competition: Measurement, decision-

making, and risk-taking. *Journal of Accounting Research* 54(3): 777-826.

Cadman, B., and M. E. Carter. 2014. Compensation peer groups and their relation with CEO pay. *Journal of Management Accounting Research* 26 (1): 57–82.

Cadman, B., M. E. Carter, and X. Peng. 2021. The participation constraint and CEO equity grants. *The Accounting Review* 96 (1): 67–89.

Chen, W., S. Jung, X. Peng, and I. X. Zhang. 2021. Outside Opportunities, Managerial Risk Taking, and CEO Compensation. *The Accounting Review* 97(2): 135-160.

Coles, J. L., Z. Li, and A. Y. Wang. 2018. Industry tournament incentives. *Review of Financial Studies* 31 (4): 1418–1459.

Core, J. E., R. W. Holthausen, and D. F. Larcker. 1999. Corporate governance, chief executive officer compensation, and firm performance. *Journal of Financial Economics* 51 (3): 371–406.

Core, J., and W. Guay. 2002. Estimating the value of employee stock option portfolios and their sensitivities to price and volatility. *Journal of Accounting Research* 40(3), 613-630.

Crane, A. D., A. Koch, and S. Michenaud. 2019. Institutional investor cliques and governance. *Journal of Financial Economics* 133 (1): 175–197.

Custódio, C., M. A. Ferreira, and P. Matos. 2013. Generalists versus specialists: Lifetime work experience and chief executive officer pay. *Journal of Financial Economics* 108 (2): 471–492.

Daniel, N. D., Y. Li, and L. Naveen. 2020. Symmetry in pay for luck. *Review of Financial Studies* 33 (7): 3174–3204.

De Angelis, D., and Y. Grinstein. 2020. Relative performance evaluation in CEO compensation: A talent-retention explanation. *Journal of Financial and Quantitative Analysis* 55 (7): 2099–2123.

El-Khatib, R., K. Fogel, and T. Jandik. 2015. CEO network centrality and merger performance. *Journal of Financial Economics* 116 (2): 349–382.

Equilar. 2023. Industry leads the way as top peer group criterion. https://www.equilar.com/blogs/554-peer-groups-study-2023.

Fama, E. F. 1980. Agency problems and the theory of the firm. *Journal of Political Economy* 88 (2): 288–307.

Faulkender, M., and J. Yang. 2010. Inside the black box: The role and composition of compensation peer groups. *Journal of Financial Economics* 96 (2): 257–270.

Faulkender, M., and J. Yang. 2013. Is disclosure an effective cleansing mechanism? The dynamics of compensation peer benchmarking. *Review of Financial Studies* 26 (3): 806–839.

Fee, C. E., and C. J. Hadlock. 2003. Raids, rewards, and reputations in the market for managerial talent. *Review of Financial Studies* 16 (4): 1315–1357.

Ferri, F., R. Zheng, and Y. Zou. 2018. Uncertainty about managers' reporting objectives and investors' response to earnings reports: Evidence from the 2006 executive compensation disclosures. *Journal of Accounting and Economics* 66(2-3): 339-365.

Firth, D. 1993. Bias reduction of maximum likelihood estimates. *Biometrika 80*(1): 27-38.

Gabaix, X., and A. Landier. 2008. Why has CEO pay increased so much? *Quarterly Journal of Economics* 123 (1): 49–100.

Gao, H., J. Luo, and T. Tang. 2015. Effects of managerial labor market on executive compensation:

Evidence from job-hopping. *Journal of Accounting and Economics* 59 (2–3): 203–220.

Giannetti, M. 2011. Serial CEO incentives and the structure of managerial contracts. *Journal of Financial Intermediation* 20 (4): 633–662.

Gopalan, R., T. Milbourn, F. Song, and A. V. Thakor. 2014. Duration of executive compensation. *Journal of Finance* 69 (6): 2777–2817.

Guay, W. R., D. J. Taylor, and J. J. Xiao. 2015. Adapt or perish: Evidence of CEO adaptability to industry shocks. Available at SSRN 2234886.

Hanneman, R. A., and M. Riddle. 2005. Introduction to social network methods.

Hansen, S., T. Ramdas, R. Sadun, and J. Fuller. 2021. The demand for executive skills. *NBER Working Paper Series*.

Hoberg, G., and G. Phillips. 2016. Text-based network industries and endogenous product differentiation. *Journal of Political Economy* 124 (5): 1423–1465.

Holmström, B. 1982. Moral hazard in teams. *The Bell Journal of Economics*, 324-340.

Holmström, B., and S. N. Kaplan. 2003. The dangers of too much governance: overreacting to corporate scandal will hobble risk taking, innovations and growth. *MIT Sloan Management Review* 45 (1): 96–97.

Hotelling, H. 1929. Stability in Competition. *Economic Journal* 39 (153): 41–57.

Hu, Y. 2005. Efficient, high-quality force-directed graph drawing. *Mathematica Journal* 10 (1): 37–71.

Jaffe, A. B. 1986. Technological Opportunity and Spillovers of R & D: Evidence from Firms' Patents, Profits, and Market Value. *American Economic Review* 76 (5): 984–1001.

Jayaraman, S., T. Milbourn, F. Peters, and H. Seo. 2021. Product market peers and relative performance evaluation. *The Accounting Review* 96(4): 341-366.

Jochem, T., T. Ladika, and Z. Sautner. 2018. The retention effects of unvested equity: Evidence from accelerated option vesting. *Review of Financial Studies* 31 (11): 4142–4186.

Kaplan, S. N., and M. Sorensen. 2021. Are CEOs Different? *Journal of Finance* 76 (4): 1773-1811.

Kaustia, M., and V. Rantala. 2021. Common analysts: method for defining peer firms. *Journal of Financial and Quantitative Analysis* 56(5): 1505-1536.

King, G., and L. Zeng. 2001. Logistic regression in rare events data. *Political Analysis* 9(2): 137-163.

Lazear, E. P. 2009. Firm-specific human capital: A skill-weights approach. *Journal of Political Economy* 117 (5): 914–940.

Lazear, E. P., and S. Rosen. 1981. Rank-order tournaments as optimum labor contracts. *Journal of Political Economy* 89 (5): 841–864.

Lee, C., P. Ma, and C. C. Wang. 2016. The search for peer firms: When do crowds provide wisdom? *Harvard Business School Accounting & Management Uni Working Paper* 15-032: 14-46.

Li, F., R. Lundholm, and M. Minnis. 2013. A measure of competition based on 10-K filings. *Journal of Accounting Research* 51(2), 399-436.

Ma, M., J. Pan, and S. R. Stubben. 2020. The Effect of Local Tournament Incentives on Firms' Performance, Risk-Taking Decisions, and Financial Reporting Decisions. *The Accounting Review* 95 (2): 283–309.

Murphy, K. J. 1999. Executive compensation. *Handbook of Labor Economics* 3: 2485–2563.

Murphy, K. J., and J. Zábojník. 2004. CEO pay and appointments: A market-based explanation for recent trends. *American Economic Review* 94 (2): 192–196.

Murphy, K. J., and J. Zábojník. 2007. Managerial capital and the market for CEOs. Available at SSRN 984376.

Na, K. 2020. CEOs' outside opportunities and relative performance evaluation: Evidence from a natural experiment. *Journal of Financial Economics* 137 (3): 679–700.

Oyer, P. 2004. Why do firms use incentives that have no incentive effects? 59 (4). *Journal of Finance* 59: 1619–1650.

Packard, H. A. 2018. Are long-term earnings targets forecasts? Doctoral dissertation, Massachusetts Institute of Technology.

Phillips, G. M. 2013. Discussion of a measure of competition based on 10-K filings. *Journal of Accounting Research* 51 (2): 437–447.

Rajgopal, S., T. Shevlin, and V. Zamora. 2006. CEOs' outside employment opportunities and the lack of relative performance evaluation in compensation contracts. *Journal of Finance* 61 (4): 1813–1844.

Schneider, T.I. 2021. Executive compensation and aspirational peer benchmarking. *Journal of Empirical Finance* 62: 121-140.

Terviö, M. 2008. The difference that CEOs make: An assignment model approach. *American Economic Review* 98 (3): 642–668.

Whited, R.L., Q.T. Swanquist, J.E. Shipman, and J.R. Moon Jr. 2022. Out of control: The (over) use of controls in accounting research. *The Accounting Review* 97(3): 395-413.

Appendix A
Variable definitions

This appendix defines all variables used in this paper. All continuous variables are winsorized at 1% and 99%.

Variables	Definition
Managerial labor classification tests: Main dependent variables and variables of interest	
Talent Flow$_{ijt+1}$	Indicator variable that takes the value of one if one of the top five executives of firm i moves to the top five executive positions of firm j within one-year gap, and zero otherwise
Selected Peer$_{ijt}$	Indicator variable that takes the value of one focal firm i select firm j as its compensation peer in year t, and zero otherwise.
Direct Potential Peer$_{ijt}$	Indicator variable that takes the value of one if firm j belongs to focal firm i's direct potential group, and zero otherwise. Direct potential peers are the firms that choose firm i as their peer, excluding firm i's selected peers.
Indirect Potential Peer$_{ijt}$	Indicator variable that takes the value of one if firm j is focal firm i's indirect potential peer, and zero otherwise. Indirect potential peers are defined as direct peers of firm i's direct peers, excluding firm i's selected peers and direct potential peers.
Louvain Potential Peer$_{ijt}$	Indicator variable that takes the value of one if firm j is focal firm i's Louvain potential peer, and zero otherwise. Louvain potential peers are firms that belong to the same Louvain group as the focal firm i, excluding firm i's selected peers, direct potential peers, and indirect potential peers.
Direct Peer Same(Diff) Product Industry$_{ijt}$	Indicator variable that takes the value of one if firm j is firm i's direct peer and belongs to the same (different) FF48 or TNIC2 industry as firm i, and zero otherwise.
Indirect Peer Same(Diff) Product Industry$_{ijt}$	Indicator variable that takes the value of one if firm j is firm i's indirect peer and belongs to the same (different) FF48 or TNIC2 industry as firm i, and zero otherwise.
Louvain Peer Same(Diff) Product Industry$_{ijt}$	Indicator variable that takes the value of one if firm j is firm i's Louvain peer and belongs to the same(different) FF48 or TNIC2 industry as firm i, and zero otherwise.
Same(Diff) Product Industry$_{ijt}$	Indicator variable that takes the value of one if firm j is direct peer, indirect peer, or Louvain peer of firm i and is within a same(different) FF48 or TNIC2 industry as firm i, and zero otherwise.
Past Peer$_{ijt}$	Indicator variable that takes the value of one if firm j is a direct/indirect/Louvain/MLC peer of firm i in the last period t-1 but not the current period t, and zero otherwise. MLC peer is a joint peer group consisting of direct, indirect, and Louvain peers.
New Peer$_{ijt}$	Indicator variable that takes the value of one if firm j is a direct/indirect/Louvain/MLC peer of firm i in the current period t but not the last period t-1, and zero otherwise. MLC peer is a joint peer group consisting of direct, indirect, and Louvain peers.
Current Peer$_{ijt}$	Indicator variable that takes the value of one if firm j is a direct/indirect/Louvain/MLC peer of firm i in both the last period t-1 and the current period t, and zero otherwise. MLC peer is a joint peer group consisting of direct, indirect, and Louvain peers.
Future Peer$_{ijt}$	Indicator variable that takes the value of one if firm j is a direct/indirect/Louvain/MLC peer of firm i in the future period t+1 but not the current period t, and zero otherwise. MLC peer is a joint peer group consisting of direct, indirect, and Louvain peers.
Tobin Q	The ratio of the sum of market value of equity and the book value of debt to total assets.
Ln(FF48 Pay Gap)	Natural logarithm of one plus the difference between the total CEO compensation of the focal firm and the second-highest total compensation within the same FF48 industry.

