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

Jae Hyoung Kim
Imperial College London

August 31, 2025

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.

Keywords: Networks, peer firms, talent wars, human capital, R&D, compensation packages, wages, labor markets, information disclosure, search traffic, co-search, peer effects.

JEL Classification: D83, D85, E24, G30, J33, O30.

[*] I am grateful to Alexander Ljungqvist and Daniel Metzger (AFA discussant) for their insightful comments. I also thank Ramin Baghai, Daniel Bergstresser, Gilles Chemla, Alvin Chen, Claudia Custodio, Adrien d'Avernas, Michael Halling, Jungsuk Han, Elizabeth Hoffman, Theresa Kuchler, Jongsub Lee, Diogo Mendes, Peter Orazem, Anna Scherbina, Yang Sun, Savitar Sundaresan, Dong Yan, and various seminar participants for helpful comments. All views expressed and any remaining errors are my own.
[†] Author address: jae-hyoung.kim@imperial.ac.uk.

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. Thus, 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] More recently, Meta has similarly pursued aggressive recruitment of top-tier talent from labor market competitors that are not necessarily its direct product market competitors.

In this study, 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 thereby 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 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

[1] Chambers et al. (1998) coin the phrase "talent wars," referring to the competition for talent among firms.
[2] See Karlgaard (2005) for an interview with Bill Gates discussing Microsoft's competitors. Similarly, Elon Musk has noted that Tesla increases compensation for its AI engineers in response to OpenAI's aggressive recruitment efforts, offering high-paying packages (Vipers and Kao, 2024). These examples illustrate that studying talent wars through the lens of product market competitors can be imprecise.

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 examples of Microsoft and Tesla suggest, labor market peers may not fully coincide with product market peers. According to traditional industry classifications, Microsoft and Tesla cannot be grouped with Goldman Sachs and OpenAI, respectively.

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 search 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). This action should increase labor market competition among firms. My difference-in-differences 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 denser and more 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 fifty percent 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 (Lee et al., 2015; Hoberg and Phillips, 2016; Li, 2017; Lee et al., 2018; Gutierrez et al., 2019; Liu and Wu, 2019; Lee and Yun, 2022). 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 the network of labor market peers does not fully coincide with product market and capital market networks in terms of network structural properties.

Second, this study contributes to the literature on peer effects (Bizjak et al., 2008; Faulkender and Yang, 2010; Albuquerque et al., 2013; Leary and Roberts, 2014; Foucault and Fresard, 2014; Kaustia and Rantala, 2015; Bailey et al., 2018; Grennan, 2019; Bailey et al., 2022). 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 I describes the data and sample construction. Section II details the identification and characteristics of the labor market network. Section III presents the empirical strategies used in this study and shows empirical results. Section IV investigates potential mechanisms. Section V concludes.

I. Data and sample

A. 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. From the DERA data library, I obtain the EDGAR log files, which capture users' search activities for company filings through the EDGAR database. These log files contain the following variables: the user's obfuscated IP address, timestamp, filer CIK, web crawler identifier, server code, and SEC document accession number. Each IP address is uniquely obfuscated so that user identities cannot be tracked. While DERA was created in 2009, it backfilled the log file data to February 1, 2003. I use the log file data starting from February 14, 2003 to December 31, 2011, as the daily logs between February 1 and February 13, 2003 are incomplete (Bauguess et al., 2018).

This study focuses on EDGAR log files of users' searches for 11-K filings because these filings provide key information about firms' labor markets. Under the Securities Exchange Act of 1934, firms are required

to file an 11-K filing annually, disclosing details about employee benefit plans. For example, 11-K filings include information on the net assets available for employee benefits. Focusing on searches for 11-K filings, I aim to identify labor market peers. I use the master index files provided by the SEC to find the corresponding accession numbers and exclude searches related to other types of filings. I discuss details on how I filter the log file data in Appendix A.

B. Labor score

Using the filtered server log files, I develop the *Labor score*, a pairwise measure of overlapping labor markets between firms, to identify distinct sets of peer firms liked through labor market connections. Inspired by Lee et al. (2015), I formally define $Labor\ score_{i,j}^{t}$ for firm *i* and firm *j* in year *t* as:

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

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 provides a detailed example of the process used to generate the *Labor score*. This pairwise measure is closely related to the *Annual search fraction*[3] developed by (Lee et al., 2015). However, to relax the assumption that users search for the base firm first, I do not restrict the analysis to chronologically adjacent searches by the same user. I focus on co-searches by the same user within a given day, regardless of the search order. For example, if a user searches for a Facebook 11-K filing and subsequently searches for a Google 11-K filing on the same day, both $Labor\ info_{Facebook,Google}$ and $Labor\ info_{Google,Facebook}$ will increase by one unit. While the measure used by Lee et al. (2015) considers only that Google is a peer of Facebook, my measure accounts for the possibility that Facebook can also be a peer of Google, creating a more reciprocal relationship between firms.

I then sort and rank each firm's labor market peers based on their *Labor score*. It should be noted that the *Labor score* between firms is symmetric, but the ranks of each firm's most important labor market peers is asymmetric. For example, in 2012, Google and Facebook share a *Labor score* of 4,585, yet Google

[3] Lee et al. (2015) define the *Annual search fraction* as the proportion of users who download a firm's fundamental information (e.g., S-1, 8-K, 10-K, 10-Q, and 14A filings) and then subsequently download the fundamental information of another firm.

is Facebook's top labor market peer (ranked #1), whereas Facebook ranks as Google's third most important peer (ranked #3). This illustrates the asymmetric nature of the ranking.

To create a network of labor market peers, I focus on each firm's top 5 labor market peers. Unlike traditional industry classifications, which assume symmetric relationships and impose transitivity,[4] this approach relaxes those constraints. By considering asymmetric ranks and focusing on the five most relevant labor market peers for each firm, this method provides a more flexible view of labor market competition. This network of labor market peers thus complements traditional industry classifications and allows for a deeper investigation into the peer effects of competition for talented employees among firms.

C. 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, Compustat, and CRSP, beginning in 2003 due to the availability of the log file data. The final sample consists of 2,765 U.S. listed firms on the NYSE, American Stock Exchange, and Nasdaq, all trading ordinary common shares.

