Competition for Talent: Evidence from a Network of Labor Market Peers[*]

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Abstract

I construct a novel network of labor market peers that is denser and more centralized compared to product and capital market networks. Using my labor market network, I provide robust evidence that focal firms spend more on R&D and suffer more talent outflows when their labor market peers increase the benefits they offer their talented employees. Focal firms use capital markets to finance their labor market responses, issuing stock and increasing cash holdings. The findings highlight the predictive effect of firms' labor market actions and provide evidence that ties labor markets and capital markets together.

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1. Introduction

In today's knowledge-driven economy, firms increasingly depend on their talented employees whose human capital is considered an economically significant determinant of firm productivity, value creation, and, ultimately, firm growth. Firms that overlap in the labor market, or "labor market peers," are likely to compete with each other, not least by attracting talented employees. Studying such "talent wars"[1] requires us to identify which firms compete with each other in the labor market. However, firms that compete in the labor market may not always be peer firms in the product market sense. According to Bill Gates, for example, Microsoft's top labor market competitor is not one of its obvious product market competitors, but Goldman Sachs.[2]

I examine whether there is a distinct set of peer firms that are related to each other through labor market links rather than product market or capital market links, and if so, whether labor market peers respond to each other's labor market actions. To my knowledge, I provide the first evidence that a network of labor market peers captures something that is economically distinct from product market and capital market networks. Having a distinct set of labor market peers makes it possible to plausibly estimate the economic effects of talent wars. I find that the labor market actions of labor market peers have predictive power for focal firm R&D spending. Also, I find that firms rely on capital markets to finance their labor market responses by issuing stock and increasing their cash holdings.

The notion of competition for talent is intuitive, but the underlying network of labor market peers is not easily observable and measurable. Thus, it is challenging to identify each firm's labor market peers empirically. To examine how firms strategically respond to each other's labor market

[1] Chambers et al. (1998) coin the phrase "the war for talent," which refers to the competition for talent among firms.
[2] See Karlgaard (2005) for the interview with Bill Gates on Microsoft's competitors.

actions, I need to identify labor market peers and establish the fact that there is a distinct set of labor market peer firms. Indirect measures of labor market peers could be computed using the Standard Industrial Classification, the North American Industry Classification System, or the Global Industry Classification Standard. However, these industry classifications are more useful for identifying product market peers and may or may not be useful for identifying labor market peers. Peer firms in the same product market may compete for talent but, as the example of Microsoft suggests, labor market peers may not fully coincide with product market peers. Microsoft cannot be grouped with Goldman Sachs according to traditional industry classifications.

To address this challenge, I create a pairwise measure of overlapping labor markets between firms. My measure uses "co-searches" by users of the SEC's EDGAR database of firms' labor market related filings, specifically their 11-K filings. These filings contain detailed information on the net assets a firm has set aside for employee benefits, as well as changes in these assets. I code two firms as having a labor market link if EDGAR users download the two firms' 11-K filings in close proximity ("co-search"). My assumption is that co-searches (noisily) reveal users' interest in comparing the two firms' employee benefits. Following Lee et al. (2015), who focus on co-searches of financial statements, I use EDGAR users' collective perceptions of which firms are related to compute a pairwise measure of overlapping labor markets for every pair of firms. This measure allows me to identify each firm's labor market peers, which are different from product and capital market peers.

Finding a distinct set of labor market peers, I use a difference-in-differences approach to identify the effects of competition for talented employees among labor market peers. As the treatment, I use another EDGAR filing. Firms file an S-8 when they plan to issue new stock to their employees. S-8 filings thus convey news about new employee stock benefits. Employee stock awards are a key way to attract and motivate talented employees (Karlgaard 2004, 2005). This action should increase labor market competition among firms. My diff-in-diff models estimate how a focal firm responds to its labor market peer's S-8 filing.

I test three hypotheses. First, I hypothesize that the network of labor market peers is distinct from product market and capital market networks. The three types of networks should not coincide if they each capture something different. I find that the network of labor market peers has different structural properties from the other two networks. The labor market network is relatively dense and centralized compared to product market and capital market networks.

Second, I hypothesize that focal firms whose labor market peers file an S-8 increase R&D spending. According to prior estimates, more than 50% of R&D spending reflects labor compensation for high-skilled employees. I use R&D spending to test whether firms increase labor compensation when their labor market peers announce an increase in employee stock awards. I find strong evidence for the hypothesis that focal firms respond to a labor market peer's S-8 filing by increasing R&D spending. This finding suggests that firms feel a need to raise the salaries and benefits of their talented employees when their labor market peers plan to increase benefits for their talented employees. A plausible interpretation is that focal firms increase their R&D spending to retain and protect their talented employees from labor market peers.

Finally, I investigate how a labor market peer's S-8 filing affects the focal firm's financing choices. One way firms can fund an increase in compensation and benefits is by raising external capital. I show that focal firms respond to their labor market peers' S-8 filings by issuing stock and thereby increasing their cash holdings.

My findings are specific to labor market networks: S-8 filings by product market peers or by capital market peers do not affect focal firms' labor market decisions unless they are also labor market peers. Simply put, talent wars are not attributable to firms' product market and capital market links.

My study contributes to three strands of existing research. First, it contributes to the literature on peer groupings. I complement recent studies on identifying labor market peers (Li, 2017; Gutierrez et al., 2019; Liu and Wu, 2019) by introducing a novel method to create a network of labor market peers and by providing the first evidence that firms' labor market peers do not fully coincide with their product market and capital market peers. Second, this study contributes to the literature on peer effects. I provide new evidence that labor market peers respond to each other to retain talented employees and that these peer effects are not due to firms' product market or capital market links. Third, this paper contributes to research on the mechanisms linking labor and finance by documenting that firms are likely to use the capital markets to finance their labor market actions. Specifically, I provide evidence that peer firms' spending on talented employees affects a focal firm's capital structure. The results provide one way in which labor markets and capital markets are linked.

The rest of the paper is structured as follows. Section 2 describes the data and sample construction. Section 3 presents the empirical strategies used in this study and shows empirical results. Section 4 explores placebo tests. Section 5 investigates potential mechanisms. Section 6 concludes.

2. Data and sample

2.1 Data collection

The main source of data is the U.S. Securities and Exchange Commission (SEC)'s Division of Economic and Risk Analysis (DERA) data library. Using the DERA data library, I obtain the EDGAR log files, which consist of information on investors' search activities for company filings through the EDGAR database.[3] The log files include the following variables: the investor IP address, the timestamp, the CIK of the filer, the web crawler identifier, the server code, and the SEC document accession number. Each IP address is uniquely obfuscated so that the identity of the investor cannot be tracked. While DERA was created in 2009, DERA backfilled the log file data to February 1, 2003. I only use the log file data starting from February 14, 2003 to December 31, 2011 because the daily log files between February 1, 2003 and February 13, 2003 are incomplete (Bauguess et al., 2018).

This study only uses the log files of investors' searches for 11-K filings because these filings contain firms' labor market information for investors. For instance, information about the net assets available for employee benefits are provided in an 11-K filing. Focusing on searches for 11-K filings can help identify labor market peers. Downloading the master index files provided by the SEC, I can find the accession number that matches 11-K filings and can drop searches for other types of filings. I discuss additional details regarding filtering the log file data in Appendix A.

2.2 Labor score

Using the filtered server log files, I create *Labor score*, a pairwise measure of overlapping labor markets between firms, to find a distinct set of peer firms that are related to each other because of the firms' labor market links. Inspired by Lee et al. (2015), I formally define $Labor\ score_{i,j}^{t}$ for firm *i* and firm *j* in year *t* as:

$$Labor\ score_{i,j}^{t} = \sum_{d=1}^{365}\left(Labor\ info_{i,j}\right)_{d}^{t} = Labor\ score_{j,i}^{t} = \sum_{d=1}^{365}\left(Labor\ info_{j,i}\right)_{d}^{t},$$

[3] The EDGAR log files also contain firms' search activities. Firms may use their rivals' information to be more competitive in the labor market, but investors' search activity accounts for most of the EDGAR log files (Bernard et al. 2020).

where $Labor\ score_{i,j}^{t}$ represents the total number of co-searches for an 11-K filing of $firm\ i$ and an 11-K filing of $firm\ j$ in year *t*. Appendix A shows an example of the procedure of generating *Labor score*. This pairwise measure is related to the *Annual search fraction*[4] (Lee et al., 2015), but, in order to relax the assumption that investors search for the base firm first, I do not restrict the data to chronologically adjacent searches by the same visitor. I focus on co-searches by the same visitor regardless of the search orders during the day. For instance, if the visitor searches for a Facebook 11-K filing and subsequently searches for a Google 11-K filing on a given day, both $Labor\ info_{Facebook,Google}$ and $Labor\ info_{Google,Facebook}$ increase by one unit. Lee et al. (2015) only consider that Google is a peer of Facebook, whereas my measure takes into account that Facebook can be also a peer of Google.

I then sort and rank each firm's labor market peers based on its *Labor score*. It should be noted that *Labor score* between firms is symmetric, but the ranking of each firm's most important labor market peers is asymmetric. For example, Google and Facebook have one single *Labor score* in the year 2012, and the score is 4,585. However, in the year 2012, Google is the most important peer for Facebook (Top 1), but Facebook is not the most important peer for Google (Top 3). In other words, the ranking is asymmetric. I use the top five labor market peers for each firm to create a network of labor market peers. Traditional industry classifications do not take into account this asymmetric ranking property. They also impose the transitivity property that firm *i* and firm *j* in the same industry should have the same peers. The asymmetric ranking and the use of the five most relevant labor market peers for each firm relax the symmetry and transitivity properties

[4] Lee et al. (2015) define the *Annual search fraction* as the proportion of investors who download a firm's fundamental information (e.g., S-1s, 8-Ks, 10-Ks, 10-Qs, and 14As) and then subsequently download another firm's fundamental information.

imposed in traditional industry classifications. Thus, this network of labor market peers is an improvement to traditional industry classifications.

2.3 Treatment sample construction

I obtain financial statement data from the Compustat database and stock data from the CRSP database. I use firms in the intersection of the log file data, the Compustat data, and the CRSP data, so the sample begins in 2003 due to the log file data availability. The final sample consists of 2,765 stock market-listed U.S. firms with ordinary common shares traded on the NYSE, American Stock Exchange, and Nasdaq.

Table 1 illustrates how to extract a treatment sample. I identify each firm's top 5 labor market peers based on *Labor score* and use the filing of an S-8 by one of its top 5 labor market peers as treatment. Then, the treatment sample consists of only firms that are shocked by the S-8 filing of a top 5 peer firm. The unit of observation in this study is a firm-fiscal quarter. I eliminate the firm-fiscal quarters that are shocked in the previous 4 quarters to find a clean treatment effect.

Inspired by Balakrishnan et al. (2014), I use the propensity score matching with 0.001 caliper and match on *Log Market Cap*, *Bid-Ask Spread*, and three lags of *Bid-Ask Spread* to find a plausible set of matched firms. These matching variables tend to control for the effects of the confound. Table 2 shows that the score matching technique allows almost the same distribution of these variables for treatment and control firms.

3. Empirical strategy and results

To plausibly estimate the peer effects of competition for talented employees among firms, I first examine how a network of labor market peers is different from product market and capital market networks. If they coincide, it means that the network of labor market peers is not capturing something new. Finding a distinct set of labor market peers, I conduct difference-in-differences regressions to find the effects of talent wars.

3.1 Underlying Assumptions

I make two assumptions when I create *Labor score* in the section above. The first assumption is that investors are co-searching firms' 11-Ks because they believe the co-searched firms are labor market peers. Simply put, I make an assumption of why investors are co-searching firms' 11-Ks. If I see an investor co-searching an 11-K filing of Microsoft and an 11-K-filing of Goldman Sachs, then I assume that the investor believes Microsoft and Goldman Sachs are labor market peers. The second assumption is that investors' beliefs are correct. I am not only assuming that investors believe the co-searched firms are peers in the labor market, but also assuming that their beliefs are, in fact, correct. For instance, I assume not only that investors believe Microsoft and Goldman Sachs are peers in the labor market, but also assume that their beliefs are correct. However, I cannot formally test whether my assumptions about beliefs are correct. Thus, I provide evidence to support my assumptions indirectly. In an interview with Bill Gates on Microsoft's competition (Karlgaard, 2004), Bill Gates asserts that Goldman Sachs is a Microsoft competitor in the labor market. I test whether my labor market network captures his belief.

Table 3 presents the top five peers of Microsoft in the year 2003 across different types of networks. I rank Microsoft's product market peers, capital market peers, and labor market peers in order of the TNIC similarity score, the *Annual search fraction*, and the *Labor score*, respectively. The TNIC similarity score is based on firms' product descriptions in 10-Ks, so the measure is based on self-reported words (Hoberg and Philips, 2016). It is possible that investors would not consider product market peers as capital market peers. Thus, I use the *Annual search fraction*, which is based on realized investors' choices, to rank each firm's capital market peers (Lee et al., 2015). Panel A of Table 3 shows that Goldman Sachs is a top 5 labor market peer of Microsoft for the year 2003. More importantly, the other two networks do not capture Goldman Sachs as a top peer of Microsoft. This finding suggests that the network of labor market peers possibly captures something distinct and indirectly supports the two assumptions above.

3.2 Networks

I formally address how the labor market network is different from product market and capital market networks in terms of network structural properties. To quantify the structural properties of the three networks, I use social network analysis methods. For example, Figure 1 shows a graph of a simplified network of Microsoft's labor market peers. This network consists of Microsoft, its top 5 peers, and each of their top 5 peers for the year 2003. Nodes represent firms, and each arrow points from a top 5 labor market peer to its focal firm. The circle node in the graph represents Microsoft. Likewise, the graphs in Figures 2 and 3 depict the simplified networks of product market peers and capital market peers, respectively. The labor market network in Figure 1 looks relatively dense and highly centralized. Each firm is likely to have arrows pointing to multiple focal firms, which implies a firm is likely to be an important peer for more than one firm, and a small number of firms are very central in the network. These graphs depicting the simplified networks reveal the possibility of sharp contrasts across labor market, capital market, and product market networks in terms of network structural properties.

Not only a graph but also a matrix can represent a network. In my setting, a cell in the matrix shows whether there is a tie between two firms. If a firm is a peer of a focal firm, they are coded to have a tie in the cell. There are two different types of matrices: undirected and directed matrices. While the directed matrix differentiates between a focal firm and its peer, an undirected matrix does not. A peer of a focal firm does not necessarily consider the focal firm a peer; thus, networks in this study are represented by directed matrices. Inspired by previous literature on networks (Freeman, 1979; Watts and Strogatz, 1998; Lee et al., 2015; Hochberg et al, 2007, 2010; Bauguess et al., 2018), I use the following five standard network-level measures in further analysis: density, reciprocity, outdegree centralization, betweenness centralization, and transitivity.

3.2.1 Density

I first explore how the labor market network is different from product market and capital market networks in terms of density. Density is a measure of interconnectedness among firms in a network and is defined as the ratio of ties present to all potential ties. Labor market peers are likely to transcend product market boundaries and capital market boundaries because labor market peers are based on a measure of the input market links. In other words, labor market peers should have more ties among firms in the network, so I predict that the density of the labor market network is the largest among the three networks.

In my setting, a tie is directed from one of the top 5 labor market peers to its focal firm. Formally, $n(n-1)$ directed ties can exist at most if there are n firms in a directed network. Thus, the density of the directed network is given by $q/(n(n-1))$, where q is the number of actual ties.

In Table 4, Panel A shows that the densities of the product market, capital market, and labor market networks are 0.0007, 0.001, and 0.003, respectively. This finding confirms the prediction that the labor market network is relatively dense when compared to the product market and capital market networks. In terms of density, the labor market network does not coincide with the other two networks.

3.2.2 Reciprocity

Similarly, reciprocity is also a measure of interconnectedness among firms in a network. However, high density is not sufficient to make the network more reciprocal because reciprocity represents the ratio of reciprocated ties present to all potential reciprocated ties. Simply put, the reciprocity of a network is the likelihood of a firm to have reciprocated ties, not directed ties. In my setting, higher reciprocity in the network indicates that a focal firm is likely to be a peer firm of its own peer firms.

Economics and finance literature discusses the notion of reciprocity (Bygrave, 1987; Lerner, 1994; Rabin, 1993; Hochberg et al., 2007, 2010). Hochberg et al. (2010) use the notion of reciprocity to show that incumbent VCs can help entrants in order to gain reciprocal access to entrants' home markets. Although helping entrants can be costly due to the expected punishment from other incumbent VCs, high reciprocity can benefit cooperating incumbent VCs.

Table 4 shows that the reciprocities of the product market, capital market, and labor market networks are 0.008, 0.009, and 0.007, respectively. They are not statistically different across the three different types of networks. In other words, a focal firm is just as likely to be a peer firm of its own peer firms in each of the three networks.

3.2.3 Outdegree centralization

While density and reciprocity measure interconnectedness within a network, centralization measures how equally firms are distributed in a network. Prior research shows a small number of firms are central in the labor market, so I expect to find high centralization in the labor market network. Outdegree centralization measures the distribution of the outdegree centrality scores of all firms in the network. An outdegree centrality score[5] is the number of focal firms a peer firm

[5] Similarly, indegree centrality score represents the number of incoming ties. In my setting, indegree centrality score measures the number of peer firms a focal firm has. So, indegree centralization is not a useful measure in this study because I restrict a focal firm's peers to its top 5 peers.

has, so outdegree centralization measures how equally the outdegree centrality scores of all firms are distributed within the network.

Formally, a network's outdegree centralization is given by $\sum_i (C_{max} - C_i)/((n-1)(n-2))$, where C_{max} is the highest outdegree centrality score observed within the network and C_i is the outdegree centrality score of firm i (Freeman, 1979). If the outdegree centralization of a network is high, it indicates that a small number of firms are central in the network.

According to Table 4, the outdegree centralizations of the product market, capital market, and labor market networks are 0.009, 0.032, and 0.067, respectively. The labor market network has the highest level of outdegree centralization of the three. This finding provides empirical evidence to support previous literature suggesting that the labor market network is dominated by a relatively small number of firms.

3.2.4 Betweenness centralization

Likewise, betweenness centralization measures how equally the betweenness centrality scores of all firms are distributed. The betweenness centrality score counts the number of shortest paths that go through each firm. Following Freedman (1979), I formally define the networks' betweenness centralization as $\sum_i (B_{max} - B_i)/((n-1)(n-2))$, where B_{max} is the highest betweenness centrality score observed in the network and B_i is the betweenness centrality score of firm i (Freeman, 1979). Panel A of Table 4 shows the betweenness centralizations of the product market, capital market, and labor market networks are 0.003, 0.011, and 0.060, respectively. The labor market network shows the highest level of betweenness centralization among the three different types of networks. This finding is consistent with the result in the outdegree centralization section, which suggests that a small number of firms are central in the labor market network.

3.2.5 Transitivity

Last, transitivity is a popular measure of how firms are locally connected in a network. Following Watts and Strogatz (1998), I use transitivity to compare the local connectedness across product, capital and labor market networks. Transitivity is defined as the ratio of transitively closed triplets of firms to all triplets of firms. A closed triplet is three firms that are connected by all possible ties. For example, high transitivity indicates that peer firms of the focal firm are likely to be peers.

I expect to find low transitivity in the labor market network because labor market peers are likely to have low overlap in product and capital space. Consider Goldman Sachs and Microsoft. In 2003, Goldman Sachs was a top 5 labor market peer of Microsoft. However, Goldman Sachs is less likely to be a labor market peer for another labor market peer of Microsoft (e.g., small IT firms). Table 4 shows that the transitivities of the product market, capital market, and labor market networks are 0.343, 0.331, and 0.194, respectively. This finding confirms the prediction that the labor market network has the lowest transitivity when compared to the other two networks.

3.3 Regression results

The results in the previous section show that the network of labor market peers is different from product market and capital market networks in terms of network structural properties. Finding a distinct network of labor market peers, I employ a standard difference-in-differences approach to find the effects of competition for talented employees among labor market peers. This empirical approach deals with identification problems and helps identify the causal effects between labor market peers' actions to attract talented employees. However, one challenge is to find a plausibly exogenous labor market action, which causes competition for talented employees among firms.

To address this challenge, I use a peer firm's S-8 filing, which conveys news about new employee stock benefits. Firms file S-8s when they plan to issue new stocks to their employees. Every S-8 includes the terms of new employee stocks. Providing new employee stocks can motivate and attract talented employees (Karlgaard, 2004, 2005). This action should increase labor market competition among firms. Thus, I evaluate how a focal firm responds to a peer's labor market action of filing an S-8. Inspired by Chang et al. (2020), I estimate the following difference-in-differences regression specification to find the effects of a labor market peer's labor market action on its focal firm's labor market action and financing choices:

$$\mathrm{Y}_{i,t} = \beta_0 + \beta_1 \mathrm{Shock}_{i,t} + \beta_2 \mathrm{PostShock}_{i,t} + \beta_3 \mathrm{X}_{i,t-1} + \mathrm{Firm\ FE} + \mathrm{Quarter\ FE} + \mathrm{FiscalQuarter\ FE} + \varepsilon_{i,t} \quad (1)$$

I use a top 5 labor market peer's S-8 filing as treatment (hereafter the S-8 shock) and find its impact on the outcome variable $\mathrm{Y}_{i,t}$. The unit of observation is a firm-quarter. To find a clean treatment effect, I do not use the treated firm-fiscal quarters that were shocked in the previous 4 quarters. $\mathrm{Shock}_{i,t}$ equals 1 if firm *i* receives the S-8 shock in fiscal quarter *t*, and 0 otherwise. $\mathrm{PostShock}_{i,t}$ is another indicator variable. This variable equals 1 if firm *i* is a treated firm between *t*-1 and *t*-4, and 0 otherwise. The regression takes into account firm, quarter, and fiscal-quarter fixed effects, and I cluster standard errors by the firm level.

β_1 and β_2 in equation (1) are the main coefficients of interest. The β_1 coefficient captures the contemporaneous effect of the S-8 shock on the outcome variable. I also track treated firms for 4 quarters after the S-8 shock to test long-term effects of the S-8 shock on the outcome variable, and the β_2 coefficient captures the long-term effects.

3.3.1 R&D spending

Using equation (1), I estimate the effects of the S-8 shock on focal firms' R&D spending. I use R&D spending to shed light on the notion of this talent war because R&D spending is highly correlated with salaries for talented employees. R&D spending is also easily accessible through the Compustat database. While the Compustat database does not extensively track human capital information such as employee wages, it measures R&D spending, which is, in fact, related to human capital. Thus, I use R&D spending to find how the focal firm responds to its peer's labor market compensation action proxied by the S-8 shock.

I formally define a firm's R&D spending as its research and development expenditures scaled by total assets of the previous fiscal quarter. I hypothesize that focal firms will increase R&D spending in response to the S-8 filing of its labor market peers. Firms have an incentive to raise the salaries and benefits of their talented employees if their labor market peers plan to issue stock options. A majority of R&D spending consists of labor compensation for high-skilled employees, so the focal firm will increase R&D spending to retain their talented employees from its labor market peers.

Column 1 of Table 5 shows that firms increase R&D spending in response to an S-8 shock. Treated firms increase their spending on R&D by 0.084 percentage points on average relative to control firms. This effect is roughly a 6% (=0.084/1.362) increase in R&D spending when compared to an average treated firm before receiving the S-8 shock. Thus, it is not only statistically significant but also economically significant. On the other hand, Column 2 shows that there is no significant difference between the spending on physical assets (e.g., property, buildings, and plants) at treated and control firms. These results are consistent with the hypothesis that firms increase spending on R&D to retain talented employees from their labor market peers.

3.3.2 Talent compensation and outflow

Firms are likely to spend more on R&D in response to the S-8 shock, but this does not fully explain how firms retain their talented employees. I examine whether R&D spending increases because firms seek to retain their talented employees by increasing talented employees' compensation. If R&D spending increases due to an increase in other factors rather than compensation, the S-8 shock may not lead to talent wars. I also examine whether the S-8 shock leads to talent outflows. If peer firms raise their employee stock benefits, focal firms may suffer more talent outflows.

Consider a talent war between firm *i* and firm *j*. While firm *i* has a talented employee (*E1*), firm *j* has two talented employees (*E2 and E3*). Suppose firm *i* increases the total compensation for *E1* using stock-based pay. *E1* is more likely to stay and work for firm *i*. In other words, the probability that firm *i* retains its talented employees increases. Additionally, *E2* and *E3* are more likely to leave firm *j* unless firm *j* provides them with increased compensation. As a result, firm *j* may strategically respond to firm *i*'s action if firm *j* wants to avoid talent outflows.

I use ExecuComp to identify a group of talented employees[6] because ExecuComp provides information about executives' annual compensation and titles. Using the annual titles of executives, I can identify chief technology officers and chief scientists. These executives are highly skilled employees with managerial and innovative talent.

Using equation (1), I examine the effects of the S-8 shock on focal firms' compensation actions and talent outflows. First, I expect focal firms are more likely to increase the salaries and benefits of CTOs and chief scientists in response to the S-8 shock. The unit of observation is a firm-fiscal quarter, and the dependent variable is the percentage change in total compensation for talented employees. Allowing for flexibility in measuring labor compensation, I compute the total compensation by adding salary, bonus, stock options, and other non-equity incentive compensation. Table 5 provides evidence that firms increase (weakly statistically significant) the compensation

[6] Using the ExecuComp database, I identify talented employees. Following Erkens (2011), I focus on the employees with annual titles that include one of the following terms: CTO, ENGINEERING, SCIENTIST, RESEARCH, and R&D. Additionally, I add to the list annual titles that include the terms PATENT, LICENSING, and SOFTWARE.

for talented employees on average in response to the S-8 shock. It is consistent with the hypothesis that labor market peers respond to each other's labor market compensation actions.

Table 5 also shows the results of talent outflow analyses. I expect focal firms are more likely to suffer talent outflows in response to the S-8 shock. I use the following three types of talent flow-related measures: *Talent outflow*, *Talent inflow,* and *#Talent*. The main measure of interest is *Talent outflow*, the total number of departures of chief technology officers and chief scientists. I measure *Talent inflow* by the total number of incoming chief technology officers and chief scientists, and *#Talent* is defined as the total number of chief technology officers and chief scientists.

According to Table 5, *Talent outflow* increases by 5.7 percentage points in response to the S-8 shock. This change indicates that focal firms are more likely to lose talented employees after receiving the shock, and this finding confirms the prediction that there is an increase in the focal firm's talent outflows when its labor market peers increase employee stock benefits. On the other hand, Table 5 shows no significant difference between *Talent inflow* and *#Talent* at treated and control firms. All these results support the claim that peers' actions in the labor market affect each other's talent compensation and outflows.

3.3.3 Labor and capital markets

The results so far suggest that the focal firm responds to its peer firms' labor market actions. The focal firm will spend more on R&D spending if its labor market peers file an S-8. Consequently, I expect that the focal firm needs to finance its labor market response through the capital market, at least in part.

I use firms' financing choices as the dependent variable in equation (1) to test the hypothesis that the S-8 shock can affect the financing choices of focal firms. Table 6 reports the difference-in-differences regression results where the dependent variables are a firm's stock issues (*StkIssues*), change in cash holdings (Δ*CashHoldings*), leverage (*Leverage*), short-term leverage (*StLeverage*), and long-term leverage (*LtLeverage*). The detailed definitions of these variables are in Appendix B.

Column 1 of Table 6 shows that firms issue more stock in response to the S-8 shock. Compared to control firms, treated firms increase their stock issues by 0.3 percentage points relative to control firms. Column 2 shows that firms increase cash holdings by 0.7 percentage points relative to control firms. The results are consistent with the hypothesis that firms use capital markets to finance their labor market actions. Columns 3 to 5, on the other hand, show no significant differences between the three types of leverage at treated firms and control firms. The results confirm the prediction that firms finance their labor market responses partially through the capital market.

3.3.4 Robustness checks

I conduct robustness tests on whether labor market peers compete with each other to attract and retain talented employees. I estimate the following dynamic regression:

$$\mathrm{Y}_{i,t} = \beta_0 + \beta_1 \mathrm{Shock}_{i,t} + \sum_{s=1}^{3} \theta_s \mathrm{PreShock}_{i,t}^{s} + \sum_{n=1}^{4} \varphi_n \mathrm{PostShock}_{i,t}^{n} + \beta_2 \mathrm{X}_{i,t-1} + \mathrm{Firm\ FE} + \mathrm{Quarter\ FE} + \mathrm{FiscalQuarter\ FE} + \varepsilon_{i,t}$$

where $\mathrm{Shock}_{i,t}$ is an indicator variable, and it equals 1 if firm *i* receives the S-8 shock in fiscal quarter *t* and 0 otherwise. $\mathrm{PreShock}_{i,t}^{s}$ is also an indicator variable and equals 1if firm *i* is a treated firm in *s* quarter preceding the S-8 shock quarter and 0 otherwise. $\mathrm{PostShock}_{i,t}^{n}$ is another indicator variable, and it equals 1 if firm *i* is a treated firm in *n* quarter after the S-8 shock quarter and 0 otherwise.

Table 7 shows that the pre-trend test rejects the existence of pre-trends, and the effects of the S-8 shock are robust, as shown in Tables 5 and 6. Column 1 of Table 7 shows that focal firms' R&D spending is positively affected by the S-8 shock, and Columns 2 and 3 provide evidence that a labor market peer's S-8 filing affects focal firm financing choices.

4. Placebo tests

Labor market peers appear to respond to each other's labor market actions. Nevertheless, it is feasible that these peers also have other links such as product market and capital market links. Suppose a focal firm's peer is not only a labor market peer but also a product market peer. Then, the results might be attributable to firms' product market links. Thus, I examine whether other types of firms' links affect the main results of this study. I consider the following two alternative networks to test the results: product market and capital market networks.

4.1 Product market network

If the effects of competition for talent are, in fact, driven by product market links among firms, the focal firm should respond to its product market peer's S-8 filing. To find the effects of a product market peer's labor market action, I use Hoberg and Philips' (2016) Text-based Network Industry Classifications, a product market network.

Table 8 presents the results of equation (1) using a product market peer's S-8 filing as treatment. Column 1 shows that the focal firm does not change R&D spending decisions in response to a product market peer's labor market action. Column 2 shows that the product market peer's S-8 filing does not affect focal firms' stock issues, but Column 3 shows that the focal firm increases cash holdings in response to the S-8 shock. These results suggest that a product market peer's S-8 filing is not likely to amount in a talent war within the labor market; however, the S-8 shock affects the focal firm's financing choices by increasing cash holdings.

4.2 Capital market network

Likewise, I examine whether the focal firm responds to the S-8 filing of its capital market peers. I use a network of capital market peers based on investors' search traffic (Lee et al., 2015). While this capital market network is similar to the labor market network, the two networks are based on search traffic of different types of filings. The capital market network is based on search traffic of 10-Ks, 10-Qs, 8-Ks, S-1s, and 14As, which do not focus extensively on firms' labor market information.

Table 9 shows that the focal firm issues more stocks in response to its capital market peer's S-8 filing. On top of that, the focal firm also increases cash holdings in response to the S-8 shock. However, a capital market peer's S-8 filing does not affect the focal firm's R&D spending. In other words, capital market peers do not drive talent wars.

5. Underlying mechanisms

The results thus far suggest that labor market peers are more likely to respond to each other's labor market compensation actions than product market and capital market peers. I further test whether these actions of labor market peers are strategic and explore what increases the strength of focal firms' labor market responses.

5.1 Top labor market peer

If a firm's labor market response is, in fact, strategic, I expect to find that the firm reacts stronger to a peer firm with higher labor market closeness. For example, to prevent talent outflows, a focal firm should respond stronger to its high-ranked labor market peer's action than its low-ranked labor market peer's action. Talented employees are likely to abandon the firm if its top labor market peer increases its labor compensation. I use a measure of each firm's top labor market peer

(Top) to investigate the sensitivity of the focal firm's labor market action in response to the S-8 shock.

Table 10 shows the results of triple-difference regressions. Column 1 shows that the coefficient estimate on the interaction term between Shock and Top is positive and weakly statistically significant. This indicates that the focal firm increases spending on R&D significantly more when its top labor market peer, as opposed to lower-ranked labor market peers, increases labor market competition by filing an S-8. Column 2 reports that the coefficient estimate on the interaction term PostShock*Top is not statistically significant, while PostShock has a positive and statistically significant coefficient. These findings suggest that a firm reacts quickly and strongly to retain talented employees in response to its top peer's labor compensation action.

5.2 First war

Suppose the focal firm responds to its labor market peer's action. If there is another peer firm that files an S-8, the focal firm is relatively less likely to respond to later S-8 shocks due to its financial constraints. Thus, I address the possibility that the focal firm becomes less responsive when its peer firms file more than one S-8 over time. I test whether the effects of earlier S-8 shocks are stronger when compared to the effects of the following S-8 shocks. To test this prediction, I use a measure of each firm's first S-8 shock (First) in my sample period.

Column 3 of Table 10 shows that Shock*First does not have a statistically significant coefficient, but Column 4 shows that the coefficient estimate on PostShock*First is positive and weakly statistically significant. The fact that the first S-8 shock has a larger positive effect on R&D spending confirms the prediction that a focal firm is more responsive to the earlier S-8 shocks.

6. Conclusion

Exploiting a novel measure of overlapping labor markets between firms, I construct a network of labor market peers and explore a competition for talent, where peer firms strategically respond to each other to retain and attract talented employees. I expect that a focal firm responds to its labor market peer's increases in benefits for talented employees.

This study uses a novel pairwise measure of labor closeness between firms to identify labor market peers. The measure is based on investors' search traffic for firms' 11-K filings, which contain the firms' employee benefits information. I find that the network of labor market peers is relatively dense and centralized, and is not constrained by product market and capital market networks.

Finding this distinct network makes it possible to plausibly estimate whether peer firms respond to each other's labor market actions. Using a difference-in-differences approach, I find that a firm spends more on R&D and suffers more talent outflows when its labor market peer increases labor market competition by filing an S-8, which conveys news about new employee stock issuances.

The effects are more pronounced for firms that have closer labor market links and that are involved in the talent war for the first time. The results are robust to dynamic regression analyses and are not attributable to firms' product market and capital market links. I also provide evidence that firms appear to use capital markets to finance their labor market responses by issuing more stocks and increasing cash holdings.

This study sheds light on the predictive effect of firms' labor market actions and provides evidence that ties labor and capital markets together. I believe that the findings in this study provide opportunities for future research to study the peer effects of firms that are connected through labor or different economic links. Future research may improve my measure of labor closeness between firms or help identify new economic links between firms and the peer effects of these new links.

Appendix A Filtering the log file data

I use four data filtering steps to clean the log files for analysis. In the first filtering step, I remove the observations that are identified as robots and web crawlers. Following Lee et al. (2015), I assume that investors are robots if they download more than 50 unique firms' filings on a given day. Also, following Loughran and McDonald (2017), I exclude the IP addresses flagged as web crawlers. In the second filtering step, I remove any search that has the server codes of 300 or higher because these numbers indicate client errors or other unrelated searches. In the third filtering step, I eliminate investors who only search for one firm's filings during the day because this study focuses on investors searching for more than one unique firm. Also, following Bauguess et al. (2018), I remove duplicate searches for the same filing by the same investor during the day. In the fourth filtering step, I only keep investors' searches for 11-K filings.

The table below uses hypothetical raw log files to illustrate the filtering steps. First, I exclude observation 12 because the IP address is flagged as a web crawler (Crawler=1). Second, I remove observation 2 because it has the server code of 300, which indicates client errors. Third, I exclude observation 1 because the visitor 1.1.1.AAA only downloads one unique firm's filing. Fourth, I exclude observations 3, 4, 6, and 8 because they are not related to 11-Ks. Finally, I exclude observation 9 because the visitor 1.1.3.CCC downloads the same 11-K on the given day. Using observations 5, 7, 10, and 11, I can acquire the following: $(Labor\ info_{B,C})_1^{2020} = 1$, $(Labor\ info_{C,B})_1^{2020} = 1$, $(Labor\ info_{C,D})_1^{2020} = 1$, and $(Labor\ info_{D,C})_1^{2020} = 1$. If the hypothetical raw log files contain information about all the searches in 2020, I can compute the following pairwise measures for the year 2020: $Labor\ score_{B,C}^{2020} = 1$, $Labor\ score_{C,B}^{2020} = 1$, $Labor\ score_{C,D}^{2020} = 1$, and $Labor\ score_{D,C}^{2020} = 1$.

Observation #	IP address	Time	Firm	Form type	Code	Crawler
1	1.1.1.AAA	1-1-2020, 4:11:01 AM	C	11-K	200	0
2	1.1.2.AAB	1-1-2020, 4:12:20 AM	B	11-K	300	0
3	1.1.2.BBB	1-1-2020, 4:13:22 AM	C	8-K	200	0
4	1.1.3.CCC	1-1-2020, 4:13:52 AM	B	8-K	200	0
5	1.1.3.CCC	1-1-2020, 4:14:53 AM	C	11-K	200	0
6	1.1.3.CCC	1-1-2020, 4:15:58 AM	A	8-K	200	0
7	1.1.3.CCC	1-1-2020, 5:13:32 AM	D	11-K	200	0
8	1.1.3.CCC	1-1-2020, 5:14:22 AM	E	8-K	200	0
9	1.1.3.CCC	1-1-2020, 5:24:32 AM	D	11-K	200	0
10	1.1.4.DDD	1-1-2020, 8:25:31 AM	B	11-K	200	0
11	1.1.4.DDD	1-1-2020, 8:26:32 AM	C	11-K	200	0
12	1.1.4.EEE	1-1-2020, 8:26:34 AM	C	11-K	300	1

Appendix B Variable definitions

StkIssues is a measure of net stock issues. It is computed by subtracting the purchase of common and preferred stock from the sale of common and preferred stock.

BidAskSpread is the difference between the ask price and the bid price. It is scaled by the average of the ask and bid prices.

Δ*CashHoldings* is the change in cash and short-term investments from the previous quarter. It is scaled by the book value of total assets in the previous quarter.

#EmpStk is a measure of the total number of public disclosures related to employee stock benefits. It is computed by counting the number of S-8 filings.

R&D is research and development expense scaled by the book value of total assets in the previous quarter.

Capex is the capital expenditure on property, plant, and equipment, which is scaled by the book value of total assets in the previous quarter.

Leverage is the ratio of total debt to the book value of total assets in the previous quarter.

StLeverage is the ratio of current liabilities to the book value of total assets in the previous quarter.

LtLeverage is the ratio of long-term debt to the book value of total assets in the previous quarter.

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Figure 1 Labor market network of Microsoft's top 5 peers in 2003

This graph illustrates a simplified network of Microsoft's labor market peers. For the purpose of brevity, I only plot Microsoft, its top 5 peers, and each of their top 5 peers for the year 2003. The graph shows how the firms in this simplified network are related in 2003. The circle node on the graph represents Microsoft, and each arrow points from a top 5 labor market peer to its focal firm.

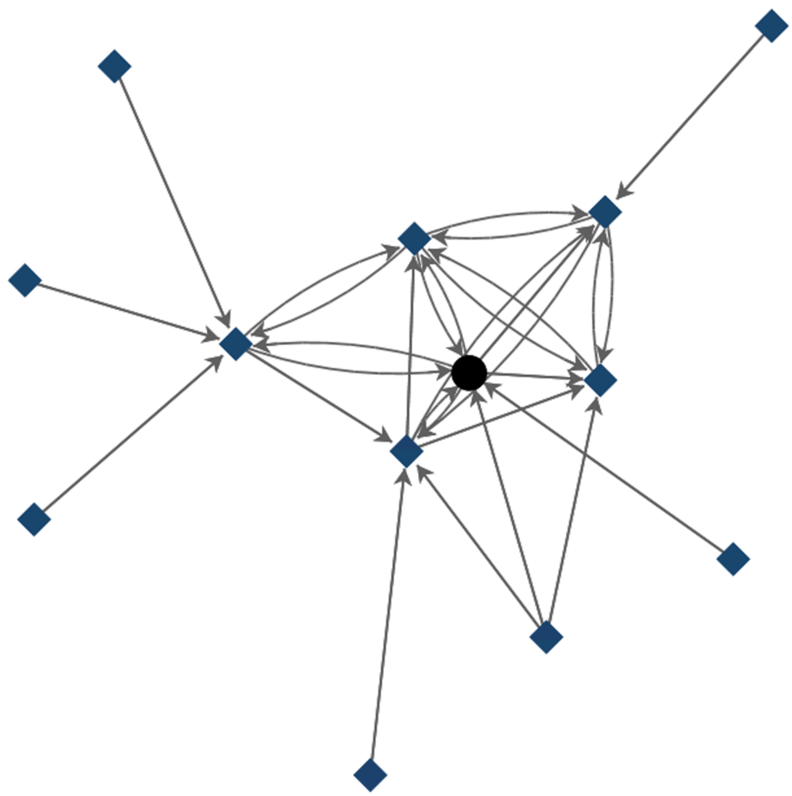

Figure 2 Product market network of Microsoft's top 5 peers in 2003
This graph illustrates a simplified network of Microsoft's product market peers. For the purpose of brevity, I only plot Microsoft, its top 5 peers, and each of their top 5 peers for the year 2003. The graph shows how the firms in this simplified network are related in 2003. The circle node on the graph represents Microsoft, and each arrow points from a top 5 product market peer to its focal firm.

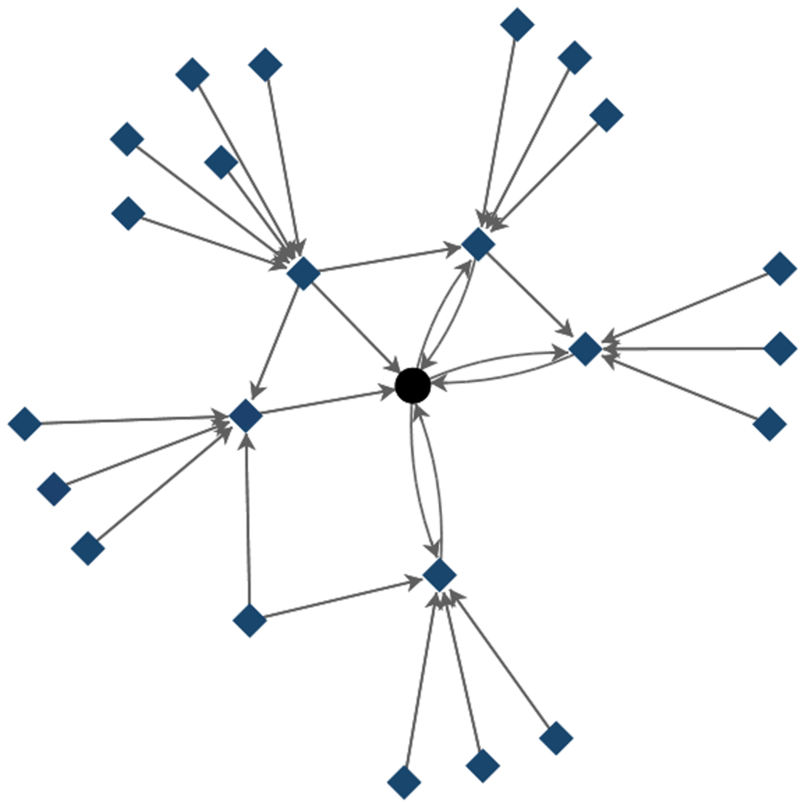

Figure 3 Capital market network of Microsoft's top 5 peers in 2003
This graph illustrates a simplified network of Microsoft's capital market peers. For the purpose of brevity, I only plot Microsoft, its top 5 peers, and each of their top 5 peers for the year 2003. The graph shows how the firms in this simplified network are related in 2003. The circle node on the graph represents Microsoft, and each arrow points from a top 5 capital market peer to its focal firm.

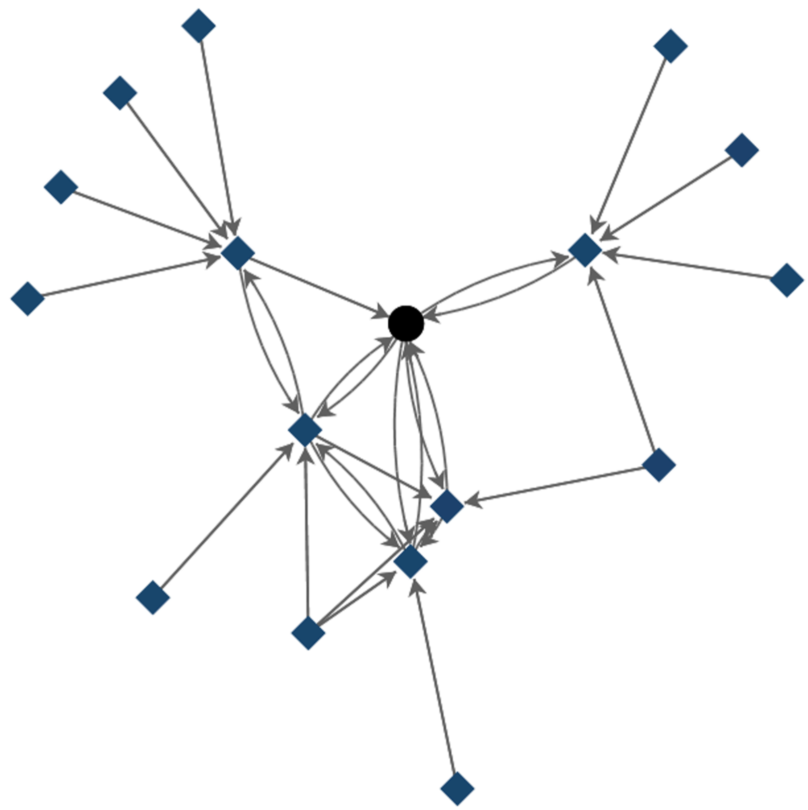

Table 1 Treatment sample formation

This table illustrates how to construct the treatment sample. I use a sample of 2,765 unique firms, which consists of the intersected firms of the log file data, the Compustat data, and the CRSP data. Then, I filter out the following firms: firms that are not listed as having ordinary common shares traded on the NYSE, American Stock Exchange, and Nasdaq; firms that are not shocked by a top 5 peer; firms that are shocked by a top 5 peer in the previous 4 quarters; firms that are not eligible for matching. Finally, the propensity score matching leads to the treatment sample consisting of 3,320 firm-quarters.

Formation steps		Total
Total labor market peers as of 2011 (by Compustat gvkey)		2,765
less: share codes>11	(879)	
less: exchange codes>3	(3)	
less: not shocked by a top 5 peer	(128)	
# firms with one or two S-8 shocks		1,755
# firm-quarters with one or two S-8 shocks		24,807
less: missing all outcome variables	(11,000)	
# firm-quarters eligible for matching		13,807
less: shocked firms in the previous 4 quarters *less*: firms not eligible for matching with 0.001 caliper	(10,487)	
# treated firm-quarters after matching		3,320
Final Treatment Sample:		
# final treated firm-quarters		3,320
# unique treated firms (by Compustat gvkey)		1,636

Table 2 Descriptive statistics

The sample includes the intersected firms of the log file, Compustat, and CRSP data. I filter out the following firms: firms that are not listed on the NYSE, American Stock Exchange, and Nasdaq with ordinary common shares. *BidAskSpread* is the difference between the ask price and the bid price. It is scaled by the average of the ask and bid prices. *StkIssues* is computed by subtracting the purchase of common and preferred stock from the sale of common and preferred stock. Δ*CashHoldings* is the change in cash and short-term investments from the previous quarter. R&D is research and development expense scaled by the book value of total assets in the previous quarter. *Capex* is the capital expenditure, scaled by the book value of total assets in the previous quarter. *#EmpStk* is a measure of the total number of public disclosures related to employee stock benefits. *Leverage* is the ratio of total debt to total assets in the previous quarter. *StLeverage* is the ratio of current liabilities to the total assets in the previous quarter. *LtLeverage* is the ratio of long-term debt to the total assets in the previous quarter.

	Treated Firms			Control Firms		
	Obs	Mean	Sd	Obs	Mean	Sd
Panel A: Product market network						
BidAskSpread	8990	1.35	2.092	8396	1.365	2.151
StkIssues	7669	0.009	0.071	7353	0.004	0.057
ΔCashHoldings	8978	0.001	0.06	8338	0.001	0.052
R&D	3343	2.659	3.838	2712	1.852	2.915
Capex	8385	0.025	0.037	7887	0.024	0.036
#EmpStk	809	1.15	0.432	628	1.174	0.512
Leverage	8585	0.207	0.205	8007	0.217	0.207
StLeverage	8604	0.04	0.074	8033	0.044	0.079
LtLeverage	8929	0.17	0.193	8290	0.176	0.192
Panel B: Capital market network						
BidAskSpread	8092	1.59	2.337	6477	1.701	2.45
StkIssues	6872	0.009	0.078	5400	0.014	0.089
ΔCashHoldings	8076	-0.001	0.068	6411	0	0.076
R&D	3136	2.789	4.013	2416	3.536	5.147
Capex	7488	0.026	0.038	5878	0.027	0.043
#EmpStk	679	1.131	0.409	393	1.109	0.328
Leverage	7728	0.206	0.207	6157	0.196	0.204
StLeverage	7745	0.042	0.079	6173	0.045	0.087
LtLeverage	8033	0.166	0.191	6382	0.153	0.185
Panel C: Labor market network						
BidAskSpread	3320	0.743	1.386	3276	0.716	1.423
StkIssues	2944	-0.002	0.046	2798	0.006	0.076
ΔCashHoldings	3319	0.003	0.044	3272	0.003	0.066
R&D	972	1.362	2.208	1590	2.9	3.866
Capex	3114	0.025	0.036	3123	0.026	0.039
#EmpStk	353	1.204	0.509	348	1.141	0.416
Leverage	3158	0.243	0.19	3113	0.205	0.217
StLeverage	3167	0.04	0.062	3117	0.033	0.065
LtLeverage	3303	0.203	0.184	3236	0.174	0.203

Table 3 Microsoft's top 5 peers

The TNIC similarity score (Hoberg and Philips, 2016) is based on firms' product descriptions in 10-Ks, and the *Annual search fraction* (Lee et al., 2015) is based on investors' search activities for 10-K, 10-Q, 8-K, and S-1 filings. The *Labor scor*e is based on investors' search activities for 11-K filings, which contain firms' labor markets information. I use the *Labor scor*e, the TNIC similarity score, and the *Annual search fraction* to construct the labor market, product market, and capital market networks, respectively. This table shows Microsoft's top 5 peers in 2003 across the three different types of networks.

	Microsoft's Peers (Product market network)	Microsoft's Peers (Capital market network)	Microsoft's Peers (Labor market network)
Panel A: Top 5 Peers of Microsoft in 2003			
Top 1	Phoenix Technologies	Dell	Intel
Top 2	RealNetworks	Oracle	Proctor & Gamble
Top 3	Sybase	Intel	Amazon.com
Top 4	Citrix Systems	Intl Business Machines	Gillette
Top 5	Corel	Wal-Mart Stores	**Goldman Sachs**
Panel B: Simplified Network Measures			
Nodes	24	17	13
Directed ties	30	30	30
Density	0.054	0.11	0.19
Reciprocity	0.11	0.30	0.36
Outdegree centralization	0.079	0.15	0.24
Betweenness centralization	0.10	0.12	0.093
Transitivity	0.11	0.66	0.54

Table 4 Network-level measures

This table shows the network-level measures across the three different types of networks. *Nodes* is the number of unique firms in a network, and *Directed ties* is the total number of ties that have directed to focal firms. *Undirected ties,* on the other hand, is the total number of undirected ties. *Density* is the ratio of ties present to all potential ties, and *Reciprocity* is the ratio of reciprocated ties present to all potential reciprocated ties. *Outdegree centralization* measures the distribution of the outdegree centrality score each firm has in a network. Similarly, *Betweenness centralization* measures how equally the betweenness centrality scores of all firms are distributed. *Transitivity* is defined as the ratio of transitively closed triplets of firms to all triplets of firms.

	Product market network		Capital market network		Labor market network	
	Mean	Sd	Mean	Sd	Mean	Sd
Panel A: Directed Network Measures						
Nodes	2655.44	235.69	2490.11	184.50	**1415.11**	92.55
Directed ties	5523	370.32	6330.33	361.30	6074.77	220.36
Density	0.0007	0.0001	0.0010	0.0001	**0.003**	0.0003
Reciprocity	0.1113	0.0056	0.1205	0.0088	0.1030	0.0180
Outdegree centralization	0.0095	0.0017	0.0325	0.0066	**0.0676**	0.0408
Betweenness centralization	0.0031	0.0019	0.0115	0.0093	**0.0600**	0.0250
Transitivity	0.3433	0.0131	0.3310	0.0358	**0.1940**	0.0303
Panel B: Undirected Network Measures						
Nodes	2655.44	235.69	2490.11	184.50	1415.11	92.55
Undirected ties	4959.22	337.46	5648.44	303.18	5510	251.76
Density	0.0014	0.0001	0.0018	0.0001	0.0055	0.0005
Reciprocity	0.0014	0.0001	0.0018	0.0001	0.0055	0.0005
Degree centralization	0.0093	0.0020	0.0324	0.0066	0.0656	0.0406
Betweenness centralization	0.1384	0.0338	0.2143	0.0521	0.1029	0.0751
Transitivity	0.1913	0.0058	0.1903	0.0170	0.1083	0.0157

Table 5 Peer effects in the network of labor market peers

This table presents the results of estimating difference-in-differences regressions where the dependent variables are *R&D*, *Capex*, *TotalComp*, *Talent outflow*, *Talent inflow*, and *#Talent*. The difference-in-differences model is the following:

$$Y_{i,t} = \beta_0 + \beta_1 \text{Shock}_{i,t} + \boldsymbol{\beta_2 \text{PostShock}_{i,t}} + \beta_3 X_{i,t-1} + \text{Firm FE} + \text{Quarter FE} + \text{FiscalQuarter FE} + \varepsilon_{i,t}$$

Definitions of all the variables used in this study are provided in Appendix B. I use a top labor market peer's S-8 filing as treatment. Control firms are matched on treated firms' asset size and bid-ask-spread. Shock is an indicator variable, and it equals 1 if a firm-quarter receives a shock and 0 otherwise. PostShock is another indicator variable, and it equals 1 if a firm-quarter is a treated firm in 4 quarters after the S-8 shock and 0 otherwise. All other explanatory variables, including controls and fixed effects, are not tabulated for the purpose of brevity. The standard errors are clustered at the firm level, and *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	R&D	Capex	TotalComp	Talent outflow	Talent inflow	#Talent
Shock	0.024	0.000	61.937	0.950	-2.776	-0.334
	0.035	0.000	40.418	2.473	2.659	0.296
PostShock	**0.084****	0.000	**80.105***	**5.721***	-5.147	-0.169
	0.041	0.000	**43.707**	**3.219**	3.750	0.425
Observations	21,921	55,570	1,468	35,634	35,634	34,902
R-squared	0.009	0.310	0.094	0.095	0.063	0.003
Firm FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Table 6 Peer effects in the network of labor market peers

This table presents the results of estimating difference-in-differences regressions where the dependent variables are *StkIssues*, Δ*CashHoldings*, *Leverage*, *StLeverage*, and *LtLeverage*. The difference-in-differences model is the following:

$$\mathrm{Y}_{i,t} = \beta_0 + \beta_1 \mathrm{Shock}_{i,t} + \boldsymbol{\beta_2 \mathrm{PostShock}_{i,t}} + \beta_3 \mathrm{X}_{i,t-1} + \text{Firm FE} + \text{Quarter FE} + \text{FiscalQuarter FE} + \varepsilon_{i,t}$$

Definitions of all the variables used in this study are provided in Appendix B. I use a top labor market peer's S-8 filing as treatment. Control firms are matched on treated firms' asset size and bid-ask-spread. Shock is an indicator variable, and it equals 1 if a firm-quarter receives a shock and 0 otherwise. PostShock is another indicator variable, and it equals 1 if a firm-quarter is a treated firm in 4 quarters after the S-8 shock and 0 otherwise. All other explanatory variables, including controls and fixed effects, are not tabulated for the purpose of brevity. The standard errors are clustered at the firm level, and *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

	(1) StkIssues	(2) ΔCashHoldings	(3) Leverage	(4) StLeverage	(5) LtLeverage
Shock	0.002*	0.003***	-0.000	0.000	-0.000
	0.001	0.001	0.001	0.001	0.001
PostShock	**0.003*** **	**0.007*** **	-0.001	-0.000	-0.001
	0.001	**0.002**	0.002	0.001	0.002
Observations	51,104	58,173	55,336	55,462	57,772
R-squared	0.022	0.027	0.020	0.007	0.011
Firm FE	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y

Table 7 Peer effects in the network of labor market peers
This table presents the results of estimating dynamic regressions where the dependent variables are R&D, Δ*CashHoldings*, and *BidAskSpread*. The dynamic regression model is the following:

$$Y_{i,t} = \beta_0 + \beta_1 \text{Shock}_{i,t} + \sum_{s=1}^{3} \theta_s \text{PreShock}_{i,t}^{s} + \sum_{n=1}^{4} \boldsymbol{\varphi_n} \textbf{PostShock}_{i,t}^{n} + \beta_2 X_{i,t-1} + \text{Firm FE} + \text{Quarter FE} + \text{FiscalQuarter FE} + \varepsilon_{i,t}$$

Definitions of all the variables used in this study are provided in Appendix B. I use a top labor market peer's S-8 filing as treatment. Control firms are matched on treated firms' asset size and bid-ask-spread. Shock is an indicator variable, and it equals 1 if a firm-quarter receives a shock and 0 otherwise. PreShock is an indicator variable, and it equals 1 if a firm-quarter is a treated firm in s quarter preceding the S-8 shock quarter and 0 otherwise. PostShock is another indicator variable, and it equals 1 if a firm-quarter is a treated firm in n quarter after the S-8 shock quarter and 0 otherwise. All other explanatory variables, including controls and fixed effects, are not tabulated for the purpose of brevity. The standard errors are clustered at the firm level, and *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

	(1) R&D	(2) ΔCashHoldings	(3) BidAskSpread
PreShock3	0.003	0.001	-0.018
	0.031	0.001	0.017
PreShock2	0.031	0.000	-0.018
	0.045	0.001	0.020
PreShock1	0.086	0.002	-0.028
	0.055	0.001	0.023
Shock	0.062	0.002	-0.035
	0.053	0.001	0.025
PostShock1	0.065	**0.003****	-0.024
	0.054	**0.001**	0.028
PostShock2	**0.151****	0.001	-0.034
	0.069	0.001	0.030
PostShock3	**0.120***	0.002	**-0.055***
	0.070	0.001	**0.032**
PostShock4	**0.178****	**0.004****	**-0.063***
	0.079	**0.001**	**0.034**
Observations	21,921	58,169	58,207
R-squared	3,088	0.015	0.169
Test preshocks=0	0.296	0.510	0.559

Table 8 Peer effects in the product market network

This table presents the results of estimating difference-in-differences regressions where the dependent variables are *R&D*, *StkIssues*, *ΔCashHoldings*, and *#EmpStk*. The difference-in-differences model is the following:

$$Y_{i,t} = \beta_0 + \beta_1 \text{Shock}_{i,t} + \beta_2 \text{PostShock}_{i,t} + \beta_3 X_{i,t-1} + \text{Firm FE} + \text{Quarter FE} + \text{FiscalQuarter FE} + \varepsilon_{i,t}$$

Definitions of all the variables used in this study are provided in Appendix B. I use a top labor market peer's S-8 filing as treatment. Control firms are matched on treated firms' asset size and bid-ask-spread. Shock is an indicator variable, and it equals 1 if a firm-quarter receives a shock and 0 otherwise. PostShock is another indicator variable, and it equals 1 if a firm-quarter is a treated firm in 4 quarters after the S-8 shock and 0 otherwise. All other explanatory variables, including controls and fixed effects, are not tabulated for the purpose of brevity. The standard errors are clustered at the firm level, and *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

	(1) R&D	(2) StkIssues	(3) ΔCashHoldings	(4) #EmpStk
Shock	0.004	-0.001	0.001	-0.012
	0.025	0.001	0.001	0.029
PostShock	-0.042	0.000	**0.001****	-0.036
	0.029	0.001	**0.001**	0.026
Test preshocks=0	0.0307	0.0434	0.210	0.937
Observations	52,844	131,612	150,396	13,224
R-squared	0.011	0.021	0.014	0.021
Firm FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y

Table 9 Peer effects in the capital market network

This table presents the results of estimating difference-in-differences regressions where the dependent variables are *R&D*, *StkIssues*, Δ*CashHoldings*, and *#EmpStk*. The difference-in-differences model is the following:

$$Y_{i,t} = \beta_0 + \beta_1 \text{Shock}_{i,t} + \beta_2 \text{PostShock}_{i,t} + \beta_3 X_{i,t-1} + \text{Firm FE} + \text{Quarter FE} + \text{FiscalQuarter FE} + \varepsilon_{i,t}$$

Definitions of all the variables used in this study are provided in Appendix B. I use a top labor market peer's S-8 filing as treatment. Control firms are matched on treated firms' asset size and bid-ask-spread. Shock is an indicator variable, and it equals 1 if a firm-quarter receives a shock and 0 otherwise. PostShock is another indicator variable, and it equals 1 if a firm-quarter is a treated firm in 4 quarters after the S-8 shock and 0 otherwise. All other explanatory variables, including controls and fixed effects, are not tabulated for the purpose of brevity. The standard errors are clustered at the firm level, and *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

	(1) R&D	(2) StkIssues	(3) ΔCashHoldings	(4) #EmpStk
Shock	-0.006	**0.003*** **	**0.003*** **	0.022
	0.039	**0.001**	**0.001**	0.030
PostShock	0.004	**0.003*** **	**0.002*** **	0.000
	0.056	**0.001**	**0.001**	0.024
Test preshocks=0	0.767	0.0995	0.570	0.632
Observations	45,960	106,794	124,693	10,464
R-squared	0.012	0.026	0.014	0.025
Firm FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y

Table 10 Top labor market peer and the first war

This table presents the results of estimating triple-difference regressions where the dependent variables are *R&D* and *Talent outflow*. Definitions of all the variables used in this study are provided in Appendix B. I use a top labor market peer's S-8 filing as treatment. Control firms are matched on treated firms' asset size and bid-ask-spread. Shock is an indicator variable, and it equals 1 if a firm-quarter receives a shock and 0 otherwise. PostShock is an indicator variable, and it equals 1 if a firm-quarter is a treated firm in 4 quarters after the S-8 shock and 0 otherwise. Top is an indicator variable, and it equals 1 if a firm-quarter is shocked by its top labor market peer and 0 otherwise. First is another indicator variable, and it equals 1 if a firm-quarter is treated for the first time and 0 otherwise. All other explanatory variables, including controls and fixed effects, are not tabulated for the purpose of brevity. The standard errors are clustered at the firm level, and *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	R&D	R&D	R&D	R&D	Talent outflow	Talent outflow	Talent outflow	Talent outflow
Shock	0.016	0.024	0.026	0.026	0.010	0.009	0.017	0.009
	0.036	0.035	0.030	0.035	0.025	0.025	0.027	0.025
PostShock	0.084**	0.086**	0.084**	0.041	0.057*	0.056*	0.057*	0.075**
	0.041	0.042	0.041	0.043	0.032	0.033	0.032	0.036
Shock*Top	**0.153***				**-0.007**			
	0.082				**0.081**			
PostShock*Top		-0.042				0.029		
		0.114				0.110		
Shock*First			-0.003				-0.023	
			0.068				0.035	
PostShock*First				**0.113***				**-0.053**
				0.065				**0.051**
Observations	21,921	21,921	21,921	21,921	35634	35634	35634	35634
R-squared	0.009	0.009	0.009	0.009	0.095	0.095	0.095	0.096
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y