Ln(TNIC2 Pay Gap)	Natural logarithm of one plus the difference between the total CEO compensation of the focal firm and the second-highest total compensation within the same TNIC2 industry.
Ln(Direct Peer Pay Gap)	Natural logarithm of one plus the difference between the total CEO compensation of the focal firm and the second-highest total compensation within the direct compensation peer group.
Ln(Indirect Peer Pay Gap)	Natural logarithm of one plus the difference between the total CEO compensation of the focal firm and the second-highest total compensation within the direct and indirect peer group of firm i.
Ln(Louvain Peer Pay Gap)	Natural logarithm of one plus the difference between the total CEO compensation of the focal firm and the second-highest total compensation within the same direct, indirect, and Louvain compensation peer group of firm i.

Managerial labor classification tests: Controls

Same SIC2$_{ijt}$	Indicator variable that takes the value of one if firm i and j belong to the SIC2 industry, and zero otherwise.
Same SIC3$_{ijt}$	Indicator variable that takes the value of one if firm i and j belong to the SIC3 industry, and zero otherwise.
Similar MV$_{ijt}$	Indicator variable that takes the value of one if the market value of firm j is between 50% and 200% the market value of firm i, and zero otherwise.
Similar Sales$_{ijt}$	Indicator variable that takes the value of one if the sales of firm j is between 50% and 200% of the sale of firm i, and zero otherwise.
Similar Assets$_{ijt}$	Indicator variable that takes the value of one if the total assets of firm j is between 50% and 200% the total assets of firm i, and zero otherwise.
Both Dow$_{ijt}$	Indicator variable that takes the value of one if both firm i and firm j belong to the Dow Jones Index, and zero otherwise.
Both S&P500$_{ijt}$	Indicator variable that takes the value of one if both firm i and firm j belong to the S&P500 Index, and zero otherwise.
Neither S&P500$_{ijt}$	Indicator variable that takes the value of one if neither firm i nor firm j belongs to the S&P500 Index, and zero otherwise.
Both CEO Chair $_{ijt}$	Indicator variable that takes the value of one if both CEOs of firm i and firm j also hold the board chair position, and zero otherwise.
Neither CEO Chair $_{ijt}$	Indicator variable that takes the value of one if neither the CEO of firm i nor the CEO of firm j also hold the board chair position, and zero otherwise.
Flow History$_{ijt}$	Indicator variable that takes the value of one if there were talent flows between firm i and j before year t, and zero otherwise.
Similar ROA$_{ijt}$	Indicator variable that takes the value of one if the return on assets of firm j is between 50% and 200% the return on assets of firm i, and zero otherwise.
Same State$_{ijt}$	Indicator variable that takes the value of one if firm i and j are headquartered in the same state, and zero otherwise.
Both MultiSeg$_{ijt}$	Indicator variable that takes the value of one if firm i and j both report more than one business segment, and zero otherwise.
Both SingleSeg$_{ijt}$	Indicator variable that takes the value of one if firm i and j both report only one business segment, and zero otherwise.
Both MultiGeo$_{ijt}$	Indicator variable that takes the value of one if firm i and j both report more than one geographical region, and zero otherwise.
Both SingleGeo$_{ijt}$	Indicator variable that takes the value of one if firm i and j both report only one geographical region, and zero otherwise.
Same Consult$_{ijt}$	Indicator variable that takes the value of one if firm i and j share the same compensation consultant.
Same TNIC2$_{ijt}$	Indicator variable that takes the value of one if firm i and j belong to the same TNIC2 industry, and zero otherwise. TNIC2 industry is developed by Hoberg and Phillips (2016) and has a granularity similar to two-digit SIC industries.

Same TNIC3$_{ijt}$	Indicator variable that takes the value of one if firm i and j belong to the same TNIC3 industry, and zero otherwise. TNIC2 industry is developed by Hoberg and Phillips (2016) and has a granularity similar to two-digit SIC industries.
Ind Ret Corr $_{ijt}$	The correlation of the monthly industry returns of firm i and j in year t.
MV$_{it\,(jt)}$	The market value of firm i (j) in year t.
MTB$_{it(jt)}$	The market-to-book ratio of firm i (j) in year t.
RET$_{it(jt)}$	The stock return of firm i (j) in year t.
ROA$_{it(jt)}$	The return-on-assets of firm i (j) in year t.
Ln(Delta)	Natural logarithm of the change in the dollar value of the executive's wealth for a one percentage point change in stock price, calculated following Core and Guay (2002).
Ln(Infirm Pay Gap)	Natural logarithm of CEO's total compensation less the median total compensation of other top executives.
Ln(Assets)	Natural logarithm of total assets (Compustat: at).
Ln(CEO Tenure)	Natural logarithm of the number of years as a firm's CEO.
Ln(CEO Age)	Natural logarithm of the age of a firm's CEO.
Sales Growth	Sales growth rate, calculated as the difference between total sales and lagged sales divided by lagged sales.
CAPEX	Total capital expenditure scaled by total assets (Compustat: capx/at).
Ind Vol	The average volatility of firms' daily stock returns in the year in the same FF48 industry.
Ln(Ind CEO Count)	Natural logarithm of the number of CEOs in the same FF48 industry.

Managerial labor competition measure tests: Main dependent variables and variables of interest

Ln(Total Pay)	Natural logarithm of one plus total compensation (Execucomp: tdc1).
Ln(Equity Pay)	Natural logarithm of one plus the total amount of stock and option awards (Execucomp: stock_awards_fv+option_awards_fv).
Ln(Cash Pay)	Natural logarithm of one plus the total amount of salary and bonus (Execucomp: total_curr).
Equity Pct	Percentage of equity pay of total CEO compensation.
Pay Duration	Average vesting period of different pay components of CEO compensation, calculated following Gopalan et al. (2014).
InDegree	In-degree centrality, defined as the number of firms selecting the focal firm as a compensation peer.
Clustering	The clustering coefficient of the firm in the compensation peer network. The clustering coefficient is defined as the number of links between its peers divided by the maximum number of links that could exist between its peers.
Louvain Density	The density of links within the Louvain group. It is defined as the number of links in the Louvain group divided by the maximum number of links that could exist in the Louvain group.
Louvain Size	The size of the Louvain group, defined as the number of firms in each Louvain group.
Eigenvector	Eigenvector centrality of the firm in the compensation peer network. It is solved by satisfying $\lambda E'E = E'AE$, where E is an eigenvector of the matrix of compensation benchmarking connections A, and λ is its associated eigenvalue. The eigenvector centrality of firm i is the element of the eigenvector E^* associated with A's principal eigenvalue λ^*.
PCOMP1	The first principal component of *InDegree*, *Clustering*, *Louvain Density*, *Louvain Size*, and *Eigenvector*, standardized to standard normal distribution.
PCOMP2	The second principal component of *InDegree*, *Clustering*, *Louvain Density*, *Louvain Size*, and *Eigenvector*, standardized to standard normal distribution.
Luck	Annualized monthly luck measure, which is estimated as the fitted value

	from regressing firm stock return on equal-weighted industry and market return over the current fiscal year (Daniel et al., 2020).
Skill	Annualized monthly skill measure, which is estimated as the intercept plus the residual from regressing firm stock return on equal-weighted industry and market return over the current fiscal year (Daniel et al., 2020).
Ln(Return Own)	The natural logarithm of one plus the firm's stock return over the current fiscal year.
Ln(Return Peer)	The natural logarithm of one plus peer stock return, which is the equal-weighted stock portfolio return of peers within the same TNIC3 industry and size quartile over the focal firm's current fiscal year.
Future ROA 1yr/2yrs/3yrs	The average annual ROA in the next 1/2/3 years.
Future Return 1yr/2yrs/3yrs	The average annual stock returns in the next 1/2/3 years.
Fitted Pay	The fitted value from the sum of products of each competition measures (*InDegree*, *Clustering*, *Louvain Density*, *Louvain Size*, and *Eigenvector*) and its coefficients estimated from regressing total compensation on all competition measures and controls (Table 5 Panel A, Column 5).

