Labor Market Competitor Network and the Transmission of Shocks*

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Abstract

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Keywords: Labor Competitors, Network, Skill Demand, Job Postings, Predictable Returns

JEL-Classification: G01, M2, D22, E24, J23, J24

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I Introduction

Over the past decades, the labor market landscape has changed dramatically with increasing competition from companies operating in different industries. For example, Wall Street and Silicon Valley are major competitors with one another when it comes to attracting talents, despite the fact that these tech and financial giants are classified into different industries based on any standard industry classifications.[1] Recently, Silicon Valley has expressed concerns about losing top talents to financial firms, signaling a reverse trend since the 2008 financial crisis.[2] In economics research, many labor market activities such as wage setting and employee poaching rely on a proper definition of labor market competitors. Furthermore, there is a growing literature that studies the interaction between labor and finance, and the need to control for common labor market conditions is pervasive. Therefore, classifying and understanding labor market competitors are essential to the study of labor economics and finance. In this paper, we develop a time-varying measure of firm-centric labor market network based on job posting data and study the transmission of labor and industry shocks on the network.

The basis for constructing the labor market network is a unique dataset that covers the near-universe of online job postings in the United States. The dataset contains more than 150 million electronic job postings over the last ten years. Each job posting reports detailed information on the employer, location of the job, occupation title, and requirements such as education level and skill sets. The job postings are collected on a daily basis. Therefore, our measure of labor market network is time-varying and reflects changes in labor market structures.

Each year, we assign a labor demand profile to each firm based on its job postings and calculate the pairwise similarity between every two labor demand profiles. Based on the labor similarity measure, we construct our novel labor market competitor network. Our first main finding is that a firm's labor market competitors significantly differ from its product market rivals. The overlap between our labor market competitor network and common product market classifications is less than 20 percent. The result suggests that practices using product market industries to proxy for labor market conditions may not be valid. Then, we show that our network is able to capture firms'

[1] See SIC, NAICS, GICS, etc

[2] For example, the Wall Street Journal coverage: https://www.wsj.com/articles/battle-royale-hedge-funds-vs-silicon-valley-1495637466, and the eFinancialCareers coverage: https://news.efinancialcareers.com/us-en/292721/silicon-valley-losing-top-talent-to-quant-hedge-funds.

labor market decisions and financial performance. Firms require similar education, experience, and skills if they are labor market competitors. Moreover, our measure provides material gains to the existing product market classifications in explaining firms' financial characteristics. Collectively, the results indicate that labor market forces are important factors in shaping firms' organizational decisions.

Our network identifies a distinct set of labor market competitors for each firm. This feature allows us to study the transmissions of labor and industry shocks, which can have different effects on the labor network. Specifically, labor market shocks affect all firms within the same labor market in the same direction. For example, negative labor shocks adversely affect all firms in the same labor market. It is different for industry shocks, which can indirectly affect firms outside of the industry through the labor market network. For example, negative industry shocks adversely affect all firms in the same industry, but may benefit firms outside the industry that share the same labor market.

We separately test the effects of labor and industry shocks on the labor market competitors. First, we examine the effects of labor market shocks by investigating stock price reactions of the firms. Shocks about a firm's labor market are proxied by the returns of its competitors (labor-linked returns). We hypothesize and find that firms' stock prices positively respond to labor market shocks. Contemporaneously, the focal firm's returns respond strongly to the returns of the labor-linked firms: the equal-weighted (value-weighted) spread between the top and bottom quintile portfolios based on the labor-linked returns is 2.50 percent (3.28 percent) per month. Furthermore, we find a strong lead-lag structure of the focal firm's returns and the labor-linked returns. The returns of the labor-linked firms have strong predictive power for the focal firm returns. A hedged long-short strategy generates an equal-weighted (value-weighted) average monthly excess returns of 78 basis points (80 basis points), or 9.36 percent (9.60 percent) per year. The economic magnitude of the effect is large, and both the equal-weighted and value-weighted results are highly statistically significant. We refer to this return predictability as "labor momentum". We find that the labor momentum phenomenon is distinct from the documented momentum effects such as the short-term reversal, medium-term momentum, industry momentum, and customer momentum. Standard factor models (CAPM, Fama and French 3-factor, Carhart 4-factor, and Fama and French 5-factor) cannot account for this phenomenon. The labor momentum effect is consistent with the view that news transmits gradually across assets.

Second, we study the transmission of industry shocks on the labor market network. The large difference between labor market competitors and product market rivals allows us to study the impact of industry shocks on labor market competitors. To this end, we use the recent financial crisis as a shock to the financial industry and apply a difference-in-differences methodology to study its impact on financial firms' labor market competitors in other industries. Because the financial industry was severely affected by the crisis, its appetite for employees decreased drastically. Therefore, financial firms' non-financial labor market competitors enjoyed a large inflow of potential applicants, which made it easier for these firms to upskill. We find that financial firms' competitors upskill significantly more than other non-financial firms following the crisis. For example, our estimates imply that relative to the 2007 level, the probability of specifying any education requirement increases by 4.6 percent in 2010 for financial firms' competitors compared to other non-financial firms. This difference-in-differences estimate implies an increase of 17.7 percent of the average requirements in 2007. The comparative "upskilling" persists through the end of our sample in 2016 for some skill requirements, such as education and experience. We also show that both financial firms' competitors and other non-financial firms have similar skill requirements prior to the crisis, suggesting parallel trends in the skill requirements of the two groups. In further analyses, we show that the upskilling is accompanied by benefits measured as better financial performance. Overall, our results suggest that the negative shock to the financial industry has led to increases in skill requirements of non-financial labor competitors, and thus product market shocks could affect firms outside of the industry through the labor network.

Our paper relates to three strands of literature. First, this paper contributes to the studies on the classification of firm peers and competitors. Early work on firm classification includes SIC, NAICS, GICS, and Fama French. These classifications are widely adopted and used by researchers in economics and finance. These industry classifications are static in nature and impose the transitivity requirement. Bhojraj and Lee (2002), Bhojraj, Lee, and Oler (2003), and Chan, Lakonishok, and Swaminathan (2007) compare the performances of these different static industry definitions. Recent work advances the classifications by relaxing the transitivity requirement and constructing more flexible measures of product market competitors. Notebly, Hoberg and Phillips (2016) analyze firms' self-reported business descriptions in their 10-K fillings and construct a text-based network industry classification (TNIC). They show that their TNIC measure outperforms traditional static industry classifications in capturing cross-sectional variation in firm characteristics. Lewellen (2015) develops firm-specific industries (FSIs) based on firms' disclosures of their primary product market competitors. Studies also use internet data to classify firms based on investors or potential employees' co-search patterns. Lee, Ma, and Wang (2015) define two firms as peers if EDGAR users search these two firms subsequently or co-search them. Li (2017) groups two firms as peers if Linkedin users view the two firms subsequently. The measure in Li (2017) overlaps more than 50 percent with traditional static product market groupings such as GICS. Lee, Mauer, and Xu (2018) construct an industry-level human capital relatedness measure assuming the same distribution of occupations at the industry-level and for any firm in the industry, and show that mergers are more likely between industries with more similar human capital. In our paper, we directly observe firms' demand for different occupations and construct a pairwise similarity measure between any two firms based on their labor demand profiles. The labor demand data we use allows us to measure competition in the labor market and construct labor market rivals at the firm-level. Importantly, we find a small overlap between labor market competitors and product market rivals, suggesting that the occupation distributions at the industry-level significantly differ from those of a given firm in the industry.

Second, our research contributes to the limited literature on labor market structure and its interaction with economic activities. Azar, Marinescu, and Steinbaum (2017), Benmelech, Bergman, and Kim (2018), and Azar, Marinescu, Steinbaum, and Taska (2018) separately develop geographical labor market concentration indexes and show that the average wages are lower for more concentrated labor markets. In this paper, we construct a flexible occupation-based labor market competitor network and use the recent financial crisis to show that industry shocks can affect labor structures of firms in other industries through the labor market competitor network.

Third, our paper relates to the large price momentum literature in finance. Jegadeesh and Titman (1993) is the first paper that documents the momentum effect in the stock market. Moskowitz and Grinblatt (1999) and Rouwenhorst (1998) document the industry momentum effect and international momentum effect, respectively. Cohen and Frazzini (2008) and Menzly and Ozbas (2010) show that news can travel along the customer-supplier relationship (customer momentum). We document a labor momentum effect which shows that news about the labor market can transmit along the labor network.

The rest of the paper is organized as follows. Section II introduces the data and gives methodological details for the construction of the labor market competitor network. Section III presents properties and examines the external validity of our measure. Section IV presents results on labor links and stock returns. Section V examines how product market shocks affect labor market competitors. We conclude in Section VI.

II Data and Methodology

II.A Burning Glass Technologies

Burning Glass Technologies Company (BGT) examines more than 40,000 online job boards and company websites to gather job postings. The company parses and deduplicates the postings into a machine-readable form, and creates labor market analytical products. BGT shows that its database captures nearly all online job postings and covers every MSA in the U.S. in 2007 and from 2010 to 2016.[3]

The BGT dataset presents a substantial advantage over databases relying on a single source such as CareerBuilder.com and Monster.com. The nearly universal coverage is important for our study because we need to construct a complete labor demand profile for each company. Another database – Job Openning and Labor Turnover Survey (JOLTS) – asks a nationally representative sample of employers of vacancies they wish to fill in the near term. However, JOLTS data is typically only available at aggregate levels and contains relatively little information about the characteristics of the vacancies. In contrast, the BGT data contains more than seventy possible standardized fields of posting characteristics. For example, it contains detailed information on occupation, geography, skill requirements, and company names. The codified skills include education and experience requirements, alongside with thousands of specific skills extracted from the text of job postings. The dataset allows us to analyze an important but largely unexplored aspect of labor demand: skill requirements within occupations. Moreover, after matching individual job postings with their employers, the BGT dataset allows firm-level analyses based on different skill levels. The richness of the BGT data comes with a few shortcomings. Notably, the dataset only covers

[3]The database lacks postings from 2008 and 2009.

postings on the internet. Even though job postings have increasingly appeared online, the types of jobs posted online may not be representative of all job openings.[4]

The BGT database contains job occupation and employer name for each posting whenever available. Employer name is missing in about 40 percent of the postings, which are primarily from recruiting websites that typically do not list the employer name. We restrict our sample to postings that include the employer name. An important step in this paper is to match the BGT database to Compustat. Since the only available firm identifier in BGT is the employer name, the matching procedure contains both machine-matching and manual-matching components. When in doubt, we manually check whether a match is successful. The procedure results in 35,333,133 job postings matched to the U.S. publicly traded companies. In most of our tests, we aggregate job postings to the firm-year level.

Table 1 reports summary statistics of the raw sample and compares the matched BGT sample to the Compustat sample.[5] The matched BGT sample represents about 65 percent of the Compustat sample by counts or 83 percent by market capitalization. The representativeness is fairly consistent across different industries. Comparing to the Compustat firms, the most under-representative industry is the Mining and Logging industry (43.3 percent) and the most over-representative industry is the Retail Trade industry (79.5 percent). In the Appendix, we plot the industry distributions of the BGT sample and the Compustat sample. Overall, we find that the matched BGT sample is representative of the publicly listed companies on major stock exchanges.

II.B Construction of the Labor Market Competitor Network

This paper constructs a distinct set of labor market competitors for each firm. The premise behind our measure is that firms competing in the same labor market tend to demand workers of the same occupations. We regard two firms as competitors if they demand similar types of workers. We aim to capture the relatedness of firms based on their labor structure using a flexible network approach.[6] This approach provides a measure of distance between firm pairs in the labor space and

[4]Hershbein and Kahn (2018) note that although BGT postings are disproportionately concentrated in occupations and industries that typically require higher skills, the distributions are relatively stable across time, and the aggregate and industry trends in the number of vacancies track other sources reasonably closely.

[5]We restrict the sample to firms listed on major stock exchanges including NYSE, Nasdaq, and AMEX.

[6]A similar approach is applied in other contexts, such as constructing product market industries from 10-k text as in Hoberg and Phillips (2016), investors peer firms as in Lee, Ma, and Wang (2015) and firm stated competitors as in Rauh and Sufi (2011), Lewellen (2012) and Lewellen (2015).

does not impose transitivity between members of the network. Our approach allows competitors of each firm to be identified based on the similarity of the occupations they demand. In this section, we describe how we construct the labor market competitor network (LMCN) and the underlying data structure.

We start with the set of unique occupations demanded by the publicly listed firms in the U.S. in 2007 and 2010-2016. The Burning Glass Technologies dataset reports the occupation name based on O*NET code in each posting.[7] We use the occupation contained in the job postings to form labor market network based on the strong tendency of occupations to cluster among firms competing in the same labor market. For each year, we construct a set of unique occupations available in the dataset, which are all the occupations indicated in our sample of job postings in that year. Because we group the postings by year, the set of unique occupations varies from year to year and reflects the up-to-date occupation list demanded by U.S. firms. There are about 1,000 unique occupations for each year in our dataset based on the O*NET code.

We use occupations indicated in a firm's total job postings to compute a pairwise labor similarity score for each pair of firms in a given year. Figure 1 shows the histogram of the number of unique occupations indicated in job postings in our sample. The mean and median are 46 and 23, respectively. The distribution is skewed with some firms demanding more than 300 occupations.

To measure the similarity between two firms, we follow prior studies and use pairwise cosine similarity scores based on the occupations demanded by each firm.[8] For each firm, we construct a binary vector indicating the occupations demanded by the firm. The length of the vector is the number of unique occupations available in the given year. Therefore, for each firm i in year t, we have a binary vector $O_{i,t}$. Each element of $O_{i,t}$ takes a value of one if the firm i in year t demands the corresponding occupation and zero otherwise. We define the labor similarity between firm i and firm j as the cosine similarity of their vectors $O_{i,t}$ and $O_{j,t}$. Specifically, the labor market similarity

[7] O*NET is a classification of job titles widely used in labor economic studies. O*NET is the nation's primary source of occupational information, including worker attributes and job characteristics. It contains descriptions of over 1000 occupations, covering the entire U.S. economy. Just like SIC codes for industry classifications, O*NET provides a common language for defining and describing occupations and job requirements. Website: `https://www.onetcenter.org/`.

[8] For a detailed review of related methods see Sebastiani (2002). For discussion on the empirical advantages of this method, see Hoberg and Phillips (2016).

between firm i and firm j in year t is defined as:

$$Labor\ Similarity = \frac{O_{i,t} \cdot O_{j,t}}{||O_{i,t}|| \times ||O_{j,t}||} \tag{1}$$

The measure is bounded from zero to one and captures the labor profile proximity between firm i and firm j as reflected through their occupation positioning across the labor market network. The cosine similarity between firm i and firm j is higher when there is a larger overlap of the occupations demanded by the two firms. For example, suppose that in the year of 2010 there are three unique occupations: economist, mathematician, and psychologist. Firm i posts vacancies for economists and mathematicians but not psychologists and firm j posts vacancies for economists and psychologists but not mathematicians. Then, firm i's job posting vector is $(1,1,0)$ and firm j's vector is $(1,0,1)$. The labor similarity between firm i and firm j for the year of 2010 is $\frac{(1,1,0)\cdot(1,0,1)}{||(1,1,0)||\times||(1,0,1)||} = \frac{1}{2}$.

So far, we have developed a continuous labor similarity measure between each pair of firms for each year. To construct the labor market competitor network, we impose a minimum threshold requirement. That is, we define firm i's labor market competitors as all firms j with pairwise cosine similarities relative to firm i above a pre-specified minimum threshold. A high threshold will result in fewer competitors. For easy comparison, we choose the threshold so that the granularity of the network is the same as that of the three-digit SIC industries (SIC3) in our sample. In other words, the percentage of firm pairwise links over all possible pair links for the LMCN is the same as that of SIC3. To mitigate the effect of firm size, we compute the median similarity score of firm i as the median score of firm i and all other firms available in a given year. We then subtract the median score from the original similarity scores to obtain our final measure of similarity scores for each firm. Therefore, a firm cannot dominate the labor market and be a competitor to all other firms.

Our goal is to construct a parsimonious measure that identifies a unique set of labor market competitors for each firm. We omit the geographic locations of the firms in order to isolate the effects of labor market competition from variations of the local economies. Of course, the labor market may have a strong geographic component. In untabulated results, we find stronger effects incorporating the geographic component into our measure by only examining firms operating in the same geographic areas. Therefore, we consider our measure a conservative way to capture labor market competitors.

The LMCN relaxes the transitivity requirement. Traditional classification methods such as the SIC, NAICS, and GICS impose transitivity requirements in their construction. In the Appendix, we graphically present the structure of the LMCN for the year 2016, which highlights the non-transitive nature of our network. The graph shows that firms are clustered into major subgroups in the labor market.

There are two central ideas in our measure. First, we summarize firms' time-varying labor demand using the near-universe of online job postings. A firm's job posting profile reveals its complete labor demand in the year. Based on the occupations demanded by firms, we assign each firm a spatial location.[9] Therefore, each firm has a unique spatial location and its own potential set of nearby competitors in this space is based on occupation overlaps. A large overlap of occupations indicates that the firms' labor demand is similar, while a longer distance between two firms indicates higher differentiation in labor input. Second, we create a network of firms in the labor market and calculate the extent to which one firm is similar to another using occupations they need. The firm-by-firm pairwise occupation similarity scores reduce high-dimensional job title vectors to a simple matrix of firm pairwise similarity scores. We then create groups using the pairwise similarity scores so that only closely related firms are identified as competitors in the labor market. Because firms may hire different occupations in different years, the network is time-varying. Each firm can have its own competitors, which can vary from year to year.

Our measure captures firms' labor demand for the same occupation in the current period and contains forward-looking information on occupations demanded by firms. Since labor is an essential input for any end product, our classification reflects the labor demanded by firms that arise from underlying production processes and business models.

II.C Labor Characteristics

To evaluate the validity and performance of the labor market competitor network, we follow the labor economics literature and construct several labor variables at the firm-level using the BGT dataset. We consider two types of labor variables. The first type relates to the percentage of high-skilled workers and the second type relates to the level of skill-requirements demanded by

[9] In the same spirit of Hoberg and Phillips (2016) in generating a spatial location for each firm using words of business description in 10-K filings. Also, see Jaffe (1986) who applies a similar methodology to patent filings.

firms. For the first category, we construct $EduRatio$, $ExpRatio$, $ComRatio$, and $CogRatio$. These are firm-level variables defined as the percentage of job postings requiring education, experience, computer skills, and cognitive skills, respectively.[10] These skill requirements represent human capital measures in which both employers and economists are interested. Also, they reflect what the economic discipline has learned about technological change over the past 20 years (e.g., Autor, Levy, and Murnane, 2003; Hershbein and Kahn, 2018). For the second category, we construct $MeanEdu$, $MeanExp$, and $MeanSkill$, which are firm-level averages of education, experience and skill requirements, respectively. Appendix C has detailed variable definitions. Upskilling of a firm is characterized as having a higher percentage of job postings requiring any of the set of skills.

Table 2 reports yearly summary statistics of the skill requirement data for the primary testing sample. In 2007, 22 percent of the vacancies require a minimum education of a bachelor's degree. The percentage increases to 31 percent in 2010 and continues to increase over the next two years to 35 percent in 2012. This is roughly a 60 percent increase from the baseline value in 2007. In 2016, the last year of our sample period, an education requirement is included in 28 percent of the job postings. The other skill requirements follow a very similar pattern as the education requirements. For experience requirements, in 2007, 12 percent of the postings require at least five years of experience. The percentage increases to 21 percent in 2012 and stays around 17 percent in the later period. For both computer skills and cognitive skills, the share of job postings specifying either skill increases more than 70 percent in 2012 relative to the level in 2007.

II.D Main Sample

To construct our main sample, we merge our pairwise labor similarity measure with firm financials and accounting information from Compustat. We require the information of labor market competitors to be available at the beginning of each fiscal year during which firm financials are measured. We require a firm to have at least three competitors[11] and exclude financial firms (SIC codes in the range 6000-6999) and firms with missing assets. Our sample is at the firm pair-year

[10] We define a job posting as demanding education if it requires a minimum education of a bachelor's degree. A posting is categorized as requesting experience if it requires at least five years of job experience. We define a posting as requiring computer skills if it contains the keyword "computer" or if it requires software knowledge. A posting is categorized as requesting a cognitive skill if it contains at least one of the following phrases or fragments: "research," "analy," "decision," "solving," "math," "statistic," or "thinking."

[11] Results remain qualitatively similar without this requirement.

level. We denote the unique list of firms as "base firms", and their labor market competitors as "LMCs" throughout the paper. Variable definitions are in Appendix C and all continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers.

III Properties of the Labor Market Competitor Network

In this section, we document the properties of the LMCN and compare it with traditional product market classifications. We first show that a firm's labor market competitors are distinct from its product market rivals. Then, we examine the LMCN's power in explaining the cross-sectional variation in base firms' labor-related characteristics and compare it with product market groupings.

III.A Descriptive Statistics

Table 3 presents the summary statistics of the sample. Panel A shows the number of unique base firms each year. We have a similar number of firms from 2010 to 2015. The smaller number of firms in 2007 is likely due to the delisting of firms during the financial crisis. We only have half of the number of firms in 2017 as in other years because of the lack of firm financials for the fiscal year ending in 2017 in Compustat. Panel B shows statistics on the number of labor competitors for each base firm. On average, a base firm has 68 LMCs. Figure 2 shows the distribution of the number of LMCs. The distribution is left-skewed, with most firms having fewer than 60 competitors in the labor market.

III.B Overlap with Product Market Classifications

Our measure groups firms based on a primary firm input – labor, and thus differs from traditional industry groups that classify firms based on their outputs. One possibility is that the set of labor market competitors is similar to the set of product market rivals. For example, Facebook and Twitter are both in the high-tech industry and demand similar workers. However, we find that the majority of labor market competitors are in different industries. We present one of the first piece of evidence showing that a firm's labor market competitors are distinct from its product market competitors. We first provide an example in the Appendix. In this example, we show a random sample of 20 labor market competitors (out of 209) for the Walt Disney Company in the year of 2016. Its competitors include firms operating in various product markets, such as healthcare and energy.

Table 4 presents the correspondence in the product market classifications of our occupation-based labor groupings. Panel A shows the average fraction of labor market competitors belonging to the same industry as the base firm for different industry classifications. Specifically, for each base firm in each year, we calculate the fraction of its labor market competitors that belong to the same industry as that of the base firm for the industry classification indicated by the column name. The number presented is the average of the fractions across base firms in each year. This panel shows a low degree of concordance between standard industry classifications of base firms and that of their labor market competitors. For example, only 15.3 percent of the firms classified as the LMCs belong to the same SIC3 industry as the base firm. The level of concordance ranges from 9.3 percent in four-digit NAICS (NAICS4) industry to 28 percent in four-digit GICS (GICS4) industry. In the untabulated results, we find that the overlap between our measure and the TNIC measure developed in Hoberg and Phillips (2016) is low at 6 percent.[12] In addition, there is no clear time series pattern of the level of concordance.

Panel B further demonstrates the difference between the LMCN and common product market classifications. This panel provides summary statistics of the degree of correspondence between our labor market groupings and alternative industry classifications for each SIC industry sector.[13] Specifically, we group base firms according to their SIC category and calculate the fraction of each base firm's LMCs that have the same industry classification indicated by the column name. We report the average of the fraction across base firms and years. We find a higher level of correspondence for base firms in the services sector, but a much lower level of correspondence for most other sectors. For example, for base firms in the wholesale sector, only 2 percent of their LMCs belong to the same SIC3 industry. We conclude that firms' labor market competitors are significantly different from their product market rivals.

[12] Although there is a low level of concordance between the labor market competitor network and the industry classifications, two firms are still more likely to be labor market competitors if they are in the same industry.

[13] The SIC industry definitions are from its official website: https://siccode.com/en/siccode/list/directory.

III.C Cross-sectional Variation: Labor Characteristics

To assess the ability of our LMCN in capturing firms' labor market decisions, we examine its ability to explain the cross-sectional variation in base firms' demand for key labor characteristics and compare the performance to that of the existing industry classifications. We follow studies in the labor economics literature (e.g., Hershbein and Kahn, 2018) and use the skill requirements for each occupation in the job postings to measure labor characteristics demanded by firms. We summarize the skill requirements at the firm-year level. To construct our testing sample, we merge our main sample with the labor characteristics measures. Since the skill variables and LMCs are available in 2007 and 2010-2016 and we require lagged information of LMCs when merging with firm financials and skill characteristics to avoid look-ahead bias, our final sample is from 2011 to 2016.

To measure the ability of our labor market competitors in explaining the cross-sectional variation in base firms' labor characteristics, we estimate the following cross-sectional regression, for each year from 2011 to 2016:

$$Skill_{i,t} = \alpha + \beta Skill_{c,t} + \epsilon_{i,t} \tag{2}$$

where $Skill_{i,t}$ is one of the skill measures for base firm i in year t. $Skill_{c,t}$ is the average of the same skill measure of the labor market competitors of firm i in year t, where the competitor network is measured in time $t-1$. The R^2 of the regression measures the extent to which labor market competitors explain the cross-section of base firms' labor characteristics. If the labor characteristics of the competitors are similar to those of the base firms, their labor characteristics should exhibit greater contemporaneous correlation with those of the base firms. Therefore, higher R^2 reflects a greater similarity of labor demand characteristics between base firms and their competitors.[14] We first present the statistics of the R^2 using our occupation-based labor market competitors (labor-based R^2). We then compare the average R^2 produced by yearly regressions using LMCs versus the average R^2 produced by peers from the base firms' standard industries (industry-based R^2). Table 5 reports the yearly labor-based R^2 for each skill measure. We find an upward trend in the R^2 over the sample period, indicating that our LMCs have increasing power in explaining the variation of base firms' labor characteristics over time.

[14] Lee, Ma, and Wang (2015) have a thorough discussion of using the R^2 to measure and compare the economic similarity between base firms and peer firms.

Table 6 compares LMCs and industry classified peers in their ability to explain the cross-sectional variation in base firms' labor characteristics. Specifically, we regress skill measures of base firm i in a given year t on the concurrent average of the skill measure of its peers. We use all firms other than firm i in an industry indicated by the column name as the peers of firm i. The table reports the average R^2 from yearly cross-sectional regressions for each skill measure using each grouping classification. Our main comparison is between LMCs and SIC3 peers because, by construction, the granularity of the LMC is the same as that of the SIC3. The results reveal that our labor network groupings outperform SIC3 and other product market groupings in the ability to explain labor characteristics of base firms. For example, the SIC3 peers on average explain 15.2 percent of the cross-sectional variation in the percentage of job postings with education requirements ($EduRatio$). This is lower than the 21.5 percent explained by the LMCs. Similarly, LMCs explain 23 percent of the cross-sectional variation in the percentage of job postings requiring cognitive skills ($CogRatio$) of the base firms, whereas SIC3 peers only explain 16.2 percent. We also examine R^2 using other industry classifications and find similar results. Overall, the evidence strongly suggests that our occupation-based measure is more informative of the labor characteristics between the base and peer firms.

III.D Cross-sectional Variation: Financial Characteristics

The previous section shows that our occupation-based labor market competitors can better explain the cross-sectional variation in base firms' demand for key labor characteristics. In this section, we examine if our labor network groupings contain information on other firm characteristics. Bloom, Brynjolfsson, Foster, Jarmin, Patnaik, Saporta-Eksten, and Van Reenen (2017) show that human capital is a main driver of productivity. They use the share of employees with a college degree in a region to proxy for human capital. Relatedly, we focus on financial performance as it captures outcomes of employing different labor inputs. We apply a similar method and estimate the following cross-sectional regression, for every year with available data (2008, and 2011-2017):

$$Var_{i,t} = \alpha + \beta Var_{c,t} + \epsilon_{i,t} \tag{3}$$

where $Var_{i,t}$ is a measure of financial performance for base firm i in year t. $Var_{c,t}$ is the average of the same performance measure of peers of firm i in year t. In addition to LMCs, we use all firms other than firm i in the SIC3 industry as the peers of firm i. The financial performance measures are from Compustat and Appendix C has details of their definitions. We investigate two broad financial characteristic measures: firm performance (NI, OIDAP, and EBIT) and firm financial decision (R&D, IK, Leverage, and LtDebt).

Table 7 reports the results based on LMC-only, SIC3-only, and both LMC and SIC3 peers. For firm performance measures, the average R^2 from the LMC-only tests is comparable to that from the SIC3-only tests. The coefficient estimates on LMC remain statistically significant when both LMC and SIC3 are included. For example, the average R^2 for the EBIT test is 8.26 percent from the LMC-only model and the average R^2 is 11.9 percent from the SIC3-only model. For firm financial decision variables, the LMC-only model is able to explain a large portion of the cross-sectional variation of the variables, even though the average R^2 is lower than that from the SIC3-only model. The coefficient estimates on LMC are statistically significant when SIC3 is also included in the models. For example, the average R^2 is 33.1 percent for R&D from the LMC-only model and the average R^2 is 38.7 percent from the SIC3-only model. Although we do not expect to find exceptional outperformance of LMCs in explaining financial performance of base firms compared to peers based on product market classifications, we find evidence that our labor network groupings are highly informative of firms' financial characteristics.

IV Labor Links and Stock Returns

In this section, we examine the effect of labor market shocks by investigating stock price reactions of the firms. We capture the news about a firm's labor market using returns of its labor-linked firms and investigate how the news travels along the labor market network. We hypothesize and show that focal firm's returns respond positively to news about its labor market. We first show that, contemporaneously, the focal firm's returns comove strongly with its labor-linked returns. Then we show that there is a strong lead-lag structure between the focal firm's returns and its labor-linked returns. The returns of labor-linked firms strongly and positively predict the focal firm's returns – a phenomenon we refer to as "labor momentum". We hypothesize and confirm that the lead-lag structure is driven by limited investor attention. News travels slowly across assets as investors with limited attention overlook the impact of specific information on economically related firms (See Moskowitz and Grinblatt, 1999, Cohen and Frazzini, 2008, Lee, Sun, Wang, and Zhang, 2018, etc). We show that the labor momentum effect is more pronounced in firms that attract less investor attention.

IV.A Labor-Linked Return

We define labor-linked return (*LabRet*) as the average monthly return of labor-linked firms in the labor market space weighted by pairwise labor similarity. Mathematically, labor-linked return for firm i at month t is defined as:

$$LabRet_{it} = \frac{\sum_{j \neq i} Labor_{ijt} \times Ret_{jt}}{\sum_{j \neq i} Labor_{ijt}} \tag{4}$$

where Ret_{jt} is the return of firm j at month t, and $Labor_{ijt}$ is the labor similarity measure between firm i and firm j at month t. In the construction of labor-linked return, the labor similarity measure serves as a weighting function in calculating the portfolio return, so that firms closer to the focal firm in labor market space are given higher weights. Self-return is excluded from the construction in the focal firm's labor-linked return. We calculate labor similarity measure at the end of each calendar year t based on firms' labor demand profile in year t, and then match the measure to the return data of year $t + 1$. Therefore, all information including the labor similarity measure is available when the portfolios are formed. We obtain the monthly data on stock returns, stock prices, and the number of shares outstanding from the CRSP database. Data on Fama-French three-factor, Carhart four-factor, and Fama-French five-factor models are from Kenneth French's website. We use the return on the 30-day Treasury bill as the risk-free rate.

Table 8 shows the summary statistics of the variables used in this section. Panel A and Panel B of Table 8 show the descriptive statistics and contemporaneous correlation of the variables, respectively. *LabRet* has a high correlation with the contemporaneous focal firm return (39.06 percent), suggesting that *LabRet* captures a large fraction of contemporaneous stock variations. *LabRet* exhibits low correlations with a number of our traditional return predictors such as size, book-to-market, profitability, and investment rate, and its correlation with momentum is low at

3.86 percent. Its correlation with the industry return is relatively high at 10.02 percent. In the subsequent analyses, we show that the return predictability of $LabRet$ holds after controlling for these variables.

IV.B Contemporaneous Returns

We first document the effects of labor-linked returns on the contemporaneous returns of the focal firms. Table 9 reports the results. For each month, we sort all firms into quintiles based on the return earned by the labor-linked returns in the month ($LabRet_t$). These quintile portfolios are rebalanced each month to maintain either equal or value weights. Table 9 shows average contemporaneous monthly excess returns or alphas from the lowest (1) to the highest (5) quintile $LabRet_t$ portfolios, as well as the average monthly return to the hedged long-short portfolio that holds the top 20 percent of firms as ranked by $LabRet_t$ and sells short the bottom 20 percent of firms as ranked by $LabRet_t$. The excess returns are computed as raw returns minus risk-free rate, and the alphas are calculated adjusting for the corresponding factor models (CAPM, Fama-French 3-factor model, Carhart 4-factor, and Fama-French 5-factor model).

Panel A and Panel B of Table 9 report results based on equal- and value-weighted portfolios. We find large spreads in focal firm returns for both the equal-weighted and value-weighted portfolios. The returns monotonically increase from the lowest quintile to the highest quintile. For equal-weighted (value-weighted) portfolios, the lowest quintile average excess return is -1.12 percent (-1.54 percent) and the highest quintile average excess return is 1.38 percent (1.74 percent) per month. The various factor models do not alter the return spread by much. Overall, we find that focal firm returns are monotonically increasing with the labor-linked returns, suggesting that labor-linked returns contain value-relevant information about the focal firms. In summary, the focal firm is highly responsive to news about the labor market as proxied by the labor-linked returns.

Finally, we decompose the contemporaneous response of focal firm returns into the direct and network (input-output table) components. In Appendix A, we delineate and solve a model following Long and Plosser (1983) and Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) but add a layer of labor market network and allow for heterogeneous labor supply. The model shows that news about the labor market affects firms both directly and through the input-output network. Using predictions from our model and applying network econometrics similar to LeSage and Pace

(2014) and Ozdagli and Weber (2017), we decompose the contemporaneous focal firm response to a direct effect and an effect induced by the input-output network emphasized in the previous network studies. Table 10 documents the decomposition results. Depending on model specifications, the network effect contributes to 17 percent to 50 percent of the total effect. We conclude that, consistent with our model, news about the labor market not only directly affects firms on the labor market network but also travels along the input-output network that has been the focus of the network studies.

IV.C Predictive Returns

In this section, we test whether the stock market takes time to incorporate news about the labor market as proxied by the labor-linked returns of focal firms. We show that there is a strong lead-lag structure between the focal firm's returns and its labor-linked returns, consistent with the view that investors have limited attention and that labor market news transmits in the network gradually.

IV.C.1 Portfolio Analyses

Table 11 reports the main results. At the beginning of each month, we sort all firms into quintiles based on the returns earned by the labor-linked returns in the previous month ($LabRet_{t-1}$). These quintile portfolios are rebalanced at the beginning of each month to maintain either equal or value weights. Table 11 shows average monthly excess returns or alphas from the lowest (1) to the highest (5) quintile $LabRet_{t-1}$ portfolios, as well as the average monthly return to the hedged long-short portfolio that holds the top 20 percent of firms as ranked by $LabRet_{t-1}$ and sells short the bottom 20 percent of firms as ranked by $LabRet_{t-1}$. The excess returns are computed as raw returns minus risk-free rate, and the alphas are calculated adjusting for the corresponding factor models (CAPM, Fama-French 3-factor model, Carhart 4-factor, and Fama-French 5-factor model).

Panel A and Panel B of Table 11 report results based on equal- and value-weighted portfolios. Specifically, we find that the equal-weighted (value-weighted) hedged portfolio yields average monthly excess returns ($XRet$) of 78 basis points (80 basis points), or 9.36 percent (9.60 percent) per year. Both the equal-weighted and value-weighted hedged portfolio average excess returns are significant at the 5 percent level. In the next four columns, we control for the known factors. The hedged long-short strategy delivers CAPM abnormal returns of 84 basis points (92 basis points) per month in the equal-weighted (value-weighted) portfolios. The same strategy delivers Fama-French 3-factor model adjusted alphas of 83 basis points (89 basis points) per month in equal-weighted (value-weighted) portfolios. Augmenting this model by adding the momentum factor generates abnormal returns of 84 basis points (85 basis points) per month in equal-weighted (value-weighted) portfolios. Finally, we use the Fama-French 5-factor model. The 5-factor adjusted alphas are 70 basis points (67 basis points) per month in the equal-weighted (value-weighted) long-short portfolios. These results show that high labor-linked returns are followed by high subsequent returns, even controlling for common risk factors.

Table 12 reports the factor loadings of the portfolios on the Carhart 4-factor and Fama-French 5-factor models in Panel A and Panel B, respectively. We show the results based on both equal-weighted and value-weighted portfolios. In Panel A, the hedged long-short portfolio has a significant and negative loading on the market excess returns (MKTRF). In other words, the strategy performs well when the market performs poorly. The long-short portfolio has small and insignificant loadings on the SMB, HML, and MOM factors, suggesting that the labor momentum is a distinct phenomenon from these documented factors. Even controlling for these risk exposures, the labor momentum strategy produces significant monthly alphas. In fact, the Carhart 4-factor adjusted alphas are slightly larger than the baseline unadjusted excess returns. In Panel B, the hedged long-short portfolio has insignificant loadings on all five factors, suggesting that the labor momentum is a distinct phenomenon from these documented factors. Controlling for these risk exposures, the labor momentum strategy produces significant monthly alphas.

We further investigate the exposures of our labor momentum strategy to the existing momentum strategies. Table 13 reports the results. Controlling for the market, the labor momentum strategy has significant exposures to the industry momentum strategies but not to the self momentum strategy or the customer momentum strategy. The alphas remain highly statistically significant and economically large in all specifications. The alpha drops by about 10 percent controlling for the industry momentum strategies. The results show that the labor momentum phenomenon is distinct from the existing momentum strategies.

IV.C.2 Cross-Sectional Analyses

In this section, we test the lead-lag structure between the focal firm returns and its labor-linked returns in a regression framework and control for a number of known cross-sectional return predictors documented in the literature. Specifically, we conduct Fama and MacBeth (1973) regressions where the dependent variable is the return of the focal firm in month t (Ret_t). The main independent variable of interest is the return of the focal firm's labor-linked firms in month $t-1$ ($LabRet_{t-1}$). We include the industry return ($IndRet_{t-1}$) based on the industry definition of Hoberg and Phillips (2016) as an independent variable to control for the industry momentum effect documented in Moskowitz and Grinblatt (1999) and Hoberg and Phillips (2018). A short-term self-return variable (Ret_{t-1}) – defined as the focal firm's stock return in month $t-1$ – is included to control for the short-term reversal effect documented in Jegadeesh, 1990, and a medium-term price momentum variable (Mom) – defined as the focal firm's stock return for the last 12 to last 1 month – is included to control for the firm momentum effect documented in Jegadeesh and Titman (1993). Other control variables include lagged size, book-to-market ratio, profitability, and capital investment rate. All explanatory variables are assigned to deciles ranging from 0 to 1, and the cross-sectional regressions are run each calendar month following the Fama and MacBeth (1973) procedure.

Table 14 reports the results of the cross-sectional regressions. Column (1) reports the baseline result where the independent variable is $LabRet_{t-1}$. Consistent with the time-series portfolio tests, $LabRet_{t-1}$ is a strong predictor of the focal firm's return in the next month. The magnitude of the point estimate is comparable to the portfolio test: the coefficient of 0.811 indicates that the average monthly return spread of the focal firms in the top and bottom deciles is 81.1 basis points. In Column (2), we include $IndRet_{t-1}$ and Ret_{t-1} in the cross-section regression. The point estimate of $LabRet_{t-1}$ is stable at 0.790 from the baseline univariate result (0.811). Column (3) includes Mom in the baseline regression, and the point estimate of $LabRet_{t-1}$ remains similar to the baseline case at 0.837. Column (4) includes $IndRet_{t-1}$, Ret_{t-1}, and Mom, and the coefficient of $LabRet_{t-1}$ is slightly below the baseline case at 0.805. In Column (5), we include size, book-to-market, profitability, and investment rate as control variables. The coefficient of $LabRet_{t-1}$ decreases slightly to 0.698 but stays statistically significant. The results with all the controls are reported in Column (6), and the point estimate on $LabRet_{t-1}$ is statistically significant at 0.685. The economic magnitude remains large across all specifications.

IV.C.3 Limited Investor Attention

In this part, we explore the mechanism of the labor momentum phenomenon and test the hypothesis that the labor momentum effect is driven by limited investor attention. If investors have limited attention, it may take time for the market to incorporate fundamental information into prices. We would expect to find a stronger effect for firms that receive less attention. We use three measures that are documented in the literature to proxy for investor attention: firm size, number of analysts following, and institutional ownership. We hypothesize that small firms, firms with few analysts following, and firms with low institutional ownership receive less attention from investors. Therefore, there should be a stronger labor momentum effect in these firms.

To test the predictions, we partition our sample based on firm size, number of analysts following, and institutional ownership. Specifically, we define a size indicator variable that equals one if a focal firm is above the sample median in the previous month in size. Similarly, we define an analyst coverage indicator variable that equals one if a focal firm is above the sample median in the previous month in its number of analysts following and we define an institutional ownership indicator that equals one if a focal firm is above the sample median in the previous fiscal-year end in its institutional ownership.

We form quintile portfolios as in the baseline analyses but within each subsample based on each indicator variable. We expect to see that the long-short hedge portfolio spreads are larger in the small size, low analyst coverage, and low institutional ownership subsamples. We report the results in Table 15. Consistent with our predictions, the long-short hedge strategy returns are much larger in the small size, low analyst coverage, and low institutional ownership subsamples. For example, the baseline strategy return is 94 basis points per month in the small size subsample but is only 46 basis points per month in the large size subsample. Similarly, the baseline strategy returns are 95 and 93 basis points in the low analyst coverage and low institutional ownership subsamples, respectively. However, they are only 64 and 50 basis points in the high analyst coverage and high institutional ownership subsamples, respectively. The results support the hypothesis that the labor momentum effect is driven by limited attention to labor market news and linkages.

V Transmission of Industry Shocks along Labor Network

The large difference between labor market competitors and product market rivals allows us to study the impact of industry shocks on labor market competitors. Specifically, identifying both the labor market location of a firm and the identity of its rivals, we examine how the labor market network relates to the product market. The industry shock we exploit is the recent financial crisis, which severely injured the financial industry. Immediately after the financial crisis, the financial industry significantly downsized, leading to a large outflow of unemployed workers with finance-related skills. Moreover, because college students determine their majors several years in advance to their graduation, these students faced difficulty in landing a financial industry job when the financial industry could no longer absorb them. These two effects lead to an increase in the unemployed finance-related workers looking for jobs after the crisis.

Recent studies show that the financial crisis affected firms' workforce structures. Hershbein and Kahn (2018) examine how the demand for skills changed over the financial crisis. They find that skill requirements in job postings differentially increased in the MSAs that were hit hard by the crisis, relative to the less hard-hit areas. They argue that recessions lower the opportunity cost for firms to restructure their business. Modestino, Shoag, and Ballance (2016) show that employers decreased the skill requirements as the labor market improved from 2010-2014 and conclude that firms opportunistically upskilled after the crisis. We hypothesize that, subsequent to the financial crisis, the financial firms' non-financial labor market competitors would benefit from the large inflow of finance-related workers. In particular, non-financial firms with high labor similarity to the financial firms would differentially increase their skill requirements in job postings after the crisis, relative to non-financial firms with low labor similarity to the financial industry.

In practice, we use the recent financial crisis as a shock to the financial industry and apply a difference-in-differences methodology to examine whether industry shocks affect firms' labor structures along the labor market competitor network. We construct a treatment group consisting of non-financial firms that are close to the financial firms (SIC codes in the range of 6000–6999) in the network. Our control group consists of the other non-financial firms. In particular, for a given non-financial firm in 2007, we calculate its total similarity score to the financial industry (FinScore) as the sum of its labor similarity score with each financial firm. The score measures a firm's labor market exposure to the financial industry. Higher total similarity score indicates higher overlap of occupations demanded by an industrial firm and firms in the financial industry. Specifically:

$$FinScore_{i,2007} = \sum_{j \in financialindustry} Labor\ Similarity_{i,j} \tag{5}$$

A firm is in the treatment group if its FinScore is above the sample median. We create an indicator variable "Treat" that equals 1 for treatment firms and 0 otherwise. In the Appendix, we compare the industry distribution of the treatment and control firms and find that the industry distributions of the two groups are similar. The treatment firms have a larger share of the information, business, and retail industries compared to the control firms. Our empirical strategy is to compare changes in skill requirements between treatment firms (those with above median FinScore) and control firms (those with below median FinScore). Specifically, we estimate the following regression:

$$Skill_{i,t} = \alpha + \beta Post_t * Treat_i + \theta_t + \gamma_i + \epsilon_{i,t} \tag{6}$$

where $Skill_{i,t}$ is a skill measure for base firm i in year t. Post is an indicator variable that equals 1 for years after 2010, and 0 otherwise. We interact Post with Treat so that the interactive variable equals 1 for treatment firms after the financial crisis. θ_t and γ_i are the time and firm fixed effects, respectively.

V.A Baseline Results

Table 16 presents the results that are estimated for the period of 2007-2010. We compare changes in skill requirements between firms with above median FinScore and others, from one year before to one year after the crisis.[15] All tests include firm fixed effects to remove any firm-specific time-invariant omitted variables that can be correlated with firm policies and skill requirements. We also control for year fixed effects to remove any economy-wide macroeconomic shocks that may affect the results. We find that the coefficient estimates of most interactions of Treat and Post are positive and statistically significant at the 1 percent level. In other words, the skill requirements of job postings increase in the non-financial firms that are closer to the financial industry in the labor market network, relative to the pre-crisis level and other non-financial firms. For example, Column

[15]Because we include firm fixed effects, the shorter period regression only includes firms with available data both before and after the crisis.

1 of Panel A shows that the coefficient estimate of $Post * Treat$ is 0.044. Therefore, relative to the 2007 level, the probability of specifying an education requirement of at least a bachelor degree in job postings increases by 4.4 percent in 2010 for firms in the treatment group compared to the firms in the control group. This difference-in-differences estimate implies an increase of 20.0 percent of the average requirements in 2007 and is significant at the 1 percent level. Column 2 of Panel A shows that, relative to the 2007 level, the probability of specifying an experience requirement of at least 5 years increases by 2.1 percent (17.5 percent of 2007 level) in 2010 for firms in the treatment group compared to the control firms. Remarkably similar patterns can be found for other skill requirements.

In Panel B, we use the continuous FinScore measure instead of the indicator variable. We standardize the FinScore so that the coefficient estimates correspond to a one-standard-deviation increase of FinScore. We find similar results using the continuous measure compared to the indicator variable approach. Overall, our results are consistent with our hypothesis that following the financial crisis, financial firms' non-financial labor market competitors benefit from the large inflow of finance-related workers than other industrial firms. In particular, non-financial firms with high labor similarity to the financial firms increase their skill requirements in job postings following the crisis.

To further test the dynamics of the changes in skill requirements, we obtain yearly estimates of the change in the skill requirements of financial-like industrial firms relative to control firms following the crisis from 2010 to 2016. Specifically, we create indicator variables for each year after the crisis and interact Treat with each year indicator. Then, we regress the skill requirements on the interactions of Treat and year indicators. Each interaction tests the difference of skill requirements between the treatment and control firms relative to the difference of 2007. Table 17 reports the results. In the early years, the majority of the coefficient estimates of the interactions are positive and significant at the 1 percent level. The point estimates and the significance levels decrease gradually over the years. Figure 3 presents the coefficient estimates of the interactions of Treat and year indicators. In the top left graph, we find that relative to the 2007 level, the probability of specifying an education requirement increases by 4.6 percent in 2010 for the treatment firms compared to other firms. The effect persists at fairly similar magnitudes and significance levels for the subsequent years, with a small dip in 2013. In 2016, we estimate that the probability of posting an education requirement is 3.2 percent larger than it was in 2007 for the treatment firms compared to the control firms. About 70 percent of the differential upskilling effect in 2010 remains six years later. The other graphs exhibit varies patterns in both the magnitudes and statistical significance. The probability of listing a cognitive requirement increases by 3.8 percent between 2007 and 2010 for the treatment firms compared to the control firms. Only about 37 percent of this increase remains in 2016 and is not statistically significant. The pattern for computer skill requirement is in stark contrast to the cognitive-related ones. The probability of listing a computer skill requirement does not change significantly between treatment and control groups. The different patterns largely reflect the fact that many firms in the treatment group are technology companies demanding more cognitive skills than computer skills. Furthermore, we see a large difference between the treatment and control firms right after the crisis. The difference gradually decreases in later periods. Thus financial firms' industrial labor market competitors benefit more from the large inflow of finance-related workers during the early period following the crisis, and the benefit reduces as financial firms gradually recover from the crisis.

In the Appendix, we plot the average of the different skill requirements for the treatment and control groups over time. Each point represents one quarter. Before the financial crisis, the skill requirements for the treatment and control groups are close to each other, suggesting parallel trends in the skill requirements of the two groups in the pre-crisis period. After the financial crisis, the skill requirements for both the treatment and control groups increase, confirming the "upskilling" results found in Hershbein and Kahn (2018) and Ballance, Modestino, and Shoag (2016). Consistent with the coefficient estimates before, the increase in skill requirements is larger for the treatment group compared to the control group, suggesting that high FinScore firms upskill more relative to low FinScore firms after the financial crisis.

V.B Firm Performance

So far we have shown that financial firms' industrial labor market competitors benefit and upskill more from the large inflow of finance-related workers than other industrial firms. Next, we examine if this upskilling is accompanied with benefits measured as better financial performance. Table 18 compares the performance of the treatment firms to that of the control firms, before and after the financial crisis. Specifically, we regress performance measures on $Post * Treat$ or $Post * FinScore$ for 2005-2012 excluding 2008 and 2009. Therefore, we compare the average change in performance from three years before the crisis to three years after. The difference-in-differences estimates suggest that the treatment firms perform better than the other firms subsequent to the crisis, indicating that the upskilling is accompanied with better performance.

Next, we shift to firms' corporate decisions, where we focus on research and development (R&D), physical investment, leverage, and long-term debt. We regress each of the variables on $Post*Treat$ or $Post*FinScore$ for 2005-2012 excluding 2008 and 2009. Table 19 documents the results. We find that, compared to the control firms, the treatment firms differentially decrease both the R&D and physical investment after the crisis. This is in contrast to the common belief that R&D investment should be coupled with upskilling. For example, Machin and Van Reenen (1998) show a significant positive association between skill upgrading and R&D intensity in seven OECD countries. In untabulated tests, we also find an unconditional positive association between R&D and all skill-requirement measures in our sample. The differential relation with investment between treatment and control firms following the crisis suggests a substitution effect between labor and capital investments. In Table 19, we also find that the treatment firms increase their leverage and long-term debt significantly more than the control firms after the crisis. Taken together, the treatment firms allocate resources to upgrade skills and spend less on capital investments. These firms also borrow more to finance the "upskilling".

The results in this section highlight the difference between our labor market competitor network and the traditional industry classification. If the labor market competitor network just captures exposures to the same industry shock, we would expect the firms linked to the financial firms to be heavily affected by the financial crisis. Therefore, these firms should have worse performance after the crisis, similar to the financial firms. We find that the opposite is true in the data: the non-financial firms that are close to the financial industry have better performance after the crisis. A simple industry exposure story cannot explain the findings.

Overall, our results suggest that the negative shock to the financial industry leads to an upgrade in skill requirements of rival industrial firms in the labor market. We show that the product market can affect labor structures of firms through the labor market network. We also find that the differential upskilling of the industrial firms leads to better firm performance and affect firms' corporate decisions.

VI Conclusion

This paper builds a novel measure of labor market competitors and highlights the importance of labor market structure in transmitting both the labor market and industry shocks. We exploit detailed labor demand information of firms to determine firm pairwise labor similarities. Our measure is firm-centric and updates every year. Each firm has its own unique set of competitors in the labor market. Our method relaxes the transitivity restriction common in industry classifications. We show that firms share a distinct group of labor market competitors relative to their product market rivals: the overlap is less than 20 percent. Our labor market competitor network explains a large fraction of the cross-sectional variation in firms' labor characteristics and performance.

We apply the labor market network in two applications and show that labor and industry shocks transmit along the network. Firstly, we examine the implications of labor market similarity for stock price discovery and stock returns. News about a firm's labor market is proxied by the monthly returns of its competitors (labor-linked return). We find that the returns of labor-linked firms have strong predictive power for the focal firm's returns. A hedged long-short strategy generates an equal-weighted (value-weighted) average monthly excess returns of 78 basis points (80 basis points), or 9.36 percent (9.60 percent) per year.

Secondly, the labor market competitor network enables us to study the transmission of industry shocks on the labor market. Using the recent financial crisis as a shock to the financial industry, we find that the non-financial firms are differentially affected based on their distance to the financial industry in the labor market network. The non-financial firms that are closer to the financial industry take advantage of the abundance of finance-related workers and upskill considerably more than firms farther away in the labor market network. Moreover, these finance-like industrial firms perform better compared to the other firms. Our labor market competitor network suggests channels through which product market shocks affect the labor market.

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Tables & Figures

Table 1: Representativeness of Burning Glass Technologies

Industry	# of Postings	# of Firms		Fraction
	BGT	BGT	Comp	BGT/Comp
Mining & Logging	452,639	97	224	43.30%
Construction	212,650	46	66	69.70%
Durable Goods	4,323,218	777	1108	70.13%
Non-Durable Goods	2,530,081	486	781	62.23%
Wholesale Trade	824,651	85	119	71.43%
Retail Trade	6,725,825	159	200	79.50%
Trans, Ware, and Util	1,418,972	100	176	56.82%
Information	3,738,519	407	635	64.09%
Finance and Insurance	5,818,988	556	905	61.44%
Real Estate & Rental	1,290,848	135	239	56.49%
Prof & Business	2,258,408	195	262	74.43%
Educational Services	123,767	15	28	53.57%
Health Care & Soc Assist	2,272,799	65	86	75.58%
Arts, Ent, & Rec	166,953	25	36	69.44%
Acco & Food	3,096,124	68	93	73.12%
Other Services	78,691	10	13	76.92%
Total	35,333,133	3,226	4,971	64.90%

Note: This table reports the summary statistics for the sample of job postings of firms listed on the major stock exchanges. The firms are grouped into 16 two-digit NAICS industries. The table also reports the distribution of Compustat firms across the same 16 industries. Appendix A has the definition of the industries.

Table 2: Skill Requirements by Year

Average Skill Requirement							
Year	EduRatio	ExpRatio	ComRatio	CogRatio	MeanEdu	MeanExp	MeanSkill
2007	0.22	0.12	0.23	0.14	5.01	1.31	4.81
2010	0.31	0.18	0.35	0.20	7.90	1.97	8.51
2011	0.34	0.20	0.40	0.23	8.54	2.10	9.32
2012	0.35	0.21	0.41	0.25	8.94	2.16	9.98
2013	0.31	0.18	0.37	0.22	8.22	1.87	9.36
2014	0.29	0.16	0.34	0.20	8.01	1.69	9.11
2015	0.31	0.18	0.37	0.20	8.48	1.92	9.55
2016	0.28	0.17	0.35	0.19	8.10	1.78	9.19

Note: This table reports summary statistics of skill requirements of job postings by year. Variable definitions are in Appendix C.

Table 3: Summary Statistics

Panel A: Base Firm Distribution			
Year	Freq.	Percent	Cum.
2007	1,774	10.75	10.75
2010	2,147	13.02	23.77
2011	2,222	13.47	37.24
2012	2,283	13.84	51.08
2013	2,479	15.03	66.11
2014	2,361	14.31	80.42
2015	2,198	13.32	93.74
2016	1,032	6.26	100
Total	16,496	100	

Panel B: Competitor Distribution						
Mean	SD	Min	25th	Med	75th	Max
67.8	75.87	3	16	39	89	399

Note: This table reports summary statistics of the main sample. Panel A shows the number of unique base firms each year. Panel B shows statistics on the number of labor market competitors for each base firm. Variable definitions are in Appendix C.

Table 4: Overlap with Product Market

Panel A: Correspondence by year

Year	SIC2	SIC3	NAICS3	NAICS4	GICS4	GICS6
2007	0.239	0.160	0.189	0.120	0.264	0.159
2010	0.202	0.129	0.150	0.093	0.219	0.134
2011	0.209	0.138	0.154	0.099	0.234	0.145
2012	0.215	0.142	0.159	0.102	0.242	0.147
2013	0.241	0.167	0.179	0.122	0.271	0.164
2014	0.245	0.169	0.184	0.126	0.280	0.172
2015	0.238	0.165	0.180	0.123	0.273	0.165
2016	0.235	0.152	0.169	0.100	0.262	0.136
Average	0.228	0.153	0.170	0.111	0.256	0.153

Panel B: Correspondence by SIC groupings

SIC Groupings	SIC2	SIC3	NAICS3	NAICS4	GICS4	GICS6
Agri, Forestry, Fishing	0.003	0.003	0.014	0.003	0.107	0.080
Mining	0.157	0.136	0.158	0.147	0.244	0.191
Construction	0.168	0.159	0.153	0.146	0.287	0.199
Manufacturing	0.201	0.121	0.215	0.121	0.231	0.132
Trans & Public Utilities	0.185	0.099	0.104	0.083	0.214	0.143
Wholesale Trade	0.092	0.021	0.080	0.019	0.157	0.078
Retail Trade	0.153	0.123	0.140	0.121	0.309	0.247
Services	0.375	0.284	0.136	0.105	0.327	0.172
Public Administration	0.007	0.007	0.014	0.008	0.161	0.054

Note: This table presents the correspondence in the product market classifications of our occupation-based labor groupings. Panel A shows the average fraction of labor market competitors (LMCs) belonging to the same industry as the base firms for different industry classification. Specifically, for each base firm in each year, we calculate the fraction of its labor market competitors that have the same industry as the base firms for the industry classification indicated by the column name. The number presented is the average of the fractions across base firms in each year. Panel B provides summary statistics of the degree of correspondence between our labor market groupings and alternative industry classifications for each SIC industry sector. The SIC industry definitions are from its official website: https://siccode.com/en/siccode/list/directory. Specifically, we group base firms according to their SIC category and calculate the fraction of each base firm's LMCs that have the same industry classification indicated by the column name. We report the average of the fractions across base firms and years. The SIC, NAICS and GICS classifications are all as of 2017.

Table 5: **Skill Requirements and Time-Series R-Squared Values**

Year	# base firms	EduRatio	ExpRatio	ComRatio	CogRatio	MeanEdu	MeanExp	MeanSkill
2011	2,068	0.236	0.184	0.184	0.181	0.130	0.176	0.176
2012	2,067	0.275	0.197	0.215	0.182	0.183	0.188	0.171
2013	2,206	0.334	0.238	0.276	0.214	0.212	0.236	0.239
2014	2,366	0.404	0.303	0.263	0.261	0.268	0.310	0.229
2015	2,273	0.392	0.285	0.274	0.252	0.246	0.298	0.239
2016	2,088	0.398	0.286	0.286	0.287	0.250	0.295	0.233

Note: This table reports the R^2 values from cross-sectional regressions of the form

$$Skill_{i,t} = \alpha + \beta Skill_{c,t} + \epsilon_{i,t} \tag{7}$$

for each year of 2011-2016. Specifically, we regress a skill measure of base firm i in a given year t on the concurrent average of the same skill measure of the labor market competitors of firm i in year t. We match firm pairs of year t with skill measures and Compustat data of year $t+1$. Each column name indicates the skill measure used in the regression. The second column reports the number of base firms used in each regression. Variable definitions are in Appendix C and all continuous variables are winsorized at the 1st and 99th percentiles.

Table 6: Skill Requirements and R-Squareds Comparison

Var	Obs	LMC	SIC2	SIC3	NAICS3	NAICS4	GICS4	GISC6
EduRatio	13,068	0.215	0.140	0.152	0.146	0.142	0.130	0.172
ExpRatio	13,068	0.250	0.205	0.213	0.208	0.197	0.195	0.233
ComRatio	13,068	0.215	0.188	0.179	0.184	0.167	0.158	0.192
CogRatio	13,068	0.230	0.144	0.162	0.147	0.155	0.142	0.186
MeanExp	13,068	0.289	0.215	0.233	0.232	0.223	0.187	0.252
MeanEdu	13,068	0.358	0.289	0.303	0.304	0.296	0.259	0.330
MeanSkill	13,068	0.365	0.291	0.308	0.309	0.296	0.252	0.329

Note: This table compares the average R^2 from yearly cross-sectional regressions of the form

$$Skill_{i,t} = \alpha + \beta Skill_{c,t} + \epsilon_{i,t} \tag{8}$$

for each skill measure from 2011 to 2016. Specifically, we regress a skill measure of base firm i in a given year t on the concurrent average of the same skill measure of its peers. We match firm pairs of year t with skill measures and Compustat data of year t+1. All regressions are conducted using the same underlying set of base firms. Each column name indicates the grouping classification used to define the peer firms. Column LMC uses the occupation-based labor market competitors as the peer firms of a base firm. In the other industry categories (e.g., SIC3), the peer firms of a base firm are all other base firms in the same industry. Each row reports average R^2 for a different variable. Variable definitions are in Appendix C and all continuous variables are winsorized at the 1st and 99th percentiles.

Table 7: Firm Financial Characteristics Comparison

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	NI	NI	NI	OIDAP	OIDAP	OIDAP	EBIT	EBIT	EBIT
LMC	0.605		0.418	0.012		0.009	0.694		0.491
	(0.165)		(0.097)	(0.003)		(0.002)	(0.156)		(0.090)
SIC3		0.543	0.426		0.612	0.588		0.647	0.507
		(0.129)	(0.098)		(0.118)	(0.122)		(0.122)	(0.095)
Obs.	15,663	15,362	15,362	15,662	15,361	15,361	15,663	15,362	15,362
R-Squared	0.0518	0.0733	0.0901	0.0147	0.0789	0.0888	0.0826	0.119	0.146

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
	R&D	R&D	R&D	IK	IK	IK	Leverage	Leverage	Leverage	LtDebt	LtDebt	LtDebt
LMC	1.195		0.679	0.876		0.443	0.781		0.480	0.786		0.487
	(0.024)		(0.028)	(0.012)		(0.021)	(0.027)		(0.031)	(0.027)		(0.034)
SIC3		0.962	0.667		0.826	0.649		0.674	0.566		0.671	0.566
		(0.004)	(0.023)		(0.010)	(0.015)		(0.012)	(0.014)		(0.012)	(0.013)
Obs.	16,496	16,208	16,208	16,308	16,017	16,017	16,496	16,208	16,208	16,420	16,131	16,131
R-Squared	0.331	0.387	0.457	0.145	0.219	0.246	0.0683	0.123	0.147	0.0683	0.125	0.149

Note: This table compares the average R^2 from yearly cross-sectional regressions of the form

$$Var_{i,t} = \alpha + \beta Var_{c,t} + \epsilon_{i,t} \tag{9}$$

using financial data from Compustat for each year with available data (2008, and 2011-2017). Specifically, we regress financial measures of base firm i in a given year t on the concurrent average of the financial measure of its peers. We match firm pairs of year t with financial measures of year $t+1$. For a given variable, all regressions are conducted using the same underlying set of base firms. Each column name indicates the grouping classification used to define the peer firms. Column LMC uses the occupation-based labor market competitors as the peer firms of a base firm. In the SIC3 industry category, the peer firms of a base firm are all other firms in the same industry. Variable definitions are in Appendix C and all continuous variables are winsorized at the 1st and 99th percentiles. Coefficient estimates, standard errors, and the average R-squareds are reported in the table.

Table 8: Summary Statistics of Labor Momentum

Panel A: Descriptive Statistics

	Mean	Sd	10%	Median	90%
LabRet (%)	0.48	5.11	-5.92	1.13	6.18
IndRet (%)	0.69	8.17	-8.50	1.08	9.01
Ret (%)	0.35	12.52	-13.77	0.42	13.93
Mom	0.07	0.45	-0.47	0.10	0.56
Size	7.06	2.01	4.38	7.05	9.72
BM	2.06	1.45	0.95	1.59	3.75
Prof	0.00	0.23	-0.12	0.02	0.09
IK	0.01	0.01	0.00	0.01	0.03

Panel B: Correlation Matrix

	LabRet	IndRet	Ret	Mom	Size	BM	Prof	IK
LabRet	1							
IndRet	0.1002	1						
Ret	0.3906	0.0467	1					
Mom	0.0386	0.2234	0.0198	1				
Size	0.0045	0.0161	0.0051	0.1868	1			
BM	-0.0015	0.0163	-0.0088	0.2434	0.1681	1		
Prof	0.0008	0.0021	0.0008	-0.0011	0.0003	-0.0027	1	
IK	-0.002	-0.0269	-0.02	-0.0207	0.0778	-0.0059	0.0024	1

Note: This table presents summary statistics for the variables used in the labor momentum section. The sample includes all NYSE/AMEX/NASDAQ-listed securities. Financial firms and utility firms are excluded from the sample. Panel A reports the descriptive statistics of the variables. Panel B reports the pairwise correlation of the variables. Variable definitions are in the Appendix C.

Table 9: Contemporaneous Response to Labor-linked Returns

Panel A: Equal-Weighted (%)					
Quintile	XRet	CAPM	3-Fac	4-Fac	5-Fac
1	-1.12	-1.64	-1.54	-1.50	-1.43
(Low)	(0.71)	(0.29)	(0.22)	(0.22)	(0.23)
2	-0.11	-0.59	-0.52	-0.48	-0.52
	(0.63)	(0.19)	(0.13)	(0.13)	(0.14)
3	0.24	-0.23	-0.16	-0.08	-0.08
	(0.61)	(0.18)	(0.12)	(0.11)	(0.13)
4	0.76	0.29	0.36	0.41	0.36
	(0.61)	(0.17)	(0.12)	(0.11)	(0.12)
5	1.38	0.92	1.02	1.11	1.30
(High)	(0.63)	(0.26)	(0.19)	(0.19)	(0.19)
High - Low	2.50	2.56	2.45	2.61	2.72
	(0.30)	(0.30)	(0.29)	(0.30)	(0.31)
Panel B: Value-Weighted (%)					
Quintile	XRet	CAPM	3-Fac	4-Fac	5-Fac
1	-1.54	-2.02	-1.99	-1.91	-2.00
(Low)	(0.66)	(0.31)	(0.29)	(0.29)	(0.31)
2	-0.16	-0.57	-0.57	-0.57	-0.61
	(0.56)	(0.22)	(0.22)	(0.23)	(0.23)
3	0.59	0.23	0.23	0.28	0.21
	(0.47)	(0.13)	(0.14)	(0.13)	(0.15)
4	1.22	0.85	0.88	0.91	0.83
	(0.48)	(0.15)	(0.14)	(0.14)	(0.15)
5	1.74	1.41	1.43	1.44	1.44
(High)	(0.46)	(0.21)	(0.20)	(0.21)	(0.22)
High - Low	3.28	3.34	3.42	3.36	3.44
	(0.40)	(0.36)	(0.37)	(0.37)	(0.39)

Note: This table reports contemporaneous excess returns for each of the labor-linked return portfolios. The table reports calendar-time portfolio abnormal returns. To construct the table, firms are ranked and assigned into quintile portfolios at the beginning of every calendar month, based on the contemporaneous returns to a portfolio of their labor-linked firms (LabRet). All stocks are equal-weighted within a given portfolio in Panel A and value-weighted in Panel B. Portfolios are rebalanced every calendar month to maintain the weights. Financial and utility firms are excluded. Excess return (XRet) is the raw return of the portfolio minus the risk-free rate. Alpha is the intercept from a regression of monthly excess returns on factor returns. Factor returns are from the Kenneth French website, and the factor models include the CAPM, the Fama-French 3-factor, the Carhart 4-factor, and the Fama-French 5-factor models. High/Low is the hedged long-short portfolio that holds the top 20 percent stocks ranked by LabRet and sells short the bottom 20 percent. Returns and alphas are in monthly percentage, and standard errors are shown in parentheses.

Table 10: Contemporaneous Network Response to Labor-linked Returns

(Percentage)	Direct-Only (1)	Baseline (2)	Industry-Demeaned (3)	Zero-Diagonal (4)
Panel A: Point Estimates				
β	2.81	1.03	2.15	2.37
	(0.35)	(0.30)	(0.39)	(0.32)
ρ		0.92	0.77	0.31
		(0.07)	(0.08)	(0.04)
Adj R-Squared	0.17	0.20	0.19	0.18
Obs	121,090	121,090	121,090	121,090
Panel B: Decomposition				
Direct Effect		1.05	2.18	2.38
Network Effect		1.05	1.54	0.48
Total Effect		2.10	3.72	2.86
Direct Effect		50%	59%	83%
Network Effect		50%	41%	17%

Note: This table reports the results of regressing firm returns on the contemporaneous labor-linked return, LabRet, and the input-output network-weighted average of firm returns. Column (1) reports estimates without the input-output network-weighted average of firm returns. Columns (2)-(4) report different variations of the baseline specifications. LabRet is assigned to deciles ranging from 0 to 1. Returns are in monthly percentage and standard errors are shown in parentheses.

Table 11: Lead-Lag Returns Portfolio Analysis

Quintile	XRet	CAPM	3-Fac	4-Fac	5-Fac
Panel A: Equal-Weighted (%)					
1	-0.11	-0.63	-0.62	-0.49	-0.43
(Low)	(0.65)	(0.27)	(0.23)	(0.21)	(0.23)
2	0.31	-0.18	-0.18	-0.10	-0.08
	(0.60)	(0.19)	(0.14)	(0.13)	(0.14)
3	0.52	0.05	0.07	0.13	0.17
	(0.57)	(0.19)	(0.12)	(0.12)	(0.12)
4	0.53	0.06	0.07	0.15	0.15
	(0.57)	(0.19)	(0.12)	(0.10)	(0.12)
5	0.67	0.21	0.21	0.35	0.27
(High)	(0.59)	(0.27)	(0.20)	(0.18)	(0.21)
High - Low	0.78	0.84	0.83	0.84	0.70
	(0.29)	(0.29)	(0.29)	(0.30)	(0.30)
Panel B: Value-Weighted (%)					
Quintile	XRet	CAPM	3-Fac	4-Fac	5-Fac
1	-0.14	-0.59	-0.63	-0.61	-0.57
(Low)	(0.57)	(0.24)	(0.24)	(0.24)	(0.25)
2	0.36	-0.06	-0.09	-0.10	-0.05
	(0.50)	(0.15)	(0.15)	(0.15)	(0.15)
3	0.60	0.22	0.19	0.18	0.23
	(0.47)	(0.16)	(0.16)	(0.16)	(0.16)
4	0.46	0.09	0.05	0.05	0.06
	(0.45)	(0.14)	(0.13)	(0.13)	(0.14)
5	0.67	0.34	0.26	0.24	0.11
(High)	(0.45)	(0.24)	(0.22)	(0.23)	(0.23)
High - Low	0.80	0.92	0.89	0.85	0.67
	(0.38)	(0.35)	(0.36)	(0.36)	(0.37)

Note: This table reports abnormal returns for the labor momentum strategy. The table reports calendar-time portfolio abnormal returns. To construct the table, firms are ranked and assigned into quintile portfolios at the beginning of every calendar month, based on the prior-month return to a portfolio of their labor-linked firms (LabRet). All stocks are equal-weighted within a given portfolio in Panel A and value-weighted in Panel B. Portfolios are rebalanced every calendar month to maintain the weights. Financial and utility firms are excluded. Excess return (XRet) is the raw return of the portfolio minus the risk-free rate. Alpha is the intercept from a regression of monthly excess return on factor returns. Factor returns are from the Kenneth French website, and the factor models include the CAPM, the Fama-French 3-factor, the Carhart 4-factor, and the Fama-French 5-factor models. High/Low is the hedged long-short portfolio that holds the top 20 percent stocks ranked by LabRet and sells short the bottom 20 percent. Returns and alphas are in monthly percentage, and standard errors are shown in parentheses.

Table 12: Factor Loadings

Panel A: Carhart 4-Factor Loadings						
Equal-Weighted						
Quintile	ALPHA	MKTRF	SMB	HML	MOM	Adj. R-Squared
1	-0.49	1.13	0.71	-0.19	-0.26	0.90
(Low)	(0.21)	(1.13)	(0.71)	(-0.19)	(-0.26)	
2	-0.10	1.12	0.60	-0.14	-0.15	0.96
	(0.13)	(0.03)	(0.06)	(0.05)	(0.04)	
3	0.13	1.05	0.65	-0.10	-0.13	0.96
	(0.12)	(0.03)	(0.06)	(0.05)	(0.04)	
4	0.15	1.04	0.66	-0.18	-0.17	0.97
	(0.10)	(0.03)	(0.05)	(0.04)	(0.03)	
5	0.35	0.94	0.87	-0.28	-0.29	0.92
(High)	(0.18)	(0.05)	(0.08)	(0.07)	(0.06)	
High - Low	0.84	-0.19	0.17	-0.09	-0.03	0.03
	(0.30)	(0.08)	(0.14)	(0.12)	(0.10)	
Value-Weighted						
Quintile	ALPHA	MKTRF	SMB	HML	MOM	Adj. R-Squared
1	-0.61	1.14	0.18	-0.22	-0.03	0.83
(Low)	(0.24)	(0.07)	(0.11)	(0.10)	(0.08)	
2	-0.10	1.09	0.09	-0.12	0.02	0.91
	(0.15)	(0.04)	(0.07)	(0.06)	(0.05)	
3	0.18	1.00	0.10	-0.13	0.03	0.89
	(0.16)	(0.04)	(0.08)	(0.07)	(0.05)	
4	0.05	1.00	-0.05	-0.17	-0.00	0.92
	(0.13)	(0.04)	(0.06)	(0.06)	(0.04)	
5	0.24	0.90	0.05	-0.32	0.05	0.75
(High)	(0.23)	(0.06)	(0.11)	(0.09)	(0.07)	
High - Low	0.85	-0.24	-0.13	-0.10	0.09	0.12
	(0.36)	(0.10)	(0.17)	(0.15)	(0.12)	

Panel B: Fama-French 5-Factor Loadings							
Equal-Weighted							
Quintile	ALPHA	MKTRF	SMB	HML	RMW	CMA	Adj. R-Squared
1	-0.43	1.13	0.60	-0.05	-0.42	-0.13	0.89
(Low)	(0.23)	(0.06)	(0.11)	(0.11)	(0.16)	(0.20)	
2	-0.08	1.13	0.55	-0.05	-0.21	-0.10	0.95
	(0.14)	(0.04)	(0.07)	(0.07)	(0.10)	(0.12)	
3	0.17	1.04	0.59	0.01	-0.20	-0.19	0.96
	(0.12)	(0.03)	(0.06)	(0.06)	(0.09)	(0.11)	
4	0.15	1.07	0.61	-0.12	-0.21	0.04	0.96
	(0.12)	(0.03)	(0.06)	(0.06)	(0.08)	(0.10)	
5	0.27	1.01	0.83	-0.22	-0.18	0.19	0.89
(High)	(0.21)	(0.06)	(0.10)	(0.10)	(0.15)	(0.18)	
High - Low	0.70	-0.12	0.23	-0.17	0.23	0.32	0.06
	(0.30)	(0.08)	(0.15)	(0.14)	(0.22)	(0.27)	
Value-Weighted							
Quintile	ALPHA	MKTRF	SMB	HML	RMW	CMA	Adj. R-Squared
1	-0.57	1.13	0.14	-0.18	-0.12	-0.08	0.83
(Low)	(0.25)	(0.07)	(0.12)	(0.12)	(0.18)	(0.22)	
2	-0.05	1.06	0.07	-0.08	-0.05	-0.17	0.91
	(0.15)	(0.04)	(0.08)	(0.07)	(0.11)	(0.14)	
3	0.23	0.94	0.09	-0.01	-0.01	-0.44	0.90
	(0.16)	(0.04)	(0.08)	(0.07)	(0.11)	(0.14)	
4	0.06	1.01	-0.06	-0.21	-0.07	0.16	0.92
	(0.14)	(0.04)	(0.07)	(0.06)	(0.10)	(0.12)	
5	0.11	0.95	0.13	-0.39	0.32	0.19	0.76
(High)	(0.23)	(0.06)	(0.11)	(0.11)	(0.16)	(0.20)	
High - Low	0.67	-0.18	-0.01	-0.20	0.45	0.27	0.15
	(0.37)	(0.10)	(-0.06)	(-1.19)	(0.27)	(0.83)	

Note: This table reports factor loadings for the labor momentum strategy. The table reports calendar-time portfolio abnormal returns. To construct the table, firms are ranked and assigned into quintile portfolios at the beginning of every calendar month, based on the prior-month return to a portfolio of their labor-linked firms (LabRet). Portfolios are rebalanced every calendar month to maintain the weights. Financial and utility firms are excluded. Alpha is the intercept from the regression of monthly excess returns on the Carhart 4-factor model in Panel A and on the Fama-French 5-factor model in Panel B. Factor returns are from the Kenneth French website. MKTRF, SMB, HML, MOM, RMW, CMA are factor loadings on the corresponding factors. Returns and alphas are in monthly percentage, standard errors are shown in parentheses, and adjusted R-squareds are reported in the last column.

Table 13: Exposures to Other Momentum Factors

(Percent)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ALPHA	0.74	0.85	0.73	0.77	0.79	0.96	0.94	0.79	0.83	0.95
	(0.38)	(0.33)	(0.30)	(0.31)	(0.37)	(0.37)	(0.32)	(0.30)	(0.31)	(0.35)
MOM	0.24					0.10				
	(0.11)					(0.11)				
IND10		0.45					0.38			
		(0.08)					(0.08)			
IND30			0.44					0.41		
			(0.06)					(0.07)		
IND49				0.48					0.43	
				(0.07)					(0.08)	
CUSTOMER					0.30					0.25
					(0.14)					(0.13)
MKTRF						-0.29	-0.18	-0.09	-0.10	-0.31
						(0.10)	(0.08)	(0.08)	(0.09)	(0.09)
Adj. R-Squared	0.06	0.28	0.39	0.35	0.05	0.15	0.31	0.40	0.36	0.18

Note: This table reports return exposures of the labor momentum strategy to other momentum factors. Alpha is the intercept from the regression of monthly excess returns on the corresponding model. MOM is the momentum strategy. IND10, IND30, and IND49 are the industry momentum strategies based on Fama French 10 industries, 30 industries, and 49 industries, respectively. CUSTOMER is the customer momentum strategy as in Menzly and Ozbas (2010). Returns and alphas are in monthly percentage, standard errors are shown in parentheses, and adjusted R-squareds are reported in the last column.

Table 14: Cross-Sectional Regressions

(Percent)	(1)	(2)	(3)	(4)	(5)	(6)
$LabRet_{t-1}$	0.811	0.790	0.837	0.805	0.698	0.685
	(0.320)	(0.286)	(0.308)	(0.281)	(0.270)	(0.234)
$IndRet_{t-1}$		0.423		0.457		0.363
		(0.255)		(0.248)		(0.227)
Ret_{t-1}		-0.465		-0.475		-0.623
		(0.454)		(0.438)		(0.437)
Mom			0.738	0.755		0.573
			(0.472)	(0.448)		(0.404)
$Size$					-0.313	-0.303
					(0.372)	(0.367)
BM					-0.080	-0.275
					(0.421)	(0.383)
$Prof$					1.677	1.638
					(0.316)	(0.304)
Inv					-0.862	-0.838
					(0.229)	(0.219)
Average R-Squared	0.005	0.014	0.014	0.022	0.026	0.039
Obs	150,963	150,963	150,963	150,963	150,747	150,747

Note: This table reports the results for six Fama-MacBeth return forecasting regressions. The dependent variable is the focal firm's monthly return (Ret). The explanatory variables include labor-linked return (LabRet), industry return (IndRet), self short-term return (Ret), momentum (Mom), log market capitalization (Size), book-to-market (BM), profitability (Prof), and capital investment rate (IK). Variable definitions are in Appendix C. All explanatory variables are assigned to deciles ranging from 0 to 1. Financial and utility firms are excluded from the sample. The coefficient estimates, Fama-MacBeth standard errors, and average R-squareds are reported in the table.

Table 15: Limited Attention

		Quintile	XRet	CAPM	3-Fac	4-Fac	5-Fac
Size	< **Median**	1	-0.09	-0.59	-0.60	-0.50	-0.37
		(Low)	(0.66)	(0.33)	(0.25)	(0.25)	(0.25)
		5	0.85	0.39	0.38	0.51	0.54
		(High)	(0.85)	(0.36)	(0.24)	(0.23)	(0.25)
		High - Low	0.94	0.98	0.97	1.01	0.91
			(0.33)	(0.33)	(0.33)	(0.34)	(0.35)
	> **Median**	1	-0.01	-0.55	-0.53	-0.39	-0.47
		(Low)	(0.67)	(0.27)	(0.26)	(0.25)	(0.28)
		5	0.45	-0.03	0.00	0.11	-0.06
		(High)	(0.59)	(0.23)	(0.21)	(0.20)	(0.22)
		High - Low	0.46	0.52	0.53	0.50	0.41
			(0.32)	(0.32)	(0.33)	(0.33)	(0.34)
Analyst	< **Median**	1	-0.23	-0.77	-0.74	-0.65	-0.56
		(Low)	(0.69)	(0.29)	(0.20)	(0.19)	(0.20)
		5	0.72	0.23	0.24	0.38	0.42
		(High)	(0.66)	(0.33)	(0.23)	(0.22)	(0.23)
		High - Low	0.95	1.00	0.98	1.02	0.98
			(0.28)	(0.28)	(0.28)	(0.29)	(0.30)
	> **Median**	1	-0.05	-0.57	-0.57	-0.42	-0.42
		(Low)	(0.66)	(0.30)	(0.28)	(0.27)	(0.29)
		5	0.59	0.14	0.13	0.25	0.11
		(High)	(0.58)	(0.27)	(0.23)	(0.22)	(0.25)
		High - Low	0.64	0.71	0.70	0.68	0.53
			(0.38)	(0.38)	(0.38)	(0.39)	(0.39)
Ownership	< **Median**	1	-0.24	-0.74	-0.73	-0.59	-0.47
		(Low)	(0.66)	(0.33)	(0.27)	(0.26)	(0.27)
		5	0.69	0.25	0.24	0.40	0.39
		(High)	(0.60)	(0.25)	(0.25)	(0.23)	(0.25)
		High - Low	0.93	1.00	0.97	0.99	0.86
			(0.33)	(0.32)	(0.32)	(0.33)	(0.33)
	> **Median**	1	0.11	-0.43	-0.42	-0.32	-0.31
		(Low)	(0.67)	(0.26)	(0.22)	(0.21)	(0.23)
		5	0.61	0.12	0.14	0.23	0.12
		(High)	(0.62)	(0.27)	(0.20)	(0.19)	(0.21)
		High - Low	0.50	0.54	0.56	0.55	0.43
			(0.31)	(0.31)	(0.31)	(0.32)	(0.33)

Note: This table reports results of a series of cross-sectional analyses to evaluate the sensitivity of labor momentum to proxies for limited investor attention. The proxies include size, number of analyst followings, and percentage of institutional ownership. For each test, we split the sample into above and below sample median based on each proxy. We report abnormal returns of the labor momentum in each of the subsamples. Results based on size, number of analyst followings, and percentage of institutional ownership, respectively. Coefficient estimates and standard errors are reported in the table.

Table 16: Transmission of Industry Shocks in the Labor Market

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	EduRatio	ExpRatio	ComRatio	CogRatio	MeanEdu	MeanExp	MeanSkill
Post*Treat	0.044	0.021	0.025	0.039	0.515	0.182	0.969
	(0.015)	(0.011)	(0.014)	(0.010)	(0.239)	(0.079)	(0.214)
Time & Firm FE	Y	Y	Y	Y	Y	Y	Y
Obs	3,122	3,122	3,122	3,122	3,122	3,122	3,122
Adj. R-squared	0.438	0.432	0.496	0.441	0.476	0.461	0.587
Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	EduRatio	ExpRatio	ComRatio	CogRatio	MeanEdu	MeanExp	MeanSkill
Post*FinScore	0.037	0.013	0.014	0.023	0.411	0.126	0.672
	(0.009)	(0.006)	(0.009)	(0.006)	(0.149)	(0.046)	(0.124)
Time & Firm FE	Y	Y	Y	Y	Y	Y	Y
Obs	3,122	3,122	3,122	3,122	3,122	3,122	3,122
Adj. R-squared	0.444	0.433	0.497	0.443	0.479	0.463	0.591

Note: This table presents regressions estimating the effect of the financial industry shocks on labor market competitors that are non-financial firms. The dependent variable is a skill requirement measure for non-financial firm i in year t. Post is an indicator variable that equals 1 for years after 2010, and 0 otherwise. Treat is an indicator that equals 1 for firms with above median FinScore, and 0 otherwise. FinScore is the standardized total similarity score of a non-financial firm to the financial industry (SIC codes in the range of 6000-6999) measured in 2007. Panel A shows estimation results using the indicator variable. Panel B shows the results using the continuous variable. All tests include time and firm fixed effects. Variable definitions are in Appendix C and all continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors reported in parentheses are clustered by firm. Constants in all tests are subsumed and not reported.

Table 17: Transmission of Industry Shocks by Year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	EduRatio	ExpRatio	ComRatio	CogRatio	MeanEdu	MeanExp	MeanSkill
2010*Treat	0.046	0.018	0.019	0.038	0.603	0.178	0.930
	(0.015)	(0.011)	(0.014)	(0.010)	(0.235)	(0.078)	(0.211)
2011*Treat	0.044	0.002	0.001	0.028	0.703	0.107	0.700
	(0.015)	(0.011)	(0.014)	(0.011)	(0.240)	(0.079)	(0.220)
2012*Treat	0.046	0.005	0.026	0.039	0.876	0.084	0.522
	(0.015)	(0.011)	(0.013)	(0.010)	(0.241)	(0.080)	(0.219)
2013*Treat	0.030	0.002	0.006	0.041	0.616	0.082	0.310
	(0.015)	(0.010)	(0.013)	(0.010)	(0.237)	(0.077)	(0.214)
2014*Treat	0.033	0.006	-0.003	0.036	0.476	0.081	0.020
	(0.015)	(0.010)	(0.014)	(0.010)	(0.237)	(0.078)	(0.216)
2015*Treat	0.042	0.011	-0.016	0.025	0.694	0.129	0.093
	(0.015)	(0.011)	(0.014)	(0.010)	(0.242)	(0.082)	(0.225)
2016*Treat	0.032	0.008	-0.026	0.014	0.498	0.091	-0.202
	(0.016)	(0.011)	(0.014)	(0.011)	(0.250)	(0.084)	(0.234)
Time & Firm FE	Y	Y	Y	Y	Y	Y	Y
Obs	12,050	12,050	12,050	12,050	12,050	12,050	12,050
Adj. R-squared	0.653	0.614	0.645	0.607	0.618	0.626	0.682

Note: This table presents yearly estimates of the change in the skill requirements of non-financial firm i on year indicators and their interactions with Treat. Treat is an indicator that equals 1 for firms with above median FinScore, and 0 otherwise. FinScore is the total similarity score of a non-financial firm to the financial industry (SIC codes in the range of 6000-6999) measured in 2007. The year is an indicator variable for each year of 2010-2016. All tests include firm fixed effects. Variable definitions are in Appendix C and all continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors reported in parentheses are clustered by firm. Constants in all tests are subsumed and not reported.

Table 18: Analyses of Performance for Financial-like Industrial Firms

	(1)	(2)	(3)	(4)	(5)	(6)
	NI	OIADP	EBIT	NI	OIADP	EBIT
Post*Treat	7.995	11.590	8.695			
	(5.103)	(5.411)	(4.592)			
Post*FinScore				6.500	8.909	6.734
				(3.038)	(3.446)	(2.713)
Time & Firm FE	Y	Y	Y	Y	Y	Y
Obs	9,063	9,063	9,063	9,063	9,063	9,063
Adj. R-squared	0.543	0.672	0.548	0.544	0.673	0.548

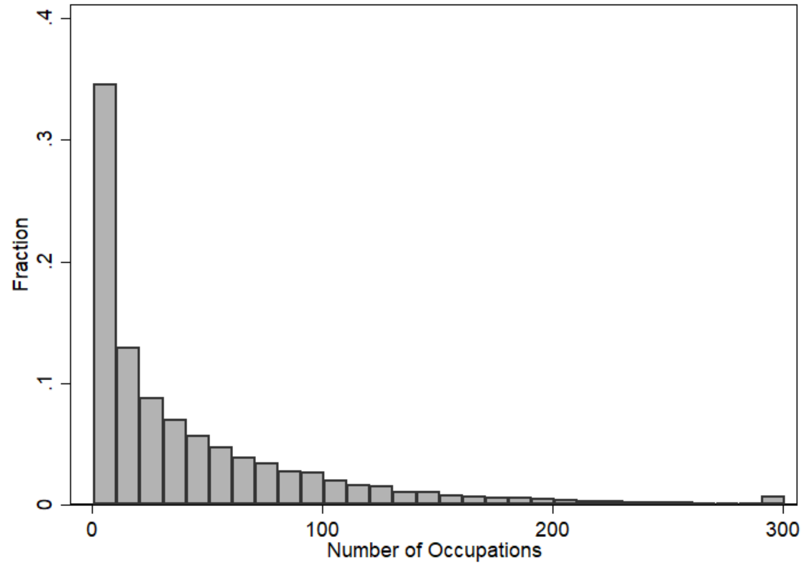
Note: This table compares the performance of the treatment firms to that of the control firms for the period of 2005-2012 excluding 2008 and 2009. The dependent variable is a financial performance measure for non-financial firm i in year t. Post is an indicator variable that equals 1 for years after 2010, and 0 otherwise. Treat is an indicator that equals 1 for firms with above median FinScore, and 0 otherwise. FinScore is the standardized total similarity score of a non-financial firm to the financial industry (SIC codes in the range of 6000-6999) measured in 2007. All tests include firm and year fixed effects. NI is net income to total employees. OIADP is operating income after depreciation to total employees. EBIT is earnings before interest and tax to total employees. Detailed variable definitions are in Appendix C. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors reported in parentheses are clustered by firm. Constants in all tests are subsumed and not reported.

Table 19: Analyses of Corporate Decisions for Financial-like Industrial Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	R&D	IK	Leverage	LtDebt	R&D	IK	Leverage	LtDebt
Post*Treat	-0.612	-0.672	1.792	2.090				
	(0.281)	(0.702)	(0.773)	(0.731)				
Post*FinScore					-0.279	-0.410	1.191	1.343
					(0.159)	(0.371)	(0.396)	(0.385)
Time & Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs	9,520	9,297	9,331	9,285	9,520	9,297	9,331	9,285
Adj. R-squared	0.829	0.624	0.760	0.751	0.829	0.624	0.760	0.751

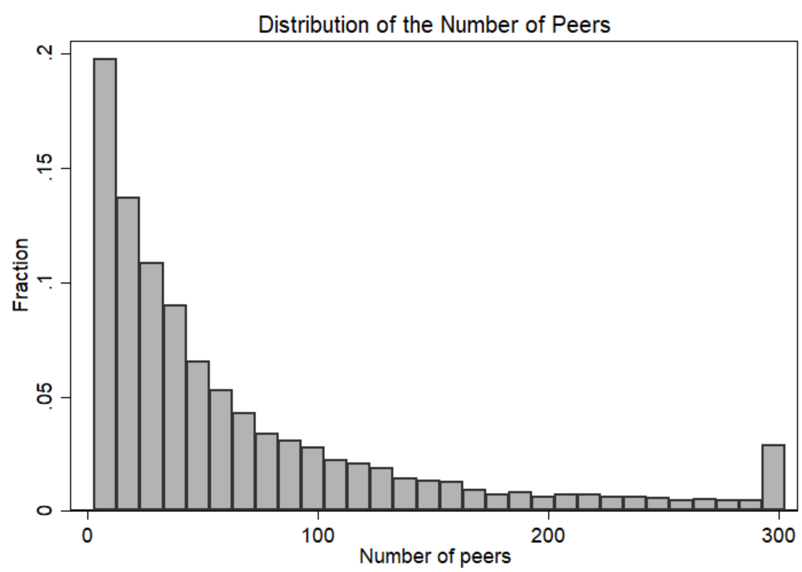
Note: This table compares the corporate decisions of the treatment firms to that of the control firms for the period of 2005-2012 excluding 2008 and 2009. The dependent variable is one of the corporate decision variables for non-financial firm i in year t. Post is an indicator variable that equals 1 for years after 2010, and 0 otherwise. Treat is an indicator that equals 1 for firms with above median FinScore, and 0 otherwise. FinScore is the standardized total similarity score of a non-financial firm to the financial industry (SIC codes in the range of 6000-6999) measured in 2007. All tests include firm and year fixed effects. R&D is research & development expenditure to total assets. IK is physical investment to property, plant and equipment. Leverage is debt to total assets. LtDebt is long-term debt to total assets. Detailed variable definitions are in Appendix C. Dependent variables are in percentage and all continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors reported in parentheses are clustered by firm. Constants in all tests are subsumed and not reported.

Figure 1: Number of Unique Occupations



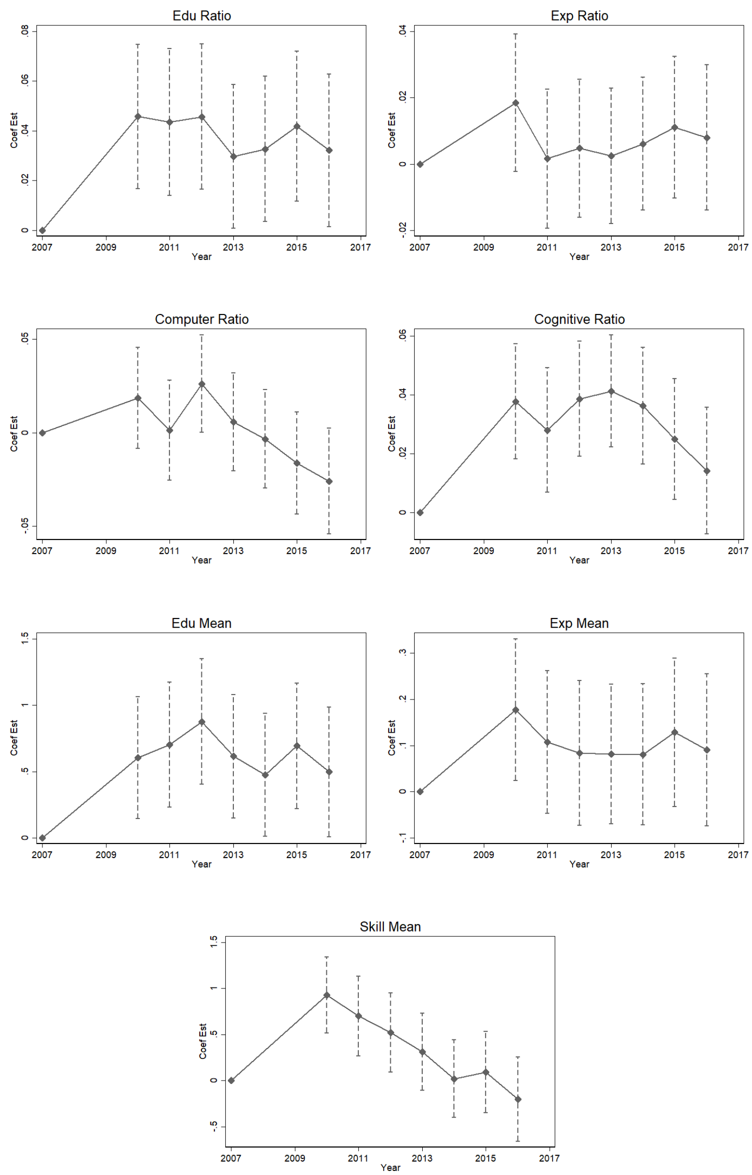
Note: This figure presents the frequency distribution of the number of unique occupations in job postings at the firm-year level.

Figure 2: Number of Labor Market Competitors



Note: This figure presents the frequency distribution of the number of labor market competitors.

Figure 3: Skill Requirements and the Financial Industry Shocks



Note: These graphs present the coefficient estimates on $Treat * Year$ from regressing skill requirements of non-financial firm i on year indicators and their interactions with $Treat$. $Treat$ is an indicator that equals 1 for firms with above median FinScore, and 0 otherwise. FinScore is the total similarity score of a non-financial firm to the financial industry (SIC codes in the range 6000-6999) measured in 2007. $Year$ is an indicator variable for each year of 2010-2016. Each graph corresponds to one skill measure. The dashed lines represent the 95 percent confidence intervals. Variable definitions are in Appendix C and all continuous variables are winsorized at the 1st and 99th percentiles.

APPENDIX

Appendix A: Two-Layer Network Model

This section develops a static model with intermediate inputs with two networks: goods market network and labor market network. The simplicity of the model allows us to focus on the transmission of shocks to the real economy via both the goods market input-output linkages and the labor market linkages, and therefore motivates our empirical specifications.

We follow Long and Plosser (1983) and Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) but add a layer of labor market network and allow for heterogeneous labor supply. We have a one-period model with variable inputs that each firm can purchase from other firms, including itself. There are multiple labor supply and firms need heterogeneous labor input in order to produce. A firm's net income determines its stock price.

Firm i's objective is to maximize profits, y_i, by choosing a set of heterogeneous labor inputs, $l_{i,1}$, $l_{i,2}$, ..., $l_{i,n}$, and a set of intermediate inputs, $x_{i,1}$, $x_{i,2}$, ..., $x_{i,m}$. Firm i takes wages, w_1, w_2, ..., w_n, and prices, p_1, p_2, ..., p_m, as given:

$$\max_{l_{i,i'} x_{j,j'}} p_i y_i - \sum_{i'=1}^{n} w_{i'} l_{i,i'} - \sum_{j'=1}^{m} p_{j'} x_{i,j'} \tag{10}$$

and

$$y_i = z_i \Pi_{i'=1}^{n} l_{i,i'}^{\gamma a_{i,i'}} \Pi_{j'=1}^{m} x_{i,j'}^{(1-\gamma) b_{i,j'}} \tag{11}$$

where γ and $1-\gamma$ are the factor shares. $a_{i,i'}$ is the share of labor input from labor force i' to firm i such that $\sum_{i'=1}^{n} a_{i,i'} = 1$ and $b_{i,j'}$ is the share of input from firm j' to firm i such that $\sum_{j'=1}^{m} b_{i,j'} = 1$. z_i is the idiosyncratic productivity shock to sector i, and we assume that productivity shocks are independent across sectors.

The representative household is endowed with s_1, s_2, ..., s_n units of labor for the corresponding labor inputs, where the supply of labor is inelastic. The household has Cobb-Douglas preferences over n distinct goods:

$$U(c_1, c_2, ..., c_m) = \Pi_{j=1}^{m} c_j^{\alpha} \tag{12}$$

where c_i is the consumption of good i.

We summarize the structure of the labor market with matrix A with entries $a_{i,i'}$. Similarly, we summarize the structure of the intersectoral trade with the input-output matrix B with entries $b_{i,j'}$. Solving the model, we have

$$d\log(Y) = [I - (1-\gamma)B]^{-1}[d\log(Z) + \gamma A d\log(S)] \tag{13}$$

Note we can rewrite the reaction of the deviation as

$$d\log(Y) = \gamma A d\log(S) + (1-\gamma) B d\log(Y) + d\log(Z) \tag{14}$$

The changes in net incomes, that is, the firms' stock prices, react to the labor market shock $d\log(S)$ and the reaction of its customers' net incomes to the shock, $Bd\log(Y)$. Equation 14 has the form of a spatial autoregression so we can use methods from spatial econometrics to decompose the overall stock market reaction to labor market shock into a direct effect and higher-order network effects. The spatial regression model is given by

$$r_t = \beta v_t + \rho B r_t + \epsilon_t \tag{15}$$

which implies that the data-generating process is

$$r_t = (I - \rho B)^{-1}[\beta v_t + \epsilon_t] \tag{16}$$

which matches the expression of Equation 14.

In Equation 16, r is a vector of firm returns, v is a vector of labor market shocks to the corresponding firms, and B is a weighting matrix that corresponds to the BEA input-output matrix. We can interpret parameter estimates in standard linear regression models as partial derivatives of the dependent variable with respect to the independent variable. However, as pointed out in Ozdagli and Weber (2017), the interpretation of parameters in a spatial model differs from linear regression models because they incorporate information from related industries. We can see this difference more clearly when we rewrite Equation 16 as:

$$r = S(B)\, v + V(B)\, \epsilon \tag{17}$$

where

$$S(B) = V(B)\, \beta \tag{18}$$

$$V(B) = (I - \rho B)^{-1} \tag{19}$$

Therefore, the overall response of firms to monetary policy shocks depends on the input-output matrix B, which governs the response of firm returns to labor market shocks through its effect on the intermediate goods production. We follow LeSage and Pace (2014) and Ozdagli and Weber (2017) in decomposition and define three scalars to measure the total, direct, and network effects separately:

Average direct effect: the average of the diagonal elements of $S(B)$ or $mean\,[tr\,(S\,(B))]$, where tr is the trace of a matrix.

Average total effect: the sum across the i^{th} row of $S(B)$ represents the total impact on firm i from the monetary policy shock.

Average network effect: the difference between the average total effect and the average direct effect.

The definitions of average direct effect and average network effect correspond to the average partial derivatives. The network method allows us to separate the direct effect of labor market shocks via the labor market network from the network effect of labor market shocks via the input-output matrix. We estimate the following empirical specification to assess whether labor market shocks might result in higher-order network effects:

$$r_t = \beta_0 + \beta_1 v_t + \rho B r_t + \epsilon_t. \tag{20}$$

Proof:

The utility function of the representative agent is

$$U\left(c_1, c_2, ..., c_m\right) = \Pi_{j=1}^{m} c_j^{\alpha} \tag{21}$$

The production function of firm i is

$$y_i = z_i \Pi_{i'=1}^{n} l_{i,i'}^{\gamma a_{i,i'}} \Pi_{j'=1}^{m} x_{i,j'}^{(1-\gamma) b_{i,j'}} \tag{22}$$

The wages are w_1, w_2, ..., w_n. Labor supply is inelastic and subject to shocks: s_1, s_2, ..., s_n.

The prices are p_1, p_2, ..., p_m.

The market clearing conditions are:

Labor market clearing:

$$\sum_{i=1}^{m} l_{i,i'} = s_{i'} \tag{23}$$

Product market clearing:

$$\sum_{i=1}^{m} x_{i,j'} + c_{j'} = y_{j'} \tag{24}$$

Profit maximization:

The maximization question is

$$\max_{l_{i,i'} x_{j,j'}} p_i y_i - \sum_{i'=1}^{n} w_{i'} l_{i,i'} - \sum_{j'=1}^{m} p_{j'} x_{i,j'} \tag{25}$$

Utility maximization:

The maximization question is

$$\max_{c_j} U\left(c_1, c_2, ..., c_m\right) \tag{26}$$

s.t. budget constraint

$$\sum_{j=1}^{m} p_j c_j = \sum_{i=1}^{n} w_i \tag{27}$$

Solution:

(1) Firm maximization.

FOC on $x_{j,j'}$

$$p_i z_i \Pi_{i'=1}^{n} l_{i,i'}^{\gamma a_{i,i'}} \left(1-\gamma\right) \frac{b_{i,j'}}{x_{i,j'}} \Pi_{j'=1}^{m} x_{i,j'}^{(1-\gamma) b_{i,j'}} - p_{j'} = 0 \tag{28}$$

$$p_i b_{i,j'} y_i = p_{j'} x_{i,j'} \rightarrow x_{i,j'} = \frac{p_i b_{i,j'} y_i}{p_{j'}} \tag{29}$$

FOC on $l_{i,i'}$

$$p_i z_i \gamma \frac{a_{i,i'}}{l_{i,i'}} \Pi_{i'=1}^{n} l_{i,i'}^{\gamma a_{i,i'}} \Pi_{j'=1}^{m} x_{i,j'}^{(1-\gamma) b_{i,j'}} - w_{i'} = 0 \tag{30}$$

$$p_i a_{i,i'} y_i = w_{i'} l_{i,i'} \rightarrow l_{i,i'} = \frac{p_i a_{i,i'} y_i}{w_{i'}} \tag{31}$$

$$\log(y_i) = \log(z_i) + \gamma \sum_{i'=1}^{n} a_{i,i'} \log(l_{i,i'}) + (1-\gamma) \sum_{j'=1}^{m} b_{i,j'} \log(x_{i,j'}) \tag{32}$$

$$= \log(z_i) + \gamma \sum_{i'=1}^{n} a_{i,i'} \log\left(\frac{p_i a_{i,i'} y_i}{w_{i'}}\right) + (1-\gamma) \sum_{j'=1}^{m} b_{i,j'} \log\left(\frac{p_i b_{i,j'} y_i}{p_{j'}}\right) \tag{33}$$

$$0 = d\log(z_i) + d\log(p_i) - \gamma \sum_{i'=1}^{n} a_{i,i'} d\log(w_{i'}) - (1-\gamma) \sum_{j'=1}^{m} b_{i,j'} d\log(p_{j'}) \tag{34}$$

(2) Utility maximization.

Lagrangian is

$$L = \Pi_{j=1}^{m} c_j^{\alpha} + \beta \left(\sum_{i=1}^{n} w_i - \sum_{j=1}^{m} p_j c_j \right) \tag{35}$$

FOC on c_j

$$\frac{\alpha}{c_j} \Pi_{j=1}^{m} c_j^{\alpha} = \beta p_j \tag{36}$$

$$c_i p_i = c_j p_j \rightarrow d\log(c_i) + d\log(p_i) = d\log(c_j) + d\log(p_j) \tag{37}$$

Then,

$$\sum_{k=1}^{n} w_k = m c_i p_i \tag{38}$$

Normalize $\sum_{k=1}^{n} w_i = m$. Then, we have that $c_i p_i = 1$. Therefore, $d\log(c) = d\log(p)$.

$$0 = d\log(z_i) + d\log(p_i) - \gamma \sum_{i'=1}^{n} a_{i,i'} d\log(w_{i'}) - (1-\gamma) \sum_{j'=1}^{m} b_{i,j'} d\log(p_{j'}) \tag{39}$$

$$0 = d\log(z_i) - d\log(c_i) - \gamma \sum_{i'=1}^{n} a_{i,i'} d\log(w_{i'}) + (1-\gamma) \sum_{j'=1}^{m} b_{i,j'} d\log(c_{j'}) \tag{40}$$

$$d\log(c_i) = d\log(z_i) - \gamma \sum_{i'=1}^{n} a_{i,i'} d\log(w_{i'}) + (1-\gamma) \sum_{j'=1}^{m} b_{i,j'} d\log(c_{j'}) \tag{41}$$

From labor market clearing condition:

$$p_i a_{i,i'} y_i = w_{i'} l_{i,i'} \rightarrow l_{i,i'} = \frac{p_i a_{i,i'} y_i}{w_{i'}} \tag{42}$$

$$\sum_{i=1}^{m} \frac{p_i a_{i,i'} y_i}{w_{i'}} = s_{i'} \rightarrow \sum_{i=1}^{m} p_i a_{i,i'} y_i = w_{i'} s_{i'} \tag{43}$$

Also, $\sum_{i=1}^{m} p_i a_{i,i'} y_i = w_{i'}$. Therefore,

$$\sum_{i=1}^{m} \frac{a_{i,i'} y_i}{c_i} = w_{i'} \tag{44}$$

From product market clearing condition:

$$x_{i,j'} = \frac{p_i b_{i,j'} y_i}{p_{j'}} \tag{45}$$

$$\sum_{i=1}^{m} x_{i,j'} + c_{j'} = y_{j'} \rightarrow \sum_{i=1}^{m} \frac{p_i b_{i,j'} y_i}{p_{j'} c_{j'}} + 1 = \frac{y_{j'}}{c_{j'}} \rightarrow \sum_{i=1}^{m} \frac{b_{i,j'} y_i}{c_i} + 1 = \frac{y_{j'}}{c_{j'}} \tag{46}$$

which implies that

$$d\log(y) = d\log(c) \tag{47}$$

and then

$$d\log(w) = -d\log(s) \tag{48}$$

Therefore,

$$d\log(c_i) = d\log(z_i) - \gamma \sum_{i'=1}^{n} a_{i,i'} d\log(w_{i'}) + (1-\gamma) \sum_{j'=1}^{m} b_{i,j'} d\log(c_{j'}) \tag{49}$$

$$= d\log(z_i) + \gamma \sum_{i'=1}^{n} a_{i,i'} d\log(s) + (1-\gamma) \sum_{j'=1}^{m} b_{i,j'} d\log(c_{j'}) \tag{50}$$

In matrix form:

$$d\log(C) = d\log(Z) + \gamma A d\log(S) + (1-\gamma) B d\log(C) \tag{51}$$

$$d\log(C) = [I - (1-\gamma) B]^{-1} [d\log(Z) + \gamma A d\log(S)] \tag{52}$$

$$d\log(Y) = [I - (1-\gamma) B]^{-1} [d\log(Z) + \gamma A d\log(S)] \tag{53}$$

Appendix B: Figures & Tables

Table A.1: Example

L Brands Inc	Yum Brands Inc
Biogen Inc	Siemens AG
Honeywell International Inc	Duke Energy Corp
Activision Blizzard Inc	Applied Materials Inc
Amgen Inc	Carnival Corp
Oshkosh Corp	Estée Lauder Companies
Whirlpool Corp	VF Corp
Novartis AG	HCA Healthcare Inc
Viacom Inc	Sysco Corp
Interpublic Group	Kimberly-Clark Corp

Note: This table presents a random twenty (out of 209) sample of the labor market competitors of the Walt Disney Company for the year of 2016.

Table A.2: Industries

Industry	NAICS
Mining and Logging	NAICS 1133, Sector 21
Construction	Sector 23
Durable Goods	NAICS 321, 327, Sector 33
Non-Durable Goods	Sector 31, NAICS 322-326
Wholesale Trade	Sector 42
Retail Trade	Sectors 44 and 45
Transportation, Warehousing, and Utilities	Sectors 22, 48, 49
Information	Sector 51
Finance and Insurance	Sector 52
Real Estate, Rental, and Leasing	Sector 53
Professional and Business Services	Sectors 54-56
Educational Services	Sector 61
Health Care and Social Assistance	Sector 62
Arts, Entertainment, and Recreation	Sector 71
Accommodation and Food Services	Sector 72
Other Services	Sector 81

Note: This table presents definitions of industries defined at the two-digit NAICS level.

Table A.3: Persistence of the Labor Market Competitor Network

	(1) Sim_t	(2) Sim_t	(3) Sim_t
Sim_{t-1}	0.71		
	(5644.82)		
Sim_{t-2}		0.63	
		(3899.22)	
Sim_{t-3}			0.58
			(2852.78)
Obs	31,414,592	22,085,017	14,939,044
Adj. R-Squared	0.50	0.41	0.35

Note: Observations are at the firm-pair-year level. T-statistics are reported in the parentheses.

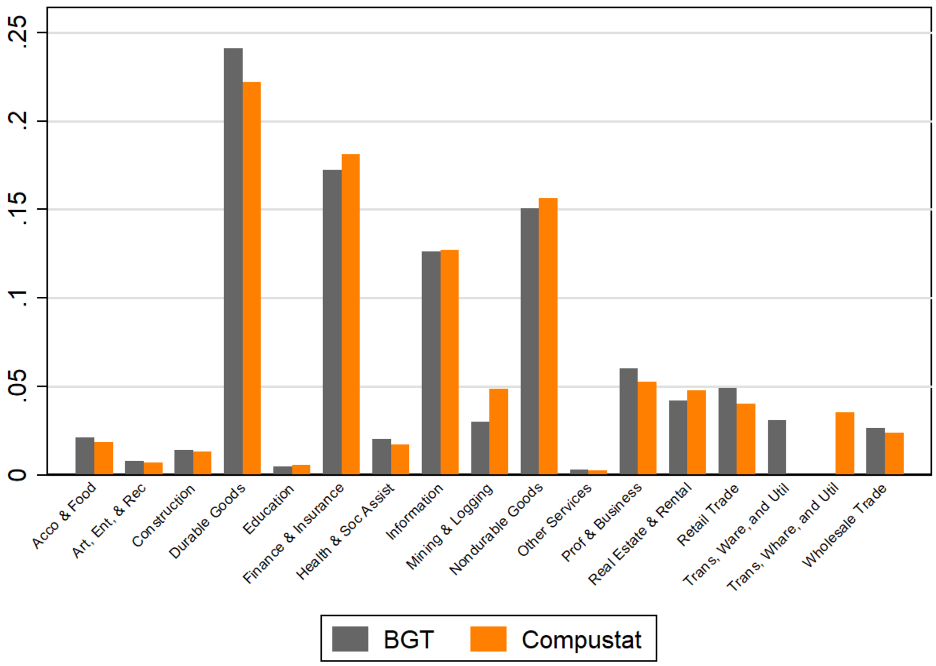
Table A.4: Portfolio Analysis with 2009 and 2010

Portfolio Returns (%)					
Quintile	XRet	CAPM	3-Fac	4-Fac	5-Fac
1	0.86	-0.24	-0.27	-0.26	-0.08
(Low)	(0.65)	(0.27)	(0.22)	(0.19)	(0.22)
2	1.04	-0.01	-0.02	-0.01	0.06
	(0.59)	(0.19)	(0.13)	(0.11)	(0.14)
3	1.36	0.34	0.31	0.33	0.36
	(0.59)	(0.21)	(0.15)	(0.11)	(0.15)
4	1.40	0.38	0.36	0.37	0.45
	(0.59)	(0.22)	(0.15)	(0.12)	(0.15)
5	1.40	0.39	0.36	0.38	0.41
(High)	(0.60)	(0.27)	(0.20)	(0.16)	(0.20)
High/Low	0.54	0.64	0.64	0.63	0.49
	(0.27)	(0.27)	(0.27)	(0.27)	(0.28)

Factor Loadings						
Quintile	ALPHA	MKTRF	SMB	HML	MOM	Adj. R-Squared
1	-0.26	1.15	0.72	-0.18	-0.26	0.92
(Low)	(0.11)	(0.03)	(0.05)	(0.05)	(0.03)	
2	-0.01	1.13	0.60	-0.09	-0.16	0.97
	(0.11)	(0.03)	(0.05)	(0.05)	(0.03)	
3	0.33	1.06	0.69	-0.14	-0.23	0.97
	(0.11)	(0.03)	(0.05)	(0.04)	(0.02)	
4	0.37	1.04	0.74	-0.12	-0.21	0.96
	(0.12)	(0.03)	(0.05)	(0.05)	(0.03)	
5	0.38	0.99	0.88	-0.16	-0.25	0.93
(High)	(0.16)	(0.04)	(0.07)	(0.07)	(0.04)	
High/Low	0.63	-0.16	0.16	0.02	0.01	0.02
	(0.03)	(0.07)	(0.12)	(0.12)	(0.19)	

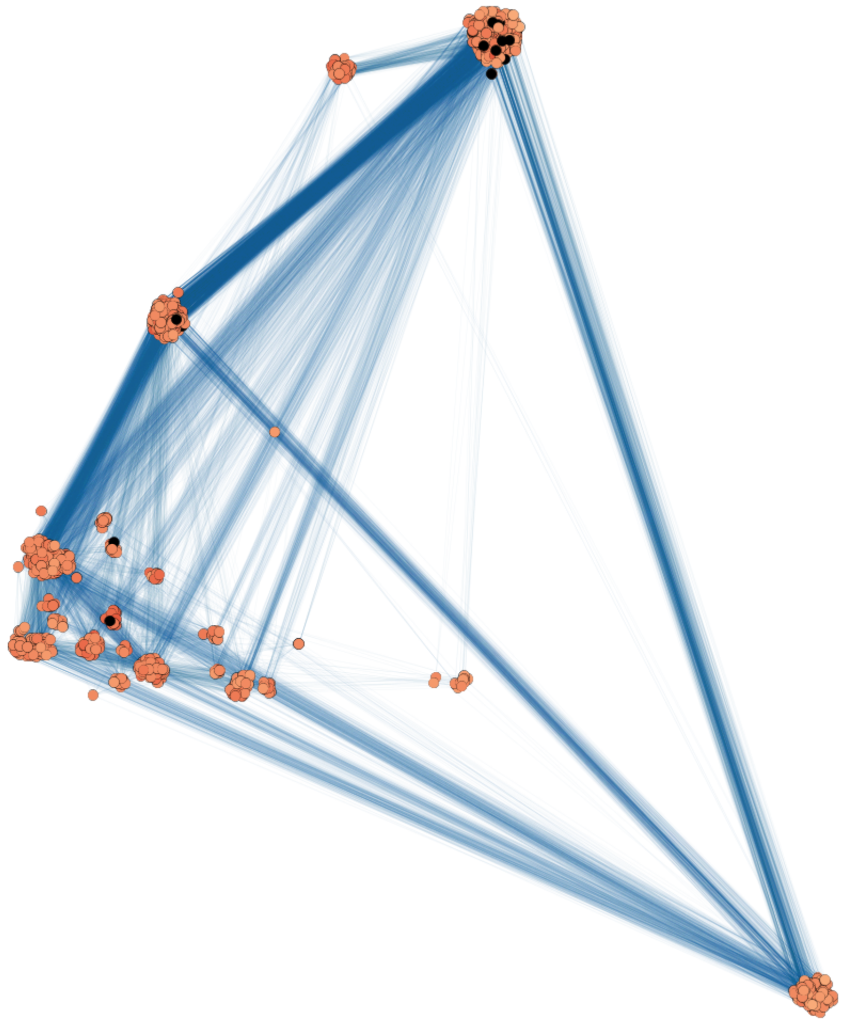
Note: This table reports abnormal returns for the labor momentum strategy including years of 2009 and 2010. The 2009 and 2010 labor momentum strategies are calculated based on the labor market competitor network.

Figure A.1: Representativeness of Burning Glass Technologies Database



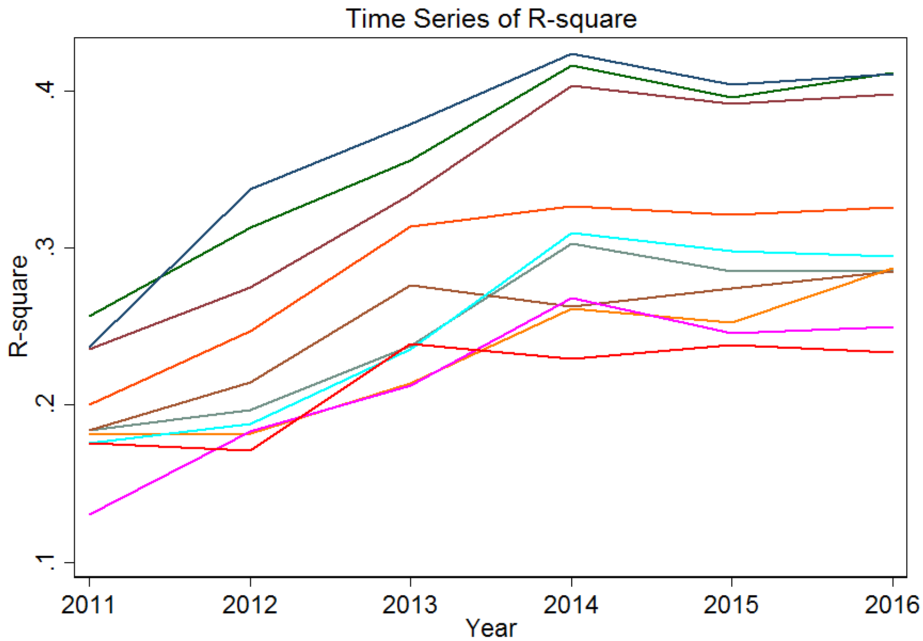
Note: This figure presents the distribution of industries in the matched BGT sample and Compustat sample. Industries are defined at the two-digit NAICS level.

Figure A.2: Network



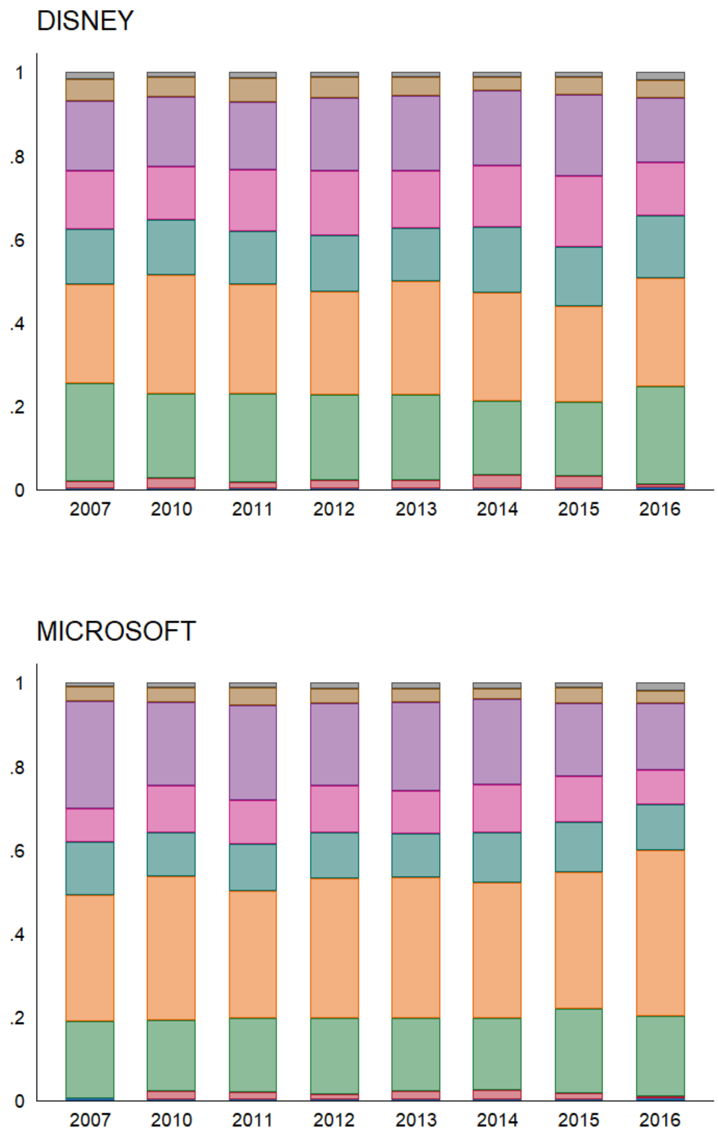
Note: This figure presents the structure of the labor market competitor network for the year of 2015. A dot represents a firm, and a line represents the connected firms as pairwise labor market competitors.

Figure A.3: Time-Series R-Squared Values of Skill Requirements



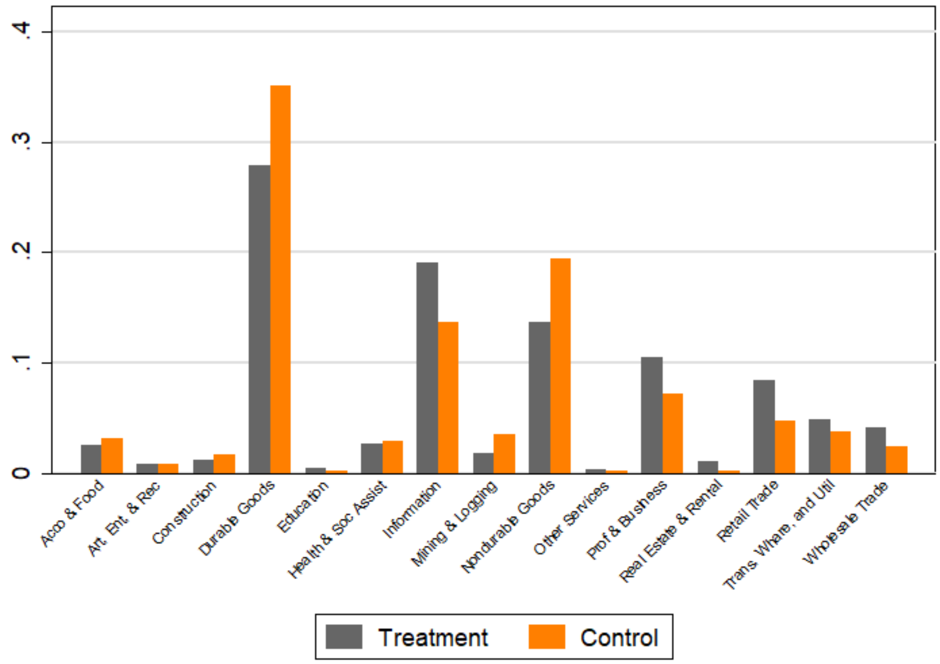
Note: This figure plots the amount of cross-sectional variation in the base firm's skill requirements explained by labor market competitors, for each skill measure. Each line represents one skill measure. Each point represents the R^2 value from a cross-sectional regression of firm i's skill measure on the average of the skill measure of its labor market competitors. The yearly cross-sectional regressions span from 2011 to 2016. Variable definitions are in Appendix C and all continuous variables are winsorized at the 1st and 99th percentiles.

Figure A.4: Evolution of Labor Market Competitors



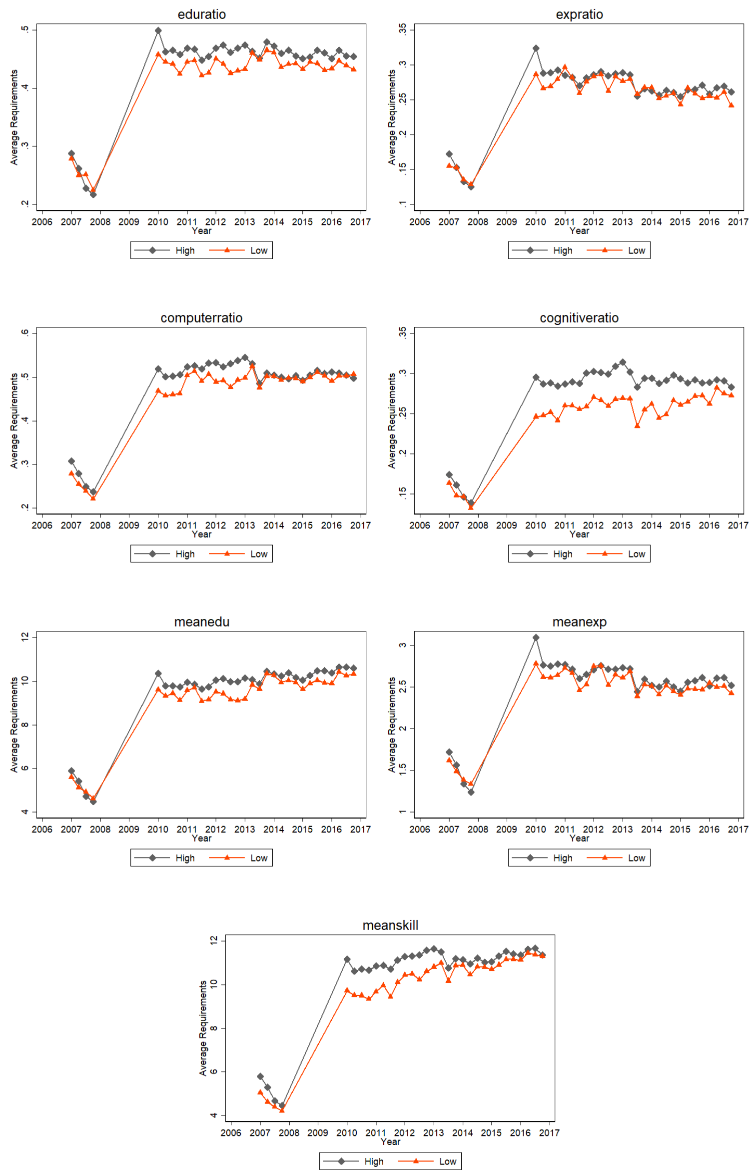
Note: This figure presents the industry compositions of the labor market competitors for Disney and Microsoft over the years. Industries are defined on one-digit SIC.

Figure A.5: Industry Distribution of High FinScore and Low FinScore Firms



Note: This figure presents the industry distribution of the high FinScore and low FinScore firms. Industries are defined at the two-digit NAICS level. Treatment group contains firms with above median FinScore and Control group contains firms with below median FinScore.

Figure A.6: Skill Requirements for High and Low FinScore Groups



Note: These graphs plot the average of the different skill requirements for the treatment and control groups over time. Each point represents one quarter. The gray line corresponds to the treatment group and the orange line corresponds to the control group. Treatment group consists of firms with above median FinScore and control group consists of firms with below median FinScore.

Appendix C: Variable Definitions

Variable	Description
EduRatio	The ratio between job posts requiring at least a bachelor degree and total job posts by a firm.
ExpRatio	The ratio between job posts requiring at least 5 years of experience and total job posts by a firm.
ComRatio	The ratio between job posts requiring computer skills and total job posts by a firm.
CogRatio	The ratio between job posts requiring cognitive skills and total job posts by a firm.
MeanSkill	The average number of skills required by a firm.
MeanExp	The average year of experience required by a firm. When a job post does not specify experience requirement, we count the experience requirement to be zero.
MeanEdu	The average year of education required by a firm. When a job post does not specify education requirement, we count the education requirement to be zero.
LabRet	The average monthly return of labor-linked firms in the labor market space weighted by pairwise labor similarity.
IndRet	Industry return based on Fama French 49 definition.
Mom	Cumulative previous 12 months returns except for the previous 1 month.
Size	Market capitalization at the end of last month measured in logarithm.
BM	The ratio of total book value of equity to total market capitalization.
Prof	Gross profitability measure as in Novy-Marx (2013)
IK	Physical expenditure (capx/ppent).
NI	Net income to total employees.
OIADP	Operating income after depreciation to total employees.
EBIT	Earnings before interest and tax to total employees.
R&D	Research & development expenditure to total assets.
Leverage	Debt to total assets.
LtDebt	Long-term debt to total assets.