Proximity to software and labor inequality: Examining the industry-level network of corporate acquisitions

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1. Introduction

The effect of information technology on labor markets has long been a subject of academic research (Autor, Levy and Murnane 2003), but recently it has gained popular attention with the recent book by Brynjolfsson and McAfee (2013). Brynjolfsson and McAfee (2013) describe how labor that we consider to be creative, interpersonal, analytical, and non-routine is becoming more subject to computer automation. However, we still don't understand what makes labor in some industries more amenable to replacement by computer automation than other industries. Anecdotally, we see that industries differ in their business processes, end products, and services, such that some are more susceptible to digitization. We also see examples of how "software is eating the world," as Andreeson (2011) described in his essay in the *Wall Street Journal,* as software and internet technologies have transformed the music, entertainment, and publishing industries. Andreeson (2011) states: "…we are in the middle of a dramatic and broad technological and economic shift in which software companies are poised to take over large swathes of the economy."

While the use of software and information technology has become more pervasive in many different industries, we don't have a systematic understanding of why the presence of software, and their corresponding labor effect, is greater in some industries than others. Some industries, particularly in the service sectors, have been relatively slow in adoption and use of IT. One explanation for unbalanced technological progress is that some routine tasks are more

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amenable to being automated by computers than others (Autor and Dorn 2013; Autor et al. 2003). But this doesn't fully explain why certain jobs in some industries become routine in their task composition, while similar jobs in other industries retain their original composition of tasks that require human presence. Firms have redesigned their work processes and organizational structures to change the task composition of some occupations such that they become more routine, and prior theory does not explain why this is done in some industries and not in others.

Another limitation of prior research has been the reliance on measures of IT investment that seem to be losing relevance given the current state of information technology, with firms migrating to cloud-based and mobile computing solutions. While IT-intensity measures such as number of personal computers (PCs) per employee, or monetary investment in software or hardware may have served their purpose well in the prior decades, researchers now need new measures that reflect how some firms are on the leading edge of IT innovation while carrying relatively slim budgets on IT hardware, software, and even on IT human capital.

In this study, we posit that the historical network of corporate acquisitions, and the changing position of firms with respect to the IT-producing industries in this network, can provide insight into the innovative restructuring of assets and resources that have enabled some of the recent digitally driven industry transformations. Restructuring of assets and resources through mergers and acquisition (M&As) represent one of several forms of reorganization that enable firms, not just to automate or integrate existing processes for performance improvements, but also to develop innovative breakthroughs driving the digital transformation of some industries. Software firms, often the small ones, have at times played a critical role in the reconfiguration of the network of external corporate relationships; and external relationships have been critical to innovative and productivity-enhancing information practices of firms in many industries (Tambe et al. 2012). Thus, understanding the role of software firms in the changing network of corporate acquisitions might reveal more about the digitally enabled transformation of some industries than internal IT investment alone.

In this study, we construct a directed-edge industry network from a set of 129,158 corporate acquisitions from 2000 to 2014, and examine the role of network position with respect to the software industries. We describe how industries' greater proximity to software industries over time represents a form of digital convergence, and argue that it corresponds with the demand for software investment in those industries (See Figures 2 and 3). The network of corporate acquisitions provides a view on channels or conduits for movement of human intellectual capital from software to non-software industries; and therefore, heterogeneity in the positioning of firms within this network can explain the readiness of some industries to digitize more rapidly than others. We find that industries with greater rates of convergence to the software industry in the acquisition network have greater investments in software, in multiple categories, as a percentage of overall capital investment. We then examine the relationship between proximity to software in this acquisition network, and the polarization (inequality) of labor income distributions within those industries. We find that industries that move closer to software in this network experience higher polarization of annual wages. Our estimation models use fixed-effects panel regressions (in both industry and year), and thus, capture the within-industry patterns over time. We also conduct a number of tests to examine the causal direction of our hypotheses.

2. Digitization and positioning in the acquisition network

Within the acquisition network, proximity to the software industry is informative for the following reasons.

First, the network represents channels or conduits for the movement of software intellectual capital. This movement can be in either of two directions: Software firms acquire non-software firms, and non-software firms acquire software firms. In the former, a firm with industry-specific knowledge or intangible resources becomes part of a firm with general software technology expertise, while the reverse happens in the latter. Table 1 shows the major software industries at the three-digit NAICS level. Table 2 shows the frequency and average value of each of these categories of acquisitions, based on our data. Most acquisitions are between non-software firms, but to the extent that one acquisition partner is highly connected to the software industry, even non-software acquisitions can affect the indirect channel to the software industry. The resulting network consists of directed edges that include paths to and from the software industry to every other industry.[2] Besides a flow of human capital, the acquisition represents a channel or conduit for intellectual property through formal as well as informal mechanisms.

Second, the acquisitions involve merger integration processes during which firms reorganize their underlying strategic assets, redesign their industry-specific business processes, and reallocate their labor to take advantage of new technologies. This would be especially the case when a software firm is involved in the merger, but more generally firms use acquisitions as opportunities to create greater efficiencies in their operations, and among other steps, use information technology to replace or complement human labor. Industries have differed in their levels of automation and digitization because many business processes are industry-specific. For example, many of the details in inventory accounting will vary from one industry to another, and thus, software that automates such processes in one industry may not necessarily be applicable to another industry. Prior research suggests that monetary investment in technology is insufficient

[2] The entire network consists of a giant component of industries; every industry in our final sample has at least one path to and from software industries in the acquisition network.

to accomplish this; effective leadership and managerial will, and the effective deployment of human IT capital, must accompany the investment (Bharadwaj 2000; Tafti et al. 2007). Industries also differ in their degree of access to intellectual human capital, and in particular, software expertise.

Third, the acquisition network helps account for the complexity of the software technology, as one that operates on a networked ecosystem of technology products and services, and its application to industry-specific processes. Innovations in software technology do not arise in a vacuum; but rather are embedded in a network of dependencies. On one hand, innovation arises within an "ecosystem characterized by a large and complex network of companies interacting with each other…" (Basole 2009, p. 1). On the other hand, software companies position themselves among different industry domains and seek competitive advantage through specializing in those domains. We use the acquisition network in order to explore such internal and external complexities.

Finally, industry-specific processes exhibit different degrees of complementarity with software. The positioning of firms within the network of acquisitions, and particularly the proximity to the software industries, defines and constrains the opportunities for technology resource development (Owen-Smith and Powell 2004; Reagans and McEvily 2003). Technology resources often take hold outside of the industry boundaries in which they are originally developed. Consequently, firms in industries with close ties to the original developer industries need to reconfigure their assets and processes, for example, by reorganizing internally or reconfiguring their external supply chains or value networks.

Hypothesis 1: In the network of corporate acquisitions, proximity to the software industry is associated with greater investment in IT and software as a portion of overall capital investment.

3. Positioning in the acquisition network and labor wage inequality

We next focus on labor income inequality and polarization as an outcome of industries' proximity to software in the acquisition network.

Researchers have attributed a large portion of overall changes in the structure of employment demand to the impact of information technology, or skill-biased technical change (SBTC). Bresnahan, Brynjolfsson and Hitt (2002) find that firm-level investments in IT correspond with greater demand for highly-educated workers; and that IT investments are complementary to certain workplace organization practices that encourage collaboration and independent decision making. Chun (2003) finds that IT capital intensity of industries explains a large portion of acceleration in demand for educated workers in those industries. Autor, Katz and Kearney (2008) find evidence for SBTC effects persisting since 1980. Autor et al. (2003) show that historical labor demand patterns can be attributed to the role of IT as a complement to abstract, cognitive and interpersonal tasks requiring high-levels of education, while IT is also a substitute for routine analytical and mechanical tasks comprising middle-educated, white collar jobs and manufacturing production jobs. This has led to greater demand for educated workers from 1970 to 2003 (Autor et al. 2003). Autor and Dorn (2013) find that computers have caused the demand for low-skilled labor to shift towards the service industries, as most of the routine tasks that are readily automated have been in non-service occupations such as "bookkeeping, clerical work, and repetitive production and monitoring activities… tasks which are most commonplace in the middle of the occupational skill and wage distribution" (Autor and Dorn

2013, p. 1559). The results has been wage growth that is U-shaped along the skill quartiles, meaning that occupations involving the lowest and highest levels of skill have accounted for a greater portion of employment wages, while occupations in the middle quartiles of skill have had much lower demand for labor and wage growth. Because computers most readily automate tasks that involve well-defined and precise procedures, and technological progress has been uneven, many of the manual and interpersonal tasks that humans naturally do well (such as facial recognition, conversation, and emotional processing) have thus far been exceedingly difficult to automate with computers (Autor and Dorn 2013). This is one source of the unbalanced technological progress leading to the polarization of employment demand.