Managerial labor competition measure tests: Controls

Ln(FF Peer Pay)	Natural logarithm of one plus the median CEO pay of firms within the same FF48 industry with sales between 50% to 200% of the focal firm.
FF Peer Num	Number of firms within the same FF48 industry with sales between 50% and 200% of the focal firm.
TRS1yr / Lag(TRS1yr)	(Lagged) annual stock return.
ROA / Lag(ROA)	(Lagged) return-on-assets, calculated as the ratio of income to total assets (Compustat: ib/at).
Ln(Revt)/Lag(ln(Revt))	(Lagged) natural logarithm of sales (Compustat: revt).
MTB / Lag(MTB)	(Lagged) market-to-book ratio, calculated as the sum of the market value of equity plus the book value of debt, divided by the book value of debt and equity.
Lag(Leverage)	Lagged leverage, calculated as total debt value over the market value of assets.
Lag(Volatility)	Lagged 12-month stock return volatility.
CEO Age	Age of the CEO.
Idio Var	The cumulative distribution function (cdf) of idiosyncratic variance. Idiosyncratic variance is measured as the error variance from regressing firm stock return on the firm's peer group stock return.
Ret Corr	Return correlation. Calculated as the slope coefficient from regressing stock return on the firm's peer group stock return.
HHI	Herfindahl index. Calculated as the sum of the squared market shares of all the firms within the same product industry.
Ln(ROA Sd)	Natural logarithm of the standard deviation of ROA in the past five years.
Ln(MV)	Natural logarithm of the market value of equity.
Ln(Ret Sd)	Natural logarithm of the standards deviation of stock return in the past five years.

Appendix B
Examples of compensation peer groups from proxy statements

This appendix provides two examples of compensation peer group disclosure in proxy statements.

Example 1: Delta Air Lines 2019 DEF 14A

Comparative Market Data and Peer Group

We believe peer group data should be used as a point of reference, not as the sole factor in our executive officers' compensation. In general, the Personnel & Compensation Committee's objective is for target total direct compensation opportunities to be competitive with the peer group, with individual variation based on the individual's performance, experience and role within Delta.

Our peer group is composed of three major U.S. airlines and eighteen other companies in the hotel/leisure, transportation/ distribution, machinery/aerospace/defense and retail industries. We selected these industries because we believe it is important

that our peer group have business characteristics that are similar to Delta's, including revenue size, market capitalization, number of employees, operating margin and global presence. In order to retain and attract the talent we need, Delta must compete with these types of companies, and if the peer group was limited to the airline industry, we would have to include companies that are a fraction of the size and scope of Delta. The Personnel & Compensation Committee, in consultation with the compensation consultant and company management, reviews and considers changes to the composition of our peer group annually. There were no changes to the peer group in 2019. The companies in our peer group are:

Airlines:	American Airlines Group Inc.	Southwest Airlines Co.	United Continental Holdings, Inc.
Hotel/Leisure:	Carnival Corporation	Marriott International, Inc.	
Transportation/ Distribution:	The Coca-Cola Company FedEx Corporation Norfolk Southern Corporation	PepsiCo, Inc. Sysco Corporation	Union Pacific Corporation United Parcel Service, Inc.
Machinery/ Aerospace/Defense:	The Boeing Company Honeywell International Inc.	L3 Technologies Textron Inc.	United Technologies Corporation
Retail:	Best Buy Co., Inc. The Home Depot, Inc.	Lowe's Corporation	Target Corporation

Example 2: Target Corporation 2019 DEF 14A

Benchmarking using compensation peer groups

Peer group market positioning is another important factor considered in determining each executive officer's Annual TDC.

The Annual TDC levels and elements described in the preceding pages are evaluated annually for each executive officer relative to our retail and general industry peer group companies. The market comparisons are determined by use of compensation data obtained from publicly available proxy statements analyzed by Semler Brossy and proprietary survey data assembled by Willis Towers Watson and Korn Ferry Hay Group.

Due to a range of factors, including the scope of NEO positions, tenure in role, and company-specific concerns, there is an imperfect comparability of NEO positions between companies. As such, market position served as a reference point in the Annual TDC determination process rather than a formula-driven outcome.

The retail peer group was formulated based on an initial screen of companies in the Global Industry Classification Standard retailing

index with revenue from core retail operations greater than $15 billion. The retail peer group is also used within our LTI plans. Target's relative performance compared to this peer group on key metrics determines overall payout for our PSU and PBRSU awards.

General industry companies are also included as a peer group because they represent companies with whom we compete for talent. Like the selected retailers, the general industry companies are large and among the leaders in their industries.

The composition of the peer groups is reviewed annually to ensure it is appropriate in terms of company size and business focus, and any changes made are reviewed with Semler Brossy and approved by the Human Resources & Compensation Committee. In fiscal 2019, we removed Gap Inc. and Sears Holdings Corporation from the retail peer group and added Nordstrom, Inc. Cigna Corporation replaced Express Scripts Holding Company within the general industry peer group due to its merger with Express Scripts Holding Company.

2019 peer groups

Retail		
Amazon.com, Inc.	Lowe's Companies, Inc.
Best Buy Co., Inc.	Macy's Inc.
Costco Wholesale Corporation	Nordstrom, Inc.
CVS Health Corporation	Publix Super Markets, Inc.
Dollar General Corporation	Rite Aid Corporation
Dollar Tree, Inc.	The TJX Companies, Inc.
The Home Depot, Inc.	Walgreens Boots Alliance, Inc.
Kohl's Corporation	Walmart, Inc.
The Kroger Co.	

General industry		
3M Company	McDonald's Corporation
Abbott Laboratories	MetLife, Inc.
Anthem, Inc.	Mondelez International, Inc.
Archer-Daniels-Midland Company	NIKE, Inc.
Cigna Corporation	PepsiCo, Inc.
The Coca-Cola Company	The Procter & Gamble Company
FedEx Corporation	Starbucks Corporation
General Mills, Inc.	United Parcel Service, Inc.
Johnson & Johnson	United Technologies Corporation
Johnson Controls International plc	UnitedHealth Group Incorporated
Marriott International, Inc.	
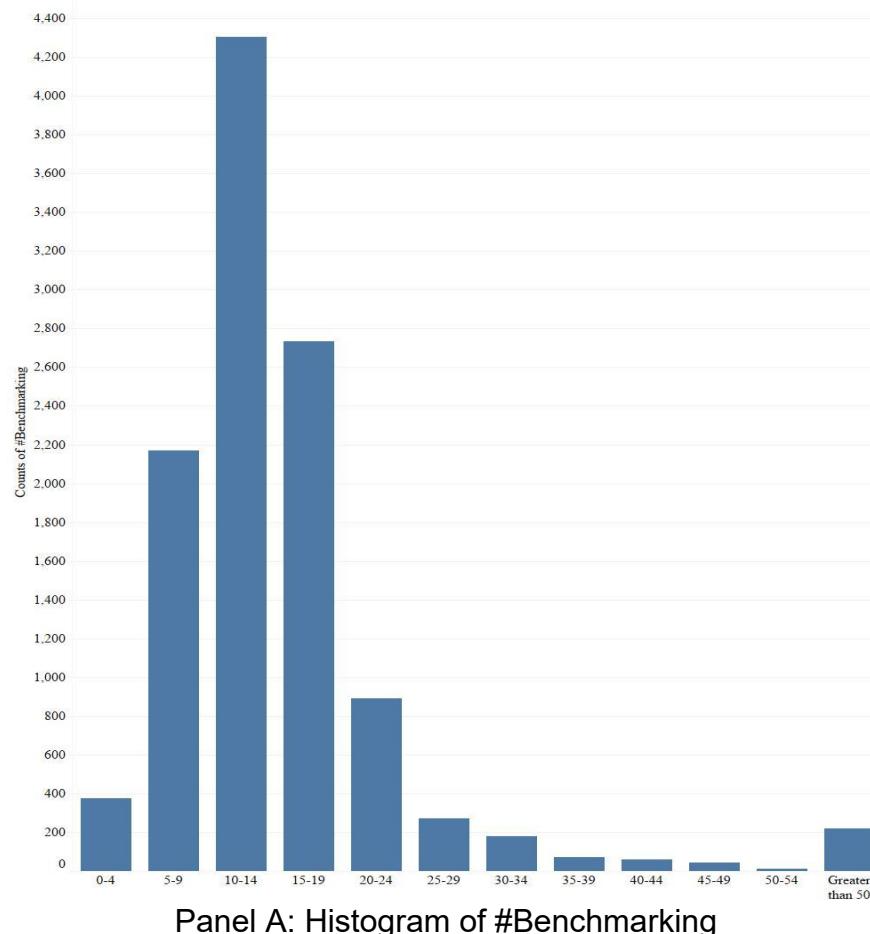
Figure 1
Word cloud of compensation peer selection criteria

This figure presents a word cloud of the common criteria for compensation peer selection, as mentioned in the proxy statements of 200 randomly selected firms in our sample with compensation peer changes. The font size of each keyword corresponds to the frequency with which the criterion is used by firms in selecting their compensation peers. The larger the font size, the more frequently firms use the criterion when selecting peers.
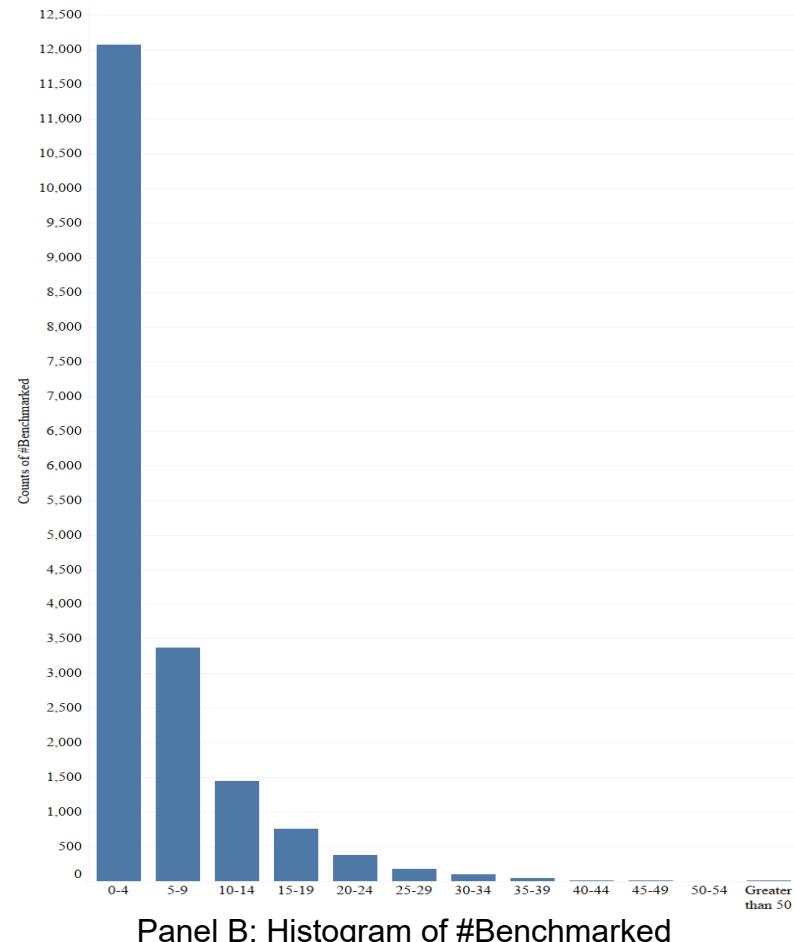
Figure 2
The distribution of #Benchmarking and #Benchmarked

This figure presents the distribution of the number of compensation peers disclosed (#Benchmarking) and the number of times a firm is selected as compensation peers (#Benchmarked) from 2006 to 2018. Panel A and Panel B show the histogram of #Benchmarking and #Benchmarked, respectively. Panel C is the heat map of #Benchmarking vs. #Benchmarked. A redder (bluer) color means more (fewer) firms fall into the intersection of #Benchmarking and #Benchmarked bins, with the number displayed in the cell.