Table 1 outlines the process for extracting the treatment sample. For each firm, I identify its top 5 labor market peers based on the *Labor score* and consider the filing of an S-8 by one of these top 5 peers as the treatment. Thus, the treatment sample includes only those firms shocked by an S-8 filing from a top 5 peer firm. The unit of observation is a firm-fiscal quarter. To isolate a clean treatment effect, I eliminate any firm-fiscal quarters that were shocked by an S-8 filing in the previous 4 quarters.

Inspired by Balakrishnan et al. (2014), I use the propensity score matching with a 0.001 caliper, matching 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 help control for potential confounding effects. Table 2 shows that the propensity score matching technique results in a nearly identical distribution of these variables between treatment and control firms.

II. Labor market peers and network measures

[4] If firm *i* and firm *j* are in the same industry, they should share the same peers.

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

A. Underlying Assumptions

I make two assumptions when I create the *Labor score* in the section above. First, I assume that when EDGAR users are co-search firms' 11-K filings, they do so because they consider the firms to be labor market peers. For example, if a user co-searches the 11-K filings of Microsoft and Goldman Sachs, I assume that the user perceives these firms as peers in the labor market. Simply put, I make an assumption about why users are co-searching firms' 11-K filings. Second, I assume that these user beliefs are correct. I not only assume that users believe Microsoft and Goldman Sachs are labor market peers, but also their beliefs are correct. However, I acknowledge that it is difficult to formally test my assumptions about beliefs. Thus, I provide indirect evidence to support these assumptions.

In an interview with Bill Gates regarding Microsoft's competition (Karlgaard, 2004), he asserts that Goldman Sachs is a competitor of Microsoft in the labor market. I aim to test whether my labor market network reflects this belief. Table 3 presents the top 5 peers of Microsoft in 2003 across different types of networks. I rank Microsoft's product market peers, capital market peers, and labor market peers based on the Text-based Network Industry Classifications (TNIC) similarity score, the *Annual search fraction*, and the *Labor score*, respectively. The TNIC similarity score is derived from firms' product descriptions in their 10-K filings, relying on self-reported words (Hoberg and Philips, 2016). Notably, a firm's product market peers may not necessarily overlap with its capital market peers. To address this, I employ the *Annual search fraction*, which reflects realized investors' choices, to rank each firm's capital market peers (Lee et al., 2015). Subsequently, I identify each firm's labor market peers using the *Labor score*. Panel A of Table 3 shows that Goldman Sachs ranks among the top 5 labor market peers of Microsoft for the year

2003. More importantly, neither of the other two networks identifies Goldman Sachs as a top peer of Microsoft.

Panel A of Figure 1 illustrates the *Labor score* in relation to the ranks of each firm's most important labor market peers. The graph reveals a power-law trend, indicating that the overlap in labor market competition among firms decreases exponentially, with only a small number of labor market peers being important to a given firm. It implies that standard industry classifications are too broad for accurately identifying labor market peers competing for talent. Panel B of Figure 1 shows that the logarithm of peer rank and the logarithm of the *Labor score* closely follow a linear trend. Applying the 0.5 adjustment factor suggested by Gabaix and Ibargimov (2011), I find that the R^2 of the log-log linear fit is 99%, confirming that the *Labor score* follows a power-law trend, in contrast to standard industry classifications.

Panel A of Table 4 shows the proportion of correspondence in standard industry classifications between the focal firm and its five closest labor market peers. Only 1% of the five closest labor market peers belong to the same product market (Hoberg and Phillips, 2016) while 5% fall within the same capital market (Lee et al., 2015). Using broader industry classifications, I find that 13%, 13%, 20%, and 13% of the five closest labor market peers share the same SIC2, NAICS3, GICS2, and GICS6 classifications as the focal firm. These findings support that my labor market network differs from product market and capital market networks.[5]

B. Network measures

I formally address how the labor market network differs from product market and capital market networks by examining their structural properties. To quantify the structural properties of the three networks, I employ social network analysis methods. Panel A of Figure 2 shows a graph of Microsoft's labor market network, consisting of Microsoft, its top 5 peers, and each of their top 5 peers for the year 2003. In the network, nodes represent firms, and arrows point from a top 5 labor market peer to its focal

[5] I also run regressions (untabulated) to examine the role of labor market peers in explaining cross-sectional variations in the labor market and innovation characteristics of focal firms. I find that labor market peers outperform product market peers in explaining these variations.

firm, with Microsoft represented as the central circular node. Panels B and C similarly depict the product market and capital market networks, respectively. The labor market network in Figure 2 appears denser and more centralized compared to the other two networks. Each firm is likely to have arrows pointing to multiple focal firms, implying that some firms serve as peers for more than one firm, with a small number of firms being highly central in the network. These graphical representations of Microsoft's networks highlight the potential sharp contrasts between labor market, capital market, and product market networks in terms of network structural properties.

Networks can also be represented using matrices. In my setting, each cell in the matrix indicates whether a tie exists between two firms. If a firm is considered a peer of a focal firm, the corresponding cell is marked as a tie. Importantly, since a firm that is considered a peer by a focal firm does not necessarily reciprocate that peer relationship, the networks in this study are represented by directed matrices. Building on prior research on networks (Freeman, 1979; Watts and Strogatz, 1998; Lee et al., 2015; Hochberg et al., 2007, 2010; Bauguess et al., 2018), I focus on three standard network-level measures for further analysis: density, centrality, and transitivity.

C. Density

I first explore how the labor market network differs from product market and capital market networks in terms of density. Density measures the level of interconnectedness among firms within a network and is defined as the ratio of actual ties to all potential ties.[6] Both general human capital and transferable skills drive firms to compete for talent not only within their own industries but also across different industries (Custodio, Ferreira, and Matos, 2019). Thus, I expect the labor market network to show the highest density among the three networks.

Panel B of Table 4 shows that the densities of the product market, capital market, and labor market networks are 0.0007, 0.001, and 0.003, respectively. These results confirm the prediction that the labor

[6] In my setting, a tie is directed from one of the top 5 labor market peers to its focal firm. Formally, in a directed network with n firms, a maximum of $n(n-1)$ directed ties can exist. Therefore, the density of the directed network is computed as $q/(n(n-1))$, where q represents the number of actual ties.

market network is denser than the product market and capital market networks. In terms of density, the labor market network is distinct from the other two networks.