We argue that the differential proximity to software within the network of acquisitions represents an additional source of unbalanced technological progress, for the reasons we describe above and summarize here: 1) The acquisition network represents channels or conduits for the movement of software intellectual capital. 2) Acquisitions and their corresponding merger integration processes present opportunities for organizational restructuring and redesign of industry-specific processes to leverage information technology for new efficiencies, that in turn, affect labor demand, and 3) The complex network of interdependencies that underlie software and internet platforms, and the differential complementarity of industry-specific knowledge and processes situated in that network reflects the differences in industries' potential for software-enabled technological progress.

Numerous recent examples suggest how IT can lead to more polarized labor markets (Schwartz 2015). Notably, the arts, entertainment, media industry has seen the greatest increase in polarization of labor wages. Pay near the top of the income scale is six times the pay near the bottom in 2014, compared to just four times in 2007 (Schwartz 2015). Our data also show a notable polarization of wages in the air transportation industry from 2002 to 2013 (see Figure 4). The healthcare industries have also experienced much greater income inequality, particularly in all of the support and administration services. At the same time, the healthcare and the motion picture and sound recording industries have exhibited extraordinarily high rates of convergence towards the software industries, in terms of their proximity within the acquisition network. Kocher and Roberts (2014) write: "Within the next decade, software tools will eliminate thousands, perhaps millions, of jobs in hospitals, insurance companies, insurance brokerages, and human resources departments."

Overall, prior research suggests that the impact of software technology has been to enhance the value of the highest levels of skill and education in the labor markets, and also to increase demand for the lowest tier in skills, while reducing demand for the middle-tier of skilled employees. We witness many contemporary examples of how information technology can create "winner take all" markets, in which a small set of elite workers are rewarded (Brynjolfsson and McAfee 2014). For example, with the digitization of books and online sales of books, Amazon not only wiped out major booksellers like Borders but also made it very difficult for small mom and pop bookstores to be viable, and it threatens the same impact on a number of other retail industries. Robots are also replacing skilled workers in manufacturing plants, inexpensive tax software is replacing the work of accountants, and automated voice recognition systems are replacing people in call centers. The Associated Press has begun using software to automatically generate stories about sports events and corporate earnings releases. As a result, AP says it can generate many times the stories that it used to when paying journalists to do it, and with fewer errors. Soon, driverless cars may be more commonplace and reduce the need for paid human drivers. Based on prior research and numerous recent examples that support it, we posit that changes in labor demand, and in particular, income inequality, will be greater in industries situated more closely to the software industries.

Hypothesis 2: In the network of corporate acquisitions, proximity of an (non-software) industry to the software industry leads to greater polarization (or inequality) in the distribution of wages among the employees within an industry.

4. Research Design and Method

4.1 Data

We merge several data sources for this study. First, we utilized data on mergers and acquisitions from SDC Platinum, a product of Thomson Reuters. We construct a dynamic network of acquisitions from a set of 129,158 completed acquisitions from 2000 to 2014. SDC Platinum is considered to be among the most comprehensive sources for acquisitions and used in many prior studies (Schilling and Phelps 2007; Tafti et al. 2013). The record of each acquisition include the dates, the description of firms, names and North American Industry Classification System (NAICS) codes of each participating firm.[3] To calculate labor inequality measures, we use a dataset of 268,823 data points from the Bureau of Labor Statistics (BLS) showing employment statistics (including mean annual wages, and number of employees) for every combination of occupation category and industry at the 3-digit NAICS level, for each year between 2000 and 2014. We retrieve annual estimates of industry-level investment in different categories of software and information technology, from the Bureau of Economic Analysis (for each year up to and including 2008). We use the full Compustat database to construct annual industry level measures for control variables. We detail these measures below within their corresponding empirical models.

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[3] http://www.census.gov/eos/www/naics/index.html

4.2 Wealth inequality measures

To calculate labor inequality measures, we use a dataset of 268,823 data points from the Bureau of Labor Statistics (BLS) showing employment statistics (including mean annual wages, and number of employees) for every combination of occupation category and industry at the 3-digit NAICS level, for each year between 2000 and 2014. We obtain the distribution statistics using this data, in particular the Gini coefficient, and ratios of the 90^{th} percentile over the 10^{th} percentile in mean annual income, as well as the ratio of 75^{th} percentile over 25th percentile of income levels. We determine the Gini the distribution of annual wage incomes for job category statistics provided by the Bureau of Labor Statistics.[4] On average, the BLS data provides information on about 260 different occupation categories for each industry in each year, which we weight by the number of employees to derive the income distributions.

Gini coefficient: The Gini coefficient is a common measure of wealth inequality.[5] It is based on the Lorenz curve distribution, or the cumulative distribution of income share among all annual-wage employees in an industry (see bottom row of Figure 4).[6] This measure represents the ratio of the area A between the line of total equality (a straight line), and the Lorenz curve, over the total area under the line of equality (A + B). As the Lorenz curve approaches the line of equality, the area A shrinks towards 0, wherein the Gini coefficient value of zero represents total equality. As the area under the Lorenz curve approaches zero, the area A approaches the total area under the line of equality (A + B), resulting in a ratio of one between A and A + B. A Gini

[4] The classification schemes for occupation types changed in 2012 BLS data, when a more detailed hierarchy of labor category levels were provided. For year 2012, we considered the "detailed" occupation category level, which represent the most detailed non-overlapping employment categories that also align closely with the previous classification system. This results in about the same number of OCC classifications per year in each industry before or after 2012: 260

[5] We use the calculation routines in Stata provided by Jenkins et al (2010) *https://ideas.repec.org/c/boc/bocode/s366002.html.*

[6] Illustration in bottom row of Fig. 4 is from **https://en.wikipedia.org/wiki/Gini_coefficient**

coefficient approaching one represents total inequality. Figure 4 compares the labor inequality of wages between the rail transport (NAICS 482) and the air transport (NAICS 481) industries, and how wage inequality changed over time, based on our data. Rail transport industries exhibit a much higher level of wage equality among employees, and the area above that Lorenz curve does not change much from 2002 through 2011. By contrast, air transport exhibits a significant increase in wage inequality from 2002 through 2013, and correspondingly, the area between the Lorenz curve and the line of equality shows a visible expansion between those years.

Our industry-level Gini coefficient measures are lower than the overall national Census numbers of wealth inequality, for the following reasons: First, we consider only the annual wage income, whereas hourly non-salaried employees tend to reside at the lowest ends of wealth distribution.[7] Second, we do not consider capital earnings, which represent the bulk of wealth at the upper ends of national wealth distribution. Third, since we consider the employees of each industry, our measure does not consider the unemployed. Finally, we expect that the dispersion of incomes within industries to be much lower than the general dispersion in the overall economy. We also used other proxies of income inequality: the ratio of 90th percentile income levels over the 10th percentile income levels, and the ratio of 75th percentile over the 25th percentile levels.

4.3 Acquisition network data

We construct network of acquisitions from a set of 129,158 acquisitions from 2000 to 2014, which we update for each year, identifying the four key software industries and the positioning of every other industry with respect to these industries in the acquisition network (see Figures 1-3).

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[7] https://www.census.gov/hhes/www/income/data/incpovhlth/2013/table4.pdf

We model each industry as a set of firms. When a firm in one industry acquires a firm in another, this creates a directed edge, which increases in weight with more acquisitions. Figure 1 illustrates how firm acquisitions that cross industry boundaries are aggregated into edge weights between nodes representing each industry. We model the path length connecting two industries to be inversely proportional to the weight of each directed edge. Hence, each acquisition shortens the directed path from the acquirer's industry to the acquired (target) firm's industry. Separately, we also control for the acquisitions that happen within the industry, and acquisitions that do not involve software firms; by virtue of an industry-level network betweenness measure as well as the logarithm of the direct number of non-software acquisitions involving the industry.