Panel A: Histogram of #Benchmarking
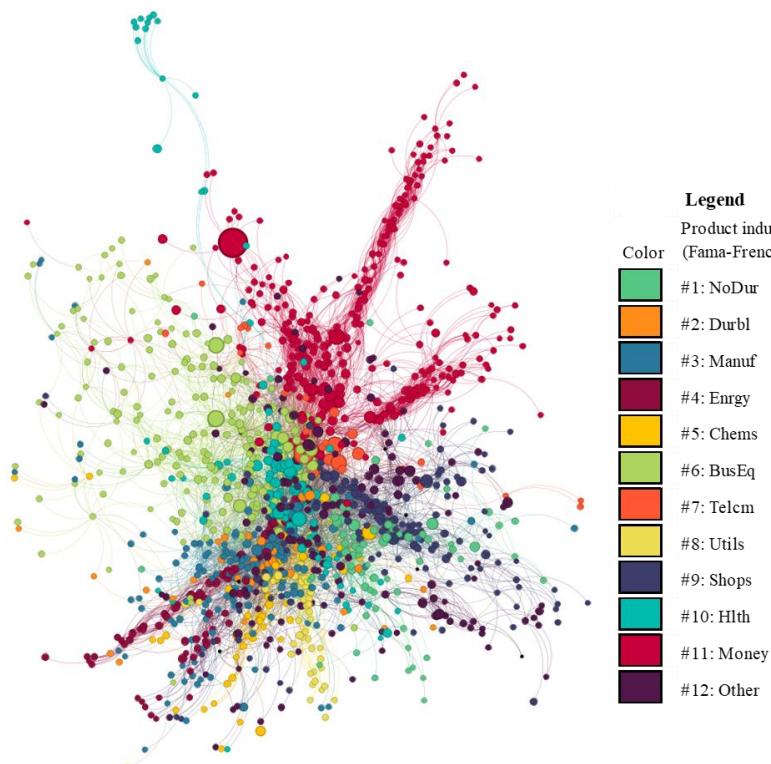
Panel B: Histogram of #Benchmarked

#Benchmarking	#Benchmarked 0-4	5-9	10-14	15-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	Greater than 50
0-4	189	36	25	5	1	1						
5-9	1,173	443	160	79	35	16	4	1		1		
10-14	2,007	1,011	473	226	112	49	30	17	4	4	1	8
15-19	1,115	634	348	230	105	52	29	11	6	4		2
20-24	338	212	109	67	47	25	13	9		4		
25-29	76	77	44	24	13	7	4	2	2			
30-34	52	36	25	18	15	6	3	3				
35-39	29	11	11	5	5		2	1				
40-44	16	10	9	9	1	1	1					
45-49	10	8	3	3	1	1	1	2				
50-54	4	4	1									
Greater than 50	70	56	20	14	5	1	2					
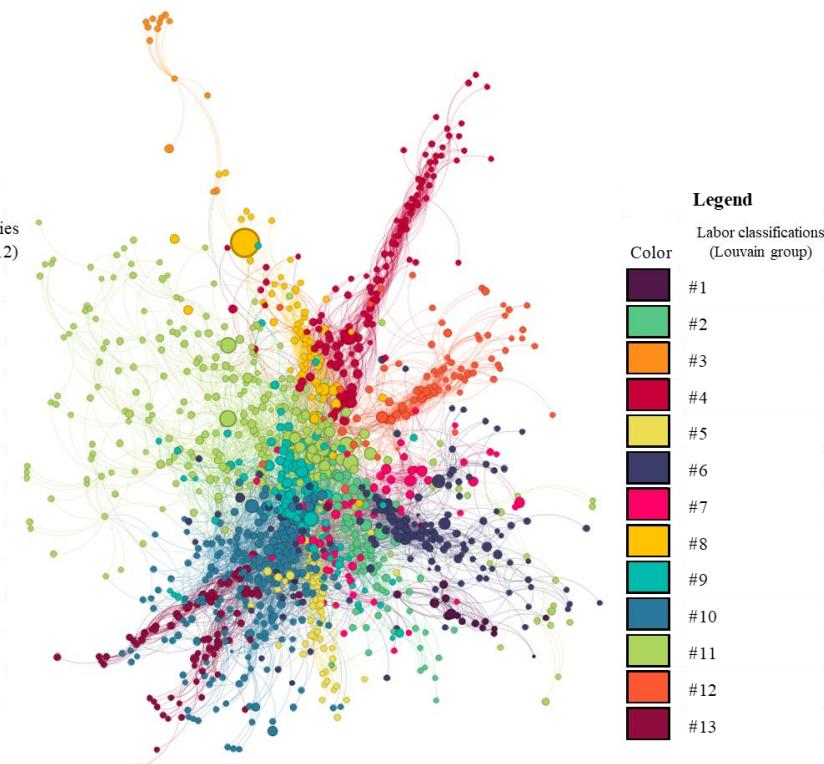
Panel C: Heat Map of #Benchmarking vs #Benchmarked

Figure 3
Compensation benchmarking network

This figure presents the compensation benchmarking network constructed based on firms' selection of peer groups in 2018. Each node represents a firm. The size of the node and the font size of the ticker is proportional to the CEO compensation. For ease of visualization, only the tickers of the top 20 firms with the highest CEO pay are shown in the nodes. The lines connecting nodes represent the benchmarking relations among firms. In Panel A, the benchmarking network is colored based on product industries, defined as Fama-French 12 (FF12) industries classification. For example, firms colored in jade green belong to FF12 industry #1 consumer nondurables; firms colored in orange belong to FF12 industry #2 consumer durables. In Panel B, the benchmarking network is colored based on managerial labor classifications (Louvain group). For example, firms colored in dark purple belong to Louvain group #1; firms colored in turquoise belong to Louvain group #9. These classifications are identified using the Louvain method based on pay benchmarking patterns.
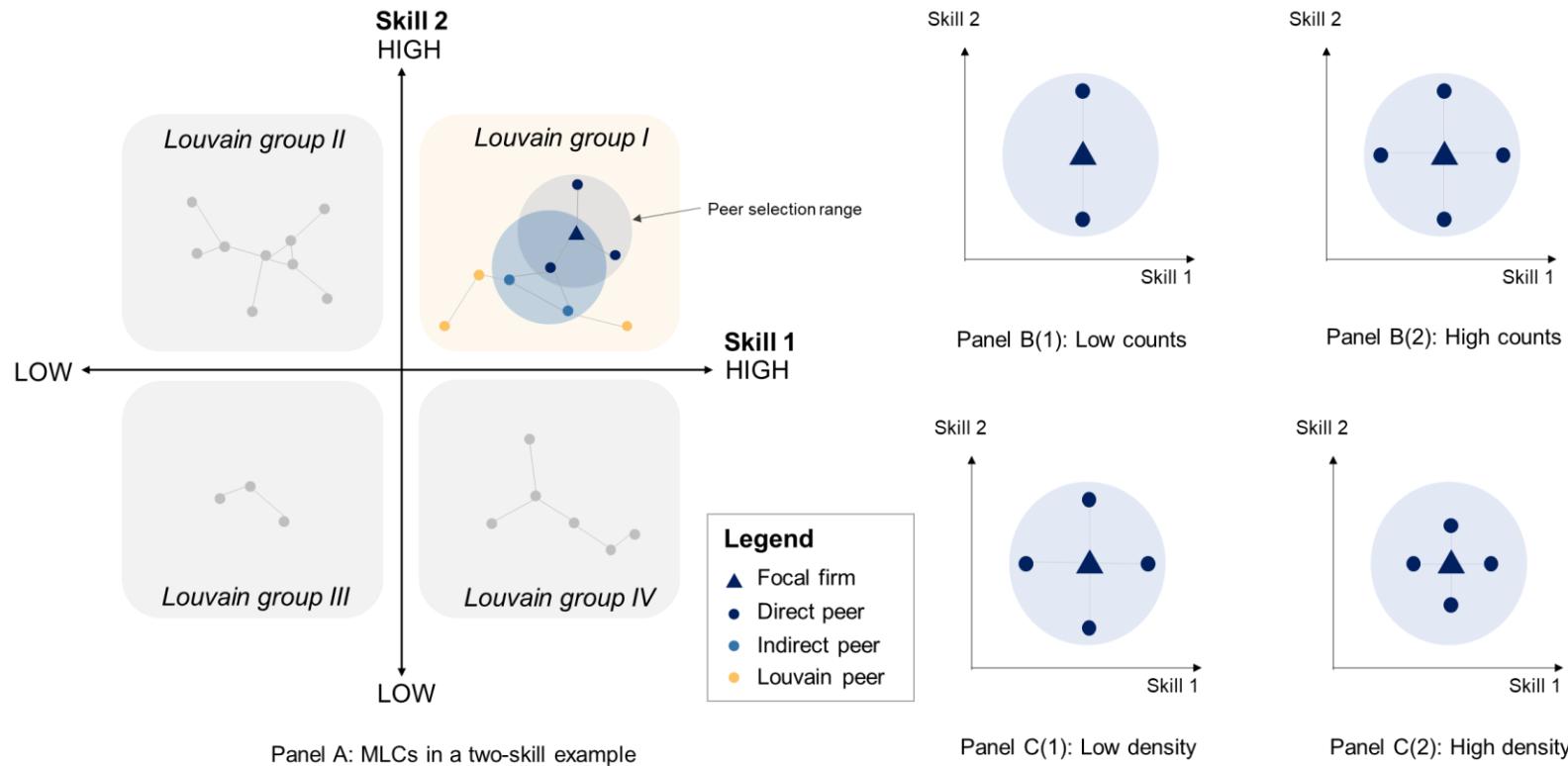
Panel A: Benchmarking network colored based on product industries