D. Centrality

While density measures overall interconnectedness in a network, centrality captures its centralization. Prior research indicates that a small number of firms tend to dominate the labor market, so I expect to find high centralization within the labor market network.

Outdegree centralization measures the distribution of the outdegree centrality scores, which count the number of focal firms a peer firm is connected to. In other words, it measures how equally firms' influence is spread within the network.[7] A high outdegree centralization score indicates that a small number of firms are highly central in the network. Panel B of Table 4 shows the outdegree centralizations for the product market, capital market, and labor market networks are 0.009, 0.032, and 0.067, respectively. The labor market network shows the highest level of outdegree centralization, confirming prior research that suggests the labor market network is dominated by a relatively small number of firms.

Similarly, betweenness centralization measures the distribution of the betweenness centrality scores, which count the number of shortest paths passing through each firm.[8] Panel B of Table 4 reports the betweenness centralizations for the product market, capital market, and labor market networks as 0.003, 0.011, and 0.060, respectively. The labor market network has the highest level of betweenness centralization, consistent with the findings from the outdegree centralization analysis, further supporting the idea that a small number of firms are highly central in the labor market network.

E. Transitivity

Last, transitivity is a widely used measure of how firms are locally connected within a network. High transitivity suggests that a firm's peers are also likely to be peers with each other. For example, in 2003, Goldman Sachs was one of Microsoft's top 5 labor market peers, but Goldman Sachs is unlikely to be a

[7] 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).
[8] Following Freedman (1979), betweenness centralization is defined as $\sum_i (B_{max} - B_i)/((n-1)(n-2))$, where B_{max} is the highest betweenness centrality score observed, and B_i is the betweenness centrality score of firm i.

labor market peer of Microsoft's other peers, such as software firms. To compare local connectedness across product, capital and labor market networks, I use transitivity as defined by Watts and Strogatz (1998).[9]

Given that only a small number of labor market peers are crucial to the focal firm, as shown in Section II.A, I expect the labor market network to show low transitivity. In other words, other networks might be too broad from a competition-for-talent perspective. Panel B of Table 4 shows that the transitivities for the product market, capital market, and labor market networks are 0.343, 0.331, and 0.194, respectively. This finding confirms my prediction that the labor market network has the lowest transitivity compared to the other two networks.

III. Empirical analysis and results

A. Empirical strategy

The results in the previous section show that the network structure of labor market peers differs from that of product market and capital market networks. 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 these 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 must file S-8 filings when they intend to issue new stock to their employees. Every S-8 filing outlines the terms of new employee stock benefits. Providing new employee stock options can retain and attract talented employees (Karlgaard, 2004, 2005). This action is expected to intensify 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. Figure 3 illustrates the timeline of S-8 filing events.

[9] Transitivity is the ratio of transitively closed triplets to all triplets of firms.

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:

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

I use a top 5 labor market peer's S-8 filing as the treatment (hereafter the S-8 shock) and find its impact on the outcome variable $Y_{i,t}$. The unit of observation is firm-quarter, and I exclude treated firm-fiscal quarters that were shocked in the previous 4 quarters to ensure a clean identification of the treatment effect. $\text{Shock}_{i,t}$ equals one if firm *i* receives an S-8 shock in fiscal quarter *t*, and zero otherwise. $\text{PostShock}_{i,t}$ equals one if firm *i* is a treated firm between *t*-1 and *t*-4, and zero otherwise. The regression takes into account fixed effects for firm, quarter, and fiscal quarter. I cluster standard errors at 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. The β_2 coefficient captures the long-term effect, reflecting the impact of the shock over subsequent four quarters.

B. R&D spending

Using equation (1), I estimate the effects of the S-8 shock on focal firms' R&D spending. I focus on R&D spending because it is highly correlated with salaries for talented employees, providing insight into the competition for talent (Hall, 2002). While the Compustat database does not extensively track human capital information such as employee wages, it measures R&D spending, which is, in fact, highly tied to compensation for talented employees. Thus, R&D spending serves as a useful measure for understanding how focal firms respond to labor market compensation actions by their peers, as indicated 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 their labor market peers. Firms have an incentive to raise salaries and benefits for their talented employees if their labor market peers plan to issue stock options. Given that a majority of R&D

spending consists of labor compensation for high-skilled employees, the focal firm will increase its R&D spending to retain these talented employees.

In Table 5, Column 1 of Panel A shows that firms increase R&D spending in response to an S-8 shock. On average, treated firms increase their R&D spending by 0.084 percentage points relative to control firms. This effect is roughly a 6% (=0.084/1.362) increase in R&D spending when compared to the average R&D spending of treated firms before the S-8 shock. Thus, it is not only statistically significant but also economically significant. On the other hand, Column 2 of Panel A shows that there is no significant difference in spending on physical assets (e.g., property, buildings, and plants) between 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.

C. Talent compensation and outflow

Firms are likely to increase their R&D spending in response to the S-8 shock; however, 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 enhancing compensation. If R&D spending increases due to factors other than compensation, the S-8 shock may not trigger talent wars. I also examine whether the S-8 shock results in talent outflows. If peer firms raise their employee stock benefits, focal firms may experience greater 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*). If firm *i* increases the total compensation for *E1* through stock-based pay, the likelihood of *E1* remaining with firm *i* increases. In other words, the probability that firm *i* retains its talented employees increases. Conversely, *E2* and *E3* are more likely to leave firm *j* unless firm *j* provides them with increased compensation. Consequently, firm *j* may need to strategically respond to firm *i*'s actions to mitigate potential talent outflows.

I use ExecuComp to identify a group of talented employees,[10] as it provides detailed information about executives' annual compensation and titles. Using the annual titles of executives, I can identify Chief Technology Officers (CTOs) and Chief Scientists, who are highly skilled employees with managerial and innovative capabilities.

Using equation (1), I examine the effects of the S-8 shock on focal firms' compensation actions and talent outflows. I expect that 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, with the dependent variable being the percentage change in total compensation for these talented employees. Allowing for flexibility in measuring compensation, I compute total compensation by summing salary, bonus, stock options, and other non-equity incentive compensation.

In Table 5, Column 3 of Panel A provides evidence that firms increase (weakly statistically significant) compensation for talented employees on average in response to the S-8 shock. This finding is consistent with the hypothesis that labor market peers respond to each other's compensation actions. Columns 4 and 5 of Panel A show that the increase in talent compensation is primarily attributable to cash compensation rather than stock compensation, representing a cost-effective way to retain talented employees (Albuquerque et al., 2022).

Table 5 also shows the results of talent outflow analyses. I expect that focal firms are more likely to experience talent outflows in response to the S-8 shock. Column 6 of Panel A shows a decrease in the number of employees following the S-8 shock. I also use two types of talent flow-related measures: *Talent outflow* and *Talent inflow*. The main measure of interest is *Talent outflow*, defined as the total number of departures of CTOs and Chief Scientists, while *Talent inflow* is measured by the total number of incoming CTOs and Chief Scientists.

[10] Using the ExecuComp database, I identify talented employees based on their annual titles. Following Erkens (2011), I focus on employees whose titles include one or more of the following terms: CTO, ENGINEERING, SCIENTIST, RESEARCH, and R&D. Additionally, I expand the list to include titles that contain the terms PATENT, LICENSING, and SOFTWARE.

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 following the shock, confirming the prediction that there will be an increase in the focal firm's talent outflows when labor market peers enhance employee stock benefits. In contrast, Table 5 shows no significant difference in *Talent inflow* between treated and control firms. All these results support the prediction that peers' actions in the labor market affect each other's talent compensation and outflows.

In Panel B of Table 5, I further examine whether these results are driven by other channels, such as product market and capital market links. I exclude labor market peers that are also product market peers or capital market peers.[11] As shown in Panel B, the peer effects not only show greater statistical significance but also greater economic significance. Together, these findings support that firms affect one another through the labor market channel.

D. Labor markets and capital markets

The results thus far suggest that the focal firm responds to the labor market actions of its peers. Specifically, the focal firm is likely to increase its R&D spending if its labor market peers file an S-8. Consequently, I expect that the focal firm may need to finance this 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 affects the financing decisions of focal firms. Table 6 reports the difference-in-differences regression results, where the dependent variables include 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 increase their stock issuance in response to the S-8 shock. Specifically, treated firms raise their stock issues by 0.3 percentage points relative to control firms. Column

[11] I thank Daniel Metzger for recommending this important test. Figure 4 shows seven distinct cases of peer firms for the focal firm, with this analysis focusing on the peer firms categorized as Group A in Figure 4.

2 further shows that firms increase their cash holdings by 0.7 percentage points relative to control firms. These results are consistent with the hypothesis that firms use capital markets to finance their labor market actions by issuing additional stock. Columns 3 to 5, on the other hand, show no significant differences between in the three types of leverage between treated and control firms. This finding confirms the prediction that firms partially finance their labor market responses through the capital markets.

E. Robustness checks

I conduct robustness tests to examine 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 that equals one if firm *i* receives the S-8 shock in fiscal quarter *t* and zero otherwise. $\mathrm{PreShock}_{i,t}^{s}$ is also an indicator variable that equals one if firm *i* is a treated firm in the *s* quarters preceding the S-8 shock quarter, and zero otherwise. $\mathrm{PostShock}_{i,t}^{n}$ is another indicator variable that equals one if firm *i* is a treated firm in *n* quarter following the S-8 shock quarter, and zero otherwise.

Table 7 shows that the pre-trend test rejects the existence of pre-trends. Additionally, the effects of the S-8 shock are robust, consistent with the findings presented in Tables 5 and 6. Specifically, 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 the financing choices of focal firms.

IV. Underlying mechanisms

Firms appear to respond to the labor market actions of their peers. Nevertheless, it is feasible that these peers are also linked through other networks, such as product or capital markets. Suppose a focal firm's peer is not only a labor market peer but also a product market peer. Then, the observed effects may be attributable to their product market connections. To address this possibility, I examine whether other types of firm connections affect the main results of this study and explore the factors that strengthen a firm's response to its labor market peers.

A. Product market network

If the competition for talent is indeed 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 actions, I use Hoberg and Philips' (2016) Text-based Network Industry Classifications (TNIC), which outlines the product market network.

Panel A of Table 8 presents the results of equation (1), using a product market peer's S-8 filing as the treatment. Column 1 shows that the focal firm does not change its 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 the focal firms' stock issues; however, Column 3 shows that the focal firm increases its cash holdings in response to the S-8 shock. These findings suggest that a product market peer's S-8 filing is unlikely to amount in a talent war within the labor market; nonetheless, the S-8 shock affects the focal firm's financing choices by increasing cash holdings.

B. 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 developed from investors' search traffic (Lee et al., 2015). While this capital market network shares similarities with the labor market network, the two networks are constructed from search traffic related to different types of filings. The capital market network is based on search traffic of 10-K, 10-Q, 8-K, S-1, and 14A filings, and does not focus extensively on firms' labor market information.

Panel B of Table 8 shows that the focal firm issues additional stock in response to its capital market peer's S-8 filing, leading to an increase in cash holdings. However, the S-8 filing of a capital market peer does not affect the focal firm's R&D spending. In other words, capital market peers do not drive talent wars.

C. Top labor market peer

I expect that a firm's labor market response will be stronger to a peer firm with greater labor market closeness. Specifically, to prevent talent outflows, a focal firm should respond stronger to the actions of its high-ranked labor market peer than those of its low-ranked counterparts. Talented employees are likely to leave the firm if its top labor market peer increases its labor compensation. I employ a measure of each firm's top labor market peer (Top) to investigate this sensitivity.

Table 9 shows the results of triple-difference regressions. Column 1 shows that the coefficient of the interaction term between Shock and Top is positive and weakly statistically significant. This finding suggests that the focal firm increases its R&D spending when its top labor market peer files an S-8, in contrast to when lower-ranked peers take similar actions. Column 2 reports that the coefficient of the interaction term PostShock*Top is not statistically significant, while PostShock itself has a positive and statistically significant coefficient. These results imply that a firm reacts quickly and strongly to retain talented employees in response to its top peer's labor compensation actions.

D. First war

Suppose the focal firm responds to its labor market peer's action. If another peer firm subsequently files an S-8, the focal firm may be relatively less likely to respond to these later S-8 shocks due to financial constraints. Thus, I examine the possibility that the focal firm becomes less responsive as its peer firms file multiple S-8 filings over time. I test whether the effects of earlier S-8 shocks are stronger compared to the effects of subsequent S-8 shocks by measuring each firm's first S-8 shock (First) during the sample period.

Column 3 of Table 9 shows that the interaction term Shock*First does not have a statistically significant coefficient. However, Column 4 shows that the coefficient of PostShock*First is positive and weakly statistically significant. This suggests that the first S-8 shock has a larger positive effect on R&D spending, confirming the prediction that a focal firm is more responsive to the earlier S-8 shocks.

E. Noncompete agreements

Noncompete agreements restrict employees from moving to rival firms after the termination of their employment contracts. When a peer firm files an S-8, the focal firm's talented employees, bound by

noncompete agreements, are less likely to respond to S-8 shocks. I examine whether the responsiveness of focal firms and their talented employees diminishes when the firms enforce noncompete agreements. For this analysis, I use the average noncompete agreement index at the state-year level (Garmaise, 2009; Custodio, Ferreira, and Matos, 2019). Specifically, I test whether the effects of S-8 shocks are diminished for firms located in states with stricter enforcement of noncompete clauses (NC).

Columns 1 and 2 of Table 10 show that the interaction terms Shock*NC and PostShock*NC do not have statistically significant coefficients, whereas the coefficients of Shock and PostShock are both positive and statistically significant. These findings indicate that a firm still takes action to retain talented employees in response to its peer's labor compensation actions, regardless of the presence of noncompete agreements. However, Column 5 of Table 10 shows that the coefficient of Shock*Noncompete is negative and statistically significant. This supports the prediction that talented employees are less responsive when the focal firm enforces noncompete agreements.

F. Strategic actions

I further investigate the concern that an S-8 filer internalizes the expected effects its labor market actions on the focal firms. If a peer firm perceives that the focal firm will respond to its labor market actions, it may be less inclined to increase the compensation of its talented employees. This internalization process can result in a smaller increase in employee benefits. I expect this internalization effect to be more pronounced when the focal firm is among the peer firms' a top 5 labor market peers (Strategic).

Column 3 of Table 10 shows that the effect of a labor maket peer's S-8 filing on the focal firm's responses diminishes when they are mutually important to one another. This suggests that if the focal firm is also important to the peer firm, the peer firm is more likely to increase employee benefits in a manner that the focal firm responses less. The results confirm that the peer firm internalizes the expected effects on the focal firm.

V. Concluding thoughts

Exploiting a novel measure of overlapping labor markets between firms, I construct a network of labor market peers and explore how firms respond to one another in the competition for talent. I hypothesize that a focal firm will respond to increase in benefits for talented employees initiated by its labor market peers.

This study uses a pairwise measure of labor closeness between firms to identify labor market peers. The measure is based on EDGAR users' search traffic for firms' 11-K filings, which contain employee benefits information. I find that the network of labor market peers is dense and centralized, largely independent of product market and capital market networks.

Finding this distinct network makes it possible to plausibly estimate how firms respond to their peers' labor market actions. Using a difference-in-differences approach, I show that firms increase R&D spending and suffers more talent outflows when their labor market peers intensify labor market competition by filing an S-8, which signals new employee stock issuances.

The effects are more pronounced for firms with closer labor market connections and those engaging in the talent war for the first time. The results are robust to dynamic regression analyses, and these findings are not attributable to product market or capital market links. I also provide evidence that firms appear to use capital markets to finance their labor market responses by issuing additional stock.

This study sheds light on the predictive effect of firms' labor market actions and provides evidence that ties labor markets and capital markets together. The findings in this study also provide opportunities for future research to explore further peer effects among firms linked through labor markets.

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Appendix A. Filtering the Log File Data.

I use a four-step filtering process to clean the log files for analysis. In the first filtering step, I remove observations identified as robots or web crawlers. Following Lee et al. (2015), I consider users are robots if they download filings from more than 50 unique firms on a given day. Also, following Loughran and McDonald (2017), I exclude IP addresses flagged as web crawlers. In the second filtering step, I remove any searches with the server codes of 300 or higher, as these numbers indicate client errors or unrelated searches. In the third filtering step, I eliminate users who only search for filing for only one firm during the day. This study focuses on users searching for filings from multiple unique firms. Following Bauguess et al. (2018), I remove duplicate searches for the same filing by the same user during the day. In the fourth filtering step, I retain only the searches related to 11-K filings.

The table below illustrates these filtering steps using hypothetical raw log files. First, I exclude observation 12 because its IP address is flagged as a web crawler (Crawler=1). Second, I remove observation 2 due to a server code of 300, indicating a client error. Third, I exclude observation 1 because user 1.1.1.AAA downloads only one unique firm's filing. Fourth, I exclude observations 3, 4, 6, and 8 because they are not related to 11-K filings. Finally, I exclude observation 9 because user 1.1.3.CCC downloads the same 11-K on the same day. Using observations 5, 7, 10, and 11, I can derive 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 comprehensive information about all searches in 2020, I can compute the following pairwise scores 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 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.

Figure 1. Distribution of the Average Labor Score.
This figure displays the distributions of the average *Labor score*. Panel A shows the average *Labor score* for the firms that are defined as the closest 100 labor market peers to a focal firm. Panel B shows the relationship between the logarithm of the peer rank and the log *Labor score* for the firms that are defined as the closest 100 labor market peers to a focal firm.

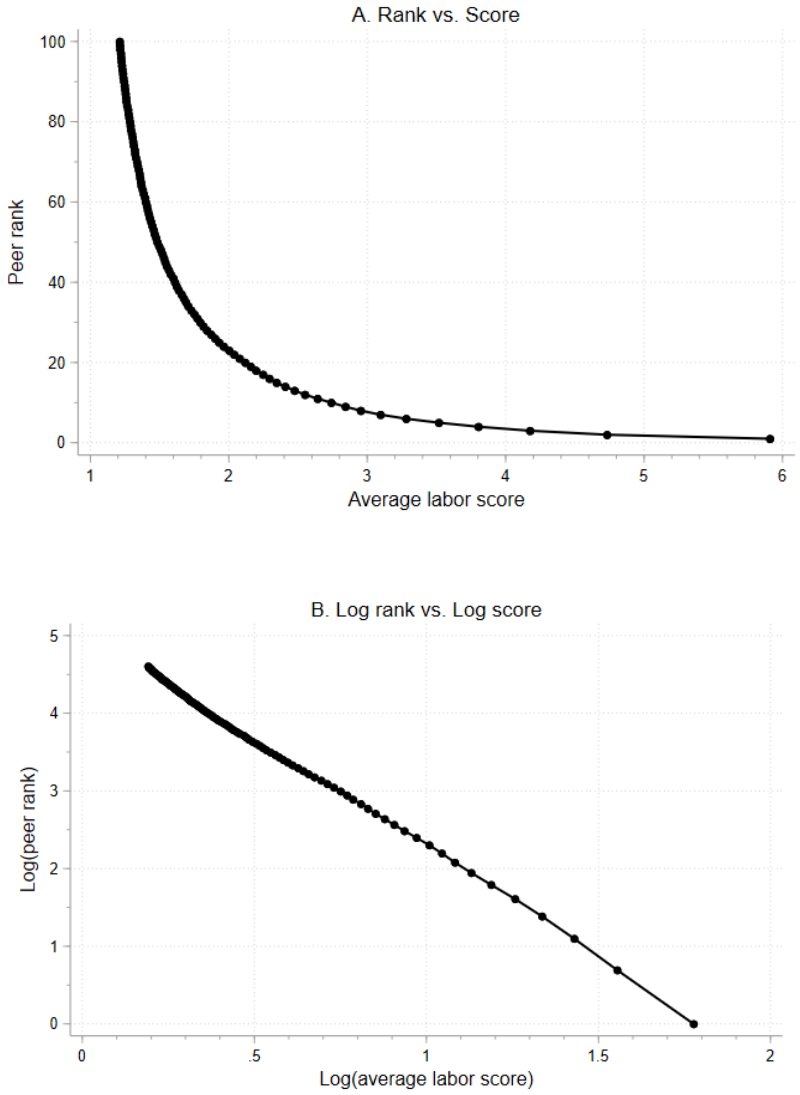
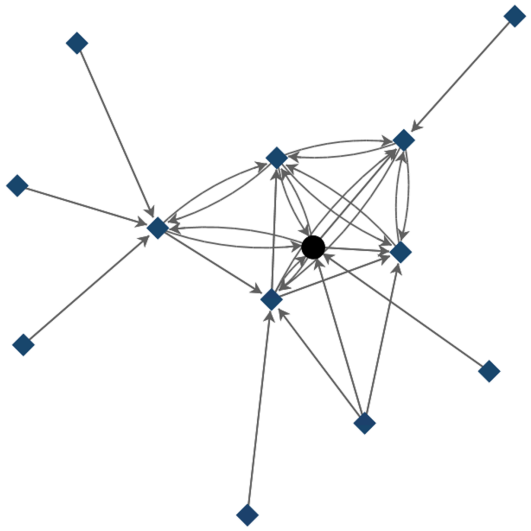
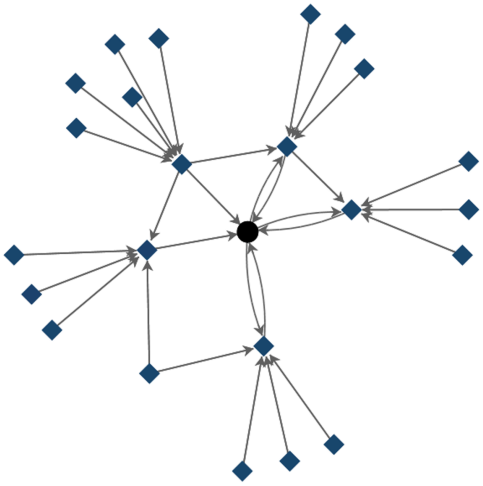


Figure 2. Network of Microsoft's Top 5 Peers in 2003.

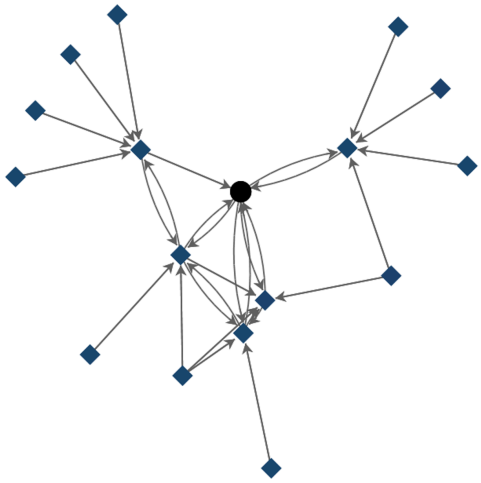
These graphs illustrate simplified networks of Microsoft's peers. For the purpose of brevity, I only plot Microsoft, its top 5 peers, and each of their respective top 5 peers for the year 2003 in each network. Each graph shows the relationships among the firms within the simplified network, with the circular node representing Microsoft. Panel A shows a simplified network of Microsoft's labor market peers, with arrows pointing from a top 5 labor market peer to its focal firm. Panel B shows a simplified network of Microsoft's product market peers, where each arrow points from a top 5 product market peer to its focal firm. Panel C shows a simplified network of Microsoft's capital market peers, with arrows pointing from a top 5 capital market peer to its focal firm.



A. Labor market network



B. Product market network



C. Capital market network

Figure 3. S-8 Timeline and Effects.

This figure illustrates the timeline associated with a firm's S-8 filing. The Securities and Exchange Commission (SEC) mandates public firms to file an S-8 if they plan to issue stock to employees. This filing provides information about employee benefits and the terms of new employee stock issues. This study specifically examines how a firm responds to an S-8 filing by one of its top 5 labor market peers in fiscal quarter *t*. The effects on fiscal quarter *t* captures short-term effects, and the average effects measured between fiscal quarters *t*+1 and *t*+4 capture the long-term effects of the filing.

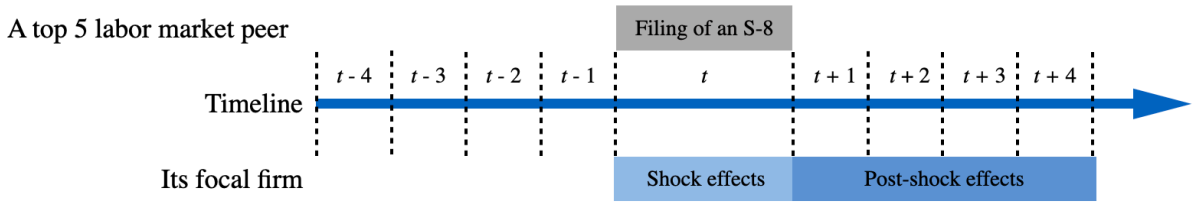


Figure 4. Product Market, Capital Market, and Labor Market Peers.
This figure illustrates seven distinct cases of peer firms to a focal firm. Firms in Group A are identified as labor market peers. Group B consists of firms that are product market peers. Group C includes firms that are capital market peers. Firms in Group D serve as both labor market and product market peers. Group E comprises firms that are both labor market and capital market peers. Group F consists of firms that are both product market and capital market peers. Finally, firms in Group G are classified as labor market, product market, and capital market peers.

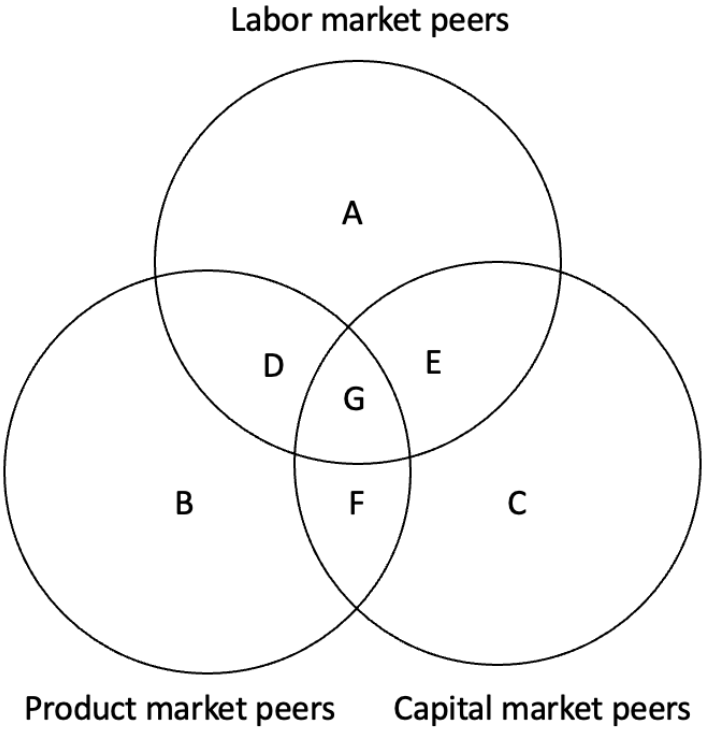


Table 1. Treatment Sample Formation.

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, Compustat data, and 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	(10,487)	
less: firms not eligible for matching with 0.001 caliper		
# 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 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	Std dev.	# obs.	Mean	Std dev.
Panel A: Product market network						
BidAskSpread	8990	1.350	2.092	8396	1.365	2.151
StkIssues	7669	0.009	0.071	7353	0.004	0.057
Δ*CashHoldings*	8978	0.001	0.060	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	1.150	0.432	628	1.174	0.512
Leverage	8585	0.207	0.205	8007	0.217	0.207
StLeverage	8604	0.040	0.074	8033	0.044	0.079
LtLeverage	8929	0.170	0.193	8290	0.176	0.192
Panel B: Capital market network						
BidAskSpread	8092	1.590	2.337	6477	1.701	2.450
StkIssues	6872	0.009	0.078	5400	0.014	0.089
Δ*CashHoldings*	8076	-0.001	0.068	6411	0.000	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
Δ*CashHoldings*	3319	0.003	0.044	3272	0.003	0.066
R&D	972	1.362	2.208	1590	2.900	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	0.190	3113	0.205	0.217
StLeverage	3167	0.040	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.

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

	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	0.05	0.11	0.19
Outdegree centralization	0.08	0.15	0.24
Betweenness centralization	0.10	0.12	0.09
Transitivity	0.11	0.66	0.54

Table 4. Correspondence with Industry Classifications and Network-Level Measures.

This table shows the proportion of correspondence between labor market peers and other industry classifications, along with the network-level measures across the three different types of networks. I first sort a focal firm's labor market peers by the *Labor score* and identify those peers. Panel A reports the average proportion of a labor market peer that falls within the same industry classification as the focal firm. The first column in Panel A shows the correspondence with product market peers as developed by Hoberg and Phillips (2010, 2014). The second column in Panel A shows the correspondence with capital market peers based on Lee et al. (2015). The remaining columns provide results based on SIC2, NAICS3, GICS2, and GICS6. In Panel B, *Nodes* is the number of unique firms within a network, and *Directed ties* is the total number of ties that have directed to the focal firms. *Density* is the ratio of existing ties to all potential ties. *Outdegree centralization* measures the distribution of the outdegree centrality score each firm has in the network. Similarly, *Betweenness centralization* measures how equally the betweenness centrality scores are distributed. *Transitivity* is defined as the ratio of transitively closed triplets of firms to all triplets of firms.

Panel A: Correspondence with industry classifications

Peer rank	Same Product	Same Capital	Same SIC2	Same NAICS3	Same GICS2	Same GICS6
1	0.02	0.09	0.14	0.14	0.21	0.13
2	0.02	0.07	0.14	0.13	0.20	0.13
3	0.01	0.06	0.13	0.13	0.19	0.12
4	0.01	0.06	0.14	0.14	0.20	0.13
5	0.01	0.05	0.13	0.13	0.20	0.12
6	0.01	0.04	0.13	0.13	0.19	0.12
7	0.01	0.04	0.13	0.13	0.19	0.12
8	0.01	0.04	0.13	0.13	0.19	0.12
9	0.01	0.04	0.14	0.14	0.20	0.13
10	0.01	0.04	0.13	0.13	0.19	0.12
Mean	0.01	0.05	0.13	0.13	0.20	0.12

Panel B: Network-level measures

	Product market network		Capital market network		Labor market network	
	Mean	Std dev.	Mean	Std dev.	Mean	Std dev.
Nodes	2655.44	235.69	2490.11	184.50	1415.11	92.55
Directed ties	5523.00	370.32	6330.33	361.30	6074.77	220.36
Density	0.0007	0.0001	0.0010	0.0001	0.0030	0.0003
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

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 include *R&D*, *Capex*, *TotalComp*, *Talent outflow*, *Talent inflow*, and *#Talent*. The difference-in-differences model is the following:

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

Definitions of all the variables used in this study are provided in Appendix B. In Panel A, I use a top labor market peer's S-8 filing as the treatment. Control firms are matched based on treated firms' asset size and bid-ask-spread. Shock is an indicator that equals one if a firm-quarter receives a shock and zero otherwise. PostShock is another indicator variable that equals one if a firm-quarter is a treated firm in the 4 quarters following the S-8 shock and zero otherwise. Panel B shows the results using labor market peers that do not overlap with product market peers or capital market peers. 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) *Capex*	(3) *TotalComp*	(4) *Cash*	(5) *#EmpStk*	(6) *#Emp*	(7) *Talent outflow*	(8) *Talent inflow*
Panel A: Peer effects in the labor market network								
Shock	0.024	0.000	61.937	0.028**	-5.144	-0.146***	0.950	-2.776
	0.035	*0.000*	*40.418*	*0.013*	*4.322*	*0.049*	*2.473*	*2.659*
PostShock	0.084**	0.000	80.105*	0.040**	-5.956*	-0.215***	5.721*	-5.147
	0.041	*0.000*	*43.707*	*0.016*	*3.215*	*0.073*	*3.219*	*3.750*
Observations	21,921	55,570	1,468	28,528	6,379	56,772	35,634	35,634
R-squared	0.009	0.310	0.094	0.029	0.033	0.015	0.095	0.063
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
Panel B: Peer effects after excluding other peer types								
Shock	0.034	0.000	60.906	0.031**	-4.204	-0.140***	0.597	-1.665
	0.037	*0.000*	*42.651*	*0.013*	*4.656*	*0.049*	*2.535*	*2.724*
PostShock	0.092**	0.000	81.166*	0.046***	-7.717**	-0.187***	5.557*	-4.284
	0.042	*0.000*	*46.165*	*0.017*	*3.325*	*0.069*	*3.299*	*3.832*
Observations	21,243	53,614	1,431	27,254	6,097	54,753	34,070	34,070
R-squared	0.009	0.311	0.093	0.028	0.037	0.017	0.097	0.065
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

Table 6. Peer effects in the Network of Labor Market Peers.

This table presents the results of estimating difference-in-differences regressions, with the dependent variables being *StkIssues*, Δ*CashHoldings*, *Leverage*, *StLeverage*, and *LtLeverage*. 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 the treatment. Control firms are matched based on treated firms' asset size and bid-ask-spread. Shock is an indicator variable that equals one if a firm-quarter receives a shock and zero otherwise. PostShock is another indicator variable that equals one if a firm-quarter is a treated firm in the 4 quarters following the S-8 shock and zero 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) Δ*CashHoldings*	(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:

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

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 the treatment. Control firms are matched based on treated firms' asset size and bid-ask-spread. Shock is an indicator variable that equals one if a firm-quarter receives a shock and zero otherwise. PreShock is an indicator variable that equals one if a firm-quarter is a treated firm in s quarter preceding the S-8 shock quarter and zero otherwise. PostShock is another indicator variable that equals one if a firm-quarter is a treated firm in *n* quarters following the S-8 shock quarter and zero 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) Δ*CashHoldings*	(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 Product Market and Capital Market Networks.

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:

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

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 the treatment. Control firms are matched based on treated firms' asset size and bid-ask-spread. Shock is an indicator variable that equals one if a firm-quarter receives a shock and zero otherwise. PostShock is another indicator variable that equals one if a firm-quarter is a treated firm in 4 quarters after the S-8 shock and zero 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)
	R&D	*StkIssues*	Δ*CashHoldings*	*#EmpStk*
Panel A: Product market network				
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*
Observations	52,844	131,612	150,396	13,224
R-squared	0.011	0.021	0.014	0.021
Test preshocks=0	0.0307	0.0434	0.210	0.937
Firm FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Panel B: Capital market network				
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*
Observations	45,960	106,794	124,693	10,464
R-squared	0.012	0.026	0.014	0.025
Test preshocks=0	0.767	0.0995	0.570	0.632
Firm FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y

Table 9. Top Labor Market Peer and the First War.

This table presents the results of estimating triple-difference regressions where the dependent variables include *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 the treatment. Control firms are matched based on treated firms' asset size and bid-ask-spread. Shock is an indicator variable that equals one if a firm-quarter receives a shock and zero otherwise. PostShock is an indicator variable that equals one if a firm-quarter is a treated firm in 4 quarters after the S-8 shock and zero otherwise. Top is an indicator variable that equals one if a firm-quarter is shocked by its top labor market peer and zero otherwise. First is another indicator variable that equals one if a firm-quarter is treated for the first time and zero 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) *R&D*	(3) *R&D*	(4) *R&D*	(5) *Talent outflow*	(6) *Talent outflow*	(7) *Talent outflow*	(8) *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	35,634	35,634	35,634	35,634
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

Table 10. Strategic Labor Market Actions and Noncompete Agreements

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 the treatment. Control firms are matched based on treated firms' asset size and bid-ask-spread. Shock is an indicator variable that equals one if a firm-quarter receives a shock and zero otherwise. PostShock is an indicator variable that equals one if a firm-quarter is a treated firm in 4 quarters after the S-8 shock and zero otherwise. NC is the average noncompete agreement index at the state-year level, developed by Garmaise (2009). Strategic is another indicator variable that equals one if the focal firm and its peer firm are mutually important to each other. 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) *R&D*	(3) *R&D*	(4) *R&D*	(5) *Talent outflow*	(6) *Talent outflow*	(7) *Talent outflow*	(8) *Talent outflow*
Shock	0.078	0.046	0.059	0.024	0.045	-0.052	-0.015	0.010
	0.075	*0.045*	*0.045*	*0.035*	*0.055*	*0.034*	*0.028*	*0.025*
PostShock	0.200***	0.330**	0.084**	0.074*	0.017	0.005	0.057*	0.036
	0.069	*0.131*	*0.041*	*0.044*	*0.047*	*0.073*	*0.032*	*0.036*
Shock*NC	-0.008				-0.023**			
	0.013				*0.010*			
PostShock*NC		-0.032				0.003		
		0.025				*0.014*		
Shock*Strategic			-0.105**				0.070*	
			0.050				*0.036*	
PostShock*Strategic				0.030				0.060
				0.049				*0.044*
Observations	9,938	9,938	21,921	21,921	15,627	15,627	35,634	35,634
R-squared	0.013	0.013	0.009	0.009	0.146	0.146	0.095	0.095
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