

INFORMATION TECHNOLOGY AND INDUSTRY CONCENTRATION

Boston University School of Law
Law & Economics Paper No. 17-41

James Bessen
Boston University School of Law

This paper can be downloaded without charge at:

<http://www.bu.edu/law/faculty-scholarship/working-paper-series/>

Information Technology and Industry Concentration

By James Bessen

Boston University School of Law

September 2017

Abstract: Industry concentration has been rising in the US since 1980. Why? This paper explores the role of proprietary information technology systems (IT), which could increase industry concentration by raising the productivity of top firms relative to others. Using instrumental variable estimates, this paper finds that industry IT system use is strongly associated with the level and growth of industry concentration. The paper also finds that IT system use is associated with greater plant size, greater labor productivity, and greater operating margins for the top four firms in each industry compared to the rest. Successful IT systems appear to play a major role in the recent increases in industry concentration and in profit margins, more so than a general decline in competition.

Keywords: information technology, computers, industry concentration, profit margins, antitrust, productivity dispersion

JEL codes: D4, O33, L10, L4

Thanks for helpful comments from Mike Meurer, Anna Salomons, Rob Seamans, Carl Shapiro, Tim Simcoe, and participants at the TPRI seminar.

Industry concentration has been rising across sectors in the US since the 1980s. Autor et al. (2017) find that from 1982 to 2012 the share of shipments made by the top four firms in four-digit industries grew 4.5% in manufacturing industries, 4.4% in service industries, 15.0% in retail industries, and 2.1% in the wholesale sector.¹ What is driving this change and what is its significance?

Some see rising concentration as a sign of decreasing competition that might lead to higher prices, less innovation, and greater wage inequality (Economist 2016). This view is bolstered by evidence of a concomitant rise in profit margins and markups (Rognlie 2015, Barkai 2016, de Loecker and Eeckhout 2017). Figure 1 shows the recent rise in profits. The black line, also drawn from the National Accounts, represents the ratio of the net operating surplus to gross value added for the corporate sector (nonfinancial and financial). The gray line is the ratio of aggregate operating income after depreciation to revenues for firms publicly listed in the US. Rising profit margins might also be a sign of declining competition.

However, that is not necessarily the case. The interpretation depends on what is causing the rise in industry concentration and firm profit margins. Declining competition is one possibility. Grullon et al. (2016) attribute the rise in industry concentration partly to lax antitrust enforcement of mergers and acquisitions. Gutierrez and Philippon (2017) suggest that growing federal regulation might be creating entry barriers, also reducing competition.

But another possibility is that some firms—but not all—benefit significantly from new technologies. Thanks to new technology, these firms earn higher profits and realize larger market share, hence higher concentration. In a careful analysis, Autor et al. (2017) find strong evidence that market share is being reallocated to “superstar” firms that outperform

¹ See also White and Yang (2017) on trends in aggregate concentration.

rivals. In this case, the superior performance of these leading firms might result from greater innovation and social benefit. But what might be causing this reallocation? The authors speculate that the underlying cause might actually be *greater* competition caused by globalization or better comparative price information. In their model, greater competition, captured by an increase in the elasticity of demand, increases the market advantage of more productive firms.

Yet greater competition does not seem to entirely explain the reallocation. For one thing, if greater competition were driving the rise in industry concentration, we might expect this effect to be greatest in those industries most affected by global trade. The evidence, however, suggests that industry concentration is increasing across almost all sectors.² Furthermore, additional factors seem to be affecting the market share of superstar firms. Several studies point to a growing divergence in firm productivity within industries; the gap between the top performing firms and the rest is growing (Andrews et al. 2016; Berlingieri et al. 2017, Decker et al. 2017). Thus resources might also be shifting to superstar firms as their relative productivity grows.

This paper explores a possible source of the reallocation: information technology systems (IT). The focus is not on general spending on information technology, but specifically on the role of proprietary mission-critical IT systems. Firms may have heterogeneous abilities to develop cutting edge IT systems because they have managers or software developers with different abilities. Also, software development typically requires large upfront fixed costs but has low marginal costs. Because of this cost structure, IT systems can have large economies of scale. In addition, some IT systems might exploit

² See Autor et al. (2017) and Table A1.

network effects. For example, Hughes and Mester (2013) see both fixed IT development costs and network effects in payment systems contributing to substantial scale economies in banking. Similarly, IT systems have helped Walmart achieve more efficient logistics, higher turnover of inventory, and greater product variety at lower cost.

These proprietary IT systems used by large banks and Walmart are crucially different from the general use of IT because they provide competitive advantage. By contrast, for example, many restaurants use off-the-shelf point of sale systems. These provide improved service but, because these systems are also widely available to competitors, they are not likely to provide a substantial competitive advantage that allows a restaurant to gain substantial market share. But firms with successful proprietary systems might well grow faster than other firms in the same industry. Proprietary IT thus provides a specific mechanism that can help explain the reallocation to more productive firms, rising industry concentration, also growing productivity dispersion between firms within industries, and growing profit margins. Below I proxy the use of proprietary systems by the share of the workforce consisting of software developers and related occupations. Firms using off-the-shelf IT will not tend to employ software developers; firms building proprietary systems will, on average.³

When the scale economies and network effects of proprietary systems are particularly strong, they may give rise to “winner-take-all” or “winner-take-most” markets. For example, IT platforms enable Amazon to dominate the market for online retail (Khan 2017). But are such big tech markets unusual or is IT creating such dominant winners across many economic sectors? Concerns about a general IT-based trend to market domination provides another reason to explore the link between IT and rising industry concentration. This paper

³ Firms can also contract with third parties for proprietary systems; I find that at an industry level purchased IT systems are correlated with inhouse development.

focuses on IT systems use across all industries where the technology is used, *excluding* industries involved in producing information technology itself.

The paper explores the impact of IT systems using a model with fixed costs of production, monopolistic competition in a differentiated product market, and heterogeneous productivity. If industries that use IT systems tend to have greater dispersion of plant-level productivity, then the model shows that these industries should have greater industry concentration and that the top firms in these industries should have relatively larger plant sizes and higher labor productivity.

The empirical analysis makes four key findings:

1. Industry use of IT systems is associated with higher industry concentration ratios (shares of sales to the top firms) and with more rapid growth in concentration ratios from 2002 to 2007. The effect is large—it accounts for most of the observed rise in concentration ratios—and an instrumental variable analysis provides some evidence that the relationship is causal. In contrast, measures of merger and acquisition activity and of entry are at best only weakly associated with changes in concentration.
2. Industry use of IT systems is associated with larger plant size (revenues per establishment) among the top four firms within each industry, both in absolute terms and relative to other firms in the industry.
3. Industry use of IT systems is associated with higher labor productivity (revenues per employee) among the top four firms within each industry, both in absolute terms and relative to other firms.
4. IT systems use is strongly associated with operating profit margins of publicly listed firms, especially for the largest firms in each industry. IT systems use can account for much of the rise in operating margins since 1980.

These findings suggest that technology plays a major role in rising industry concentration and rising firm profit margins.

Literature

Of course, concerns about rising industry concentration and its effects are not new. In the 1970s, Peltzman (1977) documented rising concentration in manufacturing industries, argued that these increases were largely the result of technological progress, and therefore antitrust authorities need not be concerned. Scherer (1979) attributed the increases largely to economies of scale, arguing that antitrust authorities could distinguish genuine scale economies from attempts to limit competition through acquisition. This period gave rise to a large literature using cross-industry studies to explore the interrelationships between market structure, firm conduct, and firm performance (see Curry and George 1983 and Schmalensee 1989 for reviews). Bain (1956) identified scale economies as one source of entry barriers. Comanor and Wilson (1967) and many others proxied scale economies by using the ratio of the output of a plant of minimum efficient size to the output of the entire industry; minimum efficient size was estimated from the distribution of plant sizes under some assumptions. But these studies did not actually identify a technological scale economy. Also, as Schmalensee (1989) argues, almost all of the variables used in these studies are endogenously determined, limiting the usefulness of the studies for policy analysis.

This paper focuses on a particular technology that can generate scale economies. Nevertheless, an analysis of the impact of IT might similarly suffer from endogeneity. After 1980, rapidly declining prices for computing exogenously gave rise to the widespread adoption of computers. However, the relative adoption across industries might be affected endogenously by existing industry structure. For instance, industries with larger establishments might have had greater need for computers to manage their production. To obtain identification, I use an instrumental variable that is arguably independent of industry structure.

This paper is related to the large literature on productivity dispersion within industries and, in particular, to several papers showing a growing divergence in firm productivity (Andrews et al. 2016; Berlingieri et al. 2017) and growing dispersion in returns to capital (Furman and Orszag 2015). Other papers specifically find that the growth in the dispersion of productivity and wages is at least partly accounted for by information technology (Abowd et al. 2007; Doms, Dunne, and Troske 1997; Dunne et al. 2004). The findings on wages are consistent with research showing that a substantial part of the growth in wage inequality is associated with differences between firms or establishments (Abowd, Kramarz, and Margolis 1999; Barth et al. 2016; Dunne et al. 2004; Mueller et al. 2015; Song et al. 2015).

A key question is why information technology should be associated with *widely* disparate levels of productivity. While the hardware components of IT systems are usually generic commodities, the systems themselves typically involve proprietary software and complementary human or organizational capital. There is a significant literature that identifies IT-related differences in productivity arising from complementary skills, managerial practices, and business models that are themselves unevenly distributed (including Bartel, Ichniowski, and Shaw 2007; Bloom et al. 2012; Bloom et al. 2014; Bloom et al. 2017; Bresnahan, Brynjolfsson, and Hitt 2002; Brynjolfsson et al. 2008; Caroli and van Reenen 2001; and Crespi, Criscuolo, and Haskel 2017). Bessen (2015) argues that skills and managerial knowledge needed to use major new technologies have often been unevenly distributed initially because much must be learned through experience, which tends to differ substantially from firm to firm. While this paper does not explore the reasons why IT systems might have diverse effects on productivity, the findings here reinforce the notion that those differences are significant.

Brynjolfsson et al. (2008) find that all industries exhibit growth in concentration from 1996-2006 but that IT intensive industries show somewhat faster growth on average during this period.⁴ The present paper goes beyond this by using a more detailed set of industries, using instrumental variables, and performing a supplementary analysis on differences between the top firms and the rest within each industry. Kurz (2017) also argues that IT has contributed to growing market power, but only identifies IT by sector.

Finally, Tambe and Hitt (2012) and Harrigan et al. (2016) also use the employment share of IT workers as an independent variable to explore firm productivity and job polarization respectively.

Theory

Hypothesis

Information technology has been widely adopted across industries since the 1970s thanks, in great part, to the dramatic decline in the price of computing. However, as the price of computers has declined, firm IT investment has shifted increasingly to software and, in particular, to custom applications. Nearly three quarters of all software investment is made by firms purchasing custom systems or developing their own applications.⁵ This suggests that firms may be investing heavily in proprietary systems that have large fixed costs but low marginal costs, giving rise to economies of scale.⁶ These are investments in technology that

⁴ Their measure of concentration is a Herfindahl index based on Compustat data.

⁵ For 2014, custom applications including own developed accounted for 73% of investment in software by private industry and government, see BEA estimates at http://www.bea.gov/national/info_comm_tech.htm.

⁶ Note that economies of scale could arise even from generic technology. For instance, mainframe computers that could handle high volumes of transactions required substantial fixed costs. But these sources of advantage sometimes dissipate over time, for instance, as time sharing services made mainframe technology available to smaller firms. The notion here is that much of the focus of IT development seems to be directed toward proprietary systems and these systems may be slower to diffuse to rivals.

are not readily available to product market rivals, giving rise to heterogeneous firm productivity with implications for industry structure.

In line with this view, this paper advances the specific hypothesis that the more that industries use information technology systems the more they will have, all else equal, greater productivity dispersion between plants and between firms. IT will generate greater productivity dispersion if the systems depend on complementary managerial or technical skills that are not easily acquired on the labor market. Firms' access to workers with critical skills may be heterogeneous if the technology is not standardized and key skills are learned on the job (Bessen 2015, 2016). In any case, some evidence suggests that wage and productivity dispersion between plants are, in fact, related to information technology (Doms, Dunne, and Troske 1997; Dunne et al. 2004).

Production

To explore the implications of this hypothesis, I use a model that is a simplified, static version of models developed by Bartelsman et al. (2013) to study productivity dispersion across countries and used by Autor et al. (2017) to study the link between industry concentration and labor's share of output. The key distinguishing features of the model are fixed and variable costs of production, heterogeneous differences in productivity, and monopolistic competition. Let total labor for firm i consist of the sum of variable labor, V_i , and fixed labor, F .⁷

$$L_i = V_i + F.$$

⁷ I assume uniform fixed costs across all firms in the industry. IT systems might involve greater fixed costs, however, incorporating variable fixed costs associated with higher productivity would not change the key results here.

The output of a plant is determined by a production function employing variable labor:

$$Y_i = A_i V_i^\gamma, \quad 0 < \gamma < 1$$

where A_i represents the firm's heterogeneous productivity, and γ is less than one to capture decreasing returns to production.⁸ Firms may have multiple plants with the same A_i for each plant.

Assume that each plant produces a single variety of a differentiated product and the representative consumer's utility is a constant elasticity of substitution function over varieties:

$$U = \left(\sum_i Y_i^\sigma \right)^{1/\sigma}, \quad 0 < \sigma < 1.$$

It is straightforward to show that utility maximization leads to an inverse demand (price) function for variety i of the form

$$P_i = b \cdot Y_i^{-1/\rho}, \quad \rho = \frac{1}{1-\sigma} > 1$$

where ρ is the price elasticity of demand. Given wage, w , the firm seeks to maximize profits,

$$\pi_i = P_i Y_i - w V_i - w F.$$

Solving the first order maximizing condition (see Appendix), three properties can be shown:

- Firms with higher productivity, A_i , will have larger plants, that is, greater revenue per plant, $R_i \equiv \hat{P}_i \cdot \hat{Y}_i$.

⁸ I model firms and plants this way because the connection between scale economies and industry concentration concerns plant size (Eckard 1994).

- Given positive fixed costs, higher productivity firms will have plants with greater output per worker, R_i/L_i .
- Also, given positive fixed costs, higher productivity plants will have higher operating margins.

These properties provide ways to test whether IT systems use is associated with a growing productivity gap between the top firms in an industry and the rest. My hypothesis assumes that IT-intensive industries will, all else equal, have higher productivity and the top firms in IT-intensive industries will have even higher productivity relative to the rest. Thus it should follow that IT-intensive industries should have larger plants with greater output per worker and higher operating margins on average and these effects should be even larger for the largest firms within these industries.

Concentration

These properties pertain to plants, not firms per se. With some assumptions about the number of plants per firm, implications can be drawn about industry concentration. For simplicity, suppose that there are two types of firms, low and high productivity, designated L and H respectively. Let m_i be the mean number of plants per firm for type i , and let n_i be the number of firms of type i . I make the assumption that $m_H \geq m_L$. This makes sense because more productive firms, being more profitable, might be able to acquire or build new plants of type H. On the other hand, less productive plants might be less likely to survive, reducing the number of plants for type L firms. In any case, this assumption is sufficient to guarantee that type H firms are larger than type L firms on average. A standard finding, echoed in the results below, is that larger firms are, on average, more productive than other firms within their industry.

Then a simple concentration ratio, namely the share of industry revenue accounted for by the top n_H firms, is

$$C_{n_H} = \frac{R_H \cdot m_H \cdot n_H}{R_H \cdot m_H \cdot n_H + R_L \cdot m_L \cdot n_L} = \frac{1}{1 + \frac{R_L \cdot m_L \cdot n_L}{R_H \cdot m_H \cdot n_H}}$$

This equation provides a useful framework for thinking about the impact of IT. My basic hypothesis is that industries using IT systems will have a higher ratio A_H/A_L on average. A greater productivity gap implies greater difference in plant size so that R_H/R_L will also be larger in these IT-using industries and, looking at the equation, these industries will also have higher concentration, all else equal. A greater productivity gap might also change the ownership of plants across firms. For example, highly productive firms, being more profitable, might expand the number of plants they own, assuming they can at least partially transfer their specialized knowledge to a new plant. Conversely, higher fixed costs might make low productivity firms less profitable, causing some to close plants. In both of these cases, however, the effect of changes in the number of plants per firm will be to enhance the increase industry concentration. As long as IT systems use is not associated with a substantial decline in the relative number of plants operated by high productivity firms, then, the paper's hypothesis implies that IT-using industries should be more highly concentrated. In this case, the rise in concentration would be associated with real changes in productivity.

On the other hand, other factors also influence industry concentration and might be responsible for the rise. For example, if rising concentration is driven mainly by merger and acquisition activity, then industries with more M&A activity should show greater concentration, all else equal. Or rising entry barriers might reduce the number of industry establishments, also raising concentration. Below I explore whether such factors are

associated with industry concentration, suggesting alternatives to an explanation based on rising productivity differences.

Data

The concentration data come from the Economic Census reports for 2002, 2007, and 2012. The Census reports the share of industry revenues (or shipments) going to the top 4, 8, 20, and 50 firms in each NAICS industry at the 2, 3, 4, 5, and 6 digit levels. In addition, it reports the number of establishments, annual payroll, and number of employees for the industry as a whole and for the top firms within the industry (the latter data are missing for manufacturing industries).

The Economic Census data have the advantage that they count all firms and establishments in each industry. Some studies have used concentration ratios computed for publicly firms listed in Compustat (Grullon et al. 2016; Gutierrez and Philippon 2017). Those data have the advantage of being available annually and for a longer period of time. But they also have some disadvantages: Compustat typically reports worldwide sales, not domestic sales, and the sample excludes private firms. If we want to analyze concentration in domestic markets, it can be misleading to use measures based on international sales. And it appears that private firms make a large difference. The Compustat concentration ratios are only weakly correlated with the ratios provided by the Economic Census.⁹ To avoid conflating issues about concentration with issues about firms' changing preferences about being publicly listed and firms' changing international exposure, I decided to employ the Economic Census data.

⁹ I ran several tests. For example, I calculated the Compustat four-firm concentration ratios for 2012 for three-digit NAICS industries. The correlation coefficient between these data and the corresponding four-firm ratios from the Economic Census was 0.196.

The paper seeks to capture the extent to which firms use proprietary IT systems. This activity is distinct from investment in IT for general uses such as word processing or telecommunications. Firms building proprietary systems will typically hire software developers and systems analysts to design, build, and maintain these systems even if much of the work is done by outside contractors. General computer use for common office applications does not require such personnel. I assume that inhouse software development is correlated with the use of contractors so that at an industry level the use of proprietary IT systems is reflected in the composition of the workforce. This variable is correlated with BEA software investment measures that do include contracted software.¹⁰

Data on the workforce come from the public use samples of the American Community Surveys for 2002, 2007, and 2012 (Ruggles et al. 2015). The measure of IT systems use for each NAICS industry is the share of hours worked by IT personnel, identified as people in the following occupations: computer systems analysts and computer scientists, operations and systems researchers and analysts, computer software developers, and computer and peripheral equipment operators.¹¹ Since the aim is to measure the use of custom IT systems, I exclude industries that are involved in creating information technology products.¹² These industries employ IT personnel in designing and producing products, not

¹⁰ The BEA/BLS Integrated GDP-Productivity accounts report the capital income of software investment by year for 61 private industries (see <https://www.bea.gov/industry/an2.htm#integrated>). I aggregated my data up to the BEA/BLS industries (my data have nearly four times as many industries) and compared the share of IT workers in the industry workforce to the share of software compensation in total gross output. The association was highly significant with a correlation coefficient of .42.

¹¹ Hours worked is calculated as weeks worked last year time usual hours worked per week times the person weight. For 2012, weeks worked is intervalled; I assign a numeric value based on the means for 2007.

¹² These include NAICS 5112, software publishers, 5181, Internet service providers and web search portals, 5182, Data Processing, Hosting, and Related Services, 5191 Other information services, 5415 Computer Systems Design and Related Services, 3341 Computer and peripheral equipment manufacturing, 3342 Communications Equipment Manufacturing, and 3344 Semiconductor and Other Electronic Component Manufacturing.

just in building systems for their own use. Also, to reduce measurement error in small industries, the sample excludes the smallest 5% of industries by employment.¹³

Although IT systems use is measured for an entire industry, these workers are likely concentrated in large establishments and firms. Among computer and mathematical occupations, over half (54%) work in establishments of 250 people or more (Hajiha 2003). This comports with the notion that large firms are better able to implement IT systems.

The American Community Surveys use modified NAICS industry codes which are aggregated to different levels. Some industries are identified at the 6-digit level while others are only identified at the 3-digit level. I match these industries to the corresponding industries in the Economic Census to obtain a sample of 730 industry-year observations over three years at different (non-overlapping) levels of industry classification.¹⁴

To instrument the IT share of hours, I use a measure derived from the Dictionary of Occupational Titles (1977). The US Department of Labor has sought to define aspects of some 14,000 distinct jobs, publishing the fourth edition of this work in 1977, before computers were widely adopted. One job characteristic is STRENGTH, which rates the physical demands of the job on a scale of 1, for sedentary occupations, to 5, for very heavy work. I flagged an occupation as being sedentary if its STRENGTH rating is less than 2. England and Kilbourne (2013) have mapped these to Census detailed occupation codes, averaging them to this higher level of aggregation. Using these occupations, I calculated the distribution of sedentary occupations across NAICS industries using the 2000 Census 5% public use sample. Below I discuss some tests on this instrument.

¹³ That is, it excludes industries with fewer than 28,748 employees.

¹⁴ There are 75 3-digit industries, 459 4-digit, 151 5-digit, and 45 6-digit industries. Note that there are some minor changes in the NAICS classification between 2002 and 2012, so that some industries are not reported for all three years.

To study firm operating margins, the main sample consists of Compustat firms traded on US exchanges between 2000 and 2014, matched to industry IT systems data, totaling 57,804 observations. I exclude firms that are missing data on market value, sales, and assets, firms where R&D exceeds half of revenues (startup mode), and I exclude the 1 percent tails of the dependent variable (operating margin, that is, operating income after depreciation before taxes, R&D, and advertising expense all divided by revenues) to counter measurement error at the extremes. I use the method of Lewellen and Badrinath (1997) with the NIPA investment deflator to calculate the net capital stocks. Stocks of R&D, advertising and marketing expenditures, and lobbying and political expenditure stocks are computed using the perpetual inventory method.¹⁵ Industry level IT capital is also calculated using the perpetual inventory method where annual investment consists of the deflated wages paid to IT personnel in the industry.¹⁶

The lobbying and campaign expenditure data come from the Center for Responsive Politics.¹⁷ The data on regulation come from Al-Ubaydli and McLaughlin (2015) and is based on an industry-relevance weighted count of words in the Code of Federal Regulations.¹⁸

¹⁵ The R&D stock is calculated assuming a 15% annual depreciation rate and an 8% pre-sample growth rate (Hall 1990); R&D expenditures are deflated using an R&D deflator. The advertising stock is based on advertising and marketing expenditures and assumes a 45% annual depreciation rate and 5% pre-sample growth rate (Villalonga 2004, p. 217). The lobbying data begin in 1998; the campaign expenditure data are assigned to the election year beginning in 2000. I assumed a 25% depreciation rate and a 6% pre-sample growth rate for each and deflated both using the GDP deflator.

¹⁶ I assume a 15% depreciation rate and a 2% pre-sample growth rate based on the average growth rate from 2000-2014. I divide the IT capital by the number of workers in each industry each year to obtain a scaled measure of IT capital per worker.

¹⁷ Data downloaded from http://www.opensecrets.org/resources/create/data_doc.php and matched to Compustat firms.

¹⁸ Al-Ubaydli and McLaughlin use an