Let A_{ijt} be the cumulative number of acquisitions by firms in industry i of firms in industry j, from year 2000 through year t. We model the weight of each edge as the inverse of the log of A_{ijt}.[8] The resulting edge weight of industry i to industry j in year t becomes $1/\log(A_{ijt} + 1)$. Using these edge weights, we calculate the shortest path from each industry i to j using Dijkstra's algorithm in the igraph package in R. We also find the *betweenness* for each industry in the network, a common measure for overall centrality in social networks. For any industry k, betweenness represents the average number of shortest paths that connects every pair of other two industries i and j on which industry k resides (Jackson 2008). We also use multiple proxies for degree centrality in this network: The logarithm of annual acquisitions not involving software firms (direct edges to non-software industries), as well of annual acquisitions by and of software

[8] For calculating the network measures, we take acquisitions as lasting permanently in their contribution to the edge weight between industries. We allow for two years of acquisition activity before computing the network measures; and so the network measures begin in year 2002. Because we have the data sample period contains a finite number of years, beginning in 2000, our econometric analysis focuses only on the relative within-industry network measures with respect to their overall industry means over time (i.e. fixed-effects analysis), rather than on cross-industry comparisons of absolute levels of network measures.

firms (out-degree from, and in-degree to software industries). We consider four separate categories of software-producing industries, as listed in Table 1 mentioned above.

To understand the relationship between acquisitions and shortest path length, we present the fixed-effects panel estimations in Table 3 as a preliminary exploration of these measures, in particular to understand the relative effect of different acquisition types on shortest path. The fixed-effects panel regressions show that the actual effect on shortest path is primarily through acquisitions by software firms, rather than when software firms are the targets of acquisitions. This helps shed some light on the results that follow next. We describe the additional control variables below as we present the empirical models, after presenting some summary statistics and graphs.

4.4 Summary statistics

It is useful to examine a few summary statistics and correlations among our main variables of interest. Table 2 shows annual averages in the number and value of acquisitions for the three different categories of acquisitions. As would be expected, the majority of acquisitions are between non-software firms (6,003 per year), and non-software acquisitions are on average much higher in value ($2.7 billion). Acquisitions of software firms by non-software firms (338 per year, $100 million/acquisition) are more prevalent and generally larger than acquisitions of non-software firms by software firms (194 per year, $49 million/acquisition). Figure 5 shows a scatter plot and best-fit regression of Gini index against shortest path length from the software publishing industry (NAICS 511), with the 95% confidence interval of the prediction; based on the network of cumulative acquisitions from 2000 through 2013. As expected, industries that are closer to the software publishing industry, with lower shortest path lengths, tend to have higher levels of income inequality. We list the industries that fall in the upper left and lower right hand side of the graph, for illustrative purposes. Notably, two industry categories stand out for their closeness to the software industry and high levels of labor inequality: the motion picture and sound industries (512), as well as ambulatory health care services (621). This is consistent with our prior reference to these industries. Figure 6 shows the longitudinal trends for the average shortest path length from the software industries to each focal industry, for each of the four major software industries. Because the shortest path measures are based on the cumulative acquisitions from 2000, we expect average shortest path lengths to decline over time, and also to reach a steady state with more cumulative acquisitions. The graph suggests the steady state to have been reached by about year 2012. Ultimately, our econometric analysis isolates the relative change in shortest path distance between industries; hence, we are agnostic to absolute levels of network measures such as shortest path, but rather care about how rapidly a shortest path distance to software declines for one industry more rapidly than another (i.e. rate of digital convergence). Figure 7 shows the longitudinal trends in betweenness centrality, comparing software and non-software industries. Interestingly, betweenness centrality is generally much higher for software industries than non-software industries; and further, betweenness centrality has been increasing for software industries while it exhibits a small and gradual decline for non-software industries.

4.5 Empirical estimation models and results

To test Hypothesis 1, we examine the effect of acquisitions by and of software firms within each non-software industry.

$$\text{Industry software investment}_{i,t} = \beta_0 + \beta_1 \log(\text{Acquisitions by Software firms})_{i,t} + \beta_2 \log(\text{Acquisitions of Software firms})_{i,t} + \beta_3 \log(\text{Acquisitions not involving software firms})_{i,t} + \beta_4 \text{Industry concentration}_{i,t} + \beta_5 \text{Market-size growth of the industry (3 years)}_{i,t} + \sum \beta_t \text{Year}_t + u_i + \varepsilon_{i,t} \quad (1)$$

The subscript i represents each non-software industry at the three-digit NAICS level. The subscript t represents the year.

For the dependent variable in equation (1), we consider five different forms of industry-level IT investment, as a proportion of overall fixed asset investments. We obtained annual industry-level investment data in software and other fixed capital investments from the Bureau of Economic Analysis (BEA). In particular, we consider pre-packaged software, custom software, firms' in-house (own-account) software, and overall IT investment. These measures are calculated as percentages of overall fixed capital investment. We provide further details about the dependent variables of software investment in the header of Table 4.

We control for all non-software acquisitions involving firms in the industry. We also control for *industry concentration*, or Herfindahl index, using calculations detailed in Bharadwaj et al. (1999). We also control for market-size growth of the industries over a three-year period up to the current year t, and overall acquisitions involving non-software firms. We calculate industry concentration and market-size growth using the full set of firm listings in the Compustat Fundamentals Annual database. We also include each of the year indicators ($Year_t$), and hence the model represents a two-way fixed effects of each year and industry individual fixed-effects (u_i). Coefficient estimates in Table 4 suggest strong support for Hypothesis 1 for software firms acquiring non-software firms (*acquisitions by software firms*), but not for the reverse, non-software firms acquiring software firms.

Next, to test Hypothesis 2, we examine the effect of acquisitions by and of software firms on the inequality of employee annual wage incomes within each non-software industry, and also examine the effect of proximity (via the shortest path lengths) to and from the main software-producing industries.

$$\text{Income Inequality}_{i,t} = \beta_0 + \beta_1 \log(\text{Acquisitions by Software firms})_{i,t} + \beta_2 \log(\text{Acquisitions of Software firms})_{i,t} + \beta_3 \log(\text{Acquisitions not involving software firms})_{i,t} + \beta_4 \text{ Industry density}_{i,t} + \beta_5 \text{ Industry average revenue}_{i,t} + \beta_6 \text{ R\&D}_{i,t} + \beta_7 \text{ Physical Capital}_{i,t} + \beta_8 \text{ Industry ROA}_{i,t} + \beta_9 \text{ Entering Firms}_{i,t} + \beta_{10} \text{ Exiting Firms}_{i,t} + \beta_{11} \text{ Industry concentration}_{i,t} + \sum \beta_t \text{Year}_t + u_i + \varepsilon_{i,t} \quad (2)$$

The unit of analysis (industry-year) is the same as in equation (1), as are the first three variables on the right-hand side of the equation. For the dependent variable in equation (2), we use the Gini index as well as the ratios of annual wages for the 90th percentile employees over the 10th percentile employee, as well as of the 75th percentile over the 25th percentile wage levels.

As in equation (1), we control for industry concentration, non-software acquisitions, and also use a two-way fixed effects scheme controlling for each year ($Year_t$) and individual industry fixed-effects (u_i). In addition, we control for average annual revenues in the industry, average R&D investment, physical capital investments, average firm profitability measured as return on assets (ROA), the number of firms entering the industry each year (*Entering Firms*), and number of firms exiting the industry, either through bankruptcy, change in industry classification, or having been acquired (*Exiting Firms)*. Like industry concentration, we calculated all of these control variables using the full set of firm listings in Compustat. Our findings in Table 5 indicate support for Hypothesis 2. Acquisitions by and of software firms have a positive effect on labor inequality in annual wages; we do not find this to be the case for acquisitions not involving software firms.

Equation (2) uses only measures of direct connection to the software industry. Indirect connections may also be important. As discussed in the hypotheses section, an industry may have relatively few direct acquisitions involving software firms, but may be connected to another industry that has many such acquisitions. Thus we consider the next model of equation (3) to consider indirect connections in the overall network.

$$\text{Gini index}_{i,t} = \beta_0 + \beta_1 \text{ Shortest Path Length To Software}_{i,t} + \beta_2 \text{ Shortest Path Length From Software}_{i,t} + \beta_3 \log(\text{Network Betweenness})_{i,t} + \beta_4 \text{ Industry density}_{i,t} + \beta_5 \text{ Industry average revenue}_{i,t} + \beta_6 \text{ R\&D}_{i,t} + \beta_7 \text{ Physical Capital}_{i,t} + \beta_8 \text{ Industry ROA}_{i,t} + \beta_9 \text{ Entering Firms}_{i,t} + \beta_{10} \text{ Exiting Firms}_{i,t} + \beta_{11} \text{ Industry concentration}_{i,t} + \sum \beta_t \text{Year}_t + u_i + \varepsilon_{i,t} \quad (3)$$

In the above equation 3, we determine the shortest path lengths to and from the software industries using the procedure discussed in the above section 4.3, where we presented Table 3 results that relate acquisitions to shortest path lengths. Equation (3) is similar to equation (2) in that only the first three right hand side variables are different. Here, we use *Shortest Path Length From Software* in place of acquisitions by software firms, *Shortest Path Length To Software* in place of acquisitions of software firms, and the logarithm of overall network *betweenness* in place of non-software acquisitions. As a proxy for centrality in the overall network that includes all industries, betweenness accounts for all of the direct and indirect connections to non-software industries. As the shortest path to or from software decreases in length, we expect greater income inequality. Hence, our hypotheses predict negative coefficient estimates for the first two right-hand terms on equation (3). We display the estimates for equation (3) in Table 6. The estimates for β_1 show limited support for Hypothesis 2 (for NAICS 511 and NAICS 519), but not the estimates for β_2.

4.6 Results

We find support for Hypothesis 1 which predicts that in the network of corporate acquisitions, proximity to the software industry is associated with greater investment in IT and software as a portion of overall capital investment (see the coefficient estimates of the *log(acquisitions by software firms)* in Table 4). This hypothesis is supported with respect to different types of IT investments, including own-account software (developed internally by firms), custom software (developed by consultancies or service providers for the firms' specific needs), prepackaged software, and system integration. We also find support for the effect of acquisition by software firms on the industries' overall IT intensity. The coefficients for own account software (1.493) and custom software (1.141) are higher than the coefficients for prepackaged software (0.636) and system integration (0.052). This difference is consistent with the argument regarding M&As as the conduits of innovation, as we might consider a non-software firms' internally developed or customized software to be a greater proxy for its IT-enabled innovation than its expenditure on prepackaged software or system integration.

We find support for Hypothesis 2 which predicts that, in the network of corporate acquisitions, a non-software industry's proximity to the software industry leads to greater polarization (or inequality) in the distribution of employee wages (see the coefficient estimates of *shortest path length from software to non-software* in Table 6). We also find support for the effect of acquisitions of and by software firms on different measures of wage inequality (see the coefficient estimates of *log(acquisitions by software)* and *log(acquisitions from software)* in Table 5).

4.7 Identification concerns and robustness tests

All estimates use two-way fixed-effects at the unit of analysis of the panel data—specifically, industry and year fixed effects. We also use robust standard errors in all estimates to correct for possible non-spherical errors and account for any heteroskedasticity. The estimation procedure takes care of a number of potential concerns with respect to inherent differences among the industries. The procedure controls for any unobserved industry features that do not change much over short periods of time. The year indicators also control for overall industry trends driven by time. The fixed-effects model has a useful feature for identification, in that it captures only the longitudinal variations within each industry, while filtering away static cross-industry variations. Thus, it controls for the unobserved features in the initial state (our first sample year) of the acquisition network that resulted from acquisition activity prior to 2000.

Finally, we employ a number of reverse-causality tests to examine the general causal direction of our hypotheses. We modified each of the estimation models into forms that test for Granger causality; in particular, by including two lags of the dependent variable in the right hand side of the estimation models. We also estimated the models by substituting the dependent variables with their one-year forward values. The coefficient estimates remained consistent with our main estimation models.[9] The Granger causality test results were consistent with our main model estimates, showing the same direction and statistical significance levels for the coefficients of interest. We also tested the reverse of the model equations, by replacing the dependent variables by their one-year lagged values; and also separately, by switching the dependent variables (software investment for H1, and labor inequality for H2) with the main right-hand side variable (respectively, acquisitions by software firms, and shortest path from software). The results indicated very weak or non-existent evidence for effects in the reverse direction: we do not find that labor inequality within an industry leads to more acquisitions by software firms, or to greater proximity from software firms in the overall network of acquisitions.

5. Conclusions

The network of corporate acquisitions can reveal how innovations in software affect multiple non-software industries, and thereby help explain the impact on those industries' labor markets. Understanding the proximity of various industries to software-producing industries, and

[9] These supplementary regression results are available upon request.

how this proximity has changed over time, provides some insight into why some industries are more susceptible to being digitized than others. The corporate acquisition network is particularly useful to understand the interconnections between industries in terms of the impacts of innovation, because most acquisitions represent irreversible investments, especially after an acquired firm (the target) is integrated into the acquiring firm as an operating and legal entity.

Firms acquire other firms when the assets they seek, such as specialized intellectual capital or brand reputation, are not readily available from market transactions. As a result, we argue that the relative positioning among industries in the network of corporate acquisitions does not change rapidly over time, but where we do see changes in this network, this will suggest dramatic changes in the organization of underlying strategic assets or industry-specific business processes that affect labor demand and the distribution of wages.

We examined how network positioning of non-software industries with respect to software-producing industries affect monetary software investments in non-software industries; and also, how positioning with respect to software can influence wage inequality among an industry's employees. We considered the entire network of acquisitions that tie software and non-software industries, and their positioning with respect to one another in that network. One important feature of corporate acquisitions for the purpose of this study is that the acquisition links are costly to form. The changing acquisition network suggests how firms are reorganizing their critical strategic assets, or industry-specific business processes; often to achieve greater efficiencies. The increasing proximity to software industry resources, in turn, leads to more polarized labor demand.

Our study presents two important contributions to the understanding of the impact of IT on labor markets. First, we expected, and found, that industries positioned more closely to software industries within the acquisition network have greater polarization in employee wages. Positioning with respect to software industries represents a new, and perhaps more context-sensitive measure of IT capability that corresponds closely with monetary software and IT investment in the past decades; but moving forward, offers a new way of understanding firms' IT capabilities and resources. As firms adopt cloud and mobile computing solutions, and utilize a combination of outsourcing, contingent labor contracts and strategic alliances to develop new IT capabilities, the measures of IT investment used commonly in prior research—such as PCs per employee, monetary IT budgets, or size of their IT operations—may become less relevant in the future. Positioning within the acquisition network can capture some of the complexity of interconnections among the technology platforms and their application to industry-specific knowledge. Second, we show that positioning within the acquisition network can be informative to understand the drivers of uneven technological progress, as well as differences in labor wage inequality among the different industries. In particular, the acquisition network represents channels or paths for the movement of intellectual capital, and allows us to consider the complexity of connections between software expertise and industry-specific knowledge, and to better understand the underlying causes of IT-driven changes in the labor market.

Figure 1 Industry-level network aggregation of cross-industry corporate acquisitions.

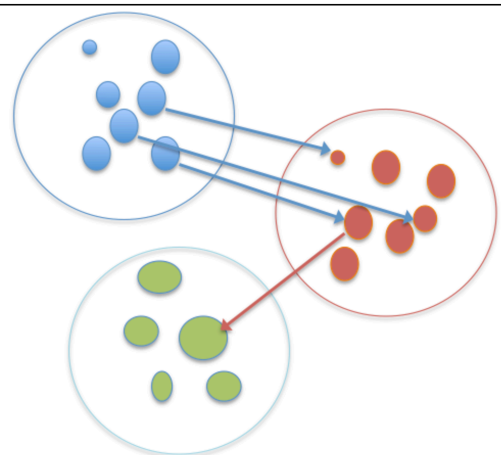
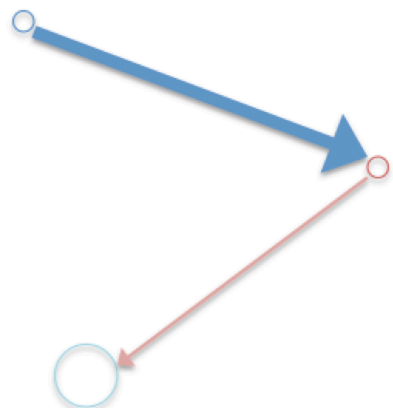
<table>
<tr>
<td>Firm level representation: Circles represent industries, and acquisitions represent the directed edges that connect certain filled ovals of different size within the industries.</td>
<td>Industry level reprsentation: Industries are collapsed to become nodes, and edge weights are proportional to the number of acquistions between industries A_{ij}. The path length between each node is inversely proportional to the edge weights, and given as 1/log(Aij + 1).</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
</table>

Figure 2 Year 2006 representation of the acquisition network; log(acquisitions) are used to weight the network edges. Our network measures of shortest path and betweenness use the total cumulative acquisitions from 2000 to each year through 2014**.** Directed edges represent an acquisition by firms in an industry (acquirers are edge sources), of firms in another industry (target firms are edge targets). Green nodes are non-software industries, while red nodes are software industries. Non-software nodes that are lighter in shade and larger in size have greater network degree. Red arrows represent acquisitions by software firms. Grey arrows represent acquisitions by non-software firms. The arrows, or directed edges, are weighted by the log of number of acquisitions. We obtained data on the acquisitions from Thomson Reuters' SDC Platinum database. We used Gephi to generate this diagram, using the Force Atlas algorithm to arrange the nodes, where larger directed edges have an attraction force that bring nodes together.

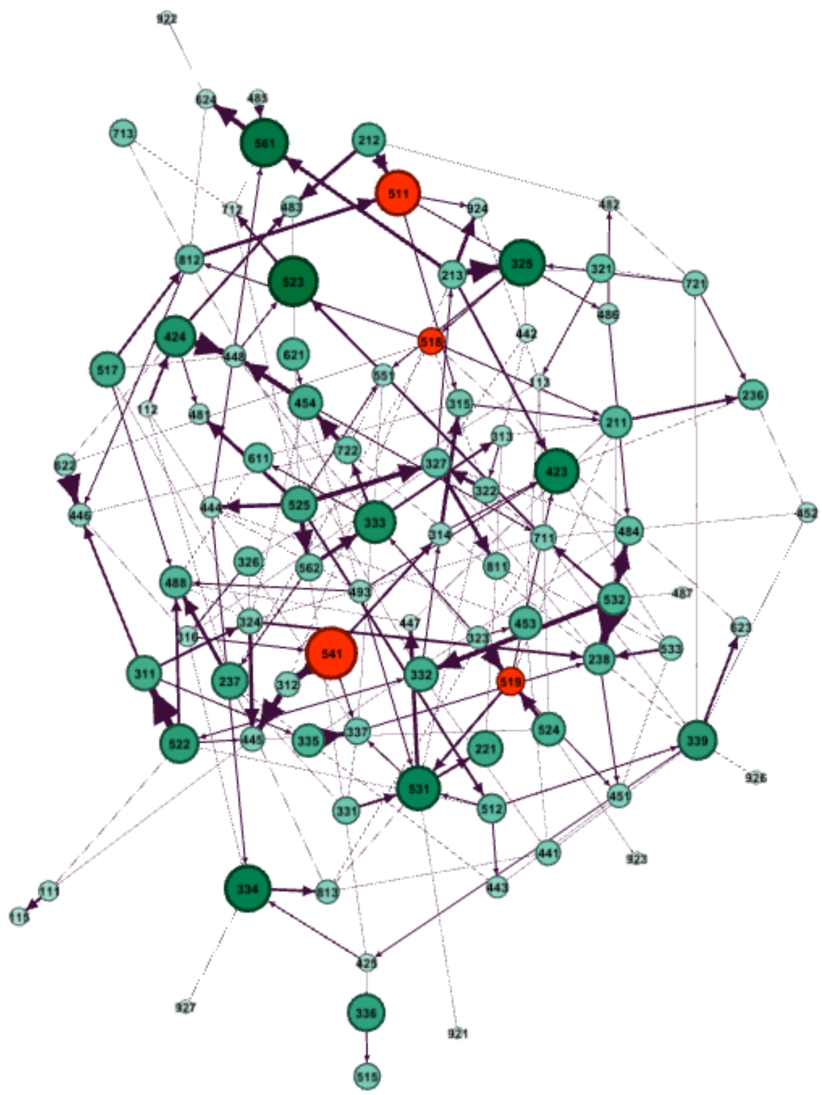


Figure 3: Software firm acquisitions of non-software firms, at the industry-level of aggregation. This network shows only network edges representing acquisitions by software firms (weighted by the log of the acquisitions). Software industries are in red. Edge thickness represents the log of the number of acquisitions by software firms. Non-software industries are in green, with size (and lightness of shade) of nodes representing the total network degree.

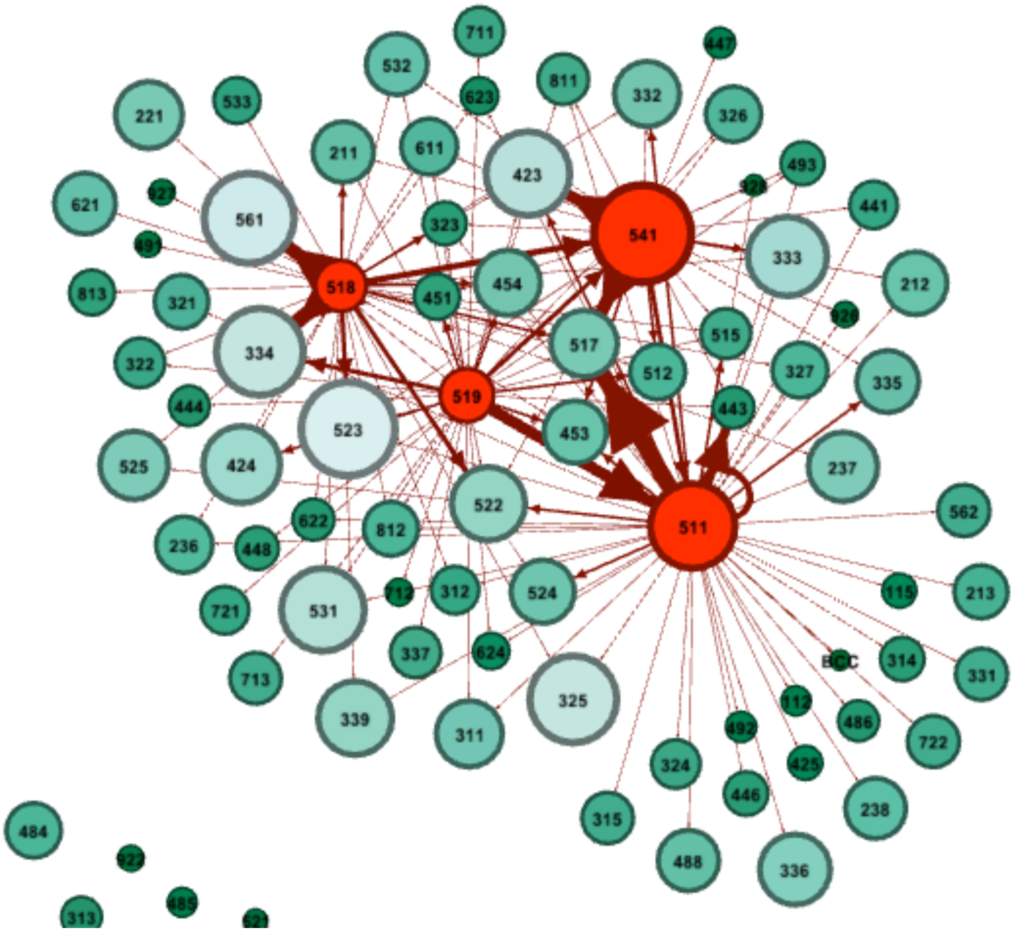
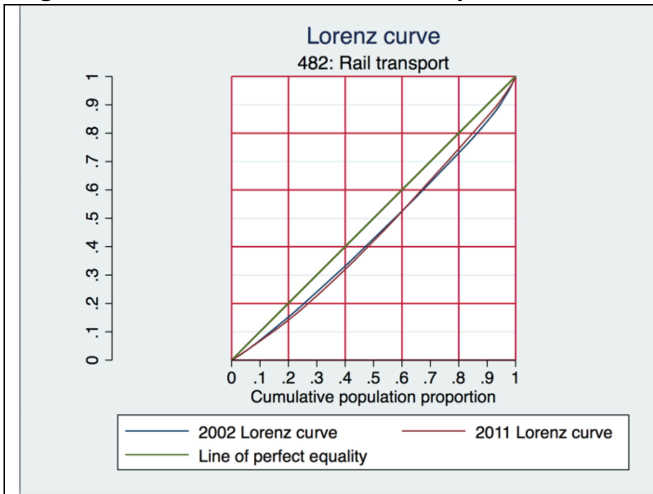
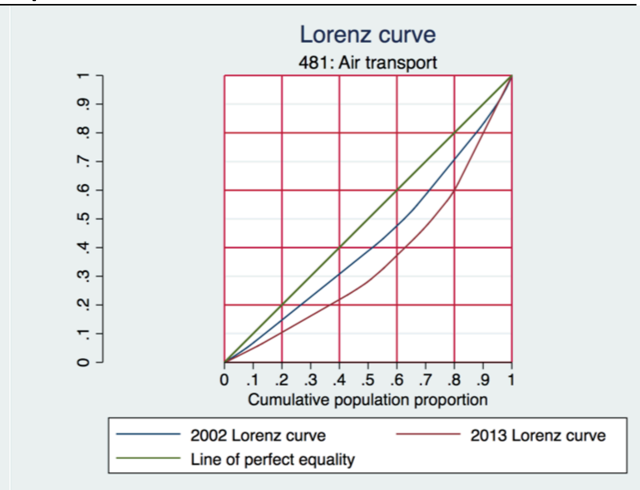
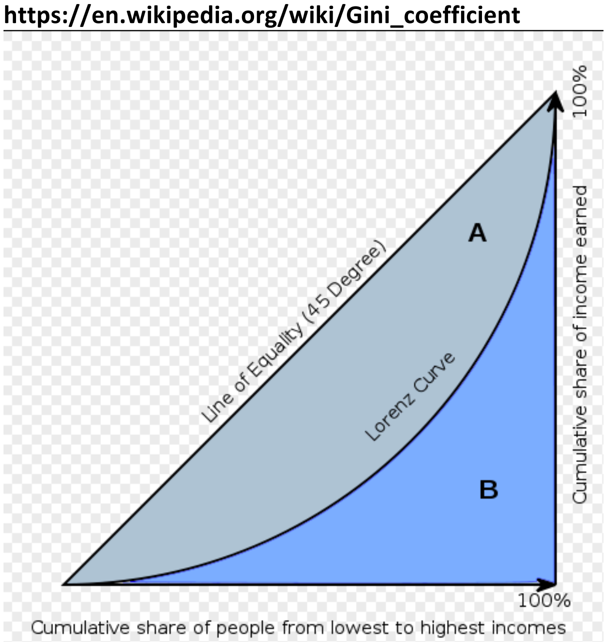


Figure 4 Lorenz curves for Rail Transport and Air Transport industries from 2002 to 2013





Sample Lorenz curve is from:
https://en.wikipedia.org/wiki/Gini_coefficient

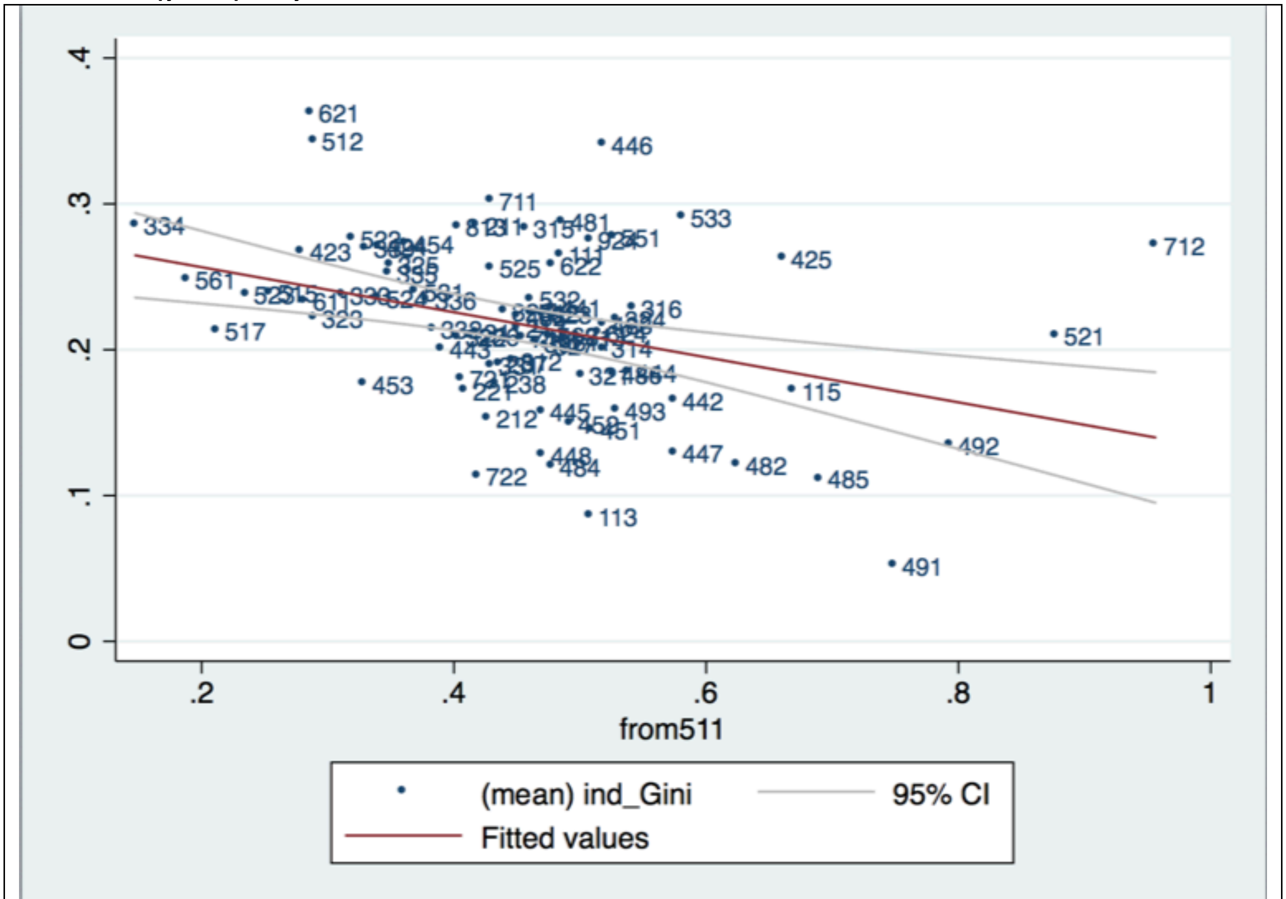


Gini coefficient= A / (A+B)

Complete inequality: Gini = 1

Complete equality: Gini = 0

Figure 5 Shortest path length from software publishing industry (NAICS 511) (x-axis) vs. Gini coefficient (y-axis) for year 2013



Close to software publishing:	Away from software publishing:
325 Chemical Manufacturing	115 Agricultural services
334 Computer and Electronic Product Manufacturing	482 Railroads
423 Computers and software whole-selling	485 Transit and Ground Passenger Transportation
446 Health and Personal Care Stores	487 Scenic and Sightseeing Transportation
512 Motion Picture and Sound Recording Industries	491 Postal service
517 Telecommunications	492 Couriers and Messengers
523 Financial services	521 Monetary Authorities-Central Bank
561 Administrative and Support Services	712 Museums, Historical Sites, and Similar Institutions
621 Ambulatory Health Care Services	

Figure 6: Shortest path distance from software to focal industry over time

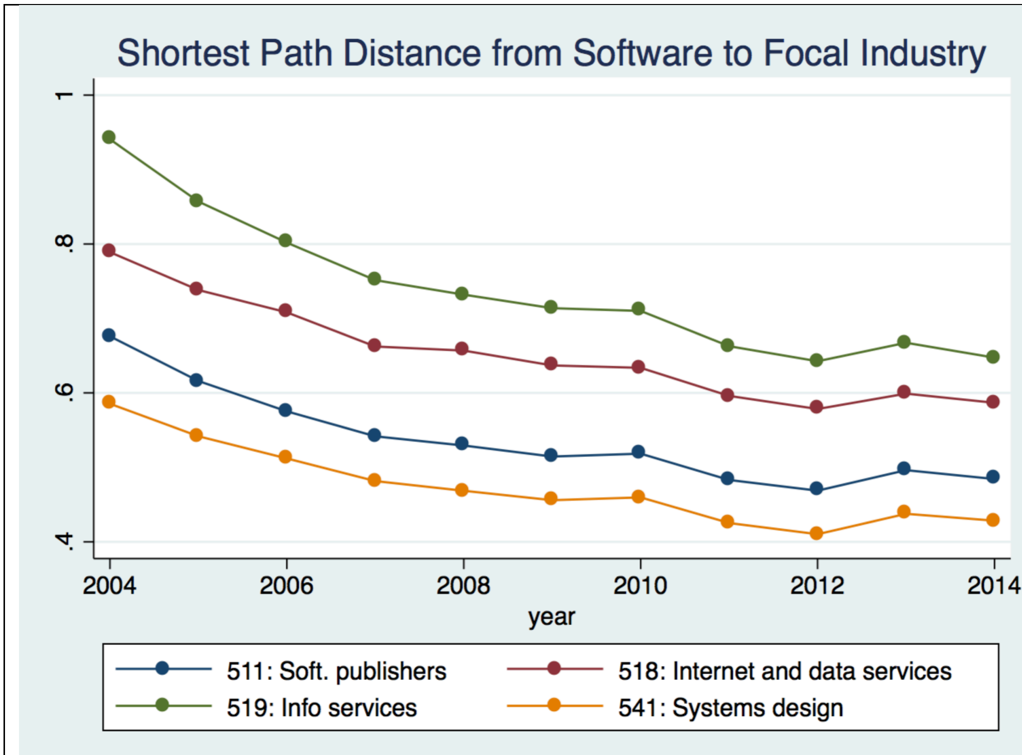


Figure 7: Betweenness centrality of software and non-software industries over time

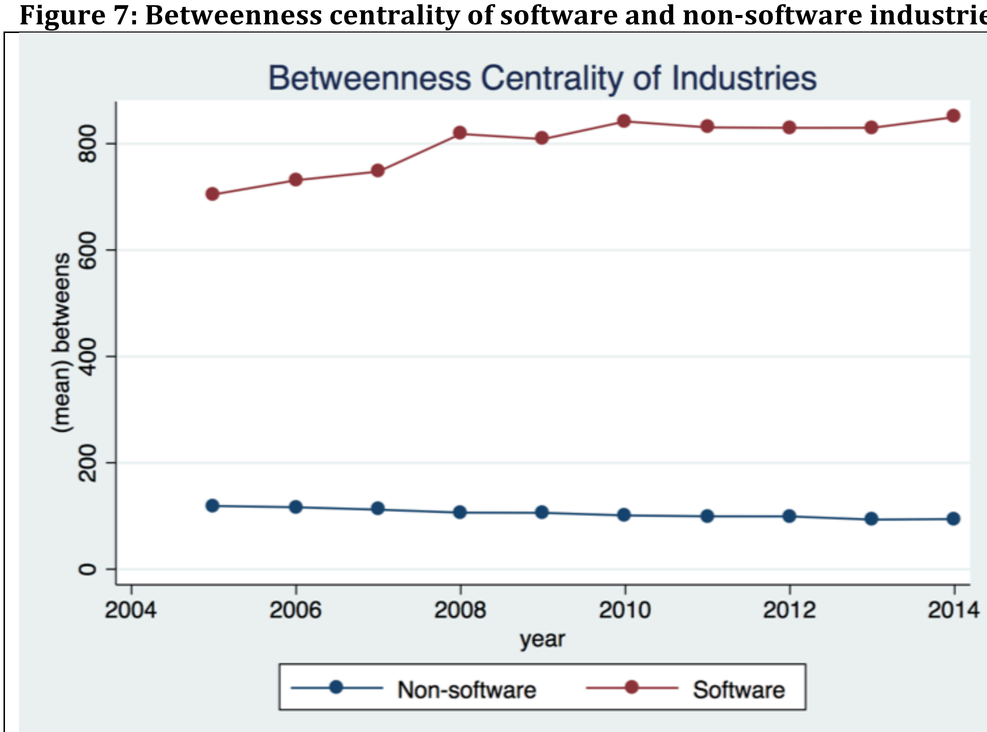


Table 1: Software industries at the three-digit NAICS level

NAICS code	Description	Examples
511	Software publishers	SAP, Oracle, Microsoft
518	Internet and data service providers	Paypal, ADP, Fiserv
519	Information services	Google, Baidu, Alibaba, Facebook
541	Systems Design	IBM, Fujitsu, Accenture

Table 2: Firm acquisitions 2000-2014, average frequency and value

	Number of acquisitions per year (average)	Average value of each acquisition
Software acquires non-software	194	$49 million
Non-software acquires software	338	$100 million
Non-software acquires non-software	6,003	$2.7 billion

Table 3 Relationship between acquisitions and shortest path lengths to and from the software industry: Fixed effects panel regressions with robust standard errors. We control for fixed effects for each industry and year. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

	Dependent variable: Shortest path FROM non-software TO software				Dependent variable: Shortest path FROM software TO non-software			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Software publishers (511)	Systems Design and Related Services (541)	Internet services and data processing (518)	General Information Services (519)	Software publishers (511)	Systems Design and Related Services (541)	Internet services and data processing (518)	General Information Services (519)
log(Acquisitions of Software firms)	-0.0136*	-0.00929	-0.00262	-0.0120	0.00163	0.00280	0.00625	-0.00161
	(0.00688)	(0.00777)	(0.00788)	(0.00914)	(0.00472)	(0.00408)	(0.00571)	(0.00483)
log(Acquisitions by Software firms)	-0.0159**	-0.0144*	-0.0173**	-0.0132	-0.0151***	-0.0108**	-0.0134***	-0.0145***
	(0.00749)	(0.00815)	(0.00803)	(0.00803)	(0.00539)	(0.00422)	(0.00504)	(0.00550)
log(Acquisitions not involving software firms)	-0.0206	-0.0228	-0.0239	-0.0212	0.00134	-0.00547	0.000984	-0.00343
	(0.0170)	(0.0186)	(0.0181)	(0.0181)	(0.00861)	(0.00879)	(0.00884)	(0.00884)
Constant	1.089***	0.917***	1.218***	1.295***	0.818***	0.717***	0.929***	1.163***
	(0.0575)	(0.0625)	(0.0602)	(0.0633)	(0.0276)	(0.0305)	(0.0289)	(0.0298)
Observations	1,140	1,140	1,140	1,140	1,136	1,136	1,136	1,136
R-squared	0.680	0.568	0.678	0.711	0.738	0.688	0.775	0.852
Number of ind3d	95	95	95	95	94	94	94	94
F stat	27.35***	15.24***	28.24***	36.98***	30.71***	25.41***	34.14***	70.14***
F test	0	0	0	0	0	0	0	0

Table 4: Acquisition-network proximity of non-software industries to the software industry, and their software investment intensity: Fixed effects panel regressions with robust standard errors. N= 703, with 83 industries. We control for industry concentration, market size growth of the industry, and fixed effects for each industry and year. Dependent variables are industry-level investment as a proportion of overall fixed asset investments; we obtained these from the Bureau of Economic Analysis (BEA). Software investment is described in BEA's document, Recognition of Business and Government Expenditures for Software as Investment: Methodology and Quantitative Impacts, 1959-98: "**Prepackaged software** is software intended for nonspecialized uses and is sold or licensed in standardized form. It typically requires little or no modification for use…**Custom software** is software tailored to the specifications of a business enterprise or government unit. It may include new computer programs as well as programs incorporating preexisting or standardized modules….**Own-account software** consists of in-house expenditures for new or significantly-enhanced software created by business enterprises or government units for their own use." Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Industry software investment$_{i,t}$ = β_0+ β_1 **log(Acquisitions by Software firms)**$_{i,t}$ + β_2 log(Acquisitions of Software firms)$_{i,t}$ + β_3 log(Acquisitions not involving software firms)$_{i,t}$ + β_4 Industry concentration$_{i,t}$ + β_5 Market-size growth of the industry (3 years)$_{i,t}$ + $\sum \beta_t$Year$_t$ + u_i + $\varepsilon_{i,t}$

VARIABLES	(1) OwnAcctSoftware	(2) CustomSoftware	(3) PrepackagedSoftware	(4) SystemIntegration	(5) IT Intensity
log(Acquisitions of Software firms)	0.155	0.0196	-0.00230	-0.00895	-0.0794
	(0.107)	(0.0821)	(0.0758)	(0.00865)	(0.314)
log(Acquisitions by Software firms)	1.493***	1.141***	0.636***	0.0529***	3.819***
	(0.206)	(0.165)	(0.117)	(0.0192)	(0.546)
log(Acquisitions not involving software firms)	-1.005**	-0.763**	-0.498*	-0.101**	-2.587**
	(0.383)	(0.318)	(0.251)	(0.0394)	(1.228)
Industry concentration (Herfindahl index)	-4.686	-3.697	-2.651	-0.344	-12.61
	(3.146)	(2.613)	(2.045)	(0.387)	(10.78)
Three-year growth in industry sales (market growth)	-0.000338	-0.000315	-0.000225	-5.29e-05	- 0.000606
	(0.000499)	(0.000438)	(0.000285)	(4.73e-05)	(0.00148)
Constant	9.608***	8.688***	7.796***	1.524***	45.04***
	(1.730)	(1.436)	(1.150)	(0.187)	(5.704)
Observations	703	703	703	703	703
R-squared	0.275	0.239	0.398	0.149	0.176
Number of ind3d	83	83	83	83	83
F stat	15.85	12.35	35.31	13.37	13.13
F test	0	0	0	0	0

Table 5: Acquisition-network proximity of non-software industries to the software industry, and labor inequality: Fixed effects panel regressions with robust standard errors. We control for fixed-effects for each industry and year, and the following time-varying factors: industry density (number of firms in the industry) and its square, market size, proportion of R&D investment over sales (R&D intensity), physical capital intensity, annual rate of firms entering and exiting the industry, industry concentration, and industry profitability. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.10.

Income Inequality$_{i.t}$ = β_0+ β_1 **log(Acquisitions by Software firms)**$_{i,t}$ + β_2 log(Acquisitions of Software firms)$_{i,t}$ + β_3 log(Acquisitions not involving software firms)$_{i,t}$ + β_4 Industry density $_{i,t}$ + β_5 Industry average revenue $_{i,t}$ + β_6 R&D $_{i,t}$ + β_7 Physical Capital $_{i,t}$ + β_8 Industry ROA $_{i,t}$ + $\sum \beta_t \text{Year}_t + u_i + \varepsilon_{i,t}$

VARIABLES	(1) Gini	(2) 90pctile_over_10pctile	(3) 75pctile_over_25pctile
log(Acquisitions of Software firms)	0.00222**	0.0553**	0.0240**
	(0.00111)	(0.0213)	(0.0107)
log(Acquisitions by Software firms)	0.00528***	0.111***	0.0496***
	(0.00160)	(0.0284)	(0.0125)
log(Acquisitions not involving software firms)	-0.00629*	-0.119*	-0.0604*
	(0.00374)	(0.0670)	(0.0309)
Industry density: Number of firms in the 3-digit industry	-1.18e-06	9.75e-06	-3.43e-05
	(2.29e-06)	(5.41e-05)	(4.30e-05)
Average annual revenues in the 3-digit industry	8.34e-07***	1.69e-05***	4.22e-07
	(2.32e-07)	(4.24e-06)	(2.60e-06)
Average R&D investment in the 3-digit industry	5.32e-05***	0.00181***	-0.000673***
	(1.45e-05)	(0.000234)	(0.000165)
Average physical capital investment in the 3-digit industry	0.00889***	0.133*	0.130**
	(0.00325)	(0.0717)	(0.0568)
Number of firms *entering* the industry	1.30e-09	0.000558	0.000250*
	(1.13e-05)	(0.000339)	(0.000149)
Number of firms *exiting* the industry	-8.56e-06	7.80e-05	-3.26e-06
	(7.45e-06)	(0.000226)	(8.38e-05)
Industry concentration (Herfindahl index)	0.0220	0.477	0.0182
	(0.0167)	(0.406)	(0.163)
Constant	0.234***	2.893***	1.842***
	(0.0167)	(0.300)	(0.141)
Observations	807	807	807
R-squared	0.105	0.107	0.079
Number of ind3d	68	68	68
F stat	8.298***	17.31***	5.159***

Table 6 Shortest path to/from software and labor inequality: Fixed effects panel regressions with robust standard errors. We control for fixed-effects for each industry and year, and the following time-varying factors: industry density (number of firms in the industry) and its square, market size, proportion of R&D investment over sales (R&D intensity), physical capital intensity, annual rate of firms entering and exiting the industry, industry concentration, and industry profitability. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.10.

Gini $\text{index}_{i,t} = \beta_0 + \beta_1$ Shortest Path Length To $\text{Software}_{i,t}$ + β_2 Shortest Path Length From $\text{Software}_{i,t}$ + β_3 log(Network $\text{Betweenness})_{i,t}$ + β_4 Industry $\text{density}_{i,t}$ + β_5 Industry average revenue $_{i,t}$ + β_6 R&D $_{i,t}$ + β_7 Physical Capital $_{i,t}$ + β_8 Industry ROA $_{i,t}$ + β_9 Entering Firms $_{i,t}$ + β_{10} Exiting Firms $_{i,t}$ + β_{11} Industry $\text{concentration}_{i,t}$ + $\sum \beta_t \text{Year}_t + u_i + \varepsilon_{i,t}$

	Dependent variable: Industry Gini index of employees' mean wages			
	(1) Software publishers (511)	(2) Internet services and data processing (518)	(3) General Information Services (519)	(4) Systems Design and Related Services (541)
Shortest path length FROM non-software TO Software	-0.0130**	-0.00974	-0.0114**	-0.00826
	(0.00605)	(0.00597)	(0.00567)	(0.00551)
Shortest path length FROM Software TO non-software	0.0248**	0.0226*	0.0235**	0.0156
	(0.0111)	(0.0120)	(0.00991)	(0.0128)
log(Network Betweenness)	0.000151	0.000146	0.000160	0.000143
	(0.000108)	(0.000108)	(0.000108)	(0.000109)
Industry density: Number of firms in the 3-digit industry	1.50e-06	2.09e-06	1.77e-06	1.42e-06
	(1.88e-06)	(1.95e-06)	(1.91e-06)	(1.91e-06)
Average annual revenues in the 3-digit industry	8.87e-07***	8.52e-07***	8.66e-07***	8.15e-07***
	(2.26e-07)	(2.24e-07)	(2.22e-07)	(2.23e-07)
Average R&D investment in the 3-digit industry	5.81e-05**	5.89e-05**	5.85e-05**	5.86e-05**
	(2.67e-05)	(2.68e-05)	(2.67e-05)	(2.68e-05)
Average physical capital investment in the 3-digit industry	0.00532*	0.00554*	0.00483	0.00508*
	(0.00299)	(0.00300)	(0.00300)	(0.00301)
Number of firms *entering* the industry	1.03e-05	1.12e-05	1.12e-05	8.03e-06
	(2.14e-05)	(2.16e-05)	(2.15e-05)	(2.15e-05)
Number of firms *exiting* the industry	-5.53e-06	-5.89e-06	-5.28e-06	-6.43e-06
	(8.71e-06)	(8.73e-06)	(8.72e-06)	(8.72e-06)
Industry concentration (Herfindahl index)	0.0285***	0.0296***	0.0288***	0.0292***
	(0.0101)	(0.0101)	(0.0101)	(0.0102)

Constant	0.206***	0.204***	0.201***	0.209***
	(0.00744)	(0.00897)	(0.00965)	(0.00760)
Observations	689	689	689	689
R-squared	0.167	0.165	0.168	0.163
Number of ind3d	66	66	66	66
F stat	5.496***	5.381***	5.519***	5.307***

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