Panel B: Benchmarking network colored based on managerial labor classifications

48
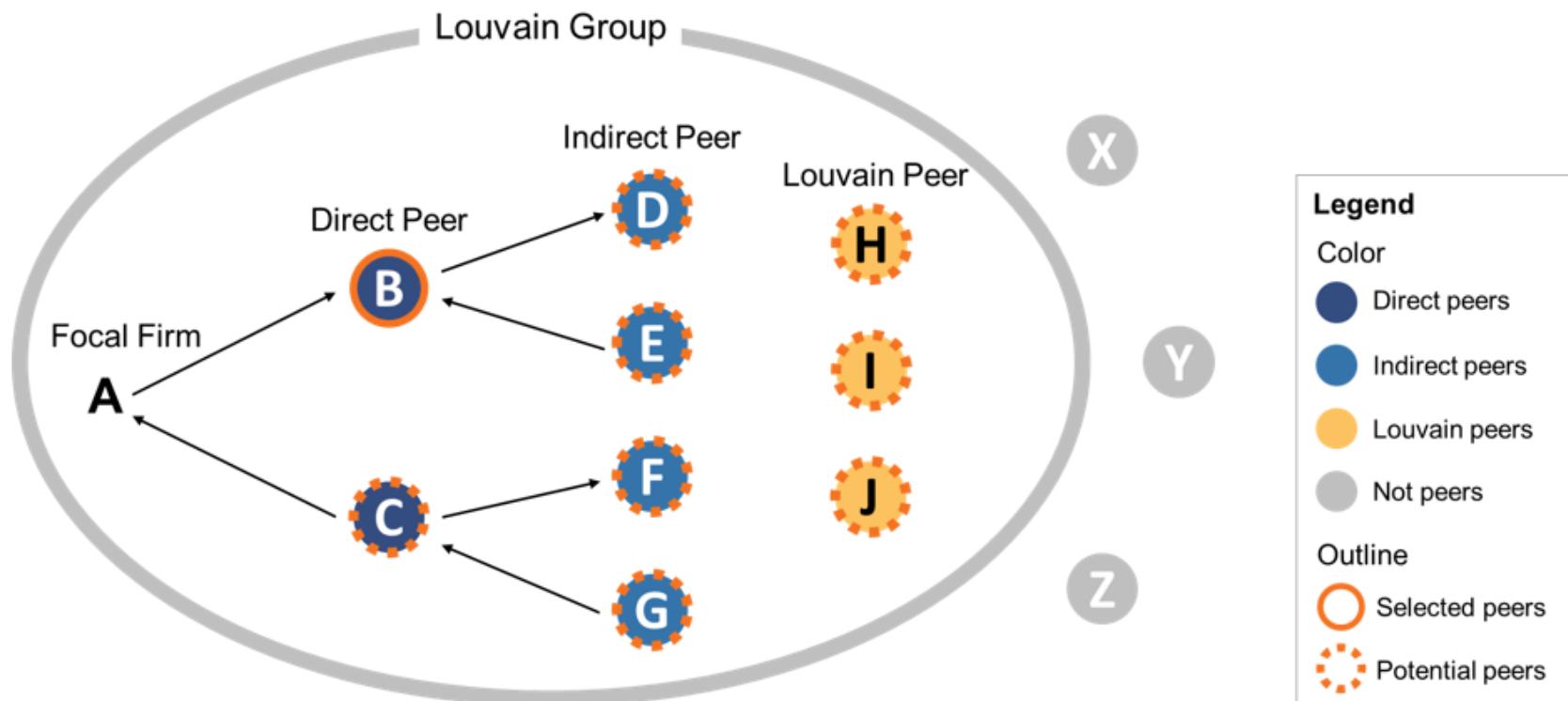
Figure 4
Illustration of managerial labor classifications and competition measures based on network analysis

This figure illustrates the network-based managerial labor classifications and competition measures using a managerial labor market space with two skills. The x-axis (y-axis) reflects the demand for Skill 1 (Skill 2). Each dot donates a firm, and the location of the firm in the x-y plane reflects weights on the two skills. For example, firms in the first quadrant place higher weights on both skills, whereas firms in the second quadrant place a high weight on Skill 2 yet a low weight on Skill 1. The line between the dots represents a benchmarking relation. The distance between the dots reflects the similarity in talent mix demands between the two firms. The shadowed circle region outside a firm represents the firm's peer selection range based on the similarity of skill demands. The direct peer, indirect peer, and Louvain peer of the example focal firm in the first quadrant are shown in different colors. The four quadrants represent Louvain group I to IV. These Louvain groups are identified based on benchmarking cluster patterns in the benchmarking network using the Louvain method. Panels B and C illustrate our network-based competition measures intended to capture outside opportunities, measured by counts of peers, and talent transferability, measured by the density of links, respectively. Panel B(1) shows a peer group with low counts, whereas B(2) shows a peer group with high counts. Panel C(1) shows a peer group with low density, whereas C(2) shows a peer group with high density.

Panel A: MLCs in a two-skill example

Panel B(1): Low counts

Panel B(2): High counts

Panel C(1): Low density

Panel C(2): High density

49

Figure 5
Illustration of managerial labor classifications

This figure illustrates MLCs (Direct Peer, Indirect Peer, and Louvain Peer) using a stylized example. Each letter in the group represents a firm. The direction of the arrow represents the benchmarking direction. For example, focal Firm A chooses Firm B as its compensation peer, whereas Firm A is chosen by Firm C as the compensation peer. The color of each circle presents a peer type. Firms B and C are direct peers of Firm A; Firms D-G are indirect peers of Firm A; Firms H-J are Louvain peers of Firm A; and Firms X-Z are not peers of Firm A. The outline of each circle represents another dimension of peer classification, either selected peers (solid) or potential peers (dotted). Firm B belongs to selected peers; Firms C-J belongs to potential peers because Firm A does not choose them as peers, yet they are identified as peers of Firm A according to MLCs.

Table 1
Descriptive characteristics of compensation peer network

Panel A: Network composition by year

Year	Focal-peer pairs	Unique focal firms	Unique peer firms
2006	9,345	710	1,284
2007	14,871	937	1,513
2008	15,172	938	1,520
2009	16,490	922	1,516
2010	16,593	934	1,468
2011	16,332	940	1,455
2012	14,792	929	1,449
2013	14,289	915	1,410
2014	13,026	902	1,404
2015	12,419	876	1,368
2016	11,035	802	1,399
2017	11,879	830	1,352
2018	10,896	768	1,285

Panel B: Summary statistics on compensation peer group

	N	Mean	Std Dev	P25	Median	P75
#Benchmarking	11,334	15.62	17.19	10.00	13.00	17.00
#Benchmarked	18,379	5.14	6.10	1.00	3.00	7.00
#Interlock	11,334	4.44	3.76	1.00	4.00	7.00
Same SIC2 percentage	11,334	0.54	0.36	0.20	0.53	0.92
Same TNIC2 percentage	11,334	0.53	0.34	0.23	0.53	0.86
Similar Sales percentage	11,334	0.67	0.25	0.50	0.69	0.88
Median peer pay minus focal firm pay	11,334	-465.24	6,773.66	-1,799.75	271.05	2,124.19
Turnover ratio	9,888	0.14	0.19	0.00	0.06	0.20
#New peers	9,888	2.65	9.17	0.00	1.00	3.00
#Old peers	9,888	12.85	10.97	8.00	11.00	15.00

Panel C: Characteristics of Louvain groups

Characteristics of Louvain groups in 2007

Louvain group	Main component industry 1	Main component industry 2	Main component industry 3	Number of component industries	Average CEO compensation	Louvain group size	Louvain group density
#1	Construction	N/A	N/A	1	6,514.20	14	0.57
#2	Retail	Apparel	Wholesale	14	5,785.70	149	0.05
#3	Electronic Equipment	Business Services	Computers	24	4,294.78	298	0.02
#4	Petroleum and Natural Gas	Machinery	Transportation	9	7,991.79	86	0.07
#5	Medical Equipment	Healthcare	Measuring and Control Equipment	18	5,414.42	91	0.05
#6	Food Products	Restaurants, Hotels, Motels	Transportation	26	6,425.46	135	0.05
#7	Pharmaceutical Products	Machinery	Construction Materials	29	5,527.30	182	0.03
#8	Pharmaceutical Products	Communication	Automobiles and Trucks	25	11,029.94	136	0.06
#9	Banking	Insurance	Trading	6	7,358.63	207	0.04
#10	Trading	N/A	N/A	1	3,742.34	68	0.11
#11	Business Services	Personal Services	Transportation	26	4,341.33	174	0.02
#12	Utilities	Banking	Transportation	13	4,747.50	96	0.12

Characteristics of Louvain groups in 2018

Louvain group	Main component industry 1	Main component industry 2	Main component industry 3	Number of component industries	Average CEO compensation	Louvain group sizes	Louvain group density
#1	Construction	N/A	N/A	1	6,061.94	16	0.35
#2	Food Products	Retail	Beer & Liquor	15	51,761.55	74	0.10
#3	Pharmaceutical Products	N/A	N/A	1	4,549.04	14	0.07
#4	Banking	Trading	Business Services	4	32,271.70	119	0.06
#5	Utilities	N/A	N/A	1	23,609.14	56	0.16
#6	Retail	Wholesale	Apparel	8	11,070.41	144	0.04
#7	Transportation	Entertainment	Restaurants, Hotels, Motels	7	18,781.05	61	0.08
#8	Insurance	Real Estate	Trading	3	14,316.86	65	0.09
#9	Pharmaceutical Products	Medical Equipment	Healthcare	7	42,020.17	103	0.08
#10	Machinery	Automobiles and Trucks	Chemicals	23	19,884.66	228	0.04
#11	Business Services	Electronic Equipment	Computers	15	46,317.71	274	0.02
#12	Trading	Real Estate	Construction Materials	3	14,929.45	80	0.09
#13	Petroleum and Natural Gas	Machinery	Utilities	6	8,167.66	75	0.08

This table describes the characteristics of the compensation peer network. Panel A shows the number of focal-peer pairs, unique focal firms, and unique peer firms in the compensation peer network by year. Panel B shows the summary statistics on compensation peer groups. #Benchmarking refers to the number of firms that the focal firm (firm A) is benchmarking against. #Benchmarked refers to the number of firms that choose the focal firm as their compensation peer. #Interlock refers to the number of firms that are both benchmarking against the focal firm and chosen as the focal firm's compensation peers. Same SIC2 (TNIC2) percentage refers to the percentage of peer firms that are within the same SIC2 (TNIC2) product market industry as the focal firm. Similar Sales percentage refers to the percentage of peer firms that have sales between 50% and 200% of sales of the focal firm. Median peer pay minus focal firm pay is the median total compensation of the compensation peers of the focal firm minus the compensation of the focal firm. The turnover ratio refers to the percentage of new peers (#New peers) among all peers (#New peers+#Old peers). Panel C shows the characteristics of Louvain groups (one of our MLCs), including the first three component product industries (defined as the FF48 industries), the number of component product industries and firms in the Louvain group, average CEO compensation within the group, and the Louvain group density in 2007 and 2018 respectively.

Table 2
Managerial labor classifications and talent flows

Panel A: Summary of talent flows

Among 595 talent flows from 2007 to 2018 from the departing firm (firm A) to the new firm (firm B) in the compensation peer network

Link type between firm A and firm B	Percent
Compensation peer group links	
Selected peer	23%
Direct potential peer	6%
Indirect potential peer	45%
Louvain potential peer	8%
Sum of the above cases	82%
Determinants in Faulkender and Yang (2010)	
Same SIC2	38%
Same SIC3	27%
Similar MV	36%
Similar Sales	38%
Similar Assets	35%
Both Dow	0%
Both S&P500	33%
Neither S&P500	27%
Both CEO chair	19%
Neither CEO chair	36%
Flow History	6%

Panel B: Talent flow prediction model

Dependent variable: Talent Flow$_{ijt+1}$	(1)	(2)	(3)	Relative margins	(4)	(5)
Selected Peer$_{ijt}$	1.603***	3.535***	2.787***	16.140	4.530***	
	(9.338)	(19.160)	(13.565)		(32.919)	
Direct Potential Peer$_{ijt}$		3.078***	2.461***	11.578	3.836***	
		(14.139)	(10.523)		(19.357)	
Indirect Potential Peer$_{ijt}$		2.263***	1.959***	7.036	2.519***	
		(17.768)	(14.616)		(21.829)	
Louvain Potential Peer$_{ijt}$		1.642***	1.394***	4.024	1.925***	
		(8.732)	(7.350)		(10.403)	
Same SIC2$_{ijt}$	1.777***	1.054***	0.497***	1.640		2.048***
	(11.856)	(7.187)	(2.753)			(14.922)
Same SIC3$_{ijt}$	0.550***	0.406***	-0.002	0.997		0.790***
	(3.409)	(2.612)	(-0.013)			(5.040)
Similar MV$_{ijt}$	0.175*	0.156*	0.138	1.147		0.237**
	(1.799)	(1.653)	(1.412)			(2.431)
Similar Sales$_{ijt}$	0.158	-0.052	0.026	1.028		0.304***
	(1.587)	(-0.534)	(0.248)			(3.245)
Similar Assets$_{ijt}$	0.074	-0.015	-0.031	0.970		0.170*
	(0.761)	(-0.150)	(-0.300)			(1.794)
Both Dow$_{ijt}$	0.208	-0.170	-0.285	0.752		0.546
	(0.303)	(-0.249)	(-0.433)			(0.805)
Both S&P500$_{ijt}$	0.544***	0.178	0.069	1.070		0.682***
	(4.465)	(1.513)	(0.499)			(5.585)
Neither S&P500$_{ijt}$	-0.244**	-0.109	0.007	1.008		-0.261**
	(-2.061)	(-0.908)	(0.054)			(-2.191)
Both CEO Chair$_{ijt}$	-0.163	-0.207*	-0.190	0.828		-0.144
	(-1.420)	(-1.792)	(-1.614)			(-1.256)

	(1)	(2)	(3)	(4)	(5)	(6)
Neither CEO Chair$_{ijt}$	0.317***	0.323***	0.243**	1.272	0.290***	
	(3.266)	(3.345)	(2.418)		(2.993)	
Flow History$_{ijt}$	2.261***	2.138***	1.766***	5.838	2.740***	
	(8.060)	(8.081)	(6.791)		(10.316)	
Similar ROA$_{ijt}$			0.009	1.008		
			(0.090)			
Same State$_{ijt}$			0.985***	2.678		
			(8.800)			
Both MultiSeg$_{ijt}$			0.181	1.196		
			(1.576)			
Both SingleSeg			0.134	1.145		
			(0.612)			
Both MultiGeo$_{ijt}$			0.207	1.231		
			(1.589)			
Both SingleGeo$_{ijt}$			-0.080	0.923		
			(-0.274)			
Same Consult$_{ijt}$			0.206	1.228		
			(1.389)			
Same TNIC2$_{ijt}$			0.777***	2.174		
			(4.745)			
Same TNIC3$_{ijt}$			0.579***	1.783		
			(3.556)			
Ind Ret Corr$_{ijt}$			1.149***			
			(3.003)			
MV$_{it}$			0.010			
			(0.199)			
MTB$_{it}$			0.008			
			(0.859)			
RET$_{it}$			-0.389***			
			(-3.258)			
ROA$_{it}$			-0.628			
			(-0.983)			
MV$_{jt}$			0.141***			
			(3.803)			
MTB$_{jt}$			0.003			
			(0.328)			
RET$_{jt}$			-0.166			
			(-1.242)			
ROA$_{jt}$			-0.248			
			(-0.456)			
Constant	-10.944***	-11.804***	-14.139***		-11.686***	-11.038***
	(-114.019)	(-96.122)	(-20.841)		(-113.036)	(-113.179)
Observations	16,635,374	16,635,374	15,823,862		16,635,374	16,635,374
Pseudo-R^2	0.086	0.119	0.140		0.097	0.075

This table presents managerial labor classifications and talent flows. Panel A provides a summary of talent flow events used in our sample. Each row shows the percentage of talent flows through one type of link between the departing firm, firm A, and the new firm, firm B. These links are based on either compensation peer group relations or product market and other relations. Selected peers are the firms that firm A chooses as its compensation peers. Direct potential peers are the firms that choose firm A but are not chosen by firm A as compensation peers. Indirect potential peers are the firms that either choose or are chosen by firm A's direct peers (selected peers and direct potential peers), excluding firm A's direct peers. Louvain group potential peers are the firms that are within the same Louvain group as firm A, excluding firm A's direct peers and indirect peers. Flow history refers to the cases where there were talent flows between firm A and firm B before. Same SIC2/3 (TNIC2/3) industry refers to cases where firm A and firm B belong to the same SIC2/3 (TNIC2/3) industry. TNIC2/3 industries are defined by Hoberg and Phillips (2016), and the granularity is equivalent to SIC2/3 industries. Panel B reports results from the talent flow prediction logistic model

(Eq. 1) using MLC and other predictors. The dependent variable *Talent Flow* $_{ijt+1}$ equals one if one of the top five executives of firm *i* moves to the top five executive positions of firm *j* within a one-year gap, and zero otherwise. *Selected Peer*, *Direct Potential Peer*$_{ijt}$, *Indirect Potential Peer*$_{ijt}$, and *Louvain Potential Peer*$_{ijt}$ are dummy variables, taking the value of one if firm *j* belongs to focal firm *i*'s selected peers, direct potential peers, indirect potential peers, or Louvain group peers described above in year *t*, and zero otherwise. All other variables are defined in Appendix A. The column titled "relative margins" shows the relative predictive margins of the indicators in column (3), defined as the ratio of the predictive margins if the indicator equals one relative to the predictive margins if the indicator equals zero. Robust z-statistics with standard errors two-way clustered at the focal firm and peer firm level are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

Table 3
Multidimensional and time-varying features of managerial labor classifications

Panel A: Managerial labor classifications versus product market industries

Dependent variable: *Talent Flow$_{ijt+1}$*	(1)	(2)	(3)	Relative margins	(4)
Direct Peer Same Product Industry$_{ijt}$	0.603***	2.255***	2.985***	19.65	
	(3.821)	(7.511)	(10.510)		
Direct Peer Diff Product Industry$_{ijt}$	2.280***	3.026***	3.279***	25.95	
	(11.892)	(14.658)	(15.156)		
Indirect Peer Same Product Industry$_{ijt}$		1.908***	2.580***	13.06	
		(7.451)	(10.873)		
Indirect Peer Diff Product Industry$_{ijt}$		1.439***	1.682***	5.35	
		(10.311)	(11.413)		
Louvain Peer Same Product Industry$_{ijt}$			1.748***	5.71	
			(6.113)		
Louvain Peer Diff Product Industry$_{ijt}$			1.391***	4.01	
			(6.134)		
Same Product Industry$_{ijt}$					2.337***
					(10.542)
Diff Product Industry$_{ijt}$					1.749***
					(13.240)
Control variables	Yes	Yes	Yes		Yes
Observations	15,823,862	15,823,862	15,823,862		15,823,862
Pseudo-R^2	0.123	0.139	0.143		0.136

Panel B: Dynamic managerial labor classifications

Dependent variable: *Talent Flow$_{ijt+1}$*	(1)	(2)	(3)	(4)	
Peer groups:	Direct peer	Indirect peer	Louvain peer	MLC peer	Relative margins
Past Peer$_{ijt}$	0.827*	0.635**	0.937***	0.465	1.593
	(1.836)	(2.312)	(3.800)	(1.482)	
New Peer$_{ijt}$	1.423***	1.022***	1.192***	1.057***	2.875
	(5.128)	(4.146)	(5.382)	(4.020)	
Current Peer$_{ijt}$	1.286***	1.915***	1.337***	2.240***	9.395
	(6.089)	(10.952)	(7.654)	(12.900)	
Future Peer$_{ijt}$	1.351***	0.649**	0.540**	0.737***	2.091
	(4.107)	(2.464)	(2.316)	(2.599)	
Control variables	Yes	Yes	Yes	Yes	
Observations	10,483,674	10,483,674	10,483,674	10,483,674	
Pseudo-R^2	0.114	0.130	0.139	0.131	

This table reports results from the talent flow prediction logistic model and demonstrates the features of MLCs. Panel A compares the predictive power of both managerial labor classifications and product market industries (Eq. 2). The dependent variable *Talent Flow$_{ijt+1}$* equals one if one of the top five executives of firm *i* moves to the top five executive positions at firm *j* within a one-year gap, and zero otherwise. *Direct Peer Same (Diff) Product Industry* is a dummy variable, taking the value of one if firm *j* is a direct peer of firm *i* and belongs to the same (different) product industry as firm *i*, and zero otherwise. *Indirect Peer Same (Diff) Product Industry* is a dummy variable, taking the value of one if firm *j* is an indirect peer of firm *i*, and belongs to the same (different) product industry as firm *i* and zero otherwise. *Louvain Peer Same (Diff) Product Industry* is a dummy variable, taking the value of one if firm *j* is a Louvain group peer of firm *i* and belongs to the same (different) product industry as firm *i*, and zero otherwise. *Same (Diff) Product Industry* is a dummy variable, taking the value of one if firm *j* belongs to the same (different) product industry as firm *i*, and zero otherwise. Product industries are defined as the joint of SIC2 and TNIC2 industries. Panel B reports results from the talent flow prediction logistic model and compares the predictive power of past, new, current, and future peers within different peer groups. *Past Peer* is a dummy variable, taking the value of one if firm *j* is a direct (column

1)/indirect (column 2)/Louvain (column 3)/MLC peer (column 4) of firm i in the past year t-1 but not the current year t, and zero otherwise. MLC peer is the joint peer group consisting of direct, indirect, and Louvain peers. *New Peer* is a dummy variable, taking the value of one if firm j is a direct/indirect/Louvain/MLC peer of firm i in the current year t but not the past year t-1, and zero otherwise. *Current Peer* is a dummy variable, taking the value of one if firm j is a direct/indirect/Louvain/MLC peer of firm i in both the past year t-1 and the current year t, and zero otherwise. *Future Peer* is a dummy variable, taking the value of one if firm j is a direct/indirect/Louvain/MLC peer of firm i in the next year t+1 but not the current year t, and zero otherwise. The control variables included are the same as the ones in column (3) of Table 2 Panel B. All other variables are defined in Appendix A. The column titled "relative margins" shows the relative predictive margins of the indicators, defined as the ratio of the predictive margin if the indicator equals one relative to the predictive margin if the indicator equals zero. Robust z-statistics with standard errors two-way clustered at the focal firm and peer firm level are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

Table 4
Descriptives on managerial labor competition measures

Panel A: Summary statistics

Variables	Observations	Mean	Median	Std Dev
Compensation and peer variables				
Total Pay	9,798	8,342.06	6,767.80	6,179.91
Equity Pay	9,750	5,063.47	3,904.33	4,641.58
Cash Pay	9,798	1,182.68	1,000.00	836.69
Equity Pct	9,738	0.55	0.59	0.23
Pay Duration (in years)	8,205	1.39	1.40	0.71
FF Peer Pay	9,798	7,060.60	5,991.51	4,222.54
FF Peer Num	9,798	21.90	16.00	18.14
Network measures				
InDegree	9,798	13.80	12.00	9.94
Clustering	9,798	0.32	0.29	0.19
Louvain Density	9,798	0.06	0.05	0.06
Louvain Size	9,798	159.38	143.00	75.91
Eigenvector	9,798	0.02	0.01	0.09
Firm and CEO characteristics				
TRS1yr	9,798	0.14	0.11	0.38
ROA	9,798	0.05	0.05	0.07
Ln(Revt)	9,798	8.32	8.24	1.36
MTB	9,798	1.94	1.57	1.16
Leverage	9,798	0.26	0.24	0.19
Volatility	9,798	0.09	0.07	0.05
CEO Age	9,798	57.41	57.00	6.49
Idio Var	9,648	0.50	0.50	0.29
Ret Corr	9,648	1.00	0.96	0.43
CEO Tenure	9,797	7.45	5.65	6.59
HHI	9,798	0.06	0.05	0.04
Other variables				
Luck	7,396	0.12	0.12	0.24
Skill	7,396	0.01	0.01	0.22
Return Own	8,564	0.10	0.08	0.36
Return Peer	8,564	0.08	0.08	0.27

Panel B: Factor loadings on managerial labor competition measures

Variables	Component 1	Component 2
InDegree	0.438	0.531
Clustering	0.523	0.327
Louvain Density	0.524	-0.454
Louvain Size	-0.455	0.537
Eigenvector	0.232	0.341
Eigenvalue of principal component	1.75	1.41
Cumulative proportion explained by principal components	35.06%	63.17%

This table shows descriptives on managerial labor competition measures. Panel A shows summary statistics. Panel B shows the factor loadings on the principal components of managerial labor competition measures. All variables are defined in Appendix A.

Table 5
Managerial labor competition measures and executive compensation

Panel A: Total compensation

Dependent variable: Ln(Total Pay)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
InDegree	0.105***				0.095***		
	(7.363)				(6.512)		
Clustering		0.048***			0.030**		
		(3.772)			(2.364)		
Louvain Density			0.043***		0.030***		
			(3.895)		(2.812)		
Louvain Size			0.040***		0.037***		
			(3.764)		(3.557)		
Eigenvector				0.019***	0.013***		
				(2.596)	(4.163)		
PCOMP1						0.069***	0.063***
						(3.839)	(3.067)
PCOMP2						0.070***	0.079***
						(3.182)	(2.909)
Ln(FF Peer Pay)	0.691***	0.710***	0.722***	0.725***	0.684***	0.697***	0.698***
	(15.131)	(15.230)	(15.628)	(15.695)	(14.962)	(14.938)	(12.417)
FF Peer Num	-0.003	-0.002	-0.002	-0.002	-0.003	-0.002	-0.003
	(-1.498)	(-1.050)	(-0.916)	(-0.934)	(-1.544)	(-1.389)	(-1.361)
TRS1yr	0.158***	0.154***	0.151***	0.152***	0.159***	0.157***	0.172***
	(7.331)	(7.046)	(6.898)	(6.928)	(7.354)	(7.239)	(6.939)
Lag(TRS1yr)	0.187***	0.174***	0.173***	0.170***	0.189***	0.181***	0.196***
	(8.549)	(7.886)	(7.811)	(7.682)	(8.617)	(8.098)	(7.535)
ROA	-0.238	-0.182	-0.190	-0.216	-0.199	-0.203	-0.201
	(-1.492)	(-1.135)	(-1.159)	(-1.329)	(-1.254)	(-1.275)	(-1.167)
Lag(ROA)	-0.234	-0.237	-0.255	-0.273*	-0.195	-0.214	-0.274
	(-1.482)	(-1.513)	(-1.594)	(-1.716)	(-1.245)	(-1.364)	(-1.569)
Lag(ln(Revt))	-0.001	0.029	0.038*	0.035*	-0.004	0.004	0.001
	(-0.034)	(1.358)	(1.789)	(1.654)	(-0.198)	(0.164)	(0.049)
Lag(MTB)	0.028*	0.034**	0.036**	0.038**	0.025	0.029*	0.030*
	(1.669)	(2.018)	(2.092)	(2.201)	(1.467)	(1.689)	(1.648)
Lag(Leverage)	0.002	-0.005	-0.004	-0.002	0.001	-0.003	0.010
	(0.024)	(-0.075)	(-0.055)	(-0.030)	(0.013)	(-0.037)	(0.128)
Lag(Volatility)	-0.734***	-0.993***	-1.016***	-1.002***	-0.756***	-0.842***	-0.908***
	(-3.276)	(-4.366)	(-4.450)	(-4.385)	(-3.383)	(-3.707)	(-3.499)
CEO Age	0.001	0.001	0.002	0.001	0.001	0.001	0.001
	(0.540)	(0.499)	(0.720)	(0.629)	(0.507)	(0.423)	(0.400)
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	No
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	No
Industry × Year FEs	No	No	No	No	No	No	Yes
Observations	9,798	9,798	9,798	9,798	9,798	9,798	9,798
Adjusted R^2	0.450	0.442	0.441	0.440	0.452	0.449	0.431

Panel B: Compensation components and pay duration

Dependent variables:	(1) Ln(Equity Pay)	(2) Ln(Cash Pay)	(3) Equity Pct	(4) Pay Duration
PCOMP1	0.151***	0.024*	0.014**	0.038**
	(2.656)	(1.776)	(2.379)	(2.003)
PCOMP2	0.236***	0.023	0.024***	0.028
	(3.176)	(1.581)	(3.435)	(1.561)
Control variables	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	9,750	9,798	9,738	8,205
Adjusted R^2	0.137	0.149	0.137	0.056

This table shows results on managerial labor competition measures and executive compensation. Panel A reports results from regressions of total CEO compensation on competition measures and controls (Eq. 3). The dependent variable, *Ln(Total Pay)*, is the natural logarithm of one plus total CEO compensation. *InDegree* is the number of firms choosing the focal firm as a compensation peer. *Clustering* is the clustering coefficient of the firm in the compensation peer network. *Louvain Density* is the density of links within the Louvain industry. *Louvain Size* is the number of firms within the Louvain industry. *Eigenvector* is the eigenvector centrality of the firm in the compensation peer network. In the regressions, *InDegree*, *Clustering*, *Louvain Density*, *Louvain Size*, and *Eigenvector* are standardized for ease of interpretation. *PCOMP1* and *PCOMP2* are the standardized first two principal components of *InDegree*, *Clustering*, *Louvain Density*, *Louvain Size*, and *Eigenvector*. Panel B reports results from regressions of executive compensation components and characteristics on competition measures and controls (Eq. 3). The dependent variables for columns (1)-(4) are *ln(Equity Pay)*, *ln(Cash Pay)*, *Equity Pct*, and *Pay Duration* respectively. *Ln(Equity Pay)* is the natural logarithm of one plus the total amount of stock and option awards. *Ln(Cash Pay)* is the natural logarithm of one plus the total amount of cash and salary. *Equity Pct* is the percentage of equity pay to total CEO compensation. *Pay Duration* is the average vesting period of different pay components of CEO compensation, calculated following Gopalan et al. (2014). Control variables, industry fixed effects, and year fixed effects are included in all regressions. Industry dummies are constructed based on FF48 industries. All other variables are defined in Appendix A. Robust t-statistics with standard errors clustered at the firm level are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

Table 6
Application 1: Participation constraints and incentive contracts

Panel A: Pay for luck

Dependent variable: *Ln(Total Pay)*	(1)	(2)	(3)
Luck	0.105***	0.123***	0.123***
	(2.710)	(3.220)	(3.230)
Skill	0.169***	0.179***	0.183***
	(4.907)	(5.247)	(5.224)
Luck × PCOMP1		0.088***	0.077***
		(2.624)	(2.696)
Luck × PCOMP2		0.076**	0.064**
		(2.026)	(2.096)
Skill × PCOMP1			0.014
			(0.415)
Skill × PCOMP2			0.050
			(1.054)
PCOMP1		0.059***	0.063***
		(4.092)	(4.488)
PCOMP2		0.063***	0.069***
		(3.999)	(4.803)
Control variables	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Observations	7,396	7,396	7,396
Adjusted R^2	0.465	0.474	0.474

Panel B: Relative performance evaluation

Dependent variable: *Ln(Total Pay)*	(1)	(2)	(3)
Ln(Return Own)	0.191***	0.199***	0.213***
	(6.761)	(7.064)	(6.079)
Ln(Return Peer)	-0.125***	-0.127***	-0.314***
	(-3.076)	(-3.107)	(-2.889)
Ln(Return Peer) × PCOMP1		0.058**	0.078**
		(1.986)	(2.559)
Ln(Return Peer) × PCOMP2		0.064**	0.070**
		(1.967)	(2.230)
Ln(Return Peer) × FF Peer Num			0.003**
			(2.248)
Ln(Return Peer) × Idio Var			0.166*
			(1.672)
Ln(Return Peer) × Ret Corr			-0.108*
			(-1.856)
Ln(Return Peer) × MTB			0.020
			(0.803)
Ln(Return Peer) × CEO Tenure			0.004
			(1.098)
Ln(Return Peer) × HHI			1.042
			(1.460)
PCOMP1		0.069***	0.069***
		(4.729)	(4.874)
PCOMP2		0.080***	0.083***
		(5.447)	(5.786)

FF Peer Num			-0.002
			(-1.268)
Idio Var			-0.013
			(-0.255)
Ret Corr			0.020
			(0.829)
MTB			-0.008
			(-0.484)
CEO Tenure			0.002
			(0.997)
HHI			0.974
			(1.236)
Control variables	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Observations	8,564	8,564	8,552
Adjusted R^2	0.437	0.446	0.447

This table applies managerial labor competition measures to explain seemingly problematic pay practices. Panel A reports results from regressions of total CEO compensation on luck and skill measures, competition measures, and controls (Eq. 5). The dependent variable, *Ln(Total Pay)*, is the natural logarithm of one plus CEO total compensation. *Luck* and *Skill* are the luck and skill components of stock returns, constructed following Daniel et al. (2020). *PCOMP1* and *PCOMP2* are the standardized first two principal components of the five competition measures. Panel B reports results from regressions of total CEO compensation on the firm's own and peer stock returns, competition measures, and controls (Eq. 6). *Ln(Return Own)* and *Ln(Return Peer)* are constructed following Albuquerque (2009) and Jayaraman et al. (2021). *Ln(Return Own)* is the natural logarithm of one plus the firm's stock return in a year. *Ln(Return Peer)* is the natural logarithm of one plus peer stock return, which is the equal-weighted stock portfolio return of peers within the same TNIC3 industry and size quartile. All other variables are defined in Appendix A. Year fixed effects and industry fixed effects are included in regressions. Industry dummies are constructed based on FF48 industries. Robust t-statistics with standard errors clustered at the firm level are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

Table 7
Application 2: The incentive role of the managerial labor market

Panel A: External tournament incentive

Dependent variable: *Tobin Q*	(1)	(2)	(3)	(4)	(5)
Ln(FF48 Pay Gap)	0.004				
	(0.474)				
Ln(TNIC2 Pay Gap)		0.008			
		(0.801)			
Ln(Direct Peer Pay Gap)			0.025***		
			(2.869)		
Ln(Indirect Peer Pay Gap)				0.050***	
				(4.585)	
Ln(Louvain Peer Pay Gap)					0.027***
					(2.860)
Ln(Delta)	0.179***	0.182***	0.179***	0.177***	0.178***
	(9.484)	(8.602)	(9.497)	(9.445)	(9.457)
Ln(Infirm Pay Gap)	0.010	0.014	0.020	0.017	0.014
	(0.686)	(0.872)	(1.261)	(1.118)	(0.931)
Ln(Assets)	-0.536***	-0.504***	-0.544***	-0.555***	-0.543***
	(-8.967)	(-7.840)	(-9.132)	(-9.295)	(-9.118)
Ln(CEO Tenure)	-0.278***	-0.253***	-0.276***	-0.269***	-0.274***
	(-5.591)	(-4.884)	(-5.564)	(-5.443)	(-5.530)
Ln(CEO Age)	7.348**	5.802*	7.251**	6.972**	7.163**
	(2.427)	(1.883)	(2.395)	(2.322)	(2.380)
TRS1yr	0.436***	0.425***	0.437***	0.440***	0.437***
	(14.934)	(13.926)	(14.971)	(15.010)	(14.956)
Sales Growth	0.197***	0.194***	0.202***	0.213***	0.203***
	(4.532)	(4.042)	(4.645)	(4.944)	(4.695)
CAPEX	2.978***	2.919***	2.990***	2.948***	2.960***
	(5.513)	(5.090)	(5.534)	(5.447)	(5.483)
Ind Vol	-12.367	-13.328	-11.741	-12.323	-12.534
	(-1.193)	(-1.215)	(-1.142)	(-1.189)	(-1.208)
Ln(Ind CEO Count)	-0.392**	-0.340*	-0.407**	-0.395**	-0.391**
	(-2.173)	(-1.886)	(-2.250)	(-2.198)	(-2.168)
Executive × Firm FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	8,108	7,173	8,108	8,108	8,108
Adjusted R^2	0.852	0.850	0.852	0.852	0.852

Panel B: Pay for competition and future performance

Dependent variables:	Pred.	(1) Future ROA 1yr	(2) Future ROA 2yrs	(3) Future ROA 3yrs	(4) Future Return 1yr	(5) Future Return 2yrs	(6) Future Return 3yrs
Fitted Pay	+	0.033**	0.031**	0.028*	0.081**	0.060*	0.050
		(2.104)	(2.027)	(1.804)	(2.185)	(1.750)	(1.487)
Ln(Revt)		0.000	0.000	-0.000			
		(0.262)	(0.033)	(-0.089)			
Ln(ROA Sd)		-0.004***	-0.004***	-0.004**			
		(-2.928)	(-2.810)	(-2.465)			
MTB					0.005	0.004	0.001
					(1.348)	(0.990)	(0.148)
Ln(MV)					-0.021***	-0.022***	-0.022***
					(-5.544)	(-5.946)	(-6.044)
Ln(Ret Sd)					0.000	-0.001	0.005
					(0.047)	(-0.195)	(0.844)
Industry FEs		Yes	Yes	Yes	Yes	Yes	Yes
Year FEs		Yes	Yes	Yes	Yes	Yes	Yes
Observations		9,156	8,173	7,214	9,137	8,151	7,193
Adjusted R^2		0.121	0.142	0.162	0.265	0.233	0.120

This table tests the incentive role of the managerial labor market. Panel A reports regressions of *Tobin Q* on proxies for tournament incentives and control variables (Eq. 7). The dependent variable is *Tobin Q*, which is the ratio of the sum of the market value of equity and the book value of debt to total assets. *Ln(FF48 Pay Gap)* is the natural logarithm of the difference in total compensation between the second-highest-paid CEO within the same FF48 industry and the CEO of the sample firm. *Ln(TNIC2 Pay Gap)* is the natural logarithm of the difference in total compensation between the second-highest-paid CEO within the same TNIC2 industry and the CEO of the sample firm. *Ln(Direct Peer Pay Gap)* is the natural logarithm of the difference in total compensation between the second-highest-paid CEO within the direct peer group and the CEO of the sample firm. *Ln(Indirect Peer Pay Gap)* is the natural logarithm of the difference in total compensation between the second-highest-paid CEO within the indirect and direct peer group and the CEO of the sample firm. *Ln(Louvain Peer Pay Gap)* is the natural logarithm of the difference in total compensation between the second-highest paid CEO within the Louvain peer group, together with the direct and indirect peer group, and the CEO of the sample firm. The above-mentioned pay gap variables are standardized for ease of interpretation. Year fixed effects and Executive×Firm fixed effects are included in regressions. Panel B reports results from regressions of future firm performance on fitted compensation and controls (Eq. 8). The dependent variables are future firm performance in one, two, and three-year windows. *Future ROA 1yr (2yrs, 3yrs)* is defined as the average of future ROA in one year (two years, three years). *Future Return 1yr (2yrs, 3yrs)* is defined as the average of future stock returns in one year (two years, three years). *Fitted Pay* is the fitted value from the sum of products of each competition measures (*InDegree*, *Clustering*, *Louvain Density*, *Louvain Size*, and *Eigenvector*) and its coefficients estimated from regressing total compensation on all competition measures and controls (Table 5 Panel A, column 5). Industry fixed effects and year fixed effects are included in regressions. Robust t-statistics with standard errors clustered at the firm level are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively