JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 58, No. 2, Mar. 2023, pp. 837–874

doi:10.1017/S0022109022000229

Technological Fit and the Market for Managerial Talent

Fred Bereskin
University of Missouri Trulaske College of Business
bereskinf@missouri.edu

Seong K. Byun
Virginia Commonwealth University School of Business Administration
sbyun@vcu.edu

Jong-Min Oh
SungKyunKwan University SKK Business School
jongmin.oh@skku.edu (corresponding author)

Abstract

We show that the similarity of a firm's technological expertise with that of other firms affects managerial labor market outcomes. Using each firm's patent portfolio to estimate its technological expertise, we find that its similarity in technological expertise with other firms is strongly related to the benchmark group used for CEO compensation and job transitions. Furthermore, we show that a firm's CEO pay is positively associated with the CEO compensation levels of technologically similar firms. Our results thus demonstrate the crucial role of technological similarity in determining the value of outside options and the boundaries of the managerial labor market.

I. Introduction

Investments in R&D and intangible capital have increased considerably over the last 4 decades and have changed the way that firms invest and grow.[1] The growing prominence of R&D capital has also led to examinations of how a firm's technological expertise affects corporate policies, such as M&A (Bena and Li (2014)), CEO selection (Pan (2017), Cummings and Knott (2018)), IPOs (Bowen

We thank an anonymous referee, Melissa Frye, Vladimir Gatchev, Jarrad Harford (the editor), John Howe, Po-Hsuan Hsu, Sima Jannati, Stefano Sacchetto, Henri Servaes, Qinghai Wang, Jessica West, Chi Zhang, and seminar and conference participants at the 2020 Financial Management Association Conference, 2020 Annual Conference of the Asia-Pacific Association of Derivatives, 2020 Conference on Asia-Pacific Financial Markets (CAFM), Korea Advanced Institute of Science and Technology (KAIST), Korea University, Seoul National University, University of Central Florida, University of Mississippi, University of Missouri, University of Seoul, University of Sydney, and Virginia Commonwealth University for valuable comments. Jong-Min Oh gratefully acknowledges financial support from the JOONGBONG Research Fund, SKK Business School.

[1]For example, studies have documented that firms are becoming more productive (Crouzet and Eberly (2019), Döttling and Perotti (2019)), are less likely to go public (Kahle and Stulz (2017), Bowen, Fresard, and Hoberg (2022)), and are more reliant on internal funds than external financing (Bates, Kahle, and Stulz (2009), Kahle and Stulz (2017)).

et al. (2022)), and cash holdings (Qiu and Wan (2015)). In this article, we examine an underexplored area, namely, the effect of technological expertise on executive compensation. Specifically, we examine whether the degree of overlap in technological expertise with other firms is an important driver of competition for managerial talent and, hence, compensation policy.

Our focus on the role of technological expertise and its overlap with peer firms in shaping compensation policy relies on the notion that firms with similar technologies are likely to value similar managerial attributes. As CEOs gain experience and greater knowledge of the businesses they run, they are also likely to gain expertise in technological domains associated with managing firms in certain technological areas. In turn, CEOs can make better decisions, for example, in hiring and obtaining the right people, converting their innovations to marketable products, protecting intellectual property, and identifying new opportunities.[2] Therefore, managers' expertise in certain technological domains is valuable not only to the given firm but also to other firms that focus on similar technology. We thus hypothesize that if the technological fit between the firm and manager is a primary consideration for companies in their search for managers, the extent that a company's technology overlaps with other firms will affect the outside option value of managers and shape the market for CEOs. This will ultimately be manifested in firms' CEO compensation policies.

Consistent with these ideas, existing studies have shown that a manager's technological expertise plays an important role in determining the degree of complementarities between firm and managerial attributes (e.g., Pan (2017)). Likewise, Cummings and Knott (2018) document a reduction in R&D productivity and growth for firms that hire CEOs who lack firm-specific expertise in the relevant technological domains.[3] Anecdotally, our focus on the role of similarities in technological expertise in shaping firms' compensation policies is also consistent with many proxy statements taking technological considerations as important factors that firms consider when choosing peer groups for benchmarking executive compensation.[4]

Conversely, simply finding that firms with similar technology compete for the same managerial talent might not be surprising, as firms competing in the same industry would presumably also share similar technology and those firms

[2]This is also consistent with anecdotal evidence (Rao (2012), Skonnard (2014), and Coon (2017)).

[3]Previous studies have emphasized that a CEO's expertise should be an essential consideration in compensation policy (e.g., Harris and Helfat (1997), Feldman and Montgomery (2015), and Cummings and Knott (2018)). Cummings and Knott (2018) provide anecdotal evidence that Hughes Aircraft experienced R&D productivity declines and was ultimately sold in pieces to Raytheon, Boeing, and other firms after C. Michael Armstrong was hired from IBM as CEO. Armstrong, lacking technological expertise in Hughes' technologies, changed R&D practices such that Hughes could no longer focus on long-term and cutting-edge technologies. Likewise, the authors document that a firm that hires a CEO lacking expertise in the firm's technical areas often struggles in furthering the firm's innovative activities.

[4]Firms often state technological similarity as an important determinant for compensation benchmark firms: Apple's 2014 proxy refers to a reliance on companies with "significant R&D and innovation for growth, and require highly skilled human capital"; Boeing's 2009 proxy notes that compensation is benchmarked against "companies that have a technology focus … comparable to Boeing"; General Motors' 2011 proxy refers to larger firms with "complex business operations, including significant research and development …"; Chevron's 2009 proxy refers to peer firms with "extensive technology portfolios, an emphasis on engineering and technical skills"; and Monsanto's proxy statement indicates that "the compensation benchmarking group of firms should have: i) science-based, research-focused, organization from the biotechnology, pharmaceutical or related industry …"

would often compete for managerial talent within the same industry (e.g., Bizjak, Lemmon, and Naveen (2008), Faulkender and Yang (2010), Bizjak, Lemmon, and Nguyen (2011), and Albuquerque, Franco, and Verdi (2013)). However, it is unclear whether the presence of firms with similar technologies should matter even when firms do not directly compete, and how much technological similarity matters over and above industry and other firm characteristics.

Given that executive-firm matching considers multiple dimensions (Pan (2017)), comparing the effects of technological similarity to existing factors allows us to tease out the effects of technology from other characteristics that might otherwise mask the effect of similarity in technology attributes. Also, ample anecdotal and empirical evidence suggests that the convergence of technology in modern firms is blurring the conventional boundaries between industries, and that the boundaries of the labor and product markets are relatively independent for executives.[5] Therefore, our study provides greater evidence of the efficiency of the managerial labor market and a clearer understanding of the role of similarities in technological expertise in executive-firm matching – and thus segmentation in the executive labor market.

We follow existing studies by using patent technology classifications to measure firms' technological expertise similarity, which is measured by their focus on certain patent technologies.[6] Existing studies have also noted that technological similarities do not reflect mere product market similarity. Anecdotally, for example, Monsanto Co. shares many technologies with firms from industries (such as food and pharmaceuticals) that are different from the agricultural chemicals industry in which it is historically positioned. Monsanto's proxy states that for technological reasons it benchmarks CEO compensation to firms operating in different industries, such as Baxter International (medical equipment), Genzyme (pharmaceuticals), Colgate-Palmolive (consumer goods), and General Mills (food). Although Monsanto and the aforementioned firms do not directly compete in the same industry, they exhibit high technological similarity.[7]

Using compensation benchmarking peer firm data and the technological overlap measure, we begin by showing that similarity in technological expertise is a significant determinant of whether a certain firm is used as a compensation

[5]See, for example, Ernst and Young (2000), Lei (2000), Bröring, Cloutier, and Leker (2006), Cunat and Guadalupe (2009), Bröring (2010), IBM (2015), McKinsey (2017), and Burgelman and Thomas (2018). Cunat and Guadalupe (2009) note that CEOs frequently change firms across industries rather than within industries: 71% (64%) of the transitions of executives between firms included in ExecuComp are between 4-digit (3-digit) SIC industries.

[6]See, for example, Jaffe (1986), Bloom, Schankerman, and Van Reenen (2013), Bena and Li (2014), Qiu and Wan (2015), Qiu, Wang, and Zhou (2018), Lee, Sun, Wang, and Zhang (2019), Byun, Oh, and Xia (2021), and McLemore, Sias, Wan, and Yuskel (2022).

[7]Using our measure of technological similarity, we are able to identify a firm's technologically related peers by examining the overlap in firms' patent classifications. For example, by examining patent classification data, one observes that Monsanto shares technological expertise with Baxter International and Genzyme in "*Drug, bio-affecting and body treating compositions*" (USPTO Class 514) and "*Chemistry: natural resins or derivatives; peptides or proteins; lignins or reaction products thereof*" (USPTO Class 530), among many others, and also shares technological proficiency with General Mills in "*Food or edible material: processes, compositions, and products*" (USPTO Class 426), among others.

benchmarking peer. In theory, firms benchmark CEO pay against other firms to correctly reflect managers' outside options (e.g., Bizjak et al. (2008), Albuquerque et al. (2013)). If technological fit plays an important role in determining the market for managers, firms should benchmark their compensation to other firms with similar technology. We find that a 1-standard-deviation increase in technological similarity is associated with a 51% increase in the odds of being a benchmarking peer. This compares to a corresponding 217% increase in the odds associated with being in the same industry, a 71% increase in the odds associated with a 1-standard-deviation increase in the stock return correlation, and a 34% decrease in the odds associated with a 1-standard-deviation increase in the firm size difference, implying an economic importance of technological similarity that is comparable to other prominent determinants of compensation benchmarking. Moreover, even within the same industry and size groups, we show that a focal firm's choice of peer firms is determined by its technological similarity to those firms.[8] Our results suggest that technological similarity plays a crucial role in firms' choice of peer group and that considering the role of technological fit is critical for demonstrating the efficiency of the labor market and the composition of the peer group.

We also implement various robustness tests to ensure that the positive relation we find between technological similarity and compensation benchmarking selection is not due to similarities among other unobserved dimensions. First, to eliminate the possibility that our results are due to the biases arising from a comparison of actual peer firms to other firms unlikely to be picked in the first place, we construct different sets of potential peers using various matching criteria, including using only the peers of a firm's own peer firms as the potential peers, and using a year, industry, size, and book-to-market matched peer sample. We show that the results are consistent with our baseline results. Second, we implement the impact threshold for a confounding variable (ITCV) test (Frank (2000)) to quantify potential omitted variables bias in our estimates and to show that the threshold for invalidating the inference from our regressions is quite high. This suggests that the possibility of an omitted variable explaining the relation between technological similarity and compensation benchmarking is low. Third, we examine coefficient stability (Oster (2019)) and present evidence that unobservables would need to be 152% as important as the included control variables to invalidate our result. Fourth, we explicitly include various additional control variables. We show that the results are robust.

We also try to mitigate endogeneity concerns by using exogenous shocks to technological similarity. Specifically, we focus on the situation in which a peer firm's technology space moves significantly closer to the focal firm, while the focal firm's technology remains relatively constant. This allows us to focus on variations in technological similarity unrelated to the decisions of the focal firm and enables us to examine whether the focal firm is more likely to choose a peer firm that converges

[8]For example, Johnson and Johnson's (J&J) 2009 proxy statement includes certain firms (such as Pfizer and Merck) as compensation benchmarking peers, but not others (such as Eli Lilly and GlaxoSmithKline), even though the excluded firms are in the same industry as J&J and are close industry peers. According to our technological similarity measure, Pfizer and Merck exhibit high similarities with J&J, whereas Eli Lilly and GlaxoSmithKline do not.

on its technology space. We find results consistent with our main results, suggesting that the positive relation between technological similarity and a firm's likelihood of being selected as a benchmarking peer is unlikely to be driven by other unobservable factors.

We then present evidence consistent with compensation benchmarking being an efficient approach to estimating the market wage for human capital, as opposed to its use reflecting managerial opportunism. We show that higher technological similarity with benchmarking peer firms increases the likelihood of a CEO who received above-median (below-median) pay in the previous year to receive at or below-median (above-median) pay in the following year. This result is obtained even after controlling for other important compensation determinants from previous studies (e.g., Bizjak et al. (2008)), and is consistent with the market-based theory of CEO compensation in that firms set CEO pay to remain competitive with firms that are competing for similar managerial talent. After establishing that technological similarity has an important effect on CEO compensation benchmarking patterns, we provide evidence that its use reflects CEOs' outside options. In particular, we show that a 1-standard-deviation increase in technological similarity increases the odds of the CEO joining a similar firm by 86%. Our finding reflects the notion that the marketability of CEOs' technological expertise is at least partly reflected in firms' technological similarity and that firms prefer to hire CEOs with a better technological fit (e.g., Pan (2017), Cummings and Knott (2018)).

Finally, we show that the CEO compensation levels of technologically similar peer firms are positively associated with CEO pay at the focal firm: CEO compensation increases by 0.258% when the median CEO compensation of technologically similar firms increases by 1%. We thus provide evidence that technological similarity plays a crucial role in the market for CEO talent and that the labor market consistently reflects CEOs' outside opportunities.

Our work contributes to several strands of the existing literature. First, we contribute to the literature focusing on the effect of similarities in technological expertise on corporate policies.[9] We add to the literature by showing that the specific types of technology associated with firms have become one of the important aspects in the competition for managerial talent. Thus, we contribute to the literature by showing that technological expertise similarity is an essential component in setting competitive CEO pay and in determining the executive-firm match.

Second, we add to the literature on CEO labor market segmentation; previous research on CEO labor market segmentation has focused on geography and industry (Cremers and Grinstein (2014), Coles, Li, and Wang (2018)); although the traditional view is that the executive labor market in the USA is not particularly

[9]Bena and Li (2014) show that firms with similar technology are more likely to merge. Cao, Ma, Tucker, and Wan (2018) show the effects of technological "peer pressure" on disclosure. Qiu and Wan (2015) show that technology-related firms' innovations promote more cash savings. Pan (2017) notes that executive-firm technology complementarity is important for their match. Byun et al. (2021) show that firms shift their research from breakthrough to incremental innovation in response to the level of innovations from technologically related peers.

geographically mobile (Kedia and Rajgopal (2009)), recent studies highlight the important role of executives' local labor market (Francis et al. (2016), Yonker (2017), Zhao (2018), and Ma, Pan, and Stubben (2020)).[10] The extent of labor market segmentation is crucial for understanding the nature of the executive labor market. For example, Gabaix and Landier (2008) note that if labor pools are segmented by industry, the referenced firm-size used in their analysis would be industry-specific (and thus lead to attenuation bias in the coefficient for the reference firm size). Our results are consistent with technological expertise being a distinct and previously overlooked aspect of CEO skill that could be transferred across a particular set of firms that share similar technology. We show that managers who are exposed to their firm's key technologies are likely to gain certain technological expertise and hence would have competitive value in the market for CEOs (particularly among firms that also focus on similar technological expertise (e.g., Cummings and Knott (2018)).

Third, we add to the literature on optimal contracting for CEO compensation.[11] The existing literature notes the role of either general and transferable managerial skills (Custodio, Ferreira, and Matos (2013), Frydman (2019)) or technology and skill complementarity (Pan (2017)). We provide evidence that the degree of technological similarity plays an important role in the managerial labor market.[12]

Finally, we contribute to the literature on peer groups for executive compensation and the debate regarding whether peer groups reflect rent-seeking behavior.[13] To capture the flow in managerial labor beyond industry and size, Faulkender and Yang (2010) and Albuquerque et al. (2013) examine whether top executives experience transitions to and from the *industry* of a potential peer, though the authors are agnostic about the factors that determine the transitions in the first place. Bizjak et al. (2011) capture other firm similarities including those in sales and performance, credit market conditions, and business complexity. We add to the literature by showing that technological similarity plays an important role in determining compensation benchmarking peers, consistent with an efficient contracting motivation.

[10]Additionally, Cziraki and Jenter (2021) discuss the role of firm-specific human capital and information asymmetries in assignment of CEOs. These papers challenge the notion of a single talent pool for the CEO labor market (Gabaix and Landier (2008), Tervio (2008)).

[11]Since many of the drivers of executive pay remain unexplained (Edmans and Gabaix (2016)), we provide evidence of an important determinant of compensation levels.

[12]Also, by presenting evidence that technological similarity provides an additional dimension in boundaries for the market for CEOs, our results complement those of Frydman and Papanikolau (2018), who show how certain improvements in technology raise the returns to identifying new growth projects (and thus lead to increases in executive compensation).

[13]See, for example, Bizjak et al. (2008), Faulkender and Yang (2010), Bizjak et al. (2011), Albuquerque et al. (2013), Cadman and Carter (2014), Francis, Hasan, Mani, and Pengfei (2016), Coles, Du, and Xie (2018), Denis, Jochem, and Rajamani (2020), Jayaraman, Milbourn, Peters, and Seo (2021), and Larcker, McClure, and Zhu (2021). A related topic is the nature of the benchmark used in relative performance evaluation (RPE), where a payout is based on firm performance relative to a group of firms. This topic is not directly related to our study, though it has been considered in other studies (Gopalan, Milbourn, and Song (2010), Gong, Li, and Shin (2011), Albuquerque (2014), De Angelis and Grinstein (2020), and Bizjak, Kalpathy, Li, and Young (2022)).

II. Empirical Design and Data

A. Technological Similarity Measure

To construct a measure of technological closeness between two firms, we define their technological similarity using the Jaffe (1986) measure of closeness, which uses the overlap in the classifications of firms' patent portfolios. Specifically, we define technological similarity between firm i and firm j in year t as

$$\text{(1)} \qquad \text{TECH\_SIMILARITY}_{ij,t} = \frac{F_{i,t}F'_{j,t}}{(F_{i,t}F'_{i,t})^{0.5}(F_{j,t}F'_{j,t})^{0.5}},$$

where $F_{i,t}$ is the one by τ vector of firm i's proportion of patents granted in technology space one through τ in year t, and τ is the number of different patent classification classes. Thus, TECH_SIMILARITY is the normalized, uncentered correlation between the two firms' patent shares. To generate the vector $F_{i,t}$ of patent shares for each year, we use the number of patents that have been applied for within that year. We do this to capture the timing of a firm's actual patenting activity, since the grant year can be many years away from when the innovation took place.

The Jaffe measure of technological similarity and similar variants have been used to examine the effects of technology spillovers (e.g., Jaffe (1986), Bloom et al. (2013)) and, more recently, to examine the effects of technological similarity on merger incidence and postmerger outcomes (Bena and Li (2014)), cash holdings (Qiu and Wan (2015)), and product disclosure (Cao et al. (2018)). We obtain patent data from Kogan, Papanikolau, Seru, and Stoffman (2017), who use patent-level information from 1926 to 2010.

B. Compensation Benchmarking

Our initial set of tests examines the role of technological similarity in determining the compensation benchmarking peer. To do so, we estimate the following logistic regression:

$$\text{(2)} \qquad \text{COMPENSATION\_PEER\_DUMMY}_{ij,t} = a + b_1\text{TECH\_SIMILARITY}_{ij,t} + b'X_{ij,t} + \text{Time FE}_t + e_{ij,t},$$

where Compensation_Peer_Dummy$_{ij,t}$ is a dummy variable that equals 1 if firm i uses firm j to benchmark its compensation in year t, and 0 otherwise; TECH_SIMILARITY$_{ij,t}$ is defined in equation (1); and $X_{ij,t}$ includes various pair-level characteristics that can also determine the likelihood of firm i choosing firm j as a benchmark. We also include year fixed effects.

In addition to our baseline model, we estimate the logistic regression with (firm i's) industry fixed effects to control for unobserved time-invariant industry effects. We also estimate the model with more stringent peer group fixed effects, where the peer group is defined as a collection of pairs with the same firm i in a given year. As an example, suppose in 2006 firm i is paired with all other firms (as firm j's); this forms the pool of potential pairs of firms that firm i can use for benchmarking compensation in 2006. All of these firms (firm i and the paired firms) will be in the same peer group. Thus, we control for effects specific to firm *i*, and the estimates will only reflect the cross-sectional variation in the joint characteristics specific to firm *i* and firm *j*, such as the two firms' TECH_SIMILARITY.

Existing studies have pointed out that pair-level analysis of compensation benchmarking likelihood can suffer from the fact that the number of actual benchmarking peers is far outweighed by the number of all potential peers, which include all permutations of firms that exist in the sample. We address this issue by implementing our test with a more restrictive set of potential peer firms in which we use the peers of peers as the sample of potential peers. Specifically, consider firm *i* to be the focal firm. Then for each of firm *i*'s actual compensation benchmarking peer firm *j*, we consider firm *j*'s compensation benchmarking peers (some of which also can be firm *i*'s benchmarking peer, although many may not be) to be the potential peers of firm *i*. Thus, firm *i*'s potential peer group consists of all the peers of its own peers, which we term the "peers-of-peer" matched sample.[14]

Our main compensation benchmark data come from Institutional Shareholder Services (ISS) Incentive Lab, which contains detailed information on compensation benchmark peers starting from 2006, the year that firms were required by the SEC to begin reporting detailed information on compensation benchmarking practices. ISS Incentive Lab mainly covers S&P 500 and S&P 400 firms and has expanded its coverage in recent years. We merge the compensation benchmark data with pairwise technological similarity data. Thus, firms are paired with all other firms in the technological similarity database to form a firm pair, which corresponds to a potential pool of candidates for benchmarking compensation. Labeling the pairwise data as firm pair *i*–*j*, we define a dummy variable COMPENSATION_PEER, which equals 1 if firm *i* benchmarks firm *j*'s compensation in setting its own CEO pay, and 0 otherwise.

We obtain financial and accounting data from Compustat and CRSP and executive compensation data from ExecuComp. We control for additional pair-level variables that have been shown to potentially affect compensation benchmarking practice: SAME_INDUSTRY, which equals 1 if firm *i* and firm *j* are from the same 3-digit SIC industry[15]; WITHIN60MI which equals 1 if the two firms' headquarters are within 60 miles of each other; STOCK_RETURN_CORR defined as the past 250 trading day daily stock return correlation between the two firms; BETA_DIFF, defined as the difference in the beta of firm *i* and firm *j* estimated using a market model with the prior 250 trading day stock return and the CRSP value-weighted market return; VOLATILITY_DIFF, the difference in the past 250 trading day daily stock return volatility; HHI_DIFF, the difference in the firms'

[14]We perform our tests using two alternative matching techniques. First, we follow the literature in constructing a randomly matched sample in which we select up to 50 potential peers from all possible peers. Second, we carry out tests on a matched sample, where we match actual benchmarking peers to up to five potential peers in the same industry and year that are similarly sized and have a similar book-to-market ratio. For brevity, we report the results from the randomly matched sample and year/industry/size/BTM-matched sample in Table IA-1 of the Supplementary Material.

[15]In Section III.C, we repeat our tests with an alternative industry definition using Hoberg and Phillip's ((2010), (2016)) text-based network industry classification (TNIC). Our results are also robust to using the North American Industry Classification System (NAICS) and the Global Industry Classification Standard (GICS).

https://doi.org/10.1017/S0022109022000229 Published online by Cambridge University Press

2-digit SIC code Herfindahl–Hirschman index; THREE_YEAR_RETURN_DIFF, the difference in the firms' past 3-year stock returns; SIZE_DIFF, the difference in the two firms' natural log of total assets (at); LEVERAGE_DIFF, the difference in the firms' book leverage ratio, defined as short-term debt (dlc) plus long-term debt (dltt), divided by total assets (at); MB_DIFF, the difference in the two firms' market-to-book ratio, defined as total assets (at) minus book value of equity (ceq) plus market value of equity (prcc_f × csho), divided by total assets (at); CASH_RATIO_DIFF, the difference in the two firms' cash ratios, defined as cash and cash equivalents (che), divided by total assets (at); and COMPENSATION_-DIFF, the difference in the two firms' CEOs' total compensation (tdc1). Each difference between two firms is the value for firm i minus the value for firm j.

Our final compensation benchmarking sample contains 609,322 firm-pair-year observations from 2006 to 2010, with 396 unique firms and 726 unique peers. Table 1 reports the summary statistics of our sample of benchmark peers. All variables, except the dummy variables, are winsorized at the 1% level. In our full sample, 2.3% of pair-year observations are compensation peers, and 4.2% of pairs are in the same industry; the average TECH_SIMILARITY is 4.3%.

Firms that compete in the same product market space might also have high technological similarity, which could reflect the impact of being in the same product market. While SAME_INDUSTRY partly controls for this effect, we construct an additional proxy for product market similarity. As in Bloom et al. (2013) we define PROD_MARKET_SIM as $\frac{M_{i,t}M'_{j,t}}{\left(M_{i,t}M'_{i,t}\right)^{0.5}\left(M_{j,t}M'_{j,t}\right)^{0.5}}$, where $M_{i,t}$ is the one by s vector of firm i's proportion of sales in a product market segment one through s in year t, and s is the total number of different segments in the market. Hence, PROD_MARKET_SIM, like TECH_SIMILARITY from equation (1), is the Jaffe distance between two firms' product market segments. Thus, two firms with perfect overlap in

TABLE 1

Summary Statistics: Compensation Benchmark Selection and Job Transition

Table 1 reports the summary statistics of the sample that we use to analyze compensation benchmarking and CEO job transitions. We report the firm-by-firm (firm i and firm j)-pair-level sample that is used to analyze the effect of technological similarity in determining the firms being used in compensation benchmarking. The data on compensation benchmarking peers come from Institutional Shareholder Services (ISS) Incentive Lab from 2006 to 2010. The sample includes all actual compensation benchmarking peers, as well as nonbenchmarking peers, to generate a total pool of all potential peers that firm i can use to benchmark compensation. All variables are defined in the Appendix. Each difference between two firms is defined as the value for firm i minus the value for firm j.

Variable	Obs.	Mean	Std. Dev.	25th	Median	75th
COMPENSATION_PEER_DUMMY	609,322	0.023	0.149	0.000	0.000	0.000
TECH_SIMILARITY	609,322	0.043	0.110	0.000	0.001	0.025
PROD_MARKET_SIM	431,286	0.025	0.147	0.000	0.000	0.000
SAME_INDUSTRY	609,322	0.042	0.202	0.000	0.000	0.000
WITHIN60MI	609,322	0.052	0.221	0.000	0.000	0.000
STOCK_RETURN_CORR	609,322	0.271	0.207	0.126	0.274	0.421
BETA_DIFF	609,322	−0.069	0.567	−0.424	−0.061	0.296
VOLATILITY_DIFF	609,322	−0.003	0.013	−0.011	−0.003	0.005
HHI_DIFF	609,322	0.003	0.085	−0.022	0.000	0.024
THREE_YEAR_RETURN_DIFF	609,322	0.041	1.186	−0.459	0.031	0.515
SIZE_DIFF	609,322	0.951	2.301	−0.601	1.000	2.545
LEVERAGE_DIFF	609,322	0.030	0.214	−0.116	0.027	0.180
MB_DIFF	609,322	0.121	1.417	−0.599	0.107	0.838
CASH_RATIO_DIFF	609,322	−0.025	0.245	−0.168	−0.014	0.118
COMPENSATION_DIFF	609,322	2,452.17	8,333.94	−1,741.34	2,161.19	6,554.63

multiple segments (or two single-segment firms operating in the same segment) will have PROD_MARKET_SIM equal to 1, whereas two firms with zero overlap will have zero PROD_MARKET_SIM.

III. Compensation Benchmark Selection Results

A. Full Sample and Random-Matched Sample

We begin by examining whether firms are more likely to benchmark CEO compensation to technologically similar firms. For this purpose, we estimate the logistic regression of compensation benchmarking likelihood from equation (2). In Panel A of Table 2, we estimate the model with the full sample. In column 1, we estimate the univariate logistic regression of TECH_SIMILARITY on COMPENSATION_PEER_DUMMY. The coefficient associated with TECH_SIMILARITY is 5.002 and is statistically significant at the 1% level, which suggests that firms with high technological similarity are more likely to be used to benchmark CEO compensation. Second, we estimate the model with other firm characteristics as additional controls and include year fixed effects in column 2 and both year and industry fixed effects in column 3. The estimates are consistent with that of column 1, with estimated coefficients of 3.766 and 3.798, respectively, for the year and year-industry fixed effects models. These estimates are statistically significant at the 1% level. The economic impact of technological similarity is also significant: a 1-standard-deviation increase in TECH_SIMILARITY (0.110) increases the odds of a firm being a compensation benchmark peer by 51.3% [exp(3.766 × 0.110) − 1]. This magnitude is comparable to that of STOCK_RETURN_CORR: In the model with year fixed effects (column 2), a 1-standard-deviation increase in the stock return correlation between two firms increases the odds of a firm being a compensation benchmark peer by 71%. Unsurprisingly, the coefficient associated with the SAME_INDUSTRY indicator is also positive: being in the same industry increases the odds of a firm being a compensation benchmark peer by 217%.

Lastly, we estimate the model with peer group fixed effects in column 4, such that the estimated coefficient for TECH_SIMILARITY will only capture the variation among the potential group of firms to which a given firm can potentially benchmark its compensation. This coefficient remains positive and statistically significant; with this model, a 1-standard-deviation increase in TECH_SIMILARITY increases the odds of being a compensation benchmarking peer by 53%.

An alternative explanation for our results is that TECH_SIMILARITY could capture the variation in product market similarity; firms that directly compete with each other are more likely to be used as compensation benchmarking peers. While SAME_INDUSTRY and STOCK_RETURN_CORR controls help to address this issue, the degree of competition and similarity in product markets can vary within a given industry. To address this concern, we include PROD_MARKET_SIM as an additional control in columns 5–8. As expected, the estimates for PROD_MARKET_SIM are positive and significant. Additionally, TECH_SIMILARITY remains positive and significant throughout.

In Panel B of Table 2, we examine the relation between technological similarity and the likelihood of a firm being chosen as a compensation benchmark peer using an alternative group of potential peers. The previous analysis in which we use the full sample (and which includes all possible pairs of firms in Compustat) implicitly uses all firms in the same year as potential candidates for benchmarking compensation. In addition, the asymmetry between actual compensation benchmarking pairs and noncompensation pairs could be a concern (actual compensation benchmark peers compose around only 2% of the final sample). To address these issues, we repeat our analysis using a "peers-of-peer" matched sample approach

TABLE 2

Compensation Benchmark Peer Selection

Table 2 contains the results from analyzing the characteristics of firms that are selected for compensation benchmarking. The estimates of the logistic regression model of compensation benchmarking peer likelihood from equation (2) are reported. The sample consists of firm-by-firm (firm *i* and firm *j*)-pair-level observations of U.S. public firms from 2006 to 2010. Panel A reports the estimates from the full sample. Panel B reports the estimates from the peers-of-peer matched sample, in which we match actual compensation peers to potential firms that are the peers of the actual peers (see Section II.B for details). The dependent variable is COMPENSATION_PEER_DUMMY, which equals 1 if firm *j* is used in benchmarking compensation for firm *i*, and zero otherwise. Our main independent variable is TECH_SIMILARITY, defined as the Jaffe (1986) similarity measure of patent portfolios between the firm pair *i*–*j*. See the Appendix for the definitions of other control variables. We estimate the logistic regression model with various fixed effects, including year (columns 2 and 6), year and industry (columns 3 and 7), and peer group fixed effects (columns 4 and 8), where peer group is defined as a cluster of pairs grouped by firm *i*-year. *t*-statistics based on standard errors double clustered by firms *i* and *j* are reported in parentheses except for the group fixed effects models in which the standard errors are clustered at the firm *i* level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: COMPENSATION_PEER_DUMMY							
	1	2	3	4	5	6	7	8
Panel A. Full Sample								
TECH_SIMILARITY	5.002***	3.766***	3.798***	3.866***	5.138***	3.704***	3.703***	3.654***
	(36.55)	(25.54)	(23.17)	(26.15)	(36.75)	(22.64)	(20.98)	(22.07)
PROD_MARKET_SIM						0.660***	0.852***	1.287***
						(4.48)	(5.09)	(7.70)
SAME_INDUSTRY		1.155***	1.447***	1.852***		0.867***	1.069***	1.327***
		(10.20)	(10.91)	(15.95)		(6.23)	(7.25)	(9.89)
WITHIN60MI		0.662***	0.812***	0.993***		0.620***	0.746***	0.975***
		(6.76)	(8.31)	(11.98)		(5.66)	(6.86)	(10.40)
STOCK_RETURN_ CORR		2.595***	2.738***	2.721***		2.641***	2.691***	2.591***
		(13.74)	(16.61)	(17.22)		(12.70)	(14.93)	(15.70)
BETA_DIFF		−0.093	0.006	0.028		−0.091	−0.059	−0.008
		(−1.06)	(0.07)	(0.30)		(−0.99)	(−0.59)	(−0.08)
VOLATILITY_DIFF		14.984***	14.662***	22.682***		15.152***	13.928***	21.250***
		(3.75)	(3.65)	(6.27)		(3.52)	(3.31)	(5.45)
HHI_DIFF		2.832***	0.296	1.639***		2.872***	0.326	1.316**
		(3.49)	(0.42)	(3.71)		(3.22)	(0.41)	(2.37)
THREE_YEAR_ RETURN _DIFF		0.074**	0.069**	0.140***		0.073**	0.074**	0.120***
		(2.52)	(2.31)	(5.58)		(2.12)	(2.40)	(4.13)
SIZE_DIFF		−0.182***	−0.207***	−0.418***		−0.192***	−0.213***	−0.427***
		(−6.23)	(−5.93)	(−11.92)		(−5.92)	(−5.63)	(−11.75)
LEVERAGE_DIFF		−0.361*	−0.561***	−0.160		−0.263	−0.405**	−0.088
		(−1.94)	(−3.24)	(−0.96)		(−1.26)	(−2.10)	(−0.51)
MB_DIFF		−0.129***	−0.141***	−0.220***		−0.120***	−0.131***	−0.191***
		(−4.33)	(−4.10)	(−9.66)		(−3.81)	(−3.52)	(−7.42)
CASH_RATIO_DIFF		−0.024	0.184	0.848***		−0.032	0.204	0.865***
		(−0.12)	(0.89)	(4.20)		(−0.15)	(0.92)	(3.93)
COMPENSATION_ DIFF		−0.000	−0.000	0.000		−0.000	−0.000	0.000*
		(−0.47)	(−0.09)	(1.16)		(−0.49)	(−0.61)	(1.83)
Year FE	No	Yes	Yes	No	No	Yes	Yes	No
Industry FE	No	No	Yes	No	No	No	Yes	No
Peer group FE	No	No	No	Yes	No	No	No	Yes
N	609,322	609,322	609,322	609,322	431,286	431,286	431,286	431,286
Pseudo-R^2	0.105	0.178	0.200	0.255	0.118	0.199	0.218	0.274

(continued on next page)

https://doi.org/10.1017/S0022109022000229 Published online by Cambridge University Press

TABLE 2 (continued)

Compensation Benchmark Peer Selection

	Dependent Variable: COMPENSATION_PEER_DUMMY							
	1	2	3	4	5	6	7	8
Panel B. Peers of Peer Matched Sample								
TECH_SIMILARITY	2.873***	2.237***	2.332***	2.840***	2.903***	2.199***	2.254***	2.728***
	(22.25)	(16.65)	(15.96)	(21.28)	(21.09)	(15.36)	(14.64)	(18.02)
PROD_MARKET_SIM						0.306***	0.415***	0.759***
						(2.93)	(3.54)	(5.89)
SAME_INDUSTRY		0.579***	0.748***	0.951***		0.455***	0.568***	0.654***
		(8.35)	(9.10)	(11.43)		(4.90)	(6.06)	(6.75)
WITHIN60MI		0.275***	0.393***	0.554***		0.240***	0.337***	0.506***
		(3.95)	(5.02)	(6.90)		(3.08)	(4.01)	(5.79)
STOCK_RETURN_CORR		1.127***	1.310***	1.649***		1.130***	1.246***	1.529***
		(8.52)	(10.37)	(11.41)		(8.18)	(9.44)	(10.01)
BETA_DIFF		0.077	0.141*	0.269***		0.121	0.148*	0.256**
		(0.94)	(1.69)	(2.84)		(1.42)	(1.69)	(2.51)
VOLATILITY_DIFF		4.133	2.347	2.524		2.548	−0.258	−0.026
		(1.21)	(0.69)	(0.67)		(0.72)	(−0.07)	(−0.01)
HHI_DIFF		1.251***	−0.258	0.111		1.202**	−0.197	0.193
		(2.65)	(−0.55)	(0.30)		(2.27)	(−0.40)	(0.43)
THREE_YEAR_ RETURN_DIFF		−0.031	−0.026	−0.056**		−0.029	−0.022	−0.069**
		(−1.41)	(−1.36)	(−2.31)		(−1.04)	(−0.81)	(−2.42)
SIZE_DIFF		0.100***	0.089***	0.063*		0.095***	0.087**	0.058
		(3.13)	(2.62)	(1.66)		(2.69)	(2.16)	(1.48)
LEVERAGE_DIFF		−0.157	−0.224	0.072		−0.107	−0.130	0.101
		(−1.07)	(−1.58)	(0.44)		(−0.65)	(−0.82)	(0.58)
MB_DIFF		0.008	−0.002	−0.031		0.008	0.001	−0.031
		(0.35)	(−0.09)	(−1.22)		(0.29)	(0.03)	(−1.14)
CASH_RATIO_DIFF		0.211	0.399**	0.820***		0.201	0.399*	0.795***
		(1.13)	(2.17)	(4.51)		(0.99)	(1.94)	(4.06)
COMPENSATION_DIFF		0.000	−0.000	−0.000		0.000	−0.000	0.000
		(0.01)	(−0.18)	(−0.15)		(0.07)	(−0.32)	(0.48)
Year FE	No	Yes	Yes	No	No	Yes	Yes	No
Industry FE	No	No	Yes	No	No	No	Yes	No
Peer group FE	No	No	No	Yes	No	No	No	Yes
N	68,385	68,385	68,385	68,385	47,697	47,697	47,697	47,697
Pseudo-R^2	0.054	0.073	0.083	0.098	0.058	0.080	0.089	0.108

(see Section II.B for details). Across all specifications, the coefficient estimate for TECH_SIMILARITY remains strongly positive and significant, consistent with our main result. Our results suggest that the estimate for TECH_SIMILARITY is unlikely to be driven by other pair-specific similarities or characteristics and point to the role of technological similarity in influencing firms' compensation benchmarking choice.

B. Peer Group Selection Within the Same Industry and Size Groups

The above results based on the full sample contain variations across different industries and size groups. Essentially, the variation in technological similarity captured above potentially explains why a firm would be chosen as a benchmarking peer even if the peer firm is not in the same industry as the focal firm. In this subsection, we test whether technological similarity can also explain why particular firms in the same industry or size groups are selected as benchmarking peers.[16]

We examine the within-industry variation in firms' peer selection. To do so, we estimate the peer selection model in equation (2) using only the subsample of firms in which the benchmarking firms and peer firms are in the same industry (i.e., SAME_INDUSTRY equals 1). Panel A of Table 3 reports the results. Although the results using the entire sample are qualitatively similar, for brevity we report the results using the peers-of-peer matched sample. We find that the effects of TECH_

TABLE 3

Compensation Peer Group: Within-Industry and Size Groups

Table 3 reports the result of examining the determinants of compensation peer selection among peers in the same industry and size groups. The sample of pairs of firms comes from peers-of-peer matched sample used in Table 2, Panel B. In Panel A, we examine the subsample of pairs of firms in which the pairs are from the same 3-digit SIC industry. In Panel B, we examine the subsample of pairs of firms in which the pairs are in the same size decile in each year where firm size is proxied by firm sales. The dependent variable is COMPENSATION_PEER_DUMMY, which equals 1 if firm *j* is an actual compensation benchmarking peer, and zero otherwise. The main independent variable is TECH_SIMILARITY, defined as the Jaffe (1986) similarity measure of patent portfolios between the firm pair *i*–*j*. We estimate the logistic regression model with various fixed effects, including year (columns 2 and 6), year and industry (columns 3 and 7), and peer group fixed effects (columns 4 and 8), where peer group is defined as a cluster of pairs grouped by firm *i*-year. All other explanatory variables are defined in Table 2. *t*-statistics based on standard errors double clustered by firms *i* and *j* are reported in parentheses, except for the group fixed effects models in which the standard errors are clustered at the firm *i* level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: COMPENSATION_PEER_DUMMY							
	1	2	3	4	5	6	7	8
Panel A. Within-Industry								
TECH_SIMILARITY	1.527***	1.498***	1.479***	1.731***	1.501***	1.429***	1.351***	1.570***
	(9.46)	(9.54)	(9.95)	(9.98)	(8.79)	(8.67)	(8.65)	(8.25)
PROD_MARKET_SIM						0.198**	0.379***	0.423***
						(2.00)	(3.62)	(3.28)
WITHIN60MI		0.327***	0.469***	0.529***		0.304***	0.419***	0.480***
		(2.99)	(4.35)	(4.04)		(2.73)	(3.79)	(3.54)
STOCK_RETURN_CORR		0.943***	1.113***	1.366***		0.656***	0.957***	1.254***
		(4.59)	(5.16)	(5.35)		(2.97)	(4.21)	(4.43)
BETA_DIFF		−0.011	−0.001	0.219		−0.027	−0.015	0.163
		(−0.10)	(−0.01)	(1.57)		(−0.24)	(−0.14)	(0.99)
VOLATILITY_DIFF		2.483	5.061	2.210		2.740	6.438	5.632
		(0.55)	(1.07)	(0.33)		(0.58)	(1.35)	(0.73)
THREE_YEAR_ RETURN_DIFF		−0.007	−0.018	−0.012		−0.026	−0.039	−0.026
		(−0.18)	(−0.50)	(−0.22)		(−0.56)	(−0.98)	(−0.43)
SIZE_DIFF		0.096*	0.096**	0.123***		0.090	0.090*	0.110**
		(1.92)	(2.04)	(2.66)		(1.64)	(1.75)	(2.25)
LEVERAGE_DIFF		0.048	0.020	0.255		0.159	0.115	0.316
		(0.23)	(0.11)	(0.92)		(0.68)	(0.55)	(1.11)
MB_DIFF		0.036	0.036	−0.041		0.038	0.034	−0.036
		(1.12)	(1.27)	(−0.93)		(0.98)	(1.03)	(−0.72)
CASH_RATIO_DIFF		0.165	0.165	0.302		0.123	0.136	0.335
		(0.94)	(0.95)	(1.15)		(0.60)	(0.68)	(1.13)
COMPENSATION _DIFF		−0.000	0.000	−0.000		0.000	0.000	0.000
		(−0.17)	(0.03)	(−0.18)		(0.09)	(0.43)	(0.31)
Year FE	No	Yes	Yes	No	No	Yes	Yes	No
Industry FE	No	No	Yes	No	No	No	Yes	No
Peer group FE	No	No	No	Yes	No	No	No	Yes
N	9,699	9,699	9,670	9,102	7,820	7,820	7,779	7,399
Pseudo-R^2	0.025	0.038	0.055	0.045	0.024	0.038	0.055	0.048

(continued on next page)

[16]For example, Johnson and Johnson's 2009 proxy statement includes certain product market competitors (such as Pfizer and Merck) as compensation benchmarking peers, but not others (such as Eli Lilly and GlaxoSmithKline), even though those firms operate in the same industry as J&J.

TABLE 3 (continued)

Compensation Peer Group: Within-Industry and Size Groups

	Dependent Variable: COMPENSATION_PEER_DUMMY							
	1	2	3	4	5	6	7	8
Panel B. Within-Size Decile								
TECH_SIMILARITY	3.064***	2.345***	2.478***	3.383***	3.074***	2.365***	2.381***	3.369***
	(13.24)	(10.40)	(9.93)	(13.16)	(12.60)	(10.14)	(9.14)	(11.55)
PROD_MARKET_SIM						0.217	0.370**	1.073***
						(1.44)	(2.32)	(5.97)
SAME_INDUSTRY		0.672***	0.868***	1.284***		0.598***	0.670***	0.864***
		(6.12)	(7.06)	(9.46)		(4.13)	(4.32)	(5.15)
WITHIN60MI		0.388***	0.540***	0.769***		0.326**	0.440***	0.802***
		(3.01)	(3.93)	(5.37)		(2.19)	(2.84)	(4.80)
STOCK RETURN_CORR		1.241***	1.480***	1.894***		1.412***	1.491***	1.725***
		(6.17)	(7.81)	(8.24)		(6.76)	(6.69)	(6.69)
BETA_DIFF		0.200	0.275**	0.171		0.250*	0.315**	0.115
		(1.61)	(2.08)	(1.12)		(1.94)	(2.12)	(0.69)
VOLATILITY_DIFF		4.134	3.436	19.765***		3.510	2.009	19.715***
		(0.85)	(0.63)	(3.13)		(0.66)	(0.34)	(2.99)
HHI_DIFF		1.131	−0.484	1.621***		0.717	0.235	1.523
		(1.42)	(−0.58)	(2.60)		(1.02)	(0.25)	(1.63)
THREE_YEAR_RETURN_DIFF		−0.025	−0.014	−0.015		0.004	0.009	−0.042
		(−0.67)	(−0.34)	(−0.33)		(0.09)	(0.18)	(−0.80)
SIZE_DIFF		0.134	0.055	−0.178*		0.084	0.048	−0.085
		(1.51)	(0.62)	(−1.78)		(0.75)	(0.45)	(−0.79)
LEVERAGE_DIFF		−0.136	−0.246	−0.052		−0.054	−0.168	−0.012
		(−0.61)	(−1.10)	(−0.20)		(−0.24)	(−0.68)	(−0.04)
MB_DIFF		−0.024	−0.050	−0.149***		−0.040	−0.054	−0.130***
		(−0.69)	(−1.39)	(−3.56)		(−1.04)	(−1.25)	(−2.60)
CASH_RATIO _DIFF		0.412	0.708***	1.037***		0.571*	0.822***	1.160***
		(1.54)	(2.80)	(3.23)		(1.95)	(2.83)	(3.28)
COMPENSATION_DIFF		−0.000	−0.000	−0.000**		−0.000	−0.000	−0.000
		(−0.87)	(−0.98)	(−2.01)		(−1.05)	(−1.12)	(−1.47)
Year FE	No	Yes	Yes	No	No	Yes	Yes	No
Industry FE	No	No	Yes	No	No	No	Yes	No
Peer group FE	No	No	No	Yes	No	No	No	Yes
N	12,967	12,967	12,966	12,344	8,749	8,749	8,749	8,203
Pseudo-R^2	0.059	0.085	0.108	0.156	0.064	0.096	0.111	0.177

SIMILARITY remain positive and statistically significant in all specifications: a 1-standard-deviation increase in TECH_SIMILARITY (0.110) increases the odds of being a compensation benchmark peer by 16%–21%. Hence, even among firms in the same industry, firms are more likely to benchmark compensation to peer firms with high degrees of technological overlap.

We also examine variations in peer selection within the same size groups. Here, we estimate the peer selection model in equation (2) with the subsample of pairs of firms in the same firm size decile, where we use firm sales as our proxy for firm size. Thus, every year, we sort firms into deciles of firm sales and keep observations if the (i,j)-pair of firms are in the same sales decile. Panel B of Table 3 reports the results. Consistent with the main results, TECH_SIMILARITY remains positive and both statistically and economically significant in all specifications in explaining peer selection among firms in the same size deciles: In the most conservative estimate, a 1-standard-deviation increase in TECH_SIMILARITY increases the odds of being a compensation benchmark peer by 29%, which is comparable to our baseline regression.

https://doi.org/10.1017/S0022109022000229 Published online by Cambridge University Press

C. Robustness Issues

One potential concern with the above analysis is that SIC codes might lack certain variations across industries. To address this concern, we use an alternative definition of industry based on Hoberg and Phillip's ((2010), (2016)) text-based network industry classification (TNIC). Their definition aims to capture firms in the same product market space by measuring the textual similarities in firms' product market descriptions, as reported in companies' annual reports.[17] We use TNIC3, which is designed with granularity comparable to the 3-digit SIC codes. We define SAME_TNIC_INDUSTRY as equal to 1 if the firm pair is in the same TNIC3 group, and 0 otherwise.

We report our results in Table IA-2 of the Supplementary Material. As expected, the coefficient for SAME_TNIC_INDUSTRY is positive and statistically significant. The magnitude is also economically significant and comparable to the baseline model: Being in the same TNIC3 industry increases the odds of being selected as a compensation benchmark peer by approximately 285%. Meanwhile, the effect of TECH_SIMILARITY remains positive and significant. In columns 2 and 3 with year fixed effects and peer group fixed effects models, a 1-standard-deviation increase in TECH_SIMILARITY increases the odds of being selected as a compensation benchmarking peer by 50% and 53%, respectively. In columns 4–6, we restrict the sample to firm pairs in the same TNIC3 group so that variations captured in the peer selection model highlight which peer firms are more likely to be selected for benchmarking compensation in that industry. Our results remain consistent; in all three specifications, the coefficients for TECH_SIMILARITY remain large and statistically significant: A 1-standard-deviation increase in TECH_SIMILARITY increases the odds of a firm being selected as a compensation benchmarking peer by at least 24% among all the peers in the same industry.

Next, we consider whether managerial entrenchment affects our analysis. Although competitive compensation is generally the stated motivation for benchmarking, previous studies have noted the possibility that managers might use compensation benchmarking to boost their pay by opportunistically selecting peers with higher pay (e.g., Bebchuk and Fried (2004), Faulkender and Yang (2010), and Bizjak et al. (2011)). In the context of the opportunistic selection of peers, self-serving managers might be more likely to choose peer firms with high technological overlap, to justify their own pay levels. Indeed, an agency-based explanation for peer group composition would suggest that technological similarity affects selection, to the extent that firms could ostensibly justify the selection decision. As a proxy for managerial entrenchment, we use the Entrenchment Index (E_INDEX) from Bebchuk, Cohen, and Ferrell (2009).[18] We examine whether the relation between technological similarity and the likelihood of a firm becoming a compensation peer depends on managerial entrenchment.[19]

[17]Other industry classification systems include NAICS, which focuses on similarities in the product process, and GICS, which focuses on product similarity. Our results are robust to using these alternative industry classifications. We note that Jayaraman et al. (2021) use product market peers to present evidence consistent with RPE with respect to forced turnover and CEO compensation.

[18]Our results remain similar when using other measures, such as the G-index or CEO-chair duality.

https://doi.org/10.1017/S0022109022000229 Published online by Cambridge University Press

We test this possibility in Table IA-3 of the Supplementary Material. Throughout all specifications, the interaction terms are small in magnitude and statistically insignificant. Thus, the relation between technological similarity and the likelihood of a firm becoming a compensation peer (at least in the context of our results) does not seem to be driven by managers' self-serving motivation. We thus provide evidence that TECH_SIMILARITY is an important determinant of the peer group decision and that its use reflects executives' outside opportunities. In the subsequent sections, we explore additional robustness tests of our main results and examine further implications of our findings.

IV. Omitted Variables and Endogeneity

While we are careful in trying to control for factors that can explain the benchmarking peer choice in our baseline model, it is admittedly not possible to exhaust all omitted variables that can explain the relation between technological similarity and compensation benchmarking choice. In this section, we attempt to address possible remaining omitted variables biases by implementing numerous approaches, each with its own unique advantages and limitations.

A. Impact Threshold for a Confounding Variable

First, to gain a sense of the magnitude of the potential omitted variables bias, we implement the ITCV test (Frank (2000)), which estimates the theoretical minimum correlation that a possible omitted variable must have with the dependent variable (compensation peer) and the independent variable (technological similarity) to invalidate the inference from our regression estimates.[20] Using the estimates from Model 8 of Table 2, we find that an omitted variable must have a residual correlation (after controlling for all existing independent variables) of 18.1% with the dependent and the independent variables of interest to invalidate our results, with an impact threshold of $0.181 \times 0.181 = 0.0327$.[21] While critical values are not associated with the impact thresholds, one can have a sense of the magnitude by comparing the threshold to the impact of the existing factors that are known to be important.

In Panel A of Table 4, we report the corresponding partial correlations and the impact of existing variables. The variable with the most impact is, not

[19]Additionally, our analysis of compensation peer selection is robust to including E_INDEX as an additional control.

[20]The ITCV approach recognizes that for an omitted variable to affect the results, it would be correlated with both the dependent and independent variable (after controlling for other explanatory variables). As derived in Frank (2000), the ITCV is the lowest product of the two partial correlations (between the dependent variable and the confounding variable, and between the independent variable of interest and the confounding variable) that would cause the coefficient of interest to be statistically insignificant. Consequently, for a high ITCV, the results are relatively robust to concerns with respect to correlated omitted variables. Other recent papers, including Larcker and Rusticus (2010), Glendening, Mauldin, and Shaw (2019), and Fich, Liu, and Officer (2020) also use the ITCV test. Larcker and Rusticus (2010) suggest that one potential benchmark for ITCV measures is the control variable's impact.

[21]Other alternative specifications from Table 2 show similar results.

https://doi.org/10.1017/S0022109022000229 Published online by Cambridge University Press

TABLE 4
Sensitivity Measures

Table 4 reports the sensitivity of our analysis to potential endogeneity issues. Panel A provides results from the Impact Threshold for a Confounding Variable (ITCV) from Frank (2000) based on our baseline regression from Table 2, column 8 with year fixed effects. The first column lists the control variables included in the regression. The second column reports the partial correlation of each of the control variables with the dependent variable (COMPENSATION_PEER_DUMMY). The third column reports the partial correlation of each of the control variables with the main independent variable (TECH_SIMILARITY). The last column reports the impact score from the ITCV test, which is a function of the partial correlations with the dependent and the independent variable. Here, the impact scores from the table give a sense of how large the possible omitted variable's correlations must be to invalidate the inferences that could be made from the estimates for TECH_SIMILARITY. Panel B provides results using Oster's (2019) measure for unobservable selection and coefficient stability.

Panel A. Impact Threshold for a Confounding Variable

Variables	Partial Correlations With Dependent Variable	Partial Correlations With Independent Variable	Impact
SAME_INDUSTRY	0.267	0.089	0.024
PROD_MARKET_SIM	0.162	0.104	0.017
STOCK_RETURN_CORR	0.079	0.070	0.006
WITHIN60MI	0.051	0.045	0.002
MB_DIFF	−0.009	−0.020	0.000
VOL_DIFF	0.010	0.014	0.000
CASH_DIFF	−0.001	0.021	0.000
STOCK_RETURN_DIFF	0.003	0.014	0.000
LEVERAGE_DIFF	−0.004	−0.002	0.000
BETA_DIFF	−0.006	−0.006	0.000
HHI_DIFF	−0.013	−0.004	0.000
COMPENSATION_DIFF	−0.002	−0.003	0.000
SIZE_DIFF	0.002	−0.040	0.000

Panel B. Oster (2019) Coefficient Stability

	Coefficient		R^2		
Model	Uncontrolled	Controlled	Uncontrolled	Controlled	δ
Year FE	0.315	0.222	0.057	0.085	1.631
Year and Ind FE	0.315	0.221	0.057	0.090	1.518
Year and peer group FE	0.315	0.209	0.057	0.110	1.702

surprisingly, SAME_INDUSTRY. Being in the same industry has a partial correlation with the dependent variable of 26.7%, but only 8.9% with TECH_SIMILARITY, giving an impact factor of 0.024. Thus, finding another variable that has the same impact as being in the same industry, after already controlling for all the controls in the model, would still not be enough to invalidate our results. Likewise, PROD_MARKET_ SIM has an impact factor of 0.017, which is well below the threshold needed to invalidate the existing inference. Thus, the ITCV tests suggest that a possible omitted variable must have a significantly large variation with technological similarity and compensation benchmarking above and beyond some of the most important control variables in the model to be able to overturn our results.

B. Unobservable Selection and Coefficient Stability

Oster (2019) suggests a coefficient of proportionality (δ) which incorporates changes in the coefficient of interest (between unrestricted and restricted regressions) and explanatory power. A δ of x would imply that unobservable factors would need to be x times as important as the unobservables to overturn the results. Her approach extends insights from Altonji, Elder, and Taber ((2005a), (2005b), and has been used in the finance and accounting literature.[22] As changes in R^2 are crucial for determining the effects of unobservable selection, the estimated effect relies on the R^2 from a hypothetical regression that includes both observed and unobserved controls (denoted $R_{\max}$). Following a replication of recent studies published in top economics journals, she recommends an estimate of $R_{\max}$ of 1.3 times the R^2 from the model that includes the observable control variables. As discussed in Oster (2019), we report the value of δ which would result in the coefficient of interest being equal to zero; a δ of 1 (the benchmark recommended by Altonji et al. (2005a) and Oster (2019)) indicates that unobservables would need to be as important as the observable control variables to produce a null effect. As we show in Panel B of Table 4, the smallest value of δ is 1.518; this indicates that unobservables would need to be 152% as important as the included control variables to accept the null. As we include the most prominent variables likely to affect peer group selection, we conclude that unobservables are unlikely to drive our results.

C. Additional Controls

Next, we complement the results from Section IV.A by explicitly adding additional controls from previous studies that might correlate with technological similarity and compensation benchmarking. Specifically, we add the following 4 control variables to our baseline model: BOARD_INDEP_DIFF, which is the difference in the percentage of independent board members to the total obtained from BoardEx, to control for firms with a similar board structure pursuing similar innovation strategy (Balsmeier et al. (2017)); VESTING_PERIOD_DIFF, defined as the difference in the maximum vesting period of CEO's compensation contract obtained from the Incentive Lab (Baranchuk, Kieschnick, and Moussawi, 2014); and the DELTA_DIFF and VEGA_DIFF, which are the differences in the delta and vega from managerial option compensation, to control for the similarities in managerial compensation and incentive structure (e.g., González-Uribe and Groen-Xu (2017)). All differences between two firms are defined as the value for firm *i* minus the value for firm *j*. We note that it is not possible to exhaust all possible confounding variables, but view this approach as supplementing our previous analysis.

We report the results in Table 5. As expected, many of the differences in the above factors exhibit a negative relation with the likelihood of a firm becoming a compensation benchmarking peer, suggesting that similar firms are indeed more likely to be chosen as a benchmarking peer, although the coefficients are not always statistically significant. Importantly for our hypothesis, TECH_SIMILARITY continues to exhibit comparable statistical significance and magnitudes even after controlling for the additional factors; this is consistent with Sections IV.A and IV.B that our main findings are unlikely to be driven by particular omitted variables.[23]

[22]See, for example, Bhagwat, Dam, and Harford (2016), Call, Martin, Sharp, and Wild (2018), Babenko, Du, and Tserlukevich (2021), and Lim and Nguyen (2021).

[23]Additionally, our results are robust to including second- and third-order polynomials of all distance measures used in Table 5, to capture the potential nonlinear effects of these factors.

TABLE 5

Additional Control Variables

Table 5 reports the estimates of the logistic regression model of compensation benchmarking peer firm selection from equation (2) with additional control variables. In addition to the control variables used in Table 2, we also add the following variables: BOARD_INDEP_DIFF, defined as the difference in the percentage of independent board members to total obtained from BoardEx; VESTING_PERIOD_DIFF, defined as the difference in the maximum vesting period of CEO's compensation contract obtained from Incentive Lab; and the DELTA_DIFF and VEGA_DIFF, which are the differences in delta and vega from managerial option compensation. Each difference between two firms is defined as the value for firm *i* minus the value for firm *j*. We estimate the logistic regression model with various fixed effects, including year (columns 1 and 4), year and industry (columns 2 and 5), and peer group fixed effects (columns 3 and 6). The estimates for the original control variables are suppressed for brevity. *t*-statistics based on standard errors double clustered by firms *i* and *j* are reported in parentheses, except for the group fixed effects models in which the standard errors are clustered at the *firm i* level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: COMPENSATION_PEER_DUMMY					
	1	2	3	4	5	6
TECH_SIMILARITY	3.856***	3.901***	4.242***	3.813***	3.806***	4.122***
	(19.85)	(19.58)	(20.28)	(17.18)	(16.57)	(17.50)
SAME_INDUSTRY	1.526***	1.593***	1.811***	1.141***	1.214***	1.303***
	(11.08)	(11.06)	(11.56)	(6.29)	(6.69)	(6.67)
WITHIN60MI	0.840***	0.854***	0.919***	0.829***	0.803***	0.874***
	(7.47)	(7.42)	(7.65)	(6.41)	(6.24)	(6.50)
BOARD_INDEP_DIFF	−0.430	−0.334	−1.426***	−0.303	−0.373	−1.441***
	(−1.52)	(−1.28)	(−5.51)	(−1.02)	(−1.28)	(−4.52)
VESTING_PERIOD_DIFF	−0.001	−0.003	−0.005**	−0.002	−0.004*	−0.005**
	(−0.52)	(−1.37)	(−2.11)	(−0.74)	(−1.69)	(−2.12)
DELTA_DIFF	0.010	0.045*	0.078***	0.027	0.041	0.072**
	(0.32)	(1.70)	(3.47)	(0.79)	(1.39)	(2.28)
VEGA_DIFF	−0.190**	−0.181**	−0.334***	−0.149*	−0.146	−0.410***
	(−2.28)	(−2.05)	(−4.04)	(−1.65)	(−1.50)	(−4.21)
PROD_MARKET_SIM				0.787***	0.850***	1.282***
				(3.27)	(3.62)	(4.85)
Existing controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	Yes	Yes	No
Industry FE	No	Yes	No	No	Yes	No
Peer group FE	No	No	Yes	No	No	Yes
N	166,868	166,868	166,868	110,535	110,535	110,535
Pseudo-R^2	0.200	0.208	0.231	0.221	0.228	0.261

D. Peer Change in Technology

We examine situations in which the technological similarity between two firms changes because of a significant change in technology for one company (peer), whereas the other company's technology (focal firm) remains unchanged, and we examine the benchmarking selection choice of the focal firm. To do so, we construct a measure that tracks the yearly changes in each firm's technology profile: $\text{TECH\_CHANGE}_{i,t-1,t} = 1 - \frac{F_{i,t-1}F'_{i,t}}{\left(F_{i,t-1}F'_{i,t-1}\right)^{0.5}\left(F_{i,t}F'_{i,t}\right)^{0.5}}$, where $F_{i,t}$ is the one by τ vector of firm i's proportion of patents granted in technology space one through τ in year t, and τ is the number of different patent classification classes. Essentially, $\text{TECH\_CHANGE}_{i,t-1,t}$ is 1 minus the uncentered correlation that was used to calculate the technological similarity across firms, but applied to the time-series changes for a given firm. We find that the average (median) TECH_CHANGE is 5.43% (1.04%) in our sample, so the technology profile is persistent over time. To identify firms that significantly change their technology profile, we define firms to have changed their technology if their year-to-year TECH_CHANGE is within the top tercile (and quartile/decile for robustness), which corresponds to a change of 3.54% (5.61%/18.0%). Based on this definition, we then identify pairs of firms in which the peer firm significantly changed in its technology profile, and the focal firm did not.

Using the sample of pairs in which peer firms significantly changed their technology profile, we identify among the potential pairs the firms where changes in technological similarity increased significantly over the year. For these groups, the focal firm's technological similarity changed since other firms became more similar to the focal firm, not vice versa. If technological similarity has a causal impact on the focal firm's benchmarking selection choice, then we expect these groups of peers to have a higher likelihood of becoming a benchmarking peer firm in subsequent years. We define a pair to have significantly converged in technology if the increase in technological similarity is at the top tercile (and quartile/decile for robustness) of the sample, which corresponds to 1.11% (1.72%/4.65%) in the changes in technological similarity. Thus, our main independent variable of interest is the dummy variable TECH_CONVERGE, which equals 1 if the pair satisfies all three criteria above, and 0 otherwise. Our dependent variable is defined as BECAME_PEER, which equals 1 if the peer firm (firm *j*) was not previously benchmarked by the focal firm (firm *i*) in year $t-1$, but became a benchmark peer in year *t*.

We report the results in Table 6. In column 1, we run a univariate regression with BECAME_PEER as the dependent variable and TECH_CONVERGE. While we believe that TECH_CONVERGE highlights the variations in the technological similarity between two companies that are relatively exogenous to the focal firm, we nonetheless add additional controls that are included in the main regressions and year fixed effects as a robustness test. In both models, the estimates for TECH_ CONVERGE are positive and statistically significant. In economic terms, convergence in technology because of a peer firm converging on the focal firm's technology space is associated with a 154% and 65% increase in the odds of becoming a benchmark peer in columns 1 and 2, respectively, supporting our main findings that technology convergence affects the focal firm's benchmarking choice and that the effect is likely to be unrelated to other factors affecting the focal firm.[24]

[24]To further mitigate the endogeneity concern, we also examine the effect of the staggered rejection of the Inevitable Disclosure Doctrine (IDD) to exploit exogenous variations in employee mobility (and hence knowledge spillovers between firms) by potentially preventing the given firm's employees from being hired by rivals (e.g., Klasa, Ortiz-Molina, Sefling, and Srini (2018), Flammer and Kacperczyk (2019), Na (2020), and Gu, Huang, Mao, and Tian (2022)). In our context, the rejection of the IDD is likely to increase inventor mobility and hence reduce the protection of a firm's proprietary knowledge, which in turn would typically increase knowledge spillovers between firms. In order to exploit these exogenous variations, we examine the effect of IDD rejection by implementing difference-in-differences analysis. In Table IA-4 of the Supplementary Material, we show that firms in states that rejected the IDD are more likely to be selected as compensation benchmarking peer firms. This is consistent with the notion that the rejection of the IDD leads to an increase in inventor mobility and hence knowledge spillovers between firms, which in turn increases the technological similarity between firms. Therefore, the results provide further support for our baseline results in Table 2. However, we also recognize the possibility that this setting might not satisfy the exclusion condition given previous research (Lin, Wei, and Yang (2020), Islam, Rahman, Sen, and Zein (2022), and Chen, Jung, Peng, and Zhang (2022)).

TABLE 6

Peer Change in Technology

Table 6 examines situations in which two firms' technology converges closer together because of one firm's (peer firm) large shift in technology, while the other firm's (focal firm) technology portfolio remains the same. We identify firms that are experiencing a large shift in technology by firms whose TECH_CHANGE, defined as 1 minus the cosine similarity of a firm's technology portfolio from year $t-1$ to t (see Section III.C for details), is in the top tercile in year t. We then define TECH_CONVERGE as a dummy variable that equals 1 for the firm pair i–j if firm j has experienced a large shift in technology and the increase in firm pair i–j's technological similarity from year $t-1$ to t is in the top tercile in year t, and zero otherwise. The main dependent variable BECAME_PEER equals 1 if firm j was not benchmarked by firm i in year $t-1$, but becomes a benchmarking peer in year t. Additional control variables include the changes (from year $t-1$ to t) of the original control variables included from Table 2. t-statistics based on standard errors double clustered by firms i and j are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: BECAME_PEER	
	1	2
TECH_CONVERGE	0.933***	0.502***
	(7.43)	(2.77)
Δ PROD_MARKET_SIM		1.701
		(0.84)
SAME_INDUSTRY		1.982***
		(12.05)
WITHIN60MI		0.730***
		(4.35)
Δ STOCK_RETURN_CORR		0.780**
		(2.24)
Δ BETA_DIFF		0.021
		(0.13)
Δ VOLATILITY_DIFF		5.122
		(1.00)
Δ HHI_DIFF		−7.530**
		(−2.20)
Δ THREE_YEAR_RETURN_DIFF		0.188***
		(3.35)
Δ SIZE_DIFF		0.003
		(0.02)
Δ LEVERAGE_DIFF		0.086
		(0.14)
Δ MB_DIFF		−0.134
		(−1.48)
Δ CASH_RATIO_DIFF		0.890
		(1.61)
Δ COMPENSATION_DIFF		−0.000**
		(−2.31)
CONSTANT	−5.600***	−5.885***
	(−69.63)	(−24.55)
Year FE		Yes
N	415,681	184,191
Pseudo-R^2	0.003	0.063

E. Other Robustness Tests and Discussion

While our approach for compensation benchmarking selection is relatively novel and allows us to test predictions about whether technology shapes the market for managerial talent, some issues could potentially arise in generalizing our results given the limitations of our data sources.

First, the technological similarity is based on observed patenting activity, which does not capture alternative intangible assets such as trade secrets. Our measure could thus misclassify firms' technological similarity with other firms that arise from trade secrets. While this limitation is broadly applicable to many of the existing studies using patent data, we attempt to gauge the significance of this issue by examining whether the effects are stronger for (or even just specific to) firms with high patenting activity compared to those with low patenting activity. In Table IA-5 of the Supplementary Material, we show that although the effects appear to be larger for firms with more patenting activity, the effect of technological similarity is economically meaningful for both high and low patenting firms, suggesting that our results are not exclusive to high patenting firms.

Second, the Incentive Lab data that we use has been historically limited to large cap (S&P 500) and a large portion of midcap (S&P 400) firms. Thus, our sample could raise a question about whether our results are specific to larger companies that are more likely to have a larger and more complex technology portfolio and hence whether these firms would place greater priority on finding a manager with the right technological fit. To examine the role of firm size, we repeat our tests with a subsample of firms divided into SMALL vs. LARGE based on the yearly median value of firm sales, and find that (Table IA-5 of the Supplementary Material) the estimates for technological similarity are positive and economically significant for both groups of firms, regardless of firm size, suggesting that even smaller firms value technological similarity in selecting benchmarking peers.

V. Competitive Benchmarking and CEO Pay

In this section, we explore the mechanism by which compensation benchmarking leads to revisions in CEO pay and the role of technological similarity. Following Bizjak et al. (2008), we first examine the subsequent changes in compensation level for CEOs with below- or above-median pay (compared to peer firms). If compensation benchmarking is motivated by the goal of paying CEOs their market wage, we expect that CEOs with below-median (above-median) pay are more likely to experience upward (downward) revisions in their compensation compared with CEOs who are already paid above (below) the median.

To examine this mechanism, we run an OLS regression where the dependent variable is the change in total compensation (scaled by total assets) from year $t-1$ to year t.[25] The main independent variable is a firm's CEO pay status relative to peers; this variable reflects how the previous year's CEO pay compared to the level of pay for benchmarking peer firms. We construct the indicator variable LOWCOMP (HIGHCOMP), equal to 1 if a CEO was paid in the bottom (top) tercile of CEO pay among benchmarking peer firms in year $t-1$, and 0 otherwise. To capture potential nonlinearity in firms' responses to low compensation compared to high compensation, we include both LOWCOMP and HIGHCOMP together in our regressions.[26]

We also construct a continuous variable, DISTANCE_FROM_PEER_MEDIAN, by subtracting the peer group median CEO pay (among the benchmarking peers) from the given firm's CEO pay in year $t-1$, scaled by total assets. To capture the potential nonlinearity in firms' responses for higher compared to lower pay, we

[25]We also try different definitions of the dependent variable by using the change in the log of total compensation. Our results remain robust.

[26]Our results are qualitatively similar if we include LOWCOMP or HIGHCOMP by themselves, or if we use medians instead of terciles for cutoffs.

https://doi.org/10.1017/S0022109022000229 Published online by Cambridge University Press

define dummy variable POSITIVE_DISTANCE which equals 1 if DISTANCE_FROM_PEER_MEDIAN is positive, and 0 otherwise; we then interact POSITIVE_DISTANCE and DISTANCE_FROM_PEER_MEDIAN. We also control for CEO tenure and stock return, and the change in sales, net income, market value, and ROA. Finally, we include time and industry fixed effects to control for unobserved time and industry factors.

We report the results in Panel A of Table 7. We find that LOWCOMP has positive and significant estimates, implying that CEOs who were paid less than the

TABLE 7

Competitive Benchmarking and CEO Pay

Table 7 examines the effect of compensation benchmarking on CEO pay and how technology overlap affects the benchmarking – CEO pay relation. Panel A examines the effect of compensation benchmarking on CEO pay. The dependent variable is the change in total compensation from year $t-1$ to year t scaled by total assets. The key independent variables are HIGHCOMP, LOWCOMP, DISTANCE_FROM PEER_MEDIAN and the interaction term between DISTANCE_FROM PEER_MEDIAN and the POSITIVE_DISTANCE indicator variable. HIGHCOMP (LOWCOMP) equals 1 if a CEO was paid in the top (bottom) tercile of CEO pay among the benchmarking peer firms in year $t-1$, and zero otherwise. DISTANCE_FROM_PEER_MEDIAN is calculated as a given firm's CEO pay minus the benchmarking peer group median CEO pay in year $t-1$, scaled by total assets. POSITIVE_DISTANCE is equal to 1 if DISTANCE_FROM_PEER_MEDIAN is positive (i.e., CEO pay is greater than the median of the benchmarking peer group), and zero otherwise. The data on compensation benchmarking peers come from Institutional Shareholder Services (ISS) Incentive Lab from 2006 to 2010. Panel B examines the effect of technological similarity on competitive benchmarking. The dependent variable in the first 2 columns is a dummy variable equal to 1 if the CEO's total compensation in the previous year was below the median pay of the benchmarking peer group but had increased to or above the median in the next year, and is zero otherwise. The dependent variable in the last 2 columns is a dummy variable equal to 1 if the CEO's total compensation in the previous year was above the median pay of the benchmarking peer group but had decreased to or below the median in the next year, and is zero otherwise. The key independent variable is MEDIAN_PEER_TECH_SIM, which is defined as the median value of TECH_SIMILARITY among the benchmarking peers. All other control variables in Panels A and B are defined in the Appendix. t-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Effect of CEO Compensation Status on CEO Pay Changes

	Dependent Variable: Change in Total Compensation/Total Assets			
	1	2	3	4
HIGHCOMP	−0.971***		−1.081***	
	(−4.86)		(−4.95)	
LOWCOMP	0.393***		0.527***	
	(2.77)		(3.38)	
DISTANCE_FROM_PEER_MEDIAN		−0.329***		−0.312***
		(−8.07)		(−7.34)
POSITIVE_DISTANCE × DISTANCE_FROM_PEER_MEDIAN		−0.401***		−0.583***
		(−3.15)		(−6.60)
POSITIVE_DISTANCE		0.175		0.202*
		(1.41)		(1.80)
ΔSALES	−0.001	−0.006	−0.019	−0.019*
	(−0.10)	(−0.80)	(−0.92)	(−1.71)
ΔNET_INCOME	−0.050	−0.065***	−0.034	−0.062**
	(−1.64)	(−2.85)	(−1.03)	(−2.54)
ΔSHAREHOLDER_WEALTH	−0.006	−0.003	−0.004	0.000
	(−1.19)	(−0.68)	(−0.80)	(0.06)
ΔROA	4.396**	3.453***	3.724	2.316**
	(2.00)	(3.62)	(1.38)	(2.44)
STOCK_RETURN	0.496**	0.419*	0.358*	0.406**
	(2.06)	(1.91)	(1.68)	(2.31)
CEO_TENURE	−0.002	−0.001	0.001	−0.003
	(−0.19)	(−0.12)	(0.08)	(−0.26)
Year FE	No	No	Yes	Yes
Industry FE	No	No	Yes	Yes
N	1,035	1,035	1,035	1,035
Adjusted R^2	0.076	0.382	0.221	0.588

(continued on next page)

TABLE 7 (continued)
Competitive Benchmarking and CEO Pay

Panel B. Effect of Technological Similarity on Competitive Benchmarking

	Dependent Variable =			
	1 if CEO Pay Previously Below Median and At or Above Median in Subsequent Year		1 if CEO Pay Previously Above Median and At or Below Median in Subsequent Year	
	1	2	3	4
MEDIAN_PEER_TECH_SIM	0.694*	0.781*	1.112***	0.932**
	(1.78)	(1.83)	(2.76)	(1.97)
MEDIAN_PEER_PROD_SIM	0.527**	0.075	−0.263	−0.300
	(2.12)	(0.27)	(−0.92)	(−0.91)
Log(SALES)	0.089	0.026	0.053	−0.012
	(1.26)	(0.31)	(0.82)	(−0.16)
Log(FIRM_AGE)	0.007	0.004	0.010**	0.004
	(1.38)	(0.61)	(1.97)	(0.74)
ROA	1.054	0.002	0.712	−0.835
	(1.23)	(0.00)	(0.87)	(−0.69)
STOCK RETURN	0.113	−0.217	−0.384	−0.537*
	(0.55)	(−0.83)	(−1.48)	(−1.65)
CEO TENURE	−0.020	−0.015	−0.008	−0.005
	(−1.31)	(−0.94)	(−0.53)	(−0.33)
RD_TO_ASSETS	−1.771	−2.380	1.467	1.947
	(−1.43)	(−1.47)	(1.15)	(1.40)
E_INDEX		−0.005		−0.007
		(−0.05)		(−0.07)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	1,209	911	1,165	878
Pseudo-R^2	0.0684	0.0529	0.0689	0.0549

middle tercile of peer compensation experience higher pay increases in the following year. Similarly, HIGHCOMP is negative and significant, suggesting that CEOs who were paid more than the top tercile of peer pay experience lower pay increases in the following year compared to CEOs in the middle tercile. Our findings that CEO compensation is adjusted toward the peer level in both directions are consistent with market-based theories of compensation. In addition, comparing the magnitudes of the coefficients for LOWCOMP and HIGHCOMP, we find that the absolute magnitudes of the estimates for LOWCOMP are about half the magnitudes of HIGHCOMP. This suggests that firms are more likely to adjust CEO pay downward if CEOs are paid more than their peers (compared to adjusting pay upward). Similarly, our estimates of DISTANCE_FROM_PEER_MEDIAN are negative and statistically significant in both specifications, suggesting that CEOs that are paid below the median peer pay are likely to experience pay adjustments upward, consistent with the estimates in columns 1 and 3. In addition, the interaction term between POSITIVE_DISTANCE and DISTANCE_FROM_PEER_MEDIAN is negative and significant, suggesting that the absolute effects of DISTANCE_FROM_PEER_MEDIAN are higher when CEO pay is above the median level (and subsequently being adjusted downward) than when CEO pay is below the median. Overall, our results are consistent with Bizjak et al. (2008) and are consistent with the use of compensation benchmarking reflecting executives' compensation levels at competing firms.

Next, we examine whether and how much of the effect of compensation benchmarking on CEO pay is related to firms' technological similarity with other firms in the labor market. Specifically, we examine the effect of competition for managerial talent on CEO pay adjustment. To do so, we examine a regression where the dependent variable is a dummy variable that equals 1 if a CEO received below-median compensation in year $t-1$ and receives compensation at or above the median level in year t, and 0 otherwise. The key independent variable of interest in our setting is the median level of technological similarity between a given firm and its benchmarking peer firms, MEDIAN_PEER_TECH_SIM. High median technological similarity among peers thus indicates that the given firm shares many similar technologies with its benchmarking peers, implying a higher degree of overlap in the demand for managerial talent. To distinguish overlap in technology from that of the product market, we include MEDIAN_PEER_PROD_SIM, defined as the median value of PROD_MARKET_SIM among the benchmarking peers. We also control for firm-related factors (log(SALES), log(FIRM_AGE), ROA, STOCK_RETURN, CEO_TENURE, RD_TO_ASSETS, and E_INDEX). We also include time and industry fixed effects to control for unobserved time and industry factors. If technological similarity reflects the degree of competition for managerial talent, we expect that the effect of compensation benchmarking on CEO pay would be more pronounced for firms with more technological similarity (firms that are exposed to greater competition for CEOs). Hence, we expect the coefficient for the MEDIAN_PEER_TECH_SIM to be positive.

Similarly, given that market-based adjustments to compensation could be either positive or negative (depending on the peer group's level), we repeat our tests using a dependent variable that is equal to 1 if a CEO received above-median compensation in year $t-1$ and receives compensation at or below the median level in year t, and 0 otherwise.[27] If technological similarly drives the competition for managerial talent, and therefore, the motivation to benchmark CEO pay, then we expect MEDIAN_PEER_TECH_SIM to remain positively associated with downward pay adjustments for firms with CEOs that previously received above-median pay.

We present our results in Panel B of Table 7. Columns 1 and 2 report the estimates of the logistic regression with the dependent variable equal to 1 if a CEO received below-median compensation in year $t-1$ and receives compensation at or above the median level in year t, and 0 otherwise. Columns 3 and 4 repeat these tests using the alternative dependent variable that is equal to 1 if a CEO received above-median compensation in year $t-1$ and receives compensation at or below the median level in year t, and 0 otherwise. Across all models, the coefficients of MEDIAN_PEER_TECH_SIM are positive and statistically significant, suggesting that technological similarity increases the likelihood of efficient benchmarking affecting CEO pay.[28]

Consistently, our results demonstrate that firms adjust CEO pay to be competitive with firms that are competing for similar managerial talent. We thus show that technology-related managerial talent is likely to be an important consideration in a competitive labor market.

[27]We thank our reviewer for pointing out the two cases.

[28]The number of observations for columns 1 and 2 compared to columns 3 and 4 differ slightly due to the presence of industry fixed effects, as some industries do not have variation in below-median to above-median or above-median to below-median transitions within the industry.

VI. CEO Job Transitions

The underlying hypothesized mechanism for how technological similarity affects compensation benchmarking is the presence of a competitive labor market for CEOs. In this section, we examine the validity of this mechanism by examining whether greater technological similarity between firms increases the likelihood of CEO transitions between firms.[29] Specifically, we study whether an executive who transitions between two companies (and is the CEO of one or both firms) moves to a firm with greater technological overlap compared to their previous firm. If the technology-related compensation benchmarking peers are selected purely opportunistically, we would not expect to see a positive relation between firms' technological similarity and the likelihood of CEOs moving between firms. Conversely, if competition for technological expertise is an important factor in determining compensation benchmarking, we would expect to see a higher likelihood of CEOs moving to firms with greater technological similarity.

Since CEO transitions between firms involve two firms, we use a conditional logit model to estimate the likelihood of two firms being an actual CEO transition pair (compared to a pseudo-pair). We thus run the following conditional logit model using our sample of actual CEO transition pairs and the matched control sample of pseudo-CEO-transition pairs:

$$(3)\qquad \text{ACTUAL\_TRANSITION}_{ijm,t} = \begin{array}{l} \alpha + \beta_1 \text{TECH\_SIMILARITY}_{ijm,t-1} \\ + \beta_2 X_{ijm,t-1} + \beta_3 Y_{im,t-1} + \beta_4 Z_{jm,t-1} \\ + \text{GROUP\_FE}_m + \varepsilon_{ijm,t}, \end{array}$$

where the dependent variable is $\text{ACTUAL\_TRANSITION}_{ijm,t}$, which is equal to 1 if the pair of a CEO's pretransition firm i and posttransition firm j is the actual transition for the pair m, and 0 otherwise (i.e., this variable equals 0 if the observation is a pseudo-transition pair). $\text{TECH\_SIMILARITY}_{ijm,t-1}$ is our independent variable of interest and is the overlap in patent portfolios (as defined in Section II.A), measured in the year prior to the actual or pseudo-CEO-transition pair. $X_{ijm,t-1}$ is a vector of control variables that reflects similarities between a CEO's pretransition firm (i) and posttransition firm (j). $X_{ijm,t-1}$ includes $\text{SAME\_INDUSTRY\_INDICATOR}_{ijm,t-1}$, which equals 1 if the i–j pair is in the same 3-digit SIC industry, $\text{SAME\_STATE\_INDICATOR}_{ijm,t-1}$, which equals 1 if the i–j pair is incorporated in the same state, WITHIN60MI, which equals 1 if the two firms' headquarters are within 60 miles of each other. $Y_{im,t-1}$ and $Z_{jm,t-1}$ is a vector of control variables that includes the CEO's pretransition (i) and posttransition (j) firm characteristics. Both vectors include ROA (EBITDA divided by the book value of total assets), LEVERAGE (the book value of debt, divided by the book value of total assets), CASH_TO_ASSETS (cash and short-term investments divided by the book value of total assets), and the natural logarithm of RD_TO_ASSETS (research and development divided by the book value of total assets).

[29]A CEO transition occurs when an individual is listed in ExecuComp (as a named executive officer) for two distinct firms and is a CEO of at least one of those firms.

To construct the actual and pseudo-transition samples to estimate equation (3), we first identify the actual CEO transition pairs. We use ExecuComp data from 1992 to 2010 and define an actual CEO transition pair as a CEO at firm *i* who moves to firm *j* or vice versa. We do not restrict our sample to purely CEO-to-CEO transitions, but simply require that a current executive in ExecuComp becomes the CEO at a new firm or that the current CEO moves to another firm recorded in ExecuComp. In addition to the actual CEO transition pairs in our sample, we also generate a control sample of pseudo-transition pairs. For each actual transition pair in the year, pseudo-pairs are formed by pairing actual pretransition firm *i* with up to five matched pseudo-posttransition firms based on the actual posttransition firm *j* characteristics (i.e., industry, firm size, and book-to-market ratio) and by pairing the actual posttransition firm *j* with up to five matched pseudo-pretransition firms based on the actual pretransition firm *i* characteristics.[30] For example, if there was a CEO transition from firm *i* (actual pretransition firm) to firm *j* (actual posttransition firm), we match the potential posttransition firms that have characteristics that are similar to the actual transition firm *j*. This, in turn, allows us to examine the determinants that influence firm *i* to select firm *j* instead of other potential peer firms when firm *i* has a vacancy in the CEO position. Since transition can occur because firm *j* has a CEO position vacancy, in which case firm *j* also wants to select peer firms from all potential peer firms, we also match up to five potential pretransition firms that have similar characteristics as firm *i*, which is the actual pretransition firm that we observe.[31] Matching criteria for constructing the control sample are intended to control for time, industry, firm size, and growth opportunities.

Our CEO transition sample contains 1,165 firm-pair-level observations (based on the year, industry, size, and book-to-market matched sample) from 1992 to 2010, with 108 firm-pair-level observations being the actual CEO transition sample, and 1,057 firm-pair observations being the pseudo-transition sample. Although the SAME_INDUSTRY indicator can be used to control for similarities in product market industries, we also control, as in Section II.B, for the overlap in firms' product market segments (PROD_MARKET_SIM). Since Compustat segment data reduces our sample somewhat, models including this additional control have 845 firm-pair-level observations (with the industry, year, size, and book-to-market matched sample), with 80 firm-pair observations for the actual CEO transitions sample, and 765 firm-pair observations for the pseudo-transitions sample.

Panel A of Table 8 presents the summary statistics for our CEO transition samples. The mean (median) technological overlap between a CEO's pretransition and his/her posttransition firm, captured by TECH_SIMILARITY, is 24.7%

[30]Thus, for each of the actual transition pairs there are up to 11 firm pairs, comprising one actual pre- and post-transition firm pair, five actual pretransition firm/pseudo posttransition firm pairs, and five pseudo pretransition firm/actual posttransition firm pairs. Any event with zero successful matches is excluded from our analysis that uses the pseudo-matched data, as we use transition pair fixed effects in those analyses.

[31]We try to further limit our matched control sample such that all potential peers have CEO vacancies as well. Among this limited sample in which all firms are experiencing CEO turnovers, we perform as robustness tests the same matching and analyses as in Table 8. Results remain robust and are available on request.

https://doi.org/10.1017/S0022109022000229 Published online by Cambridge University Press

TABLE 8
CEO Job Transitions

Table 8 reports the effect of technological similarity between a given firm and its peers on CEO job transition likelihood. In Panel A, we report the summary statistics on the CEO transition sample that we use to analyze the characteristics of the firm where the CEO is hired once he/she leaves the previous job. The CEO job transition data come from ExecuComp, where we track the time-series position of each CEO. All variables are defined in the Appendix. Panel B reports the results from conditional logit regressions of the likelihood of an observation being an actual (as opposed to a hypothetical) CEO transition on the technological overlap between the pre- and post-transition firm pair and other control variables. The dependent variable is a binary variable that takes the value of 1 if the observation is an actual CEO transition. This variable takes the value of zero if the observation is a pseudo-firm-pair in the control group. See Section VI for greater detail regarding how the actual- and pseudo-firm-pairs are constructed. The sample period is from 1992 to 2010. Our key independent variable is TECH_SIMILARITY, defined as the Jaffe (1986) similarity measure of patent portfolios between the firm pair *i–j*. Constant terms are estimated, but not reported. *t*-statistics (based on standard errors clustered at the actual pair group level) are reported in parentheses. All specifications include pair group fixed effects. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. CEO Job Transition Sample Statistics

	Actual CEO Transitions (*N* = 80)			Pseudo-CEO Transitions (*N* = 765)		
	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median
Pair characteristics						
TECH_SIMILARITY	0.247	0.254	0.156	0.093	0.157	0.022
SAME_INDUSTRY_INDICATOR	0.263	0.443	0.000	0.139	0.346	0.000
PROD_MARKET_SIM	0.203	0.375	0.000	0.068	0.229	0.000
SAME_STATE_INDICATOR	0.475	0.503	0.000	0.380	0.486	0.000
WITHIN60MI	0.125	0.333	0.000	0.055	0.228	0.000
CEO's pretransition firm characteristics						
ROA	0.127	0.087	0.119	0.113	0.123	0.120
LEVERAGE	0.184	0.141	0.182	0.184	0.151	0.177
CASH_TO_ASSETS	0.185	0.176	0.121	0.188	0.186	0.116
ln(RD_TO_ASSETS)	0.070	0.061	0.054	0.068	0.067	0.048
STOCK_RETURN	2.888	5.841	0.850	2.417	5.363	0.758
FIRM_AGE	3.253	0.699	3.367	3.099	0.759	3.219
FIRM_SIZE	8.027	1.389	7.957	7.518	1.683	7.619
BTM	0.472	0.286	0.397	0.487	0.294	0.399
CEO's post-transition firm characteristics						
ROA	0.126	0.093	0.126	0.117	0.125	0.129
LEVERAGE	0.196	0.151	0.175	0.200	0.154	0.192
CASH_TO_ASSETS	0.199	0.180	0.156	0.189	0.190	0.120
ln(RD_TO_ASSETS)	0.059	0.046	0.046	0.058	0.059	0.043
STOCK_RETURN	5.461	10.685	0.726	4.671	9.608	0.758
FIRM_AGE	3.222	0.743	3.450	3.145	0.733	3.296
FIRM_SIZE	8.068	1.804	7.850	7.767	1.979	7.685
BTM	0.596	0.683	0.436	0.550	0.576	0.428
CEO characteristics	Actual CEO transitions (*N* = 57)			Pseudo-CEO transitions (*N* = 488)		
Prefirm CEO_AGE	3.922	0.108	3.951	3.965	0.124	3.970
Prefirm CEO_TENURE	1.353	0.691	1.386	1.477	0.782	1.609
Postfirm CEO_AGE	4.021	0.118	4.025	4.005	0.123	4.007
Postfirm CEO_TENURE	1.615	0.697	1.792	1.642	0.788	1.792

Panel B: Effect of Technological Overlap on CEO Job Transition

	Year/Industry/Size Match			Year/Industry/Size/BTM Match		
	1	2	3	4	5	6
TECH_SIMILARITY	4.506***	3.461***	2.641**	5.244***	4.395***	2.383*
	(6.23)	(4.12)	(2.43)	(6.31)	(4.55)	(1.94)
SAME_INDUSTRY_INDICATOR		1.002	0.896		1.213*	1.236
		(1.17)	(0.97)		(1.72)	(1.45)
PROD_MARKET_SIM		1.893***	0.797		1.463**	0.019
		(2.67)	(1.08)		(2.47)	(0.02)
SAME_STATE_INDICATOR		0.489*	0.097		0.558**	0.103
		(1.75)	(0.27)		(2.16)	(0.28)
WITHIN60MI		0.593	0.660		1.157**	0.512
		(0.98)	(0.96)		(2.01)	(0.60)
COMPENSATION_DIFF			0.033*			0.036*
			(1.72)			(1.78)
Prefirm characteristics						
ROA		1.582	−0.211		1.835	0.131
		(1.07)	(−0.08)		(1.54)	(0.06)

(continued on next page)

TABLE 8 (continued)
CEO Job Transitions

Panel B: Effect of Technological Overlap on CEO Job Transition (continued)

	Year/Industry/Size Match			Year/Industry/Size/BTM Match		
	1	2	3	4	5	6
STOCK_RETURN		0.021	0.084***		0.068***	0.070***
		(0.83)	(2.80)		(2.80)	(2.60)
LEVERAGE		1.670	1.112		2.062*	2.181*
		(1.58)	(1.01)		(1.96)	(1.68)
CASH_TO_ASSETS		0.651	0.553		1.263	−0.136
		(0.81)	(0.49)		(1.31)	(−0.10)
ln(RD_TO_ASSETS)		6.240**	0.826		1.162	1.357
		(1.99)	(0.23)		(0.48)	(0.44)
FIRM_AGE		0.797***	0.441		0.951***	0.761*
		(4.37)	(1.61)		(2.87)	(1.92)
BTM		0.286	0.719			
		(0.65)	(1.16)			
Postfirm characteristics						
ROA		1.029	0.899		0.079	−1.885
		(0.61)	(0.42)		(0.06)	(−1.32)
STOCK_RETURN		0.039*	0.073***		0.050**	0.057*
		(1.90)	(2.92)		(2.31)	(1.67)
LEVERAGE		−0.666	−0.121		−0.117	−0.293
		(−0.60)	(−0.11)		(−0.10)	(−0.26)
CASH_TO_ASSETS		1.166	0.004		0.513	0.174
		(1.48)	(0.00)		(0.58)	(0.18)
ln(RD_TO_ASSETS)		0.695	−0.597		−1.505	−4.779
		(0.22)	(−0.18)		(−0.60)	(−1.24)
FIRM_AGE		0.329	−0.299		0.268	0.016
		(1.48)	(−0.94)		(1.12)	(0.06)
BTM		0.577***	1.078***			
		(2.63)	(2.75)			
CEO characteristics						
Prefirm CEO_AGE			−4.167***			−6.284***
			(−3.01)			(−4.34)
Prefirm CEO_TENURE			−0.223			−0.037
			(−1.19)			(−0.21)
Postfirm CEO_AGE			0.771			1.533
			(0.49)			(1.03)
Postfirm CEO_TENURE			0.026			−0.034
			(0.13)			(−0.17)
Group fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
No of obs.	856	856	537	845	845	545
Pseudo-R^2	0.130	0.224	0.171	0.153	0.250	0.164

(15.6%) in the actual transition sample, with a fairly large standard deviation (25.4%). TECH_SIMILARITY is much smaller for the pseudo-CEO-transition sample, an observation that is consistent with our hypothesis that, of the set of transitions that could have occurred (the union of the actual and pseudo-control samples), the CEO transitions that actually occurred are those where the pre and posttransition firms have greater technological overlap. As expected from previous studies, similarities in the product market also seem to be an important factor in CEO job switching. For the actual (pseudo) transition sample, an average of 26.3% (13.9%) of pre- and post-transition firm pairs are in the same 3-digit SIC industries, and the mean of similarities in product market segments between the pre- and post-transition firm pairs is approximately 20.3% (6.8%). Thus, it is important to control for the product market similarities.

https://doi.org/10.1017/S0022109022000229 Published online by Cambridge University Press

Panel B of Table 8 reports the estimates of the CEO job transition likelihood model from equation (3). Columns 1–3 estimate the model based on a year/industry/size-matched sample. In a simple univariate model in column 1, the coefficient for TECH_SIMILARITY is 4.506 and is statistically significant at the 1% level. Similarly, when we include additional firm- and pair-specific controls, such as whether the two firms are in the same industry (SAME_INDUSTRY indicator) or are in the same state (SAME_STATE indicator), the coefficient estimate for TECH_SIMILARITY remains consistently positive and significant (column 2). The economic significance is also large. For a 1-standard-deviation increase in TECH_SIMILARITY, the odds of CEO transition increase by about 86% (a 46.2% increase in the probability) based on the coefficient in column 2. Furthermore, the results are robust to including COMPENSATION_DIFF as an additional control (column 3). In columns 4–6, we repeat the estimation of the year/industry/size/BTM sample. The effect of TECH_SIMILARITY remains comparable throughout all specifications.

Our results on CEO transitions are consistent with those of Cummings and Knott (2018), who document that firms that hire CEOs with relevant technological expertise are associated with higher subsequent R&D productivity.[32] Similarly, our results imply that technological similarity plays a significant role in the market for CEOs. This is consistent with our baseline findings that firms are more likely to use technologically similar firms as compensation benchmarks.

VII. Implications of Technological Similarity for CEO Pay Levels on Peer Compensation

Given the evidence that firms are more likely to choose technologically similar peers for their peer groups, we examine whether the level of CEO compensation at technologically similar peer firms correlates with a firm's own CEO pay. To test this relation, we estimate the following regression:

$$\text{(4)} \quad \ln(\text{CEO\_COMPENSATION}) = a + b_1 \ln(\text{MEDIAN\_TECH\_PEER\_COMP}) + b_2 \ln(\text{MEDIAN\_IND\_PEER\_COMP}) + b'X + \text{Time FE} + \text{Ind FE} + e,$$

where ln(MEDIAN_IND_PEER_COMP) is the median level of total compensation of CEOs in the same industry (defined as peer CEOs in the same product market space) and ln(MEDIAN_TECH_PEER_COMP) is the median level of compensation of peer CEOs in a close technology space. In identifying peers that are in a close

[32]We follow Cummings and Knott (2018) and examine the effect of technological expertise on R&D productivity after the new CEO is hired. In untabulated tests, we use the transition sample from ExecuComp and find that when a CEO moves to a new firm, the technological similarity between the former and new firm increases the new firm's longer-term R&D productivity. This positive association provides evidence that the CEO's technological expertise helps a new firm experience reliable long-run R&D productivity. Our result is consistent with our findings in this section that firms would like to hire CEOs who have similar technological expertise, resulting in CEOs' transitions between technologically related firms.

technology space, we define two firms as being technology peers with each other if their TECH_SIMILARITY is in the top 10% for a given year.[33] In calculating the median peer compensation, we follow existing studies in examining 1-year-lagged total peer compensation, in addition to using the contemporaneous year compensation, since board members would not have complete information on the compensation levels of contemporaneous peers when determining CEO pay for a given year.[34]

We report the estimate for equation (4) in Table 9. First, we estimate the regression with year fixed effects in columns 1–4. Using the log of the median compensation level of peers with high levels of technological similarity (ln(MEDIAN_TECH_PEER_COMP)), we find that the log of total CEO compensation (ln(CEO_COMPENSATION)) is positively correlated with the contemporaneous compensation level of technology peers. The coefficient associated with ln(MEDIAN_TECH_PEER_COMP) in the baseline model with other firm-level controls is 0.258, which is statistically significant at the 1% level. Thus, a 1% increase in the compensation level of a technology peer is associated with a 0.258% increase in a firm's own compensation. This is consistent with the proposed channel of technological similarity influencing the competitive market for CEOs. In column 2, we estimate our model with the log median level of industry peer compensation. As expected, the median level of compensation for a same-industry peer is positively correlated with the firm's own CEO compensation: A 1% increase in the median level of industry peer compensation is associated with a 0.246% increase in CEO pay. The estimate for ln(MEDIAN_TECH_PEER_COMP) is reduced in the presence of the control for industry peer compensation, but is still economically meaningful: A 1% increase in the compensation level of the median technology peer is associated with a 0.174% increase in CEO pay.[35]

We repeat our analyses with additional industry-year fixed effects in columns 5 and 6. Thus, the estimate for ln(MEDIAN_TECH_PEER_COMP) captures the within-industry-year variation in the median level of compensation among firms with similar technology. Consistent with the other specifications, CEO pay is positively correlated with both the median compensation level of technology peers and the median compensation level of industry peers.

Our results from this table provide further support for the hypothesis that technological similarity influences the market for managerial talent; CEOs' compensation is positively affected by the compensation of their firms' technological peers.

[33]We also use various alternative thresholds and definitions to check the robustness of our results.

[34]Since the analysis of peer compensation on CEO pay does not require the use of Incentive Lab data, our final sample contains firm-level observations from 1992 (the beginning of ExecuComp's coverage) until 2010 (the last available year of the patent database). Our final sample consists of 4,515 firm-year observations with 829 unique firms.

[35]We also repeat our analyses with lagged peer compensation, instead of contemporaneous peer compensation, to reflect the possibility that board members affecting CEO pay in a given year would generally not have complete information about peer compensation in that same year. Columns 3 and 4 present the results on the coefficient estimate for lagged ln(MEDIAN_TECH_PEER_COMP). The results are robust to using lagged peer compensation.

TABLE 9

The Effects of Peer Compensation Level on CEO Compensation

Table 9 contains the results of the analysis of the relation between technological peer compensation and CEO pay. The estimates for the OLS regression model from equation (4) are reported. The dependent variable is ln(CEO_COMPENSATION), defined as the natural log of the CEO's total compensation. The main independent variable is ln(MEDIAN_TECH_PEER_COMP), defined as the median level of peer CEO compensation in the similar technology space. In particular, we define a firm as being a TECHNOLOGY_PEER with another firm if the pairwise TECH_SIMILARITY (see Section II.A) between the two firms is in the top 10% for a given year. See the Appendix for the definitions of other control variables. Columns 1–4 estimate the regression with year fixed effects, and columns 5 and 6 estimate the regression with industry-year fixed effects (industry defined with the 2-digit SIC). *t*-statistics based on standard errors clustered by firm are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: ln(CEO_COMPENSATION)					
	1	2	3	4	5	6
$\ln(\text{MEDIAN\_TECH\_\_PEER\_COMP})_t$	0.258***	0.174**			0.212***	
	(3.73)	(2.52)			(3.08)	
$\ln(\text{MEDIAN\_TECH\_PEER\_COMP})_{t-1}$			0.269***	0.216***		0.218***
			(3.80)	(3.06)		(2.93)
ln(MEDIAN_IND_PEER_COMP)		0.246***				
		(3.71)				
$\ln(\text{MEDIAN\_IND\_PEER\_COMP})_{t-1}$				0.168**		
				(2.47)		
ln(SALES)	0.391***	0.381***	0.392***	0.384***	0.400***	0.399***
	(24.72)	(22.71)	(24.79)	(22.86)	(22.70)	(20.91)
STOCK_RETURN	0.252***	0.249***	0.252***	0.252***	0.240***	0.246***
	(7.90)	(7.83)	(7.85)	(7.87)	(7.50)	(7.45)
$\text{STOCK\_RETURN}_{t-1}$	0.118***	0.118***	0.124***	0.127***	0.122***	0.111***
	(3.28)	(3.29)	(3.45)	(3.53)	(3.34)	(2.70)
ROA	−0.778**	−0.790**	−0.742*	−0.725*	−0.767**	−0.847**
	(−2.00)	(−2.04)	(−1.88)	(−1.84)	(−1.97)	(−2.04)
ROA_{t-1}	−0.692*	−0.640*	−0.708*	−0.693*	−0.580	−0.599
	(−1.86)	(−1.73)	(−1.89)	(−1.86)	(−1.56)	(−1.54)
LEVERAGE_{t-1}	0.361**	0.321**	0.370***	0.341**	0.387***	0.361**
	(2.58)	(2.32)	(2.64)	(2.47)	(2.72)	(2.35)
MB_{t-1}	0.155***	0.154***	0.154***	0.152***	0.144***	0.144***
	(7.71)	(7.71)	(7.68)	(7.62)	(6.92)	(6.39)
CEO_TENURE	0.00451	0.00397	0.00448	0.00419	0.00582	0.00644
	(1.18)	(1.03)	(1.18)	(1.10)	(1.51)	(1.61)
CEO_AGE	−0.00655**	−0.00664**	−0.00638*	−0.00647**	−0.00437	−0.00343
	(−1.99)	(−2.02)	(−1.94)	(−1.97)	(−1.31)	(−0.97)
CEO_IS_CHAIR	0.165***	0.156***	0.164***	0.158***	0.159***	0.164***
	(3.68)	(3.48)	(3.68)	(3.55)	(3.54)	(3.48)
Year FE	Yes	Yes	Yes	Yes	No	No
Industry-year FE	No	No	No	No	Yes	Yes
N	4,515	4,515	4,515	4,515	4,515	4,515
Adjusted R^2	0.491	0.495	0.491	0.493	0.509	0.493

VIII. Conclusion

In this article, we demonstrate the crucial role of firms' technology in shaping the labor market for managers; our results demonstrate how recognizing technology's role provides greater evidence of the efficiency of the executive labor market. We begin by showing that firms are more likely to benchmark their compensation to peers with high technological similarity, even after controlling for important confounding factors. This effect is robust to controlling for corporate governance, and we present evidence consistent with the effect of technological similarity on peer groups not being associated with agency problems. Our finding is consistent with firms selecting peer groups for executive compensation based on executives' outside opportunities, and not as a means of upwardly biasing CEO compensation.

We then show that the effects of technological similarity manifest in other important aspects of the executive labor market. In particular, when CEOs move to other firms, they are more likely to move to companies with similar technological expertise, supporting our hypothesis that firms with similar technology also have comparable demand for managers that best complement that technology. Consistent with this evidence, we show that CEO pay is positively associated with the level of pay at peer firms with similar technology.

Our examination of the role of technological similarity thus presents a series of results consistent with the presence of a competitive labor market for managers affecting managerial compensation practices and labor market segmentation. Our results speak to the important role that technology and technological fit plays in determining the nature of managers' labor market.

Appendix. Variable Definitions

Pair-Level Variables

BETA_DIFF: The difference (firm i minus firm j) between firm i and firm j's betas estimated using a market model with the prior 250 trading day stock return and CRSP value-weighted market return.

BECAME_PEER: Equals 1 if firm j was not benchmarked by firm i in year $t-1$, but has become a benchmarking peer in year t.

BOARD_INDEP_DIFF: The difference (firm i minus firm j) in the percentage of independent board members to total obtained from BoardEx.

CASH_RATIO_DIFF: The difference (firm i minus firm j) in the two firms' cash ratios, defined as cash and cash equivalents (che), divided by total assets (at).

COMPENSATION_DIFF: The difference (firm i minus firm j) in CEO's total compensation between the two firms.

COMPENSATION_PEER_DUMMY: Equals 1 if firm j is used in benchmarking compensation for firm i, and zero otherwise.

DELTA_DIFF: The difference (firm i minus firm j) in the delta from managerial option compensation.

HHI_DIFF: The difference (firm i minus firm j) in the firms' 2-digit SIC code HHI Index.

LEVERAGE_DIFF: The difference (firm i minus firm j) in the firms' book leverage ratio defined as short-term debt (dlc) plus long-term debt (dltt), divided by total assets (at).

MB_DIFF: The difference (firm i minus firm j) in the two firms' market-to-book ratio, defined as total assets (at) minus book value of equity (ceq) plus market value of equity (prcc_f $\times$ csho), divided by total assets (at).

PROD_MARKET_SIM: The cosine similarity in two firms' product market segments.

SAME_INDUSTRY: Equals 1 if firm i and firm j are from the same 3-digit SIC industry, and zero otherwise.

SIZE_DIFF: The difference (firm i minus firm j) in the two firms' natural log of total assets (at).

STOCK_RETURN_CORR: Equals the past 250 trading day daily stock return correlation between the two firms.

TECH_SIMILARITY: The cosine similarity in patent portfolio between the two firms (see Section II.A for details).

THREE_YEAR_RETURN_DIFF: The difference (firm i minus firm j) in the firms' past 3-year stock returns.

VEGA_DIFF: The difference (firm i minus firm j) in the vega from managerial option compensation.

VESTING_PERIOD_DIFF: The difference (firm i minus firm j) in the maximum vesting period of CEO's compensation contract obtained from Incentive Lab.

VOLATILITY_DIFF: The difference (firm i minus firm j) in the past 250 trading day daily stock return volatility.

WITHIN60MI: Equals 1 if firm i and j are headquartered within 60 miles, and zero otherwise.

Firm-Level Variables

BTM: The book value of equity divided by market value of equity.

CASH_TO_ASSETS: Total cash and cash equivalents (che) divided by total assets (at).

CEO_COMPENSATION: The total compensation (tdc1) reported from ExecuComp.

CEO_TENURE: The number of years in which the CEO has served as CEO at the firm.

CEO_AGE: The CEO's age reported from ExecuComp.

CEO_IS_CHAIR: Equals 1 if the CEO is also the chairman of the board, and zero otherwise.

DISTANCE_FROM_PEER_MEDIAN: Calculated by a given firm's CEO pay minus the benchmarking peer group median CEO pay in year $t-1$, scaled by total assets.

E_INDEX: Entrenchment Index from Bebchuk et al. (2009).

FIRM_AGE: The number of years a firm has been in Compustat.

HIGHCOMP: Equals 1 if a CEO was paid in the top tercile of CEO pay among the benchmarking peer firms in year $t-1$, and zero otherwise.

LOWCOMP: Equals 1 if a CEO was paid in the bottom tercile of CEO pay among the benchmarking peer firms in year $t-1$, and zero otherwise.

LEVERAGE: Short-term debt (dlc) plus long-term debt (dltt), divided by total assets (at).

MB: Total assets (at) minus book value of equity (ceq), plus market value of equity (prcc_f $\times$ csho), divided by total assets (at).

MEDIAN_PEER_TECH_SIM: The median value of TECH_SIMILARITY among the benchmarking peers.

MEDIAN_PEER_PROD_SIM: The median value of PROD_MARKET_SIM among the benchmarking peers.

MEDIAN_TECH_PEER_COMP: The median level of peer CEO compensation in the similar technology space. A firm is considered to be in the same technology space if the pairwise TECH_SIMILARITY between the two firms is in the top 10% for a given year.

MEDIAN_IND_PEER_COMP: The median level of CEO pay for peer firms in the same 2-digit SIC industry.

NET_INCOME: Net income (ni) reported from Compustat.

POSITIVE_DISTANCE: Equals 1 if DISTANCE_FROM_PEER_MEDIAN is positive, and zero otherwise.

RD_TO_ASSETS: R&D expense (xrd) divided by total assets (at).

ROA: EBITDA scaled by book value of total assets.

SALES: Firm's sales (sale) from Compustat.

SAME_STATE_INDICATOR: Equals 1 if the moved CEO's pre- and post-transition firms are incorporated in the same state, and zero otherwise.

SHAREHOLDER_WEALTH: The stock price at the end of fiscal year multiplied by the number of shares outstanding (prcc_f × csho).

STOCK_RETURN: The past 12-month stock return, including dividends.

Supplementary Material

To view supplementary material for this article, please visit https://doi.org/10.1017/S0022109022000229.

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