Technological Fit and the Market for Managerial Talent

Fred Bereskin, Seong K. Byun and Jong-Min Oh*

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* Fred Bereskin is with the Trulaske College of Business at University of Missouri (bereskinf@missouri.edu). Seong Byun is with the School of Business Administration at the Virginia Commonwealth University (sbyun@vcu.edu). Jong-Min Oh is with the SKK Business School at the SungKyunKwan University (jongmin.oh@skku.edu). We thank Melissa Frye, Vladimir Gatchev, John Howe, Po-Hsuan Hsu, Sima Jannati, Stefano Sacchetto, Qinghai Wang, Jessica West, Chi Zhang, and seminar participants at the University of Central Florida, University of Mississippi, Seoul National University, KAIST, Korea University, and University of Missouri for valuable comments.

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1. Introduction

Investments in R&D and intangible capital have increased considerably over the last four decades, and have changed the way 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 et al., 2019), and cash holdings (Qiu and Wan, 2015). In this paper, we examine an under-explored area – 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 how it overlaps with peer firms in shaping compensation policy relies on the simple argument that firms with similar technology 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, this helps them make better decisions in, for example, hiring and obtaining the right people, converting their innovations to marketable products, protecting intellectual property, and identifying new opportunities and threats.[2] Furthermore, the expertise of the manager in certain technological domains is not only valuable to the firm, but also to other related firms with focusing 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

[1] For example, previous studies have documented that firms are becoming more productive (Crouzet and Eberly 2019; Döttling and Perotti, 2019), less likely to go public (Kahle and Stulz, 2017; Bowen, Fresard, and Hoberg, 2019), and more reliant on internal funds over external financing (Bates, Kahle, and Stulz, 2009; Kahle and Stulz, 2017).
[2] This is also consistent with anecdotal evidence, such as: (1) "The Evolving Executive: Five Skills All Modern CEOs Should Have," by Fred Coon, *Forbes* (2017), (2) "Great CEOs Must be Either Technical or Financial," by Venkatesh Rao, *Forbes* (2012), and (3) "Why Tech-Savvy CEOs rule the World," by Aaron Skonnard, *Inc.* (2014).

overlaps with other firms will impact 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 the 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 the fact that many firms' proxy statements describe technological considerations as one of the important factors in choosing the peer group used for CEO compensation benchmarking.[4]

Conversely, simply finding that firms with similar technology compete for the same managerial talent might not be surprising given that firms competing in the same industry would presumably also share similar technology, and that firms 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; Albuquerque, Franco, and Verdi, 2013). However, whether the presence of firms with similar technologies should matter even when firms do not directly

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[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; Cummings and Knott, 2018). Cummings and Knott (2018), for example, provide anecdotal evidence that Hughes Aircraft, which had been one of the market leaders as a defense electronics firm, experienced R&D productivity declines, and was ultimately sold in pieces to Raytheon, Boeing and others after C. Michael Armstrong was hired from IBM as CEO. Armstrong, who lacked technological expertise in Hughes' technologies, had changed R&D practices such that Hughes could no longer focus on long-term and cutting-edge technologies. Likewise, the authors also document that an open-ended interview indicates that firms that hire CEOs who lack expertise in a firm's technological areas often exhibit negative outcomes on its innovations.

[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"; Monsanto's proxy statement indicates that "the compensation benchmarking group of firms should have: 1) science-based, research-focused, organization from the biotechnology, pharmaceutical or related industry".

compete with each other, and how much technological similarity matters over and above industry and other firm characteristics are still open questions. Given that executive-firm matching should consider multiple dimensions including firm size, industry experience, and technological expertise (e.g., Pan, 2017), comparing the effects of technological similarity to existing factors allows us to tease out the effects of technology from other characteristics – which could otherwise mask the effect of similarity in technology attributes. In addition, ample anecdotal and empirical evidence suggests that the convergence of technology in modern corporations is blurring the conventional boundaries between industries, and that the boundaries of the labor and product markets are relatively independent for executives (e.g., Ernst & Young, 2000; Lei, 2000; Bröring et al., 2006; Bröring, 2010; IBM, 2015; McKinsey, 2017; Cunat and Guadalupe, 2009; Burgelman and Thomas, 2018).[5] Therefore, examining technological similarity provides greater evidence of the efficiency of the managerial labor market, and helps us understand the role of similarities in technological expertise on executive-firm matching.

We follow existing studies in using patent technology classifications to measure the firms' similarity of technological expertise, measured with their patent technologies. Our measure of technological similarity has been widely used in both the economics and finance literature (e.g., Jaffe, 1986; Bloom, Schankerman, and Van Reenen, 2013; Bena and Li, 2014; Qiu and Wan, 2015; Qiu, Wang, and Zhou, 2018; Byun, Oh, and Xia, 2019; Lee, Sun, Wang, and Zhang, 2019). Existing studies have pointed out that technological similarities do not merely reflect product market similarity. For example, Monsanto Co., which had historically been positioned in the agricultural chemicals industry, also shared many technologies with firms from other industries

[5] According to Cunat and Guadalupe (2009), CEOs frequently change firms across industries rather than within industries: 71% of the transitions of executives between firms included in Execucomp are between four-digit SIC industries (64% between three-digit SIC industries).

such as the food and pharmaceutical industries. Indeed, Monsanto stated in its proxy statement that for technological reasons it benchmarked 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 did not compete directly in the same industry, they exhibited high technological similarity.[6]

Using the compensation benchmarking peer firm information and the technology overlap measure, we begin by showing that similarity in technological expertise is a significant determinant for whether a certain firm is used for benchmarking compensation. Since firms in theory benchmark CEO pay to those of other firms to correctly reflect managers' outside options (e.g., Bizjak et al., 2008; Albuquerque et al., 2013), firms should benchmark their compensation to other firms with similar technology if technological fit plays an important role in determining the market for managers. We find that a one standard deviation increase in technological similarity is associated with a 48.7% increase in the odds of being a benchmarking peer. This compares to a corresponding 400% increase in the odds associated with being in the same industry, and a 59.9% decrease in the odds associated with one standard deviation increase in the firm size difference, implying an economic importance of technological similarity that is comparable to other prominent determinants of compensation. 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.[7] Our results suggest that technological similarity has a crucial role on the

[6] Using our measure of technological similarity, we are able to identify a firm's technologically-related peers by looking at the overlap in firms' patent classifications. For example, by looking at the patent classifications from the patents generated by firms, Monsanto Co. 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 expertise with General Mills in "*Food or edible material: processes, compositions, and products*" (USPTO Class 426), among others.

[7] For example, Johnson & 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 these firms

determinants of peer benchmark choice, and that considering the role of technological fit is critical to demonstrate the efficiency of the labor market and the composition of the peer group.

As in Bizjak et al. (2008), we 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. Following Bizjak et al.'s (2008) approach, we demonstrate that technological similarity increases the likelihood of a CEO receiving below-median pay in the previous year receiving at or above-median pay in the following year. This result is obtained even after controlling for other important compensation determinants, as in Bizjak et al. (2008), and is consistent with the notion that firms set CEO pay to remain competitive with firms that are competing for similar managerial talent. In addition, we show that our results are robust to controlling for corporate governance and managerial entrenchment.

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 the labor market. In particular, we first show that a one standard deviation increase in technological similarity between two firms increases the odds of the CEO joining a similar firm by 91%. This result is obtained even after controlling for a host of important factors such as an indicator for the same industry, product market similarity, and firm and CEO characteristics. Our finding reflects the notion that the marketability of CEOs' technological expertise is at least partly reflected in firms' technological similarity, and that firms have preferences to hire CEOs with 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%

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are all in the same industry as J&J and are close industry peers. According to our technological similarity measure, Pfizer and Merck, indeed, exhibit high similarities with J&J while Eli Lilly and GlaxoSmithKline do not.

when the median CEO compensation of technologically similar firms increases by 1%. We also show that firms with greater technological similarity tend to pay their CEOs more, consistent with the notion that CEOs at firms with more overall technological similarity have broader outside options.[8] Our results thus indicate that technological similarity plays a crucial role in the market for CEO talent. Our results also provide evidence consistent with the managerial labor market consistently reflecting CEOs' outside opportunities, as opposed to corporate governance problems.[9]

Our work contributes to several strands of the existing literature. First, our paper contributes to the literature focusing on the effect of similarities in technological expertise on corporate policies (e.g., Bena and Li, 2014; Qiu and Wan, 2015; Pan, 2017; Cao, Ma, Tucker, and Wan, 2018; and Byun et al., 2019).[10] We add to the literature by showing that the specific types of technology that a company owns and hence the technological expertise has become one of the important aspects in the competition for managerial talent. Thus, we contribute to the literature that the similarity in technological expertise between firms is an essential part in setting competitive CEO pay, and hence in retaining and hiring the manager with the right fit.

Second, we add to the literature on optimal contracting for CEO compensation and the market for managerial talent (e.g., Murphy, 1999; Murphy and Zabojnik, 2004; Garicano and

[8] Choi, Cicero, and Mobbs (2019) present evidence that SEC Rule 33-8732A revealed executives' outside options, and resulted in compensation increases and increased departures for executives with more apparent outside opportunities. Our study, using overall technological similarities to peers, presents an alternative approach to evaluating executives' outside opportunities, especially in the technological space.

[9] These results are consistent with the effects of CEOs' outside opportunities on wages dominating firms' ability to select from a deeper labor pool. Our evidence is consistent with Pan (2017) providing evidence that managers receive a greater proportion of the increased productivity resulting from good matches, reflecting "a scarcity of managerial skill at the top of the labor pool" and with Chaigneau and Sahuguet (2018), who show that when managerial skills are highly transferable between firms, a CEO with high ability captures most of the associated market value.

[10] Bena and Li (2014) show that firms with similar technology are more likely to merge. Cao et al. (2018) show the effects of technological "peer pressure" on disclosure. Qiu and Wan (2015) show that technology-related firms' innovations promote more cash savings. Byun et al. (2019) show that firms shift their research direction from breakthrough to incremental innovation in response to the level of innovations from technologically related peers.

Rossi-Hansbern, 2006; Gabaix and Landier, 2008; Gao, Luo, and Tang, 2015; Marinovic and Povel, 2017; Pan, 2017; Frydman, 2019). Existing literature notes that general and transferable managerial skills reflected in, for example, the level of business education (Frydman, 2019) or CEOs' prior industry experience (Custodio, Ferreira, and Matos, 2013) are positively related to the manager's outside option value, and hence their compensation levels. Conversely, Pan (2017) emphasizes that executive-firm matching is multidimensional, and finds that specific technology and skill complementarity between firm and executive play important roles in the matching process. We add to this literature by providing direct evidence that the degree of technological similarity plays an important role in the labor market for managers and firms' optimal compensation policies. Moreover, given that we provide evidence that similarities in technological expertise reflect CEOs' outside options, the broad trends in the convergence of technology across firms can drive up the levels of managerial compensation. Hence, what the recent literature has attributed to the increase in the relative importance of general managerial skills may simply reflect the fact that technologies across firms are converging over time.[11]

Third, we contribute to the literature on compensation peer groups, and the debate into whether peer groups reflect rent-seeking behavior (e.g., 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 et al., 2019; Larcker et al., 2019).[12] To capture the flow in managerial labor beyond industry and size, Faulkender and Yang (2010) and Albuquerque et al. (2013) examine whether the top executives had experienced transitions to and

[11] Also, by presenting evidence that technological similarity provides an additional dimension in boundaries for the market for CEOs, our results complement 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).
[12] 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 its construction has been considered in other studies (Gong, Li, and Shin, 2011; Albuquerque, 2014; Bizjak et al., 2019).

from the *industry* of a potential peer firm, though they remain agnostic about the factors that determined transitions in the first place. Bizjak et al. (2011) captures firm similarities across broader dimensions, including similarities in sales and performance, credit market conditions, and the degree of business complexity. Our paper adds to the literature by showing that technological similarity plays an important role in determining compensation benchmarking peers, consistent with the efficient contracting motivation for compensation benchmarking.

2. Empirical Design and Data

2.1 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 utilizes the overlap in the classifications of their patent portfolios. Specifically, we define technological similarity between *Firm i* and *Firm j* in year *t* as:

$$Tech\ Similarity_{ij,t} = \frac{F_{i,t}F'_{j,t}}{(F_{i,t}F'_{i,t})^{0.5}(F_{j,t}F'_{j,t})^{0.5}}, \quad (1)$$

where F_{it} is the 1 by τ vector of *Firm i*'s proportion of patents granted in technology space 1 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_{it} 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, in examining the effect of technological similarity on merger incidence and post-merger outcomes (Bena and Li, 2014), cash holdings (Qiu and Wan, 2015), and product disclosure (Cao, Ma, Tucker, and Wan, 2018). We obtain patent data from Kogan, Papanikolau, Seru, and Stoffman (2017), who use patent-level information from 1926 to 2010.[13]

2.2 Compensation benchmarking

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

$$Compensation\ Peer_{i,j,t} = a + b_1\ Tech\ Similarity_{i,j,t} + b'X_{i,j,t} + Time\ FE_t + e_{i,j,t}, \qquad (2)$$

where $Compensation\ Peer_{i,j,t}$ is a dummy variable that equals one if *Firm i* uses *Firm j* to benchmark its compensation in year *t*, and zero otherwise, $Tech\ Similarity_{i,j,t}$ is defined in equation (1), and $X_{i,j,t}$ includes various pair-level and firm-level characteristics that may also determine the likelihood of *Firm i* benchmarking *Firm j*. We also include year fixed effects to control for the effect of the aggregate time-series trend.

In addition to our baseline model, we also 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 peer group is defined as the collection of pairs with the same *Firm i* in a given year. As an example, suppose Apple Inc. (as *Firm i*) is paired with all other firms (as *Firm j'*s) in 2006, which are the pool of potential pairs of firms that Apple can use for benchmarking compensation in year 2006. All of those firms (Apple and paired firms) will be in the same peer group. Thus, any *Firm i* specific effects are controlled

[13] The data is available at Prof. Noah Stoffman's website; we thank him and his coauthors for sharing their dataset.

for, and the estimates will only reflect the cross-sectional variation in *Firm i* and *Firm j*-specific characteristics, such as *Tech Similarity* between the two firms.

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 are 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 matched sample with a more restrictive set of pairs of firms;[14] to control for the possibility that *Tech Similarity* between two firms (*Firms i* and *j*) may simply capture the fact that *Firm i* is simply more closely related to firms in a certain industry cluster, we generate a matched sample using the procedure described below.

We begin with the firm-by-firm (*Firm i* and *Firm j*) pair level observations of U.S. public firms from 2006 to 2010 that are identified as being compensation benchmarking peers (i.e., *Firm i* benchmarks to *Firm j*). For each compensation benchmarking peer *Firm j* in a given year, we identify another firm in the same industry and in the same size and book-to-market decile. We identify up to five matching firms to generate pseudo peers (*Firm i* and the matched firms) that could have been chosen as compensation benchmarking peers for *Firm i*, but were not chosen. Thus, in addition to limiting the potential number of pairs in running the logistic regression, our matched sample ensures that the likelihood of *Firm j* being the actual compensation peer to *Firm i* is not driven by the fact that *Firm j* happens to reside in an industry in which *Firm i* typically chooses benchmarking peers from nor by its size or growth opportunities profile (as proxied by the book-to-market ratio).[15]

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[14] Following the existing literature, we also estimate the logistic regression by matching the actual compensation benchmarking peers to 50 randomly selected non-peers, such that the balance between actual peers and non-peers is well balanced. The results are reported in Appendix A.

[15] We also implement a less restrictive matching procedure in which we exclude book-to-market from the matching criteria, and obtain similar results. The results are reported in Appendix A.

Our main compensation benchmark data comes from Institutional Shareholder Services' (ISS) Incentive Lab, which contains detailed information on compensation benchmark peers starting from 2006, the year in which 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 the pairwise technological similarity database. 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 a *Firm i* and *Firm j* pair, 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 zero otherwise.

We complement the technological similarity and compensation benchmark data with financial and accounting data from Compustat and CRSP, and executive compensation data from Execucomp. Specifically, we follow previous studies by controlling for additional pair-level variables that have been shown to potentially affect compensation benchmarking practice: *Same Industry* dummy, which equals one if *Firm i* and *Firm j* are from the same three-digit SIC industry[16]; *Stock Return Correlation,* 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' two-digit SIC code Herfindahl-Hirschman

[16] In Section 3.3, 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 North American Industry Classification System (NAICS) and the Global Industry Classification Standard (GICS).

Index; *3-Year Return Diff*, the difference in the firms' past three 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); *Compensation Diff*, the difference in the two firms' CEOs' total compensation (tdc1). We also include additional firm characteristics as controls, including *Firm Size*, *MB*, and *Cash Ratio*.

Our final compensation benchmarking sample contains 533,914 firm-pair-year observations from 2006 to 2010, with 334 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 4.6% of pairs are in the same industry; the average *Tech Similarity* is 4.4%.

Firms that compete in the same product market space might also have high technological similarity. Thus, high technological similarity may simply reflect the impact of being in the same product market. While *Same Industry* controls for this effect, we also construct an additional proxy for product market similarity. Specifically, we define (following Bloom et al. (2013)) *Product Market Similarity* as the Jaffe distance between two given firms following Equation (1), using the overlap in firms' product market segments as reported in the Compustat Segment data. Thus, two firms with perfect overlap in multiple segments will have *Product Market Similarity* equal to one, while two firms with zero overlap will have zero *Product Market Similarity*. We obtain *Product*

Market Similarity for 387,947 firm-pair-year observations in our sample; its average is 2.8%, and ranges from 0% to 100%.

3. Compensation Benchmark Selection Results

3.1 Full sample and random-matched sample

In this section, we present results regarding the role of technological similarity on the market for managerial talent by examining whether firms are more likely to benchmark their CEO compensation to firms that are technologically similar. For this purpose, we estimate the logistic regression of compensation benchmarking likelihood from Equation (2).

First, 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 on *Tech Similarity* is positive at 5.110, 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 also estimate the model with additional firm characteristics as additional controls, and also 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 3.576 and 3.613, respectively for the year and year/industry fixed effects models. These values are statistically significant at the 1% level. The economic impact of technological similarity is also significant: A one standard deviation increase in *Tech Similarity* (0.111) increases the odds of being a compensation benchmark peer by 48.7% (exp(3.576×0.111)-1). This magnitude is comparable to that of *Stock Return Correlation*: In the model with year fixed effects (Column (2)), a one standard deviation increase in the stock return correlation between two firms increases the odds of being a compensation benchmark peer by

70%. Unsurprisingly, the coefficient on the *Same Industry* dummy is also positive: Being in the same industry increases the odds of being a compensation benchmark peer by about 400%.

Lastly, we estimate the model with peer group fixed effects in Column (4), such that the estimated coefficient on *Tech Similarity* will only capture the variation among the potential group of firms to which a given firm can potentially benchmark its compensation. The estimated coefficient on *Tech Similarity* remains positive (3.953) and statistically significant at the 1% level. In economic magnitude, a one standard deviation increase in *Tech Similarity* increases the odds of being a compensation benchmarking peer by 55%.

An alternative explanation for our results is that *Tech Similarity* may simply capture the variation in product market similarity; firms that compete directly with each other are more likely to be included in compensation benchmarking. While *Same Industry* and *Stock Return Correlation* controls help to address this issue, the degree of competition and similarity in the product market space can vary within a given industry. To alleviate this concern, we also include *Product Market Similarity* (see Section 2.2 for details) as an additional control in Columns (5) – (8). As expected, the estimates on *Product Market Similarity* are positive and statistically significant. However, the estimates on *Tech Similarity* remains positive and both statistically and economically significant.

In Panel B, we examine the relation between technological similarity and the likelihood of being chosen as a compensation benchmark peer in a more stringent empirical setting. The previous analysis in which we use the full sample (and which includes all possible pairs of firms in the Compustat universe) implicitly uses all firms in the same year as potential candidates for benchmarking compensation. In addition, the asymmetry between actual compensation benchmarking pairs and non-compensation pairs may also be a concern (only around 2% of the final sample are actual compensation benchmark peers). To address these issues, we repeat our analysis using a year/industry/size/BTM matched sample (see Section 2.2 for details).

Panel B of Table 2 reports the estimates based on the matched sample. We repeat the same sets of fixed effects and control variables as Panel A. For all specifications, the coefficient estimate on *Tech Similarity* remains strongly positive and significant, which is consistent with our main result. Overall, these results suggest that the estimate on *Tech Similarity* is unlikely to be driven by other pair-specific similarities or characteristics, and point to the role of technological similarity in influencing compensation benchmarking choice.

3.2 Peer group selection within same industry and size groups

The above results based on the total sample contain variations across different industry and size groups. In other words, the variations in technological similarity captured above potentially explain why a firm may be chosen as a benchmarking peer even if the peer firm does not reside in the same industry as the focal firm. In this subsection, we test whether technological similarity can also explain why certain firms in the same industry or size groups are selected as benchmarking peers. For example, Johnson & Johnson's 2009 proxy statement includes certain product market competitors (such as Pfizer and Merck) as compensation benchmarking peers, and not others (such as Eli Lilly and GlaxoSmithKline) even though those firms operate in the same industry as J&J.

First, we examine the within-industry variation in 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 (*Firm i*) and peer firms (*Firm j*) reside in the same industry (i.e., *Same Industry* dummy equals 1). The results are reported in Panel A of Table 3. For brevity, we report the results using the Year/Industry/Size/BTM matched sample, though the results using the whole sample or random sample are qualitatively similar. We find that the effects of *Tech Similarity* remain positive and statistically significant in all specifications: A one standard deviation increase in *Tech Similarity* (0.111) increases the odds of being a compensation benchmark peer by between 23.1% and 35.5%. Hence, firms are more likely to benchmark compensation to peer firms with high degrees of technology overlap, even among firms in the same industry.

Second, we also examine the 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, for every year, firms are sorted into deciles of firm sales, and we keep observations if the (*i*,*j*) – pair of firms are in the same sales decile. We report the results in Panel B of Table 3. Consistent with the main results, *Tech Similarity* remains positive and both statistically and economically significant in all specifications in explaining peer selection likelihood among firms in the same size deciles: In the most conservative estimate, a one standard deviation increase in *Tech Similarity* (0.111) increases the odds of being a compensation benchmark peer by 34.1% (exp(2.642×0.111)-1). While the economic magnitude of the impact is relatively small compared to the full sample, the magnitude is comparable to other effects that are considered to be of first-order, such as being in the same industry (61.6% in the same specification).

3.3 Alternative Industry Definitions

One potential issue with the above analysis is that SIC codes, while popular in finance research, might be lacking in capturing true variations across industries. Since we wish to separate the technology from the industry factor, it is important to consider other industry definitions to assure that the similarity in technological expertise that we are emphasizing is not the mere manifestation of different industry definitions. In this subsection, we thus use an alternative definition of industry based on Hoberg and Phillip's (2010, 2016) text-based network industry classification (TNIC) which aims to capture firms residing in the same product market space by measuring the textual similarities in firms' product market descriptions reported in the companies' annual reports.[17] Specifically, we utilize TNIC3 available from the Hoberg and Phillips Data Library, which is designed with comparable granularity as three-digit SIC codes. We define *Same TNIC Industry* as equal to one if the firm-pair is in the same TNIC3 industry, and zero otherwise.

We report the results in Table 4. First, in Columns (1) to (3) of Table 4, we run the compensation benchmarking peer selection model from Equation (2) using the TNIC-based industry definition. As expected, the coefficient on *Same TNIC Industry* dummy variable is positive and statistically significant. The magnitude is also economically significant and comparable to the baseline model based on SIC codes: Being in the same TNIC3 industry increases the odds of being selected as a compensation benchmark peer by approximately 500%. Meanwhile, the effect of *Tech Similarity* also remains positive and significant. In Columns (2) and (3) with year fixed effects and peer group fixed effects models, a one-standard-deviation increase in *Tech Similarity* increases the odds of being selected as a compensation benchmarking peer by 48.6% (exp(3.569×0.111)-1) and 54.6% (exp(3.923×0.111)-1), respectively.

Next, as in Section 3.2, we restrict the sample to only the firm-pairs that reside in the same TNIC3 industry so that the variations captured in the peer selection model examines which peer firms are more likely to be selected for benchmarking compensation within that industry. We provide results in Columns (4) to (6). Again, the results are consistent with our baseline model. In

[17] Other industry classification systems include North American Industry Classification System (NAICS), which focuses on similarities in the product process, and Global Industry Classification Standard (GICS), which focuses on product similarity. Our results are robust to using these alternative industry classifications.

all three specifications with the univariate model, year-fixed effects model, and peer group-fixed effects models, the coefficients on *Tech Similarity* remain large and statistically significant: A one-standard-deviation increase in *Tech Similarity* increases the odds of being selected as a compensation benchmarking peer by 22.6% among all the peers in the same industry in the most conservative estimate in Column (5) with year-fixed effects. These estimates are comparable to the baseline estimates from Table 3, and suggest that technological similarity provides meaningful explanatory power in explaining why some industry peers are more likely to be chosen as compensation benchmarking peers than other firms in the same product market space.

3.4 Effects of corporate governance and entrenchment

While compensation for the competitive labor market for managers is generally the stated motivation for compensation 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; Bizjak et al., 2011). In this section, we examine the potential role of managerial entrenchment. As proxies for managerial entrenchment and self-serving behaviors, we utilize the *Governance Index* from Gompers, Ishii, and Metrick (2003), defined as the index based on the number of antitakeover provisions in corporate charters and bylaws, and the *Entrenchment Index* from Bebchuk, Cohen, and Ferrell (2009), which uses a subset of antitakeover provisions from Gompers et al. (2003).[18]

[18] Other than the governance and entrenchment indexes, we also examine whether the CEO is the chairman of the Board of Directors; our results remain qualitatively similar.

We examine whether the relation between technological similarity and compensation peer likelihood is *conditional* on the level of managerial entrenchment.[19] In the context of 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 expect that technological similarity would affect selection, to the extent that firms could ostensibly justify the selection decision.

We test this possibility in Table 5 based on the Year/Industry/Size/BTM matched sample of peer firms and pseudo-peers.[20] In Panel A, we examine the interaction term between *Tech Similarity* and *High Governance Index*, which equals one if a firm has above median *Governance Index*, and zero otherwise. In Panel B, we repeat the test with the interaction term between *Tech Similarity* and the *High Entrenchment Index*. Throughout all specifications, the interaction terms are small in magnitude and statistically insignificant. Thus, the relation between technological similarity and compensation peer likelihood (at least in the context of our results) does not seem to be driven by the self-serving motivation of the managers.

Consequently, we provide evidence that *Tech Similarity* is an important determinant of the peer benchmarking decision, and that its use reflects executives' outside opportunities. In the subsequent sections, we examine additional implications of these findings, and what we can learn about the managerial labor market from the role of *Tech Similarity*.

4. Competitive Benchmarking and CEO Pay

[19] Additionally, we repeat our main analysis of compensation peer selection with the Governance and Entrenchment indices as additional controls. As we report in Appendix B, the results with these controls are qualitatively similar to our main finding that technological similarity increases the probability of compensation peer selection.
[20] The results based on the full panel and randomly matched sample are similar.

In this section, we explore the mechanism in 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 pay below the median level of peer pay. If compensation benchmarking is motivated by the goal of paying CEOs their market wage, we expect that CEOs with pay below the median (compared to peer firms) are more likely to experience upward revisions in their compensation than CEOs with above median pay.

To examine this intuition, we run the following OLS regression: The dependent variable is the change in total compensation from year *t*-1 to year *t*.[21] The main independent variable is a firm's CEO pay status relative to peers, which reflects whether the previous year's CEO pay was below the median pay of benchmarking peer firms. Specifically, we construct an indicator variable *LowComp* equal to one if a CEO was paid below the median CEO pay among the benchmarking peer firms in year *t*-1, and zero otherwise. We also construct a continuous variable, *Distance from peer group median*, by taking the difference between the given firm's CEO pay and the median CEO pay among the benchmarking peers in year *t*-1. We also control for the log of firm size, CEO tenure, and change in sales, net income, and market value, as in Table 4 of Bizjak et al. (2008). We include time and industry fixed effects to control for unobserved time and industry factors.

We report the results in Table 6. As shown in Panel A, both *LowComp* and *Distance from peer group median* have positive and significant coefficients, implying that CEOs who were paid less than the median experience higher pay increases in the following year (compared to CEOs who were paid at or above median pay). The results are consistent with Bizjak et al. (2008), suggesting that compensation benchmarking affects CEO pay, and is consistent with the use of compensation benchmarking reflecting executives' compensation levels at competing firms.

[21] The results remain comparable if we use the change in log total compensation as the dependent variable.

Next, we examine whether and how much of the effect of compensation benchmarking on CEO pay documented above is related to firms' technological similarity to other firms in the labor market. To do so, we follow from Bizjak et al. (2008): The dependent variable is a dummy variable that equals one if a CEO received below-median compensation in year *t*-1 and receives compensation at or above the median in year *t,* and zero 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. High median technological similarity among the peers thus indicates that the given firm shares many similar technologies with its benchmarking peers, which may imply a higher degree of overlap in the demand for managerial talent. To distinguish technology-related overlap with product market overlap, we include *Median Peer Product Similarity*, defined as the median value of *Product Market Similarity* among the benchmarking peers. We also control for firm-related factors (log of sales, log of firm age, ROA, stock-return, and RD-to-assets), and for CEO- and governance-related factors (CEO tenure 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 higher technological similarity that are exposed to greater competition for CEOs. Hence, we expect the coefficient on the median level of technological similarity to be positive.

We present these results in Panel B of Table 6. Column (1) reports the estimate of the univariate logistic regression with *Median Peer Tech Similarity*. Column (2) reports the results of the multivariate regression. Column (3) includes *Median Peer Product Similarity* as an additional control. Column (4) includes the Entrenchment Index from Bebchuk et al. (2009) as an additional control for governance, which may affect compensation through self-serving motivation. Across all models, the coefficients on median technological similarity is positive and statistically significant.

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 the competitive labor market.

5. CEO Job Transitions

The underlying mechanism that we hypothesize for how technological similarity affects compensation benchmarking is the presence of a competitive labor market for CEOs. In this section, we further examine the validity of this mechanism by examining whether greater technological similarity between firms increase the likelihood of CEO transitions between firms.[22] Specifically, we study whether executives who transition between two companies (and are CEOs of one or both firms) move to a firm with greater technological overlap with 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 one of the important factors 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 involves two firms pairing together, we follow the 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:

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

$$Actual\ Transition_{ijm,t} = \alpha + \beta_1 Tech\ Similarity_{ijm,t-1} + \beta_2 X_{ijm,t-1} + \beta_3 Y_{im,t-1}$$

$$+\beta_4 Z_{jm,t-1} + Group\ FE_m + \varepsilon_{ijm,t}\ , \quad (3)$$

where *Actual Transition*$_{ijm,t}$ is the dependent variable, and equal to one if the pair of a CEO's pre-transition firm *i* and post-transition firm *j* is the actual transition for the pair *m*, and zero otherwise (i.e., this variable equals zero if the observation is a pseudo transition pair). *Tech Similarity*$_{ijm,t-1}$ is our independent variable of interest, and is the overlap in patent portfolios as defined in Section 2.1, 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 pre-transition firm (*i*) and post-transition firm (*j*). $X_{ijm,t-1}$ includes *Same Industry Indicator*$_{ijm,t-1}$ which equals one if the *i,j* pair is in the same three-digit SIC industry, and *Same State Indicator*$_{ijm,t-1}$ which equals one if the *i,j* pair is incorporated in the same state. $Y_{im,t-1}$ and $Z_{jm,t-1}$ are vector of control variables that include CEO's pre-transition (*i*) and post-transition (*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 *R&D-to-assets* (*R&D-to-assets* calculated as Research and Development divided by the book value of total assets).

In order to construct the actual and pseudo transition samples to estimate Equation (3), we first identify the actual CEO transition pairs. Specifically, we use Execucomp data from 1992 to 2010 and define an actual CEO transition pair if a CEO at firm *i* moves to firm *j*, or vice versa. Here 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 the 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 pre-transition firm *i* with up to five matched pseudo post-transition firms based on the actual post-transition firm *j* characteristics (*i.e.*, industry, firm size, and book-to-market ratio) and by pairing the actual post-transition firm *j* with up to five matched pseudo pre-transition firms based on the actual pre-transition firm *i* characteristics.[23] Matching criteria for constructing the control sample is 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 transitions sample, and 1,057 firm-pair observations being the pseudo transitions sample. Although *Same Industry Indicator* can be used to control for similarities in product market industries, we also control, as in Section 2.2, for the overlap in firms' product market segments (*Product Market Similarity*). Since Compustat segment data reduces our sample somewhat, models including this additional control has 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 7 presents the summary statistics of our CEO transition samples. The mean (median) technology overlap between a CEO's pre- and post-transition firms, *Tech Similarity*, is 24.7% (15.6%) in the actual transition sample, with 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), CEO transitions that actually occurred are those

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

where the pre- and post-transition 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 three-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 effects of product market similarities.

Panel B of Table 7 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 on *Tech Similarity* 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* dummy) or reside in the same state (*Same State* dummy), the coefficient estimate on *Tech Similarity* remains consistently positive and significant (Column (2)). The economic significance is also large. For a one standard deviation increase in *Tech Similarity*, the odds of CEO transition increases by about 91% (a 47.6% 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) through (6), we repeat the estimation on the Year/Industry/Size/BTM sample. The effect of *Tech Similarity* remains comparable throughout all specifications.

Our results on CEO transitions between technologically-related firms are consistent with Cummings and Knott (2018), who document that firms that hire CEOs with relevant technological domain expertise are associated with higher subsequent R&D productivity.[24] Similarly, our results

[24] We follow Cummings and Knott (2018) and examine the effect of technological expertise on R&D productivity after the new CEO is hired. In an untabulated test, we use the transition sample from Execucomp (as in Cummings and Knott (2018)) and find that when a CEO moves from the former firm to the new firm, technological similarity between the former and the new firms indeed increases the R&D productivity of the new firm in the long-run. This

suggest that technological similarity plays a significant role in determining the boundary of the market for CEOs, which is consistent with our baseline findings that firms are more likely to benchmark compensation to firms that are also technologically similar.

6. Implications of Technological Similarity for CEO Pay Levels

Given our findings that technological similarity significantly affects compensation benchmarks and CEO transitions, we proceed by examining the impact on CEO compensation.

6.1. Effects of peer compensation

First, given the evidence that firms are more likely to choose peers with similar technology to benchmark their compensation, we examine whether the level of CEO compensation at peer firms that are technologically similar correlate with a firm's own CEO pay. To test this relation, we estimate the following OLS regression:

$$\ln(CEO\ Compensation) = a + b_1\ \ln(Median\ Tech\ Peer\ Compensation) +$$

$$b_2\ \ln(Median\ Industry\ Peer\ Compensation) + b'X + Time\ FE + Ind\ FE + e, \quad (4)$$

where *ln(Median Industry Peer Compensation)* is the median level of total compensation of CEOs in the same industry (defined as peer CEOs that reside in the same product market space) and *ln(Median Tech Peer Compensation)* is the median level of compensation of peer CEOs that reside closely in the same technology space. In identifying peers that reside in a close technology space, we define two firms as being a *Technology Peer* with each other if their *Tech Similarity* is in the top 10% for a given year.[25] In calculating median peer compensation, we follow existing studies

positive association provides evidence that the CEO's technological expertise helps a new firm experience reliable long-run R&D productivity. This 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.

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

in also examining one year lagged total peer compensation, in addition to using contemporaneous year compensation, since board members would not have complete information on contemporaneous peer compensation levels in determining CEO pay for a given year.[26]

We report the estimate of Equation (4) in Table 8. 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 technology peer compensatio*n)), 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 on *ln(Median technology peer compensation*) in the baseline model (Column (1)) with other firm-level controls is 0.258, and is statistically significant at 1% level. Thus, a 1% increase in technology peer compensation level 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 (*ln(Median industry peer compensation)*) to control for the effect of firms competing for CEO talent in the same product market space. As expected, the median level of same industry peer compensation 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 on *ln(Median technology peer compensation*) is reduced in the presence of the industry peer compensation control, but is still economically meaningful: A 1%

[26] 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), up to 2010, the last available year of the patent database. Our final sample consists of 4,515 firm-year observations with 829 unique firms.

increase in the compensation level of the median technology peer is associated with a 0.174% increase in CEO pay.[27]

Finally, we repeat our analyses with additional industry fixed effects, which we report in Columns (5) through (8). Thus, the estimate on *ln(Median technology peer compensation*) captures the within-industry variation in the median level of compensation among firms with similar technology. Consistent with the earlier results, 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; CEO compensation is positively impacted by the compensation of their firms' technological peers.

6.2. Aggregate technological similarity and compensation levels

In this subsection, we examine the extent that a firm's *overall* exposure to technological similarity explains the variations in executive compensation in the last two decades.

To do so, we follow Gabaix and Landier (2008) in creating a sample of CEO compensation from Top 500 and 1000 firms by market cap in each year from 1992 to 2010. We then construct a firm-level proxy for overall technology overlap, *Aggregate Tech Similarity*, by aggregating the pair-wise *Tech Similarity* at the firm level. Similarly, we define *Aggregate Product Market Similarity* as the aggregate sum of the pairwise *Product Market Similarity*. To examine whether

[27] 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 on lagged *ln(Median technology peer compensation)*. In both models, the estimate on lagged *ln(Median technology peer compensation)* is positive and statistically and economically significant.

the variations in executive compensation for large public U.S. firms can be partly explained by the variations in aggregate technological similarity, we estimate the following regression:

$$\ln(CEO\ Compensation)_{i,t+1} = a + b_1\ Aggregate\ Tech\ Similarity_{i,t}$$
$$+b'X_{i,t}\ + Time\ Trend_t + e_{i,t}, \tag{5}$$

where the vector $X_{i,t}$ contains *ln(Market Cap of 250th Firm)* which is the natural log of the market capitalization of the 250th largest firm in the market (Gabaix and Landier, 2008), and the same set of firm-level controls from the *Peer Compensation* mode, in addition to the natural log of the firm's own market capitalization as an additional control. We also include *RD/Total Assets* to control for the variation in technological similarity that may be due to the large increase in corporate R&D investments in the last few decades. Aside from firm-specific controls, we include the time trend variable to control for simultaneous but spurious trends over time.

We report the estimates of Equation (5) in Table 9, Panel A.[28] In Columns (1) through (4), we examine the variations in CEO compensation for Top 500 firms (based on market capitalization) each year. In a univariate regression, the estimated coefficient on *Aggregate Tech Similarity* is 0.010, and is statistically significant at the 1% level. Economically, a one standard deviation increase in *Aggregate Tech Similarity* is associated with a 24.6% (100 × 0.01 × 24.59) increase in CEO compensation. In addition, the adjusted R^2 is 7.7%, suggesting that the overall variation in technological similarity can explain a significant amount of variation in CEO compensation, consistent with the notion that greater technological competition can induce greater competition for managerial talent.[29]

[28] In Appendix C, we report the separate summary statistics for the Top 500 and Top 1,000 sample.
[29] We recognize that the role of a firm's increased technological similarity on compensation is an empirical question, since an alternative hypothesis would be that increased technological similarity creates a deeper executive labor pool.

In columns (2), (3), and (4), we add additional variables to the regressions, such as the linear time trend variable and market concentration (*HHI*) index (Column (2)), as well as the aggregate product market similarity measure (Column (3)) and various market and firm characteristics (Column (4)) to control for other potential factors that can explain the secular trend and the cross-sectional variation in CEO compensation. Although the magnitude of *Aggregate Tech Similarity* becomes somewhat smaller in the presence of other covariates, it remains strongly positive and significant: In the presence of full controls, a one standard deviation increase in *Aggregate Tech Similarity* is associated with a 4.9% (100 × 0.002 × 24.59) increase in CEO compensation. The results are also consistent when we examine the variations in the sample of Top 1,000 firms, rather than Top 500 firms by market capitalization (Column (5) through (8)).

We then study the extent that technological similarity explains the within-industry variation in CEO pay by estimating the following regression:

$$\ln(CEO\ Compensation)_{i,t+1} = a + b_1\ Aggregate\ Tech\ Similarity_{i,t} + b'X_{i,t}$$
$$+Year\ FE_t + Industry\ FE_{i,t} + e_{i,t}, \qquad (6)$$

where our year and industry fixed-effects enable us to examine cross-sectional variations within each industry.[30] We report the results from these regressions in Table 9, Panel B. In the sample of Top 500 firms, *Aggregate Tech Similarity* remains positive and significant, both without (Columns (1) and (2)) and with industry fixed effects (Columns (3) and (4)). Our results are robust to controlling for the initial compensation level, such that cross-sectional persistence is unlikely to explain the loadings on *Aggregate Tech Similarity*. Likewise, in the sample of Top 1,000 firms,

[30] The sample of compensation trend and cross-sectional data for Top 500 firms contains 2,711 unique firm-year observations from 1992 to 2010 with 420 unique firms from 1992 to 2010. The sample of Top 1,000 firms contains 4,583 firm-year observations with 792 unique firms.

the association between *Aggregate Tech Similarity* and CEO compensation remains comparable in statistical and economic significance (Columns (5) through (8)).

These results further support the hypothesis that technological similarity is an important factor that determines the market for managerial talent – in this section, by demonstrating that it is an important determinant of the variation in CEO compensation.

7. Conclusion

In this paper, we demonstrate the crucial role of firms' technology in shaping the labor market for managers, and show how recognizing its 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 confounding factors like product market similarity, stock return correlation, and firm size difference. This effect is robust to controlling for corporate governance, and we present evidence consistent with the effect of technological similarity on peer group determinants not being associated with agency problems. Our finding is consistent with compensation peer groups being selected consistent with executives' outside opportunities, and not as a means of upwardly biasing CEO compensation.

We then show that the effects of technological similarity are manifested 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 also show that CEO pay is positively correlated with the level of pay from peer firms with similar technology. Moreover, we show that firms' technological similarity with other firms can explain both the time-series and the cross-sectional variation in CEO pay.

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

References

Abudalla, H. (2020). Five changes to expect at Nike as Donahoe takes charge. *Just-Style*, 14 January.

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

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

Bates, T. W., Kahle, K. M., & Stulz, R. M. (2009). Why do US firms hold so much more cash than they used to?. The journal of finance, 64(5), 1985-2021.

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

Bebchuk, L. & Fried, J. (2004). Pay without performance: The unfilled promise of executive compensation. Harvard University Press. Cambridge, MA.

Bena, J., & Li, K. (2014). Corporate innovations and mergers and acquisitions. *The Journal of Finance*, 69(5), 1923-1960.

Bizjak, J., Kalpathy, S., Li, F.Z., & Young, B. (2019). The role of peer firm selection in explicit relative performance awards. Working paper.

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

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

Blackman, D., (1997). For big fees, Towers Perrin gave clients similar reports. *Wall Street Journal*. March 11.

Bloom, N., Schankerman, M., & Van Reenen, J. (2013). Identifying technology spillovers and product market rivalry. *Econometrica*, 81(4), 1347-1393.

Bowen, D.E. III, Fresard, L., & Hoberg, G. (2019). Technological disruptiveness and the evolution of IPOs and sell-outs. Working paper.

Bröring, S. (2010). Developing innovation strategies for convergence − is ‘open innovation’ imperative? *International Journal of Technology Management*, 49(1/2/3), 272-294.

Bröring, S., Cloutier, M., & Leker, J. (2006). The front end of innovation in an era of industry convergence: evidence from nutraceuticals and functional foods. *R&D Management*, 36(5), 487-498.

Burgelman, R., & Thomas, J. (2018). How cross-boundary disruption-from-above superseded incumbents' sustaining innovation in the mobile industry: qualitative, graphical and computational insights. Working paper.

Byun, S. K., Oh, J. M., & Xia, H. (2019). Incremental versus Breakthrough Innovation: The Role of Technology Spillovers. *Management Science*, Forthcoming.

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

Cao, S., Ma, G., Tucker, J. & Wan, C. (2018). Technological peer pressure and product disclosure. *The Accounting Review* 93(6), 95-126.

Chaigneau, P. & Sahuguet, N. (2018). The effect of monitoring on CEO compensation in a matching equilibrium. *Journal of Financial and Quantitative Analysis* 53(3), 1297-1339.

Choi, D., Cicero, D. & Mobbs, S. (2019). CEO marketability, employment opportunities, and compensation: Evidence from compensation peer citations. Working paper.

Coles, J., Du, F. & Xie, D. (2018). Compensation peer choice and managerial capital. Working paper.

Crouzet, N., & Eberly, J. C. (2019). Understanding weak capital investment: The role of market concentration and intangibles (No. w25869). National Bureau of Economic Research.

Cummings, T., & Knott, A. (2018). Outside CEOs and innovation. *Strategic Management Journal*, 39(8), 2095-2119.

Cunat, V. & Guadalupe, M. (2009). Globalization and the provision of incentives inside the firm: the effect of foreign competition. *Journal of Labor Economics*, 27(2), 179-212.

Custodio, C., Ferreira, M.A., & Matos, P. (2013). Generalists versus specialists: Lifetime work experience and Chief Executive Officer pay. *Journal of Financial Economics*, 108(2), 471-492.

Denis, D.K., Jochem, T., & Rajamani, A. (2019). Shareholder governance and CEO compensation: The peer effects of say on pay. *Review of Financial Studies*, Forthcoming.

Döttling, R., & Perotti, E. (2019). Redistributive trends. Working paper.

Ernst & Young. (2000). Convergence. *The biotechnology industry report*.

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

Feldman, E. R., & Montgomery, C. A. (2015). Are incentives without expertise sufficient? Evidence from Fortune 500 firms. *Strategic Management Journal*, 36(1), 113–122.

Francis, B., Hasan, I., Mani, S. & Pengfei, Y. (2016) Relative peer quality and firm performance. *Journal of Financial Economics*, 122, 196-219.

Frydman, C. (2019). Rising through the ranks: The evolution of the market for corporate executives, 1936-2003. *Management Science*, 65(11), 4951-4979.

Frydman, C. & Papanikolau (2018). In search of ideas: Technological innovation and executive pay inequality. *Journal of Financial Economics* 130(1), 1-24.

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

Gao, H., Luo, J., & Tang, T. (2015). Effects of managerial labor market on executive compensation: Evidence from job-hopping. *Journal of Accounting and Economics*, 59(2-3), 203-220.

Garicano, L., & Rossi-Hansberg, E. (2006). Organization and inequality in a knowledge economy. *The Quarterly Journal of Economics*, 121(4), 1383-1435.

Gompers, P., Ishii, J., & Metrick, A. (2003). Corporate governance and equity prices. *The Quarterly Journal of Economics*, 118(1), 107-156.

Gong, G., Li, L. Y., & Shin, J. Y. (2011). Relative performance evaluation and related peer groups in executive compensation contracts. *The Accounting Review*, 86(3), 1007-1043.

Harris, D., & Helfat, C. (1997). Specificity of CEO human capital and compensation. *Strategic Management Journal*, 18(11), 895–920.

Hoberg, G., & Phillips, G. (2010). Product market synergies and competition in mergers and acquisitions: A text-based analysis. *The Review of Financial Studies*, 23(10), 3773-3811.

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

IBM. (2015). Redefining boundaries – Insights from the global C-suite studies. *IBM Institute for Business Value*.

Institutional Shareholder Services (2017). U.S. peer group selection methodology and issuer submission process: Frequently asked questions. *Report.*

Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits and market value. *American Economic Review* 76(5), 984-1001.

Kahle, K. M., & Stulz, R. M. (2017). Is the US public corporation in trouble?. Journal of Economic Perspectives, 31(3), 67-88.

Knott, A. (2008). R&D/returns causality: Absorptive capacity or organizational IQ. *Management Science*, 54(12), 2054–2067.

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2), 665-712.

Lan, C. (2019). Industry as peer group criterion. *Harvard Law School Forum on Corporate Governance*. https://corpgov.law.harvard.edu/2019/02/09/industry-as-peer-group-criterion/

Larcker, D., McClure, C., & Zhu, C. (2019). Peer group choice and Chief Executive Officer compensation. Working paper.

Lee, C.M.C., Sun, S.T., Wang, R., & Zhang, R. (2019). Technological links and predictable returns. *Journal of Financial Economics* 132(3), 76-96.

Lei, D. (2000). Industry evolution and competence development: The imperatives of technological convergence. *International Journal of Technology Management*, 19(7/8), 699-738.

Macher, J., Miller, N. H., & Osborne, M. (2017). Finding Mr. Schumpeter: An Empirical Study of Competition and Technology Adoption. Working Paper.

Marinovic, I., & Povel, P. (2017). Competition for talent under performance manipulation. *Journal of Accounting and Economics*, 64(1), 1-14.

McKinsey. (2017). Competing in a world of sectors without borders. *McKinsey Quarterly*.

Murphy, K. J. (1999). Executive compensation. *Handbook of labor economics*, 3, 2485-2563.

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

Pan, Y. (2017). The determinants and impact of executive-firm matches. *Management Science* 63(1), 185-200.

Thomas, L. (2019). Walmart poaches ex-Google, Amazon exec Suresh Kumar for new CTO role. https://www.cnbc.com/2019/05/28/walmart-poaches-ex-google-amazon-exec-suresh-kumar-for-new-cto-role.html, May 28.

Qiu, J., & Wan, C. (2015). Technology spillovers and corporate cash holdings. *Journal of Financial Economics*, 115(3), 558-573.

Qiu, J., Wang, J. & Zhou, Y. (2018). Technology and return predictability. Working paper.

Tita, B. (2017). Arconic names former GE executive Chip Blankenship as CEO. *Wall Street Journal*. October 23.

Table 1: Summary Statistics – Compensation Benchmark Selection and Job Transition

This table 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 that are being used in compensation benchmarking. The data on compensation benchmarking peers comes from Institutional Shareholder Services (ISS) Incentive Lab from 2006 to 2010. The sample includes all actual compensation benchmarking peers, as well as non-benchmarking peers to generate a total pool of all potential peers that *Firm i* can use to benchmark compensation. *Compensation Peer Dummy* equals one if *Firm j* is used in benchmarking compensation for *Firm i*, and zero otherwise. *Tech Similarity* is the cosine similarity in patent portfolio between the two firms (see Section 2.1 for details). *Product Market Similarity* captures the cosine similarity in two firms' product market segments. Other variables include: *Same Industry*, which equals one if *Firm i* and *Firm j* are from the same three-digit SIC industry and zero otherwise; *Stock Return Correlation*, which equals the past 250 trading day daily stock return correlation between the two firms; *Beta Diff*, defined as the difference in *Firm i* and *Firm j* betas estimated using a market model with the prior 250 trading day stock return and CRSP value-weighted market return; *Volatility Diff*, defined as the difference in the past 250 trading day daily stock return volatility; *HHI Diff*, defined as the difference in the firms' two-digit SIC code HHI Index; *3-Year Return Diff*, defined as the difference in the firms' past three 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); *Compensation Diff*, the difference in CEO's total compensation between the two firms; *Firm Size*, the natural log of Firm i's total assets; *MB*, the market-to-book- ratio of *Firm i*; *RD/AT*, defined as the R&D expense divided by total assets for *Firm i*; and *Cash/AT*, defined as *Firm i*'s total cash and cash equivalent divided by total assets.

Variable	**Obs**	**Mean**	**Std. Dev.**	**25^{th}**	**Median**	**75^{th}**
Compensation Peer Dummy	533,941	0.023	0.151	0.000	0.000	0.000
Tech Similarity	533,941	0.044	0.111	0.000	0.001	0.027
Product Market Similarity	387,947	0.028	0.154	0.000	0.000	0.000
Same Industry	533,941	0.046	0.210	0.000	0.000	0.000
Stock Return Correlation	533,941	0.272	0.207	0.127	0.275	0.423
Beta Diff	533,941	-0.068	0.562	-0.419	-0.060	0.293
Volatility Diff	533,941	-0.004	0.013	-0.011	-0.003	0.005
HHI Diff	533,941	0.000	0.084	-0.022	0.000	0.020
3-Year Return Diff	533,941	0.030	1.162	-0.457	0.033	0.517
Size Diff	533,941	0.876	2.305	-0.680	0.921	2.461
Leverage Diff	533,941	0.024	0.214	-0.123	0.017	0.172
MB Diff	533,941	0.159	1.427	-0.567	0.141	0.879
Cash Ratio Diff	533,941	-0.014	0.247	-0.160	-0.006	0.134
Compensation Diff	533,941	2,303.4	8,307.1	-1859.2	2,020.8	6,411.8
Firm Size	533,941	8.439	1.528	7.318	8.230	9.495
MB	533,941	2.115	1.061	1.390	1.822	2.564
RD/AT	533,941	0.066	0.064	0.017	0.045	0.097
Cash/AT	533,941	0.200	0.168	0.064	0.154	0.288

Table 2: Compensation Benchmark Peer Selection Likelihood

This table contains the results from the analysis of the characteristics of the firms that get chosen in 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 year/industry/size/BTM matched sample, in which we match actual compensation peers to pseudo peers with similar industry, size, and book-to-market characteristics as the actual peers that were chosen. We describe the details of the matching procedure in Section 2.2. The dependent variable is *Compensation Peer Dummy*, which equals one 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 i* and *Firm j* pair. In addition, other control variables include *Same Industry* dummy, which equals one if *Firm i* and *Firm j* are from the same three-digit SIC industry, *Stock Return Correlation*, which equals the past 250 trading day daily stock return correlation between the two firms, *Beta Diff*, defined as the difference in *Firm i* and *Firm j* betas estimated using a market model with the prior 250 trading day stock return and CRSP value-weighted market return, *Volatility Diff*, defined as the difference in the past 250 trading day daily stock return volatility, *HHI Diff*, defined as the difference in the firms' two-digit SIC code HHI Index, *3-Year Return Diff*, defined as the difference in the firms' past three 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), *Compensation Diff*, the difference in CEO's total compensation between the two firms, and *Firm i*'s *Firm Size*, *MB, RD/AT*, and *Cash/AT*. 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. The t-statistics based on standard errors clustered by firm are reported in parentheses. ***, **, and * refer to statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Full Sample

	Dependent Variable: *Compensation Peer Dummy*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Univariate	Year FE	Year and Ind. FE	Peer Group FE	Univariate	Year FE	Year and Ind. FE	Peer Group FE
Tech Similarity	5.110***	3.576***	3.613***	3.953***	5.232***	3.410***	3.417***	3.715***
	(42.82)	(24.00)	(23.83)	(25.88)	(42.70)	(21.40)	(20.92)	(21.98)
Product Market Similarity						0.956***	0.987***	1.247***
						(6.54)	(6.42)	(7.55)
Same Industry		1.620***	1.685***	1.841***		1.202***	1.277***	1.362***
		(15.37)	(14.97)	(15.59)		(9.78)	(10.10)	(10.21)
Stock Return Correlation		2.641***	2.597***	2.869***		2.622***	2.497***	2.781***
		(16.54)	(17.39)	-16.87		(15.74)	(15.65)	(15.84)
Beta Diff		-0.030	-0.020	0.004		-0.008	-0.031	-0.007
		(-0.37)	(-0.25)	(0.05)		(-0.10)	(-0.38)	(-0.07)
Volatility Diff		13.003***	12.623***	21.750***		12.950***	13.306***	20.407***
		(3.63)	(3.59)	(5.70)		(3.38)	(3.55)	(5.00)
HHI Diff		1.992***	2.110***	2.055***		1.792***	2.039***	1.913***
		(4.72)	(4.16)	(3.98)		(3.83)	(3.40)	(3.02)
3-Year Return Diff		0.069***	0.061***	0.118***		0.082***	0.076***	0.108***
		(3.63)	(3.18)	(4.69)		(3.43)	(3.22)	(3.63)
Size Diff		-0.396***	-0.400***	-0.404***		-0.391***	-0.393***	-0.414***
		(-10.82)	(-11.26)	(-10.95)		(-10.17)	(-10.44)	(-10.97)
Leverage Diff		-0.251*	-0.310**	-0.101		-0.182	-0.196	-0.019
		(-1.75)	(-2.19)	(-0.56)		(-1.10)	(-1.19)	(-0.10)
MB Diff		-0.201***	-0.206***	-0.209***		-0.183***	-0.186***	-0.185***
		(-9.07)	(-9.27)	(-8.92)		(-7.18)	(-7.24)	(-7.03)
Cash Ratio Diff		0.577**	0.564**	0.533**		0.653***	0.636***	0.588**
		(2.53)	(2.42)	(2.42)		(2.65)	(2.58)	(2.50)
Compensation Diff		-0.000	-0.000	0.000		-0.000	-0.000	0.000
		(-0.46)	(-0.67)	(1.08)		(-0.40)	(-0.98)	(1.46)
Firm Size		0.526***	0.522***	0.000		0.493***	0.496***	0.000
		(9.00)	(9.06)			(8.44)	(8.53)	
MB		0.225***	0.250***			0.209***	0.226***	
		(5.74)	(6.71)			(4.69)	(5.63)	
RD/AT		-1.887**	-2.275***			-2.144**	-2.066**	
		(-2.42)	(-2.62)			(-2.53)	(-2.19)	
Cash/AT		-1.224***	-0.967**			-1.406***	-1.031**	
		(-2.68)	(-2.23)			(-2.79)	(-2.19)	
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	533,941	533,941	533,941	533,941	387,947	387,947	387,947	387,947
Pseudo R^2	0.112	0.223	0.229	0.248	0.125	0.239	0.245	0.271

Panel B: Industry/Size/BTM Matched Sample

	Dependent Variable: Compensation Peer Dummy							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Univariate	Year FE	Year and Ind. FE	Peer Group FE	Univariate	Year FE	Year and Ind. FE	Peer Group FE
Tech Similarity	2.731***	2.712***	2.956***	3.804***	2.863***	2.549***	2.683***	3.451***
	(14.66)	(12.89)	(14.00)	(15.50)	(14.22)	(11.22)	(11.73)	(12.78)
Product Market Similarity						0.401**	0.563***	1.063***
						(2.55)	(3.40)	(5.15)
Same Industry		0.483***	0.629***	1.034***		0.400***	0.471***	0.670***
		(4.89)	(5.95)	(8.55)		(3.33)	(3.88)	(4.86)
Stock Return Correlation		1.101***	1.227***	1.736***		1.306***	1.296***	1.856***
		(6.93)	(7.98)	(8.46)		(7.78)	(7.28)	(7.82)
Beta Diff		0.275**	0.356***	0.629***		0.330***	0.365***	0.689***
		(2.45)	(3.05)	(4.08)		(2.83)	(3.00)	(4.13)
Volatility Diff		5.077	5.348	9.101		2.956	3.748	2.369
		(1.03)	(1.07)	(1.39)		(0.56)	(0.68)	(0.34)
HHI Diff		-1.864**	-22.421***	-26.196***		-2.018**	-23.080***	-27.492***
		(-2.54)	(-18.49)	(-21.03)		(-2.10)	(-15.56)	(-18.04)
3-Year Return Diff		0.177***	0.182***	0.281***		0.205***	0.212***	0.313***
		(5.77)	(6.34)	(7.75)		(5.95)	(6.11)	(6.80)
Size Diff		-0.051	-0.042	0.004		-0.056	-0.049	-0.017
		(-1.41)	(-1.14)	(0.09)		(-1.34)	(-1.14)	(-0.35)
Leverage Diff		0.011	0.009	0.294		-0.035	0.004	0.404
		(0.06)	(0.06)	(1.27)		(-0.19)	(0.02)	(1.54)
MB Diff		-0.085***	-0.107***	-0.119***		-0.089***	-0.088**	-0.098**
		(-2.82)	(-3.37)	(-3.26)		(-2.60)	(-2.37)	(-2.34)
Cash Ratio Diff		1.277***	0.811***	0.606*		1.579***	1.031***	0.938***
		(4.16)	(2.59)	(1.88)		(4.76)	(3.08)	(2.66)
Compensation Diff		-0.000*	-0.000**	-0.000**		-0.000	-0.000	-0.000
		(-1.82)	(-2.10)	(-2.20)		(-1.07)	(-1.54)	(-1.36)
Firm Size		0.164***	0.093***	0.000		0.116***	0.080**	0.000
		(4.58)	(2.60)			(3.09)	(2.06)	
MB		0.081*	0.078*			0.111**	0.071	
		(1.81)	(1.82)			(2.31)	(1.52)	
RD/AT		-3.408***	-2.000***			-3.054***	-1.383*	
		(-4.84)	(-2.60)			(-3.99)	(-1.65)	
Cash/AT		-1.923***	-0.977**			-2.315***	-1.224***	
		(-4.61)	(-2.36)			(-5.24)	(-2.70)	
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	16,101	16,101	16,101	16,101	12,021	12,021	12,021	12,021
Pseudo R^2	0.045	0.103	0.146	0.188	0.052	0.111	0.148	0.205

Table 3: Compensation Peer Group – Within Same Industry and Size Groups

This table 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 the year/industry/size/BTM matched sample utilized in Table 2 Panel B. In Panel A, we examine the subsample of pairs of firms in which the pairs are from the same three-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 one 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 *Firm i* and *Firm j* pair. 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 as in Table 2. The t-statistics based on standard errors clustered by firm are reported in parentheses. ***, **, and * refer to statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Within Same Industry

	Dependent Variable: Compensation Peer Dummy							
	(1) Univariate	(2) Year FE	(3) Year and Ind. FE	(4) Peer Group FE	(5) Univariate	(6) Year FE	(7) Year and Ind. FE	(8) Peer Group FE
Tech Similarity	2.239***	2.167***	2.279***	2.737***	2.047***	1.877***	1.934***	2.373***
	(8.43)	(8.01)	(8.53)	(8.33)	(7.70)	(6.67)	(7.01)	(6.79)
Product Market Similarity						0.494***	0.863***	1.248***
						(3.28)	(5.29)	(5.79)
Stock Return Correlation		1.029***	1.323***	1.991***		0.741**	1.045***	2.018***
		(3.85)	(5.08)	(4.89)		(2.56)	(3.51)	(4.30)
Beta Diff		-0.106	-0.101	-0.352		0.026	0.077	-0.176
		(-0.57)	(-0.55)	(-1.40)		(0.12)	(0.39)	(-0.55)
Volatility Diff		-18.944**	-22.352***	-24.745**		-22.600***	-28.592***	-22.587
		(-2.40)	(-2.87)	(-2.01)		(-2.62)	(-3.26)	(-1.57)
3-Year Return Diff		-0.119**	-0.123**	-0.143**		-0.096	-0.098*	-0.114
		(-2.25)	(-2.41)	(-2.00)		(-1.60)	(-1.72)	(-1.41)
Size Diff		0.086	0.102	0.137*		0.045	0.043	0.000
		(1.31)	(1.51)	(1.74)		(0.63)	(0.58)	(0.00)
Leverage Diff		0.442	0.361	1.442***		0.467	0.406	1.833***
		(1.43)	(1.24)	(3.35)		(1.51)	(1.40)	(3.89)
MB Diff		0.077	0.093*	0.162***		0.066	0.108*	0.160**
		(1.61)	(1.83)	(2.60)		(1.27)	(1.95)	(2.29)
Cash Ratio Diff		0.522	-0.093	-0.448		0.877**	0.062	-0.389
		(1.41)	(-0.23)	(-0.95)		(2.08)	(0.13)	(-0.73)
Compensation Diff		0.017**	0.015*	0.024*		0.012	0.009	0.007
		(2.07)	(1.93)	(1.80)		(1.37)	(1.09)	(0.46)
Firm Size		0.109**	0.050			0.126**	0.081	
		(2.03)	(0.91)			(2.23)	(1.39)	
MB		0.072	0.019			0.110	0.011	
		(1.03)	(0.25)			(1.50)	(0.15)	
RD/AT		-0.602	-0.222			-1.198	-0.835	
		(-0.79)	(-0.27)			(-1.42)	(-0.89)	
Cash/AT		-1.308**	-0.103			-1.862***	-0.304	
		(-2.46)	(-0.17)			(-3.18)	(-0.46)	
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	4,355	4,355	4,306	3,286	3,559	3,559	3,450	2,617
Pseudo R^2	0.046	0.083	0.107	0.126	0.039	0.085	0.118	0.155

Panel B: Within Same Size Decile

	Dependent Variable: Compensation Peer Dummy							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Univariate	Year FE	Year and Ind. FE	Peer Group FE	Univariate	Year FE	Year and Ind. FE	Peer Group FE
Techs Similarity	2.659***	2.820***	2.956***	3.650***	2.921***	2.644***	2.642***	3.562***
	(7.18)	(7.46)	(7.66)	(8.21)	(7.09)	(6.60)	(6.63)	(7.30)
Product Market Similarity						0.797***	1.009***	1.589***
						(3.17)	(3.85)	(4.47)
Same Industry		0.748***	0.884***	1.407***		0.466**	0.480**	0.814***
		(4.42)	(4.68)	(5.43)		(2.36)	(2.41)	(3.03)
Stock Return Correlation		1.001***	1.236***	1.580***		1.158***	1.205***	1.607***
		(3.77)	(4.39)	(3.75)		(3.88)	(3.62)	(3.16)
Beta Diff		-0.606***	-0.803***	-1.221***		-0.671***	-0.785***	-1.303***
		(-3.42)	(-4.48)	(-4.07)		(-3.20)	(-3.79)	(-4.04)
Volatility Diff		3.700	5.731	3.109		14.331	13.617	21.621
		(0.47)	(0.72)	(0.25)		(1.64)	(1.56)	(1.57)
HHI Diff		1.849**	22.943***	23.607***		3.170**	22.794***	21.511***
		(2.25)	(9.30)	(8.35)		(2.49)	(6.75)	(5.92)
3-Year Return Diff		-0.148**	-0.128**	-0.170**		-0.156**	-0.124*	-0.169*
		(-2.51)	(-2.15)	(-1.97)		(-2.36)	(-1.86)	(-1.69)
Size Diff		-0.086	-0.156	-0.081		-0.148	-0.159	-0.065
		(-0.77)	(-1.17)	(-0.47)		(-1.10)	(-1.05)	(-0.31)
Leverage Diff		0.547*	0.667**	0.477		0.719**	0.793**	0.886
		(1.74)	(2.13)	(0.94)		(1.97)	(2.24)	(1.56)
MB Diff		-0.030	-0.020	-0.053		-0.026	0.014	0.014
		(-0.44)	(-0.26)	(-0.57)		(-0.37)	(0.18)	(0.14)
Cash Ratio Diff		1.689***	1.329***	1.359**		1.713***	1.371***	1.519***
		(3.39)	(2.68)	(2.57)		(3.26)	(2.66)	(2.74)
Compensation Diff		0.031***	0.032***	0.031*		0.038***	0.039***	0.041**
		(3.32)	(3.20)	(1.92)		(3.52)	(3.55)	(2.21)
Firm Size		0.323***	0.258***			0.285***	0.246***	
		(6.51)	(4.67)			(5.23)	(4.10)	
MB		0.152**	0.083			0.237***	0.119	
		(2.05)	(1.01)			(2.95)	(1.37)	
RD/AT		-2.772**	-0.996			-3.587***	-1.600	
		(-2.46)	(-0.78)			(-2.99)	(-1.22)	
Cash/AT		-1.805***	-0.963			-1.905***	-1.058*	
		(-3.31)	(-1.64)			(-3.37)	(-1.79)	
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	4,583	4,583	4,577	2,941	3,273	3,273	3,252	2,008
Pseudo R^2	0.035	0.146	0.191	0.233	0.046	0.156	0.188	0.265

Table 4: Compensation Peer Group – TNIC Industry

This table reports the estimates of the logistic regression model of compensation benchmarking peer likelihood from Equation (2) using an alternative definition of industry based on Hoberg and Phillip's (2010, 2016) text-based network industry classification (TNIC). The sample consists of firm-by-firm (*Firm i* and *Firm j*) pair level observations of U.S. public firms from 2006 to 2010. The dependent variable is *Compensation Peer Dummy*, which equals one 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 i and Firm j pair. All other explanatory variables are defined as in Table 2, but instead of the *Same Industry* dummy variable, we include *Same TNIC Industry*, equal to one if *Firm i* and *Firm j* are from the same TNIC industry. Columns (1)-(3) reports the estimates using the full sample using a univariate model, year fixed-effects model, and peer group fixed-effects model, respectively. Columns (4)-(6) report the estimates from the restricted sample of peers that reside in the same TNIC industry, with a univariate model, year fixed effects model, and peer group fixed effects model, respectively. A peer group is defined as a cluster of pairs grouped by *Firm i-year*. The t-statistics based on standard errors clustered by firm are reported in parentheses. ***, **, and * refer to statistical significance at 1%, 5%, and 10% levels, respectively.

	Dependent Variable: Compensation Peer Dummy					
	Total Sample			Within Same TNIC Industry		
	(1)	(2)	(3)	(4)	(5)	(6)
	Univariate	Year FE	Peer Group FE	Univariate	Year FE	Peer Group FE
Tech Similarity	5.111***	3.569***	3.923***	2.093***	1.836***	2.192***
	(42.82)	(25.21)	(26.91)	(12.18)	(10.75)	(11.15)
Same TNIC Industry		1.796***	2.015***			
		(18.55)	(19.53)			
Stock Return Correlation		2.536***	2.825***		2.195***	2.766***
		(15.84)	(16.37)		(11.92)	(12.01)
Beta Diff		-0.033	0.031		-0.155	0.088
		(-0.41)	(0.32)		(-1.59)	(0.71)
Volatility Diff		13.258***	21.848***		10.436***	12.576**
		(3.72)	(5.82)		(2.67)	(2.38)
HHI Diff		1.908***	2.531***		4.535**	1.542
		(4.70)	(4.78)		(2.22)	(0.86)
3-Year Return Diff		0.067***	0.136***		0.089***	0.099**
		(3.41)	(5.16)		(2.93)	(2.14)
Size Diff		-0.388***	-0.393***		-0.314***	-0.309***
		(-10.73)	(-10.74)		(-7.69)	(-6.47)
Leverage Diff		-0.287**	-0.122		-0.402**	-0.505*
		(-1.97)	(-0.67)		(-2.08)	(-1.77)
MB Diff		-0.219***	-0.219***		-0.211***	-0.193***
		(-10.39)	(-9.88)		(-6.67)	(-4.88)
Cash Ratio Diff		0.630***	0.593***		1.007***	0.425*
		(2.79)	(2.73)		(4.49)	(1.80)
Compensation Diff		-1.203	3.687		-3.769	1.527
		(-0.39)	(1.06)		(-0.72)	(0.21)
Firm Size		0.508***			0.181***	
		(8.71)			(4.48)	
MB		0.260***			0.290***	
		(6.66)			(7.19)	
RD/AT		-2.093***			-2.627***	
		(-2.66)			(-4.20)	
Cash/AT		-1.373***			-2.240***	
		(-3.02)			(-7.38)	
Year FE	No	Yes	No	No	Yes	No
Industry FE	No	No	No	No	No	No
Peer Group FE	No	No	Yes	No	No	Yes
N	533,941	533,941	533,941	16,767	16,767	16,174
Pseudo R^2	0.112	0.224	0.250	0.041	0.159	0.169

Table 5: Peer Selection Likelihood and Corporate Governance/Entrenchment

This table reports whether the relation between *Tech Similarity* and compensation peer likelihood varies conditional on the strength of corporate governance and entrenchment. We examine the effect from the good governance group compared to the poor governance group based on their *Governance Index* from Gompers et al. (2003), and *Entrenchment Index* from Bebchuk et al. (2009). We define observations as *High Governance Index* (*High Entrenchment Index*) for firm-years with above median values of *Governance Index* (*Entrenchment Index*). In Panel A, the main estimate of interest is the interaction term *Tech Similarity* × *High Governance Index*. In Panel B, we use the interaction term *Tech Similarity* × *High Entrenchment Index*. The main sample is the year/industry/size/book-to-market matched sample from Table 2. The dependent variable is *Compensation Peer Dummy*, which equals one 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 i* and *Firm j* pair. The same set of control variables used in Table 2 are also included. 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. The t-statistics based on standard errors clustered by firm are reported in parentheses. ***, **, and * refer to statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Governance Index

	Dependent Variable: Compensation Peer Dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
	Year FE	Year and Ind. FE	Peer Group FE	Year FE	Year and Ind. FE	Peer Group FE
Tech Similarity	2.702***	2.918***	3.675***	2.549***	2.633***	3.335***
	(8.70)	(9.62)	(10.64)	(7.52)	(7.90)	(8.74)
Tech Similarity × *High Governance Index*	0.339	0.406	0.661	0.302	0.431	0.597
	(0.76)	(0.90)	(1.19)	(0.63)	(0.89)	(1.00)
High Governance Index	0.022	-0.030		0.081	-0.039	
	(0.17)	(-0.26)		(0.62)	(-0.31)	
Product Market Similarity Control	No	No	No	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes
Peer Group FE	No	No	No	No	No	No
N	14,327	14,327	14,327	10,875	10,875	10,875
Pseudo R^2	0.107	0.152	0.194	0.115	0.151	0.210

Panel B: Entrenchment Index

	Dependent Variable: Compensation Peer Dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
	Year FE	Year and Ind. FE	Peer Group FE	Year FE	Year and Ind. FE	Peer Group FE
Tech Similarity	2.755***	2.996***	3.763***	2.620***	2.737***	3.398***
	(11.30)	(12.36)	(12.06)	(9.29)	(9.79)	(9.57)
Tech Similarity ×	0.014	0.010	0.190	-0.064	-0.046	0.199
High Entrenchment Index	(0.04)	(0.03)	(0.42)	(-0.17)	(-0.12)	(0.42)
High Entrenchment Index	0.050	0.128		0.115	0.131	
	(0.46)	(1.26)		(0.94)	(1.06)	
Product Market Similarity Control	No	No	No	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes
Peer Group FE	No	No	No	No	No	No
N	14,721	14,721	14,721	11,102	11,102	11,102
Pseudo R^2	0.105	0.150	0.192	0.113	0.149	0.209

Table 6: Competitive Benchmarking and CEO Pay

This table examines the effect of compensation benchmarking on CEO pay, and how technology overlap impacts 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*. The key independent variables are the dummy variable *LowComp* and the continuous variable *Distance from peer group median*. *LowComp* equals one if a CEO was paid below the median CEO pay among the benchmarking peer firms in year *t*-1 and zero otherwise. *Distance from peer group median* is calculated by taking the difference between the given firm's CEO pay and the median CEO pay among the benchmarking peers in year *t*-1. The data on compensation benchmarking peers comes from Institutional Shareholder Services (ISS) Incentive Lab from 2006 to 2010. Other control variables include the log of sales, CEO tenure, and the differences between the current year and the previous year's sales, net income, and shareholder wealth. Panel B examines the effect of technological similarity on this effect. The dependent variable is a dummy variable that is equal to one if the CEO's total compensation in the previous year was below the median pay of the benchmarking peer group but has gone above the median, and is zero otherwise. *Median Peer Tech Similarity* is the median value of *Tech Similarity* among the benchmarking peers. *Median Peer Product Similarity* is the median value of *Product Market Similarity* among the benchmarking peers. *Tech Similarity* and *Product Market Similarity* are defined as in Table 1. Additional control variables include the log of sales, log of firm age, ROA, stock return, CEO tenure, R&D to assets, and the entrenchment index (*E-Index* is the Entrenchment Index from Bebchuk et al. (2009)). *T*-statistics (based on standard errors clustered at the firm level) are reported in parentheses. All specifications include year and industry fixed-effects. The control variables are winsorized at the top and bottom 1%. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Effect of CEO Compensation Status on Changes in CEO Pay

	Dependent variable: Change in total compensation			
	(1)	(2)	(3)	(4)
LowComp	**3,319.813*** **		**3,793.077*** **	
	(10.07)		**(9.75)**	
Distance from peer group median		**0.485*** **		**0.547*** **
		(8.08)		**(7.68)**
Log(sales)	-35.323	-19.641	117.872	131.668
	(-0.50)	(-0.22)	(1.18)	(0.80)
Sales Diff	0.182***	0.159***	0.136**	0.101
	(3.55)	(2.70)	(2.14)	(1.29)
Net Income Diff	0.104	0.052	0.058	0.018
	(0.69)	(0.37)	(0.35)	(0.12)
Shareholder Wealth Diff	0.014	0.016	0.019	0.023
	(0.82)	(0.86)	(0.99)	(1.09)
CEO Tenure	20.733	44.716	11.285	40.281
	(1.04)	(1.15)	(0.50)	(0.87)
Constant	-1,790.546**	-110.760	-3,178.855***	-1,367.758
	(-2.58)	(-0.14)	(-3.14)	(-0.85)
Year FE	No	No	Yes	Yes
Industry FE	No	No	Yes	Yes
Observations	1,040	1,040	1,040	1,040
Adjusted-R^2	0.139	0.287	0.215	0.365

Panel B: Effect of Technological Similarity on Competitive Benchmarking

	Dependent Variable=1 if CEO pay previously below median but went above median			
	(1)	(2)	(3)	(4)
Median Peer Tech Similarity	**0.783****	**0.914****	**0.694***	**0.781***
	(2.12)	**(2.50)**	**(1.78)**	**(1.83)**
Median Peer Product Similarity			0.527**	0.075
			(2.12)	(0.27)
Log of Sales		0.066	0.089	0.026
		(0.98)	(1.26)	(0.31)
Log of Firm Age		0.007	0.007	0.004
		(1.51)	(1.38)	(0.61)
ROA		1.029	1.054	0.002
		(1.21)	(1.23)	(0.00)
Stock Return		0.117	0.113	-0.217
		(0.58)	(0.55)	(-0.83)
CEO Tenure		-0.021	-0.020	-0.015
		(-1.36)	(-1.31)	(-0.94)
RD-to-assets		-1.659	-1.771	-2.380
		(-1.39)	(-1.43)	(-1.47)
E-Index				-0.005
				(-0.05)
Constant	-1.014***	-1.729***	-1.911***	-0.964
	(-6.82)	(-2.77)	(-2.99)	(-1.11)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	1,225	1,209	1,209	911
Pseudo R^2	0.0552	0.0655	0.0684	0.0529

Table 7: CEO Job Transition Likelihood

This table 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 comes from Execucomp, where we track the time-series position of each CEO. All the variables are defined as in Table 1, except *Same State Indicator,* defined as an indicator variable equal to 1 if the acquirer and target are incorporated in the same state, and 0 otherwise; *BTM*, defined as the book value of equity divided by market value of equity; and *ROA*, defined as EBITDA scaled by book value of total assets. Panel B reports the results from conditional logit regressions of the likelihood of an observation being an actual (as opposed to hypothetical) CEO transition on the technology 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 one 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. Following Bena and Li (2014), the sample contains, for each actual transition, pseudo deals formed by pairing the actual pre-transition firm with up to five hypothetical matches (in the same year, industry, and closest in total assets; or in the same year, industry, and closest in total assets and book-to-market, to the actual post-transition firm) and by pairing the actual post-transition firm with up to five hypothetical matches (in the same year, industry, and closest in total assets; or in the same year, industry, and closest in total assets and book-to-market, to the actual pre-transition firm). The sample period is from 1992 to 2010. Our main independent variable is *Tech Similarity*, defined as the Jaffe (1986) similarity measure of patent portfolios between *Firm i* and *Firm j* pair. *Same Industry Indicator*, *Product Market Similarity,* and *Same State Indicator* are defined same as in Table 1. The pre- and post-transition firm controls are *ROA*, *Stock Return*, *Leverage*, *Cash-to-assets*, the natural logarithm of *R&D-to-assets*, *Firm Age*, and *BTM*. 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. The control variables are winsorized at the top and bottom 1%. *, **, and *** refer to 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	SD	Median	Mean	SD	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
Product Market Similarity	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
CEO's Pre-Transition Firm Characteristics						
ROA	0.127	0.087	0.119	0.113	0.123	0.120
Stock Return	2.888	5.841	0.850	2.417	5.363	0.758
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(R&D-to-assets)	0.070	0.061	0.054	0.068	0.067	0.048
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
Stock Return	5.461	10.685	0.726	4.671	9.608	0.758
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(R&D-to-assets)	0.059	0.046	0.046	0.058	0.059	0.043
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)		
Pre-firm CEO Age	3.922	0.108	3.951	3.965	0.124	3.970
Pre-firm CEO Tenure	1.353	0.691	1.386	1.477	0.782	1.609
Post-firm CEO Age	4.021	0.118	4.025	4.005	0.123	4.007
Post-firm 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*****	**3.603*****	**2.732*****	**5.244*****	**4.556*****	**2.507****
	(6.23)	**(4.46)**	**(2.65)**	**(6.31)**	**(5.13)**	**(2.14)**
Same industry Indicator		0.994	0.941		1.159*	1.234
		(1.18)	(1.06)		(1.74)	(1.47)
Product Market Similarity		1.823***	0.703		1.319**	0.009
		(2.61)	(0.94)		(2.20)	(0.01)
Same State indicator		0.561**	0.146		0.658***	0.143
		(2.06)	(0.40)		(2.59)	(0.42)
Compensation Diff			0.032*			0.034*
			(1.73)			(1.77)
Pre-firm characteristics						
ROA		1.611	-0.281		1.958	0.350
		(1.10)	(-0.11)		(1.58)	(0.16)
Stock Return		0.017	0.086***		0.057**	0.072***
		(0.68)	(2.75)		(2.56)	(2.61)
Leverage		1.654	1.034		2.051**	2.152*
		(1.59)	(0.94)		(2.02)	(1.66)
Cash-to-assets		0.731	0.516		1.379	-0.241
		(0.95)	(0.47)		(1.45)	(-0.17)
ln(R&D-to-assets)		6.365**	0.766		1.333	1.179
		(2.00)	(0.21)		(0.58)	(0.40)
Firm Age		0.768***	0.418		0.888***	0.697*
		(4.17)	(1.56)		(2.82)	(1.88)
BTM		0.293	0.714			
		(0.68)	(1.17)			
Post-firm characteristics						
ROA		1.079	0.853		0.311	-1.750
		(0.66)	(0.42)		(0.21)	(-1.26)
Stock Return		0.040*	0.078***		0.048**	0.061*
		(1.94)	(3.11)		(2.21)	(1.78)
Leverage		-0.644	-0.070		-0.016	-0.280
		(-0.58)	(-0.06)		(-0.01)	(-0.24)
Cash-to-assets		1.243	0.109		0.730	0.172
		(1.60)	(0.13)		(0.83)	(0.17)
ln(R&D-to-assets)		0.968	-0.313		-0.719	-4.251
		(0.30)	(-0.09)		(-0.29)	(-1.08)
Firm Age		0.289	-0.352		0.225	0.010
		(1.29)	(-1.06)		(0.94)	(0.04)
BTM		0.569***	1.019***			
		(2.63)	(2.88)			
CEO characteristics						
Pre-firm CEO Age			-4.311***			-6.363***
			(-3.22)			(-4.42)
Pre-firm CEO Tenure			-0.211			-0.021
			(-1.13)			(-0.12)
Post-firm CEO Age			0.883			1.508
			(0.58)			(1.03)
Post-firm CEO Tenure			-0.002			-0.034
			(-0.01)			(-0.17)
Group fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	856	856	537	845	845	545
Pseudo R^2	0.130	0.220	0.166	0.153	0.238	0.162

Table 8: The Effects of Peer Compensation Levels on CEO Compensation

This table contains the analysis of the relation between technological peer compensation and CEO pay. The estimates of 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 compensation)*, defined as the median level of peer CEO compensation that are in the similar technology space. In particular, we define a firm as being a *Technology Peer* with another firm if the pair-wise *Tech Similarity* (see Section 2.1) between the two firms is in the top 10% for a given year. The main control variables include *ln(Median industry peer compensation)* defined as the median level of CEO pay for peer firms in the same two-digit SIC industry. We also estimate the regression with lagged peer compensation (*ln(Median technology peer compensation)*$_{t-1}$ and *ln(Median industry peer compensation)*$_{t-1}$) instead of contemporaneous compensation. Other control variables include *ln(Sales)*, defined as the natural log of the firm's sales in 2004 dollars, *Stock Return*, the past 12-month stock return, including dividends, *ROA*, defined as net income (ni), divided by total assets (at), *Leverage*, defined as short-term debt (dlc) plus long-term debt (dltt), divided by total assets (at), *MB*, defined as the 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), *CEO Tenure*, defined as the number of years in which CEO has been in the position, *CEO Age*, defined as the CEO's age, and *CEO is Chair*, defined as a dummy variable equal to one if the CEO also serves as the chairman, and zero otherwise. Columns (1) – (4) estimate the regression with year fixed effects, and columns (5)-(9) estimate the regression with year and two-digit SIC industry fixed effects. The t-statistics based on standard errors clustered by firm are reported in parentheses. ***, **, and * refer to statistical significance at 1%, 5%, and 10% levels, respectively.

	Dependent variable: *ln(CEO compensation)*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Year Fixed-Effects				Year and Industry Fixed-Effects			
ln(Median technology peer compensation)	0.258***	0.174**			0.212***	0.170**		
	(3.73)	(2.52)			(3.08)	(2.51)		
ln(Median technology peer compensation)$_{t-1}$			0.269***	0.216***			0.217***	0.211***
			(3.80)	(3.06)			(3.12)	(3.08)
ln(Median industry peer compensation)		0.246***				0.288***		
		(3.71)				(3.74)		
ln(Median industry peer compensation)$_{t-1}$				0.168**				0.042
				(2.47)				(0.58)
ln(Sales)	0.391***	0.381***	0.392***	0.384***	0.400***	0.399***	0.400***	0.400***
	(24.72)	(22.71)	(24.79)	(22.86)	(22.70)	(22.52)	(22.67)	(22.56)
Stock Return	0.252***	0.249***	0.252***	0.252***	0.240***	0.237***	0.241***	0.241***
	(7.90)	(7.83)	(7.85)	(7.87)	(7.50)	(7.39)	(7.47)	(7.49)
Stock Return$_{t-1}$	0.118***	0.118***	0.124***	0.127***	0.122***	0.115***	0.127***	0.127***
	(3.28)	(3.29)	(3.45)	(3.53)	(3.34)	(3.16)	(3.47)	(3.47)
ROA	-0.778**	-0.790**	-0.742*	-0.725*	-0.767**	-0.788**	-0.740*	-0.736*
	(-2.00)	(-2.04)	(-1.88)	(-1.84)	(-1.97)	(-2.02)	(-1.88)	(-1.86)
ROA$_{t-1}$	-0.692*	-0.640*	-0.708*	-0.693*	-0.580	-0.592	-0.595	-0.602
	(-1.86)	(-1.73)	(-1.89)	(-1.86)	(-1.56)	(-1.59)	(-1.59)	(-1.60)
Leverage$_{t-1}$	0.361**	0.321**	0.370***	0.341**	0.387***	0.387***	0.395***	0.394***
	(2.58)	(2.32)	(2.64)	(2.47)	(2.72)	(2.71)	(2.77)	(2.76)
MB $_{t-1}$	0.155***	0.154***	0.154***	0.152***	0.144***	0.144***	0.143***	0.143***
	(7.71)	(7.71)	(7.68)	(7.62)	(6.92)	(6.98)	(6.93)	(6.92)
CEO Tenure	0.005	0.004	0.004	0.004	0.006	0.006	0.006	0.006
	(1.18)	(1.03)	(1.18)	(1.10)	(1.51)	(1.51)	(1.50)	(1.50)
CEO Age	-0.007**	-0.007**	-0.006*	-0.006**	-0.004	-0.004	-0.004	-0.004
	(-1.99)	(-2.02)	(-1.94)	(-1.97)	(-1.31)	(-1.25)	(-1.31)	(-1.30)
CEO is Chair	0.165***	0.156***	0.164***	0.158***	0.159***	0.159***	0.159***	0.159***
	(3.68)	(3.48)	(3.68)	(3.55)	(3.54)	(3.53)	(3.54)	(3.54)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes	Yes	Yes	Yes
N	4,515	4,515	4,515	4,515	4,515	4,515	4,515	4,515
Adj. R^2	0.491	0.495	0.491	0.493	0.509	0.510	0.509	0.509

Table 9: CEO Compensation – Time-Series and Cross-Sectional Variations

This table contains analysis of the variation in firms' technology overlap in explaining the time-series and cross-sectional variation in CEO pay. Panel A examines the variation in CEO pay among the largest 500 and 1000 firms in the market (Top 500 and Top 1000, respectively) in a panel dataset with a linear-time trend. Panel B examines the within-industry cross-sectional variation in CEO pay with year and industry fixed effects (regression model from Equation (6)). The dependent variable is *ln(CEO Compensation)*$_{t+1}$, defined as the natural log of CEO total compensation in the subsequent year. The main independent variable is *Aggregate Tech Similarity*, defined as the aggregate sum of pair-wise *Tech Similarity* by firm/year (See Section 2.1 for the detailed definition of pairwise *Tech Similarity*). In addition, we also include *Aggregate Product Market Similarity*, defined as the firm-level aggregate sum of pair-wise *Product Market Similarity* by firm/year. Other control variables include *HHI Index* defined as the HHI Index using two-digit SIC, *ln(Market Cap of 250th Firm)*, defined as the natural log of market capitalization of the 250th largest firm in the market by market cap, *ln(Market Cap)*, defined as the natural log of the firm's market capitalization in 2004 dollars, and *Market Return*, defined as the CRSP value-weighted market return. Other firm characteristics are also included as additional controls: *Stock Return* is the past 12-month stock return, including dividends. *ROE* is net income, divided by total shareholder equity; *Sales/Total Assets*, is sales (sale) divided by total assets (at); *MB* is the 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); *RD/Total Assets* is the firm's R&D expense (xrd), divided by total assets (at); *CEO Tenure* is the tenure of the CEO in that position; *CEO Age* is defined as the CEO's age; *CEO is Chair* is a dummy variable that equals one if the CEO also serves as the chairman, and zero otherwise. The t-statistics based on standard errors clustered by firm are reported in parentheses. ***, **, and * refer to statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Variations in CEO compensation

	Dependent Variable: *ln(CEO Compensation)*$_{t+1}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Top 500 Firms				Top 1000 Firms			
Aggregate Tech Similarity	0.010***	0.010***	0.009***	0.002**	0.012***	0.013***	0.012***	0.001*
	(8.62)	(8.88)	(8.58)	(2.49)	(10.72)	(11.28)	(10.56)	(1.75)
HHI Index		0.236	0.404**	0.144		0.544***	0.742***	0.208**
		(1.40)	(2.21)	(1.10)		(3.66)	(4.73)	(1.99)
Aggregate Product Market Similarity			0.001**	0.001			0.002***	0.001**
			(2.34)	(1.33)			(3.34)	(2.16)
ln(Market Cap of 250th Firm)				0.148*				0.114**
				(1.93)				(2.08)
ln(Market Cap)				0.184***				0.134***
				(4.22)				(4.50)
Stock Return				0.303***				0.390***
				(8.57)				(19.08)
ROE				-0.024				-0.113
				(-0.21)				(-1.25)
ROA				-1.713***				-0.675
				(-2.79)				(-1.64)
Sales/Total Assets				0.123*				0.116**
				(1.66)				(2.18)
MB				-0.021				-0.047**
				(-0.84)				(-2.38)
Market Return				0.873**				0.715**
				(2.09)				(2.30)
RD/Total Assets				0.938				0.573
				(1.58)				(1.35)
CEO Tenure				0.002				0.007*
				(0.37)				(1.82)
CEO Age				0.000				-0.005
				(0.02)				(-1.32)
CEO is Chair				0.154**				0.162***
				(2.23)				(3.65)
Constant	8.347***	7.893***	7.815***	4.376***	7.909***	7.451***	7.360***	4.142***
	(143.12)	(85.28)	(75.21)	(6.62)	(157.48)	(95.37)	(87.02)	(8.77)
Time Trend	No	Yes	Yes	Yes	No	Yes	Yes	Yes
N	2,711	2,711	2,711	2,711	4,583	4,583	4,583	4,583
Adj. R^2	0.077	0.124	0.130	0.269	0.098	0.131	0.138	0.414

Panel B: Within-industry variation

	Dependent Variable: *ln(CEO Compensation)$_{t+1}$*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Top 500 Firms				Top 1000 Firms			
Aggregate Tech Similarity	0.003**	0.002**	0.003**	0.003**	0.002*	0.002**	0.002*	0.002**
	(2.50)	(2.41)	(2.47)	(2.24)	(1.74)	(2.09)	(1.82)	(2.23)
HHI Index	0.178	0.184	0.511*	0.546*	0.225**	0.198**	0.251	0.251
	(1.33)	(1.49)	(1.77)	(1.96)	(2.05)	(1.98)	(1.14)	(1.20)
Aggregate Product Market Similarity	0.001*	0.001	0.002	0.001	0.001***	0.001*	0.002***	0.002**
	(1.88)	(1.34)	(1.16)	(0.91)	(2.69)	(1.79)	(2.63)	(2.05)
Stock Return	0.221***	0.204***	0.233***	0.223***	0.140***	0.133***	0.139***	0.134***
	(4.56)	(4.57)	(4.77)	(4.87)	(4.45)	(4.43)	(4.34)	(4.35)
ln(Market Cap)	0.319***	0.289***	0.309***	0.290***	0.407***	0.360***	0.403***	0.355***
	(10.70)	(9.84)	(9.16)	(8.94)	(21.85)	(18.49)	(19.27)	(16.22)
ROE	0.015	-0.107	-0.081	-0.137	-0.091	-0.170*	-0.123	-0.180*
	(0.12)	(-0.89)	(-0.57)	(-1.02)	(-0.93)	(-1.78)	(-1.15)	(-1.76)
ROA	-1.351**	-0.976	-0.901	-0.617	-0.489	-0.450	-0.184	-0.159
	(-2.08)	(-1.57)	(-1.25)	(-0.90)	(-1.14)	(-1.12)	(-0.40)	(-0.38)
Sales/Total Assets	0.104	0.129*	0.059	0.047	0.108*	0.119**	0.042	0.044
	(1.28)	(1.68)	(0.61)	(0.52)	(1.90)	(2.21)	(0.65)	(0.76)
MB	-0.043	-0.032	-0.044*	-0.038	-0.056***	-0.037**	-0.051**	-0.034*
	(-1.64)	(-1.44)	(-1.71)	(-1.62)	(-2.76)	(-2.06)	(-2.48)	(-1.84)
R&D/Total Assets	0.442	0.827	0.516	1.028*	0.328	0.410	0.330	0.627
	(0.83)	(1.53)	(0.94)	(1.69)	(0.80)	(1.01)	(0.79)	(1.47)
CEO Tenure	-0.005	-0.004	-0.005	-0.004	0.004	0.002	0.005	0.003
	(-0.96)	(-0.94)	(-1.04)	(-0.84)	(1.10)	(0.62)	(1.32)	(0.79)
CEO Age	-0.003	-0.003	-0.001	-0.001	-0.007*	-0.008**	-0.005	-0.007*
	(-0.52)	(-0.74)	(-0.17)	(-0.26)	(-1.78)	(-2.36)	(-1.39)	(-1.87)
CEO is Chair	0.081	0.073	0.038	0.042	0.122***	0.103***	0.113***	0.103***
	(1.54)	(1.39)	(0.66)	(0.78)	(3.32)	(2.84)	(3.01)	(2.80)
Initial ln(CEO Compensation)		0.221***		0.203***		0.213***		0.216***
		(4.79)		(3.86)		(6.75)		(6.31)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	No	No	Yes	Yes
N	2,452	2,452	2,452	2,452	4,275	4,275	4,275	4,275
Adj. R^2	0.292	0.336	0.339	0.369	0.435	0.467	0.468	0.495

Appendix A: Compensation Benchmark Peer Selection – Robustness

This table contains additional results from our compensation benchmark peer selection analysis using an alternative matching procedure. In Panel A, we run the logistic regression based on a randomly matched sample in which we randomly select 50 firms for each Firm i-Firm j pair of an actual compensation benchmarking pair. In Panel B, we repeat the logistic regression based on a year/industry/size matched sample (see Section 2.2 for details). We define *Compensation Peer Dummy*, which equals one if *Firm j* is an actual compensation benchmarking peer, and zero otherwise. For each firm-by-firm pair, we also measure *Tech Similarity*, defined as the Jaffe (1986) similarity measure of patent portfolios between *Firm i* and *Firm j*. The same set of control variables used in Table 2 are also included. 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 clustered by firm are reported in parentheses. ***, **, and * refer to statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Randomly-Matched Sample

	Dependent Variable: Compensation Peer Dummy							
	(1) Univariate	(2) Year FE	(3) Year and Ind. FE	(4) Peer Group FE	(5) Univariate	(6) Year FE	(7) Year and Ind. FE	(8) Peer Group FE
Tech Similarity	5.855***	2.704***	3.037***	3.500***	6.021***	2.723***	2.935***	3.263***
	(32.57)	(15.52)	(18.19)	(17.89)	(31.33)	(14.84)	(16.37)	(15.19)
Product Market Similarity						0.674***	0.789***	1.174***
						(6.14)	(6.78)	(7.92)
Same Industry		0.382***	0.606***	0.837***		0.118	0.301***	0.458***
		(4.73)	(7.34)	(8.35)		(1.18)	(3.01)	(4.00)
Stock Return Correlation		1.481***	1.558***	1.970***		1.563***	1.496***	1.973***
		(9.25)	(10.38)	(10.60)		(9.61)	(9.00)	(9.54)
Beta Diff		0.123	0.216**	0.404***		0.159*	0.207**	0.369**
		(1.33)	(2.28)	(2.86)		(1.76)	(2.19)	(2.55)
Volatility Diff		6.463	6.284*	10.011*		7.064*	7.135*	7.591
		(1.62)	(1.75)	(1.82)		(1.74)	(1.87)	(1.28)
HHI Diff		-3.026**	-27.861***	-30.992***		-3.555**	-26.940***	-29.224***
		(-2.51)	(-22.78)	(-25.91)		(-2.31)	(-19.26)	(-22.79)
3-Year Return Diff		0.098***	0.107***	0.210***		0.122***	0.131***	0.230***
		(3.54)	(4.88)	(6.21)		(3.94)	(4.93)	(5.66)
Size Diff		-0.061**	-0.048*	-0.036		-0.035	-0.028	-0.036
		(-2.19)	(-1.85)	(-1.15)		(-1.17)	(-0.96)	(-1.02)
Leverage Diff		0.095	0.062	0.471**		0.042	-0.019	0.346
		(0.71)	(0.51)	(2.46)		(0.28)	(-0.13)	(1.52)
MB Diff		-0.220***	-0.244***	-0.262***		-0.218***	-0.210***	-0.231***
		(-7.80)	(-8.83)	(-8.31)		(-6.97)	(-6.59)	(-6.29)
Cash Ratio Diff		0.688***	0.177	0.144		0.819***	0.211	0.181
		(2.67)	(0.69)	(0.55)		(2.85)	(0.75)	(0.63)
Compensation Diff		-0.000	-0.000	-0.000		-0.000	-0.000	-0.000
		(-1.37)	(-1.24)	(-1.01)		(-0.89)	(-0.93)	(-0.44)
Firm Size		0.167***	0.111***	0.000		0.100***	0.085***	0.000
		(4.74)	(3.65)			(3.04)	(2.69)	
MB		0.216***	0.236***			0.233***	0.194***	
		(5.18)	(6.32)			(5.53)	(5.09)	
RD/AT		-3.768***	-2.004***			-3.623***	-1.640***	
		(-6.51)	(-3.68)			(-6.04)	(-2.85)	
Cash/AT		-1.541***	-0.332			-1.822***	-0.390	
		(-4.21)	(-0.96)			(-4.50)	(-1.01)	
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	61,516	61,516	61,516	61,516	44,607	44,607	44,607	44,607
Pseudo R^2	0.155	0.303	0.312	0.361	0.174	0.323	0.332	0.390

Panel B: Year/Industry/Size Matched Sample

	Dependent Variable: Compensation Peer Dummy							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Univariate	Year FE	Year and Ind. FE	Peer Group FE	Univariate	Year FE	Year and Ind. FE	Peer Group FE
Tech Similarity	18.907***	4.244***	4.322***	4.925***	24.231***	4.125***	4.175***	4.674***
	(19.46)	(20.85)	(20.82)	(24.69)	(20.35)	(19.71)	(19.34)	(21.50)
Product Market Similarity						1.068***	1.113***	1.578***
						(6.07)	(5.85)	(7.47)
Same Industry		1.897***	1.957***	2.302***		1.355***	1.419***	1.597***
		(14.54)	(13.89)	(17.18)		(9.51)	(9.66)	(10.18)
Stock Return Correlation		2.446***	2.434***	2.782***		2.499***	2.424***	2.772***
		(14.77)	(15.72)	(16.60)		(14.14)	(14.77)	(15.51)
Beta Diff		-0.033	-0.040	-0.040		-0.002	-0.039	-0.054
		(-0.35)	(-0.42)	(-0.39)		(-0.02)	(-0.42)	(-0.47)
Volatility Diff		13.442***	12.977***	23.018***		12.616***	12.987***	19.055***
		(3.07)	(2.96)	(5.52)		(2.73)	(2.81)	(4.27)
HHI Diff		2.018***	2.133***	1.994***		1.913***	1.822***	1.609**
		(4.76)	(4.35)	(4.10)		(3.86)	(3.04)	(2.52)
3-Year Return Diff		0.078***	0.071***	0.146***		0.098***	0.095***	0.138***
		(3.58)	(3.28)	(5.42)		(3.71)	(3.71)	(4.15)
Size Diff		-0.433***	-0.433***	-0.458***		-0.426***	-0.426***	-0.476***
		(-11.20)	(-11.55)	(-11.60)		(-10.19)	(-10.35)	(-11.17)
Leverage Diff		-0.313*	-0.377**	-0.189		-0.160	-0.161	0.108
		(-1.87)	(-2.29)	(-0.92)		(-0.84)	(-0.83)	(0.51)
MB Diff		-0.224***	-0.224***	-0.238***		-0.200***	-0.196***	-0.213***
		(-8.86)	(-8.75)	(-8.88)		(-6.66)	(-6.64)	(-6.74)
Cash Ratio Diff		0.804***	0.781***	0.717***		0.828***	0.785***	0.758***
		(3.18)	(2.99)	(2.85)		(3.06)	(2.87)	(2.80)
Compensation Diff		-0.000	-0.000	0.000		-0.000	-0.000*	0.000
		(-0.55)	(-0.96)	(1.10)		(-0.86)	(-1.67)	(1.31)
Firm Size		0.485***	0.479***			0.455***	0.455***	
		(8.20)	(7.91)			(7.36)	(7.21)	
MB		0.224***	0.237***			0.205***	0.214***	
		(4.87)	(5.46)			(3.77)	(4.57)	
RD/AT		-2.648***	-2.971***			-2.724***	-2.634**	
		(-2.87)	(-2.70)			(-2.74)	(-2.30)	
Cash/AT		-1.408**	-1.037*			-1.441**	-0.940	
		(-2.32)	(-1.79)			(-2.21)	(-1.55)	
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	52,799	52,799	52,799	52,799	39,822	39,822	39,822	39,822
Pseudo R^2	0.057	0.108	0.169	0.184	0.070	0.120	0.166	0.193

Appendix B: Robustness Test on Peer Selection Likelihood with Governance Control

This table reports robustness tests on peer selection likelihood analyses with additional controls for corporate governance and entrenchment. In Panel A, we add *Governance Index* as an additional control variable, where the *Governance Index* is the number of antitakeover provisions from Gompers et al. (2003). In Panel B, we replace *Governance Inde*x with *Entrenchment Index*, defined as the subset of antitakeover provisions from and Bebchuk et al. (2009). The main sample is the year/industry/size/book-to-market matched sample from Table 2. The dependent variable is *Compensation Peer Dummy*, which equals one 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 i* and *Firm j* pair. The same set of control variables used in Table 2 are also included. 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 clustered by firm are reported in parentheses. ***, **, and * refer to statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Governance Index Control

	Dependent Variable: Compensation Peer Dummy							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Year FE	Year and Ind. FE	Peer Group FE	OLS	Year FE	Year and Ind. FE	Peer Group FE
Tech Similarity	2.848***	2.821***	3.059***	3.893***	2.983***	2.659***	2.785***	3.533***
	(13.98)	(11.95)	(13.03)	(14.19)	(13.63)	(10.54)	(11.07)	(11.90)
Product Market Similarity						0.491***	0.625***	1.154***
						(3.13)	(3.76)	(5.54)
Same Industry		0.499***	0.648***	1.048***		0.373***	0.454***	0.659***
		(4.73)	(5.82)	(8.19)		(3.15)	(3.74)	(4.65)
Governance Index		0.024	0.025			0.045**	0.025	
		(1.17)	(1.35)			(2.02)	(1.21)	
Other Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
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	14,327	14,327	14,327	14,327	10,875	10,875	10,875	10,875
Pseudo R^2	0.048	0.107	0.152	0.194	0.055	0.116	0.152	0.210

Panel B: Entrenchment Index Control

	Dependent Variable: Compensation Peer Dummy							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Year FE	Year and Ind. FE	Peer Group FE	OLS	Year FE	Year and Ind. FE	Peer Group FE
Tech Similarity	2.827***	2.760***	2.993***	3.835***	2.952***	2.589***	2.713***	3.478***
	(14.33)	(12.10)	(13.16)	(14.49)	(13.83)	(10.53)	(11.04)	(11.99)
Product Market Similarity						0.471***	0.617***	1.156***
						(3.10)	(3.84)	(5.77)
Same Industry		0.491***	0.651***	1.050***		0.375***	0.456***	0.654***
		(4.83)	(6.06)	(8.44)		(3.22)	(3.83)	(4.72)
Entrenchment Index		-0.012	0.019			0.011	0.011	
		(-0.40)	(0.71)			(0.34)	(0.37)	
Other Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
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	14,721	14,721	14,721	14,721	11,102	11,102	11,102	11,102
Pseudo R^2	0.048	0.105	0.150	0.192	0.055	0.112	0.149	0.209

Appendix C: CEO Compensation Summary Statistics

This table contains the summary statistics of the sample that we used to analyze the effect of peer compensation on CEO pay, and also the time-series trend and cross-sectional variation in CEO pay over time. Panel A reports the summary statistics of the peer compensation sample, which is based on the firm-level sample of U.S. public firms from 1992 to 2010 from Execucomp. *ln(CEO Total Compensation)* is the natural log of the CEO's total compensation (tdc1) in 2004 dollars. *ln(Median Tech Peer Compensation)* is the median level of peer CEO compensation that are in the similar technology space. In particular, we define a firm as being a *Technology Peer* with another firm if the pair-wise *Tech Similarity* (see Section 2.1) between the two firms is in the top 10% for a given year. *ln(Median Industry Peer Compensation)* is the median level of CEO pay for peer firms in the same two-digit SIC industry. *ln(Sales)* is the natural log of the firm's sales in 2004 dollars. *Stock Return* is the past 12-month stock return, including dividends. *ROA* is net income (ni), divided by total assets (at). *Leverage* is short-term debt (dlc) plus long-term debt (dltt), divided by total assets (at). *MB* is the 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). *CEO Tenure* is the number of years in which CEO has been in the position. *CEO Age* is the age of the CEO. *CEO is Chair* is the dummy variable equal to one if the CEO also serves as the chairman, and zero otherwise. Panel B and Panel C report the summary statistics of the compensation sample consists of Top 500 and Top 1,000 firms by market cap from 1992 to 2010. *Aggregate Tech Similarity* is defined as the aggregate sum of pair-wise *Tech Similarity* by firm/year. Likewise, *Aggregate Product Market Similarity* is the firm-level aggregate sum of pair-wise *Product Market Similarity* by firm-year. *HHI Index* is the HHI Index defined using two-digit SIC code. *ln(Market Cap of 250th Firm)* is the natural log of market capitalization of the 250th largest firm in the market by market cap. *ln(Market Cap)* is the natural log of the firm's market capitalization in 2004 dollars.

Panel A: Peer Compensation Sample

Variable	Obs	Mean	Std. Dev.	Min	Max
ln(CEO Total Compensation)	4,515	8.37	1.00	5.87	10.67
ln(Median Tech Peer Compensation)	4,515	8.43	0.34	7.61	9.25
ln(Median Industry Peer Compensation)	4,515	8.03	0.34	7.17	8.83
ln(Sales)	4,515	7.71	1.64	3.93	11.51
Stock Return	4,515	0.14	0.43	-0.68	1.98
ROA	4,515	0.12	0.06	-0.12	0.28
Leverage	4,515	0.19	0.15	0.00	0.58
MB	4,515	2.31	1.50	0.85	8.88
CEO Tenure	4,515	6.73	6.83	0.00	32.00
CEO Age	4,515	56.01	6.53	39.00	73.00
CEO is Chair	4,515	0.66	0.47	0.00	1.00

Panel B: Compensation Trend and Cross-Section - Top 500 Firms

Variable	Obs	Mean	Std. Dev.	Min	Max
ln(CEO Total Compensation)	2,711	8.78	0.89	6.07	10.98
Aggregate Tech Similarity	2,711	45.62	25.77	4.78	115.75
Aggregate Product Market Similarity	2,711	49.37	55.91	0.02	275.71
HHI Index	2,711	0.21	0.18	0.04	0.97
ln(Market Cap of 250th Firm)	2,711	8.61	0.30	6.32	8.97
ln(Market Cap)	2,711	0.21	0.47	-0.60	2.29
Stock Return	2,711	9.18	1.20	7.32	12.44
ROE	2,711	0.17	0.19	-0.53	1.04
ROA	2,711	0.13	0.06	-0.03	0.29
Sales/Total Assets	2,711	-0.18	0.44	-1.43	0.90
MB	2,711	2.66	1.88	0.94	11.39
Market Return	2,711	0.02	0.04	-0.20	0.10
RD/Total Assets	2,711	0.06	0.05	0.00	0.25
CEO Tenure	2,711	5.91	6.11	0.00	30.00
CEO Age	2,711	55.92	6.21	40.00	70.00
CEO is Chair	2,711	0.72	0.45	0.00	1.00

Panel C: Compensation Trend and Cross-Section - Top 1000 Firms

Variable	Obs	Mean	Std. Dev.	Min	Max
ln(CEO Total Compensation)	4,583	8.39	0.95	5.95	10.67
Aggregate Tech Similarity	4,583	39.43	24.59	2.67	111.76
Aggregate Product Market Similarity	4,583	45.77	52.83	0.05	275.71
HHI Index	4,583	0.21	0.17	0.04	0.95
ln(Market Cap of 250th Firm)	4,583	8.62	0.30	6.32	8.97
ln(Market Cap)	4,583	0.22	0.51	-0.63	2.48
Stock Return	4,583	8.28	1.46	5.86	12.21
ROE	4,583	0.14	0.18	-0.63	0.90
ROA	4,583	0.13	0.06	-0.10	0.29
Sales/Total Assets	4,583	-0.16	0.46	-1.65	0.91
MB	4,583	2.47	1.66	0.91	10.00
Market Return	4,583	0.01	0.04	-0.20	0.10
RD/Total Assets	4,583	0.06	0.06	0.00	0.27
CEO Tenure	4,583	5.88	6.11	0.00	30.00
CEO Age	4,583	55.57	6.74	39.00	73.00
CEO is Chair	4,583	0.66	0.48	0.00	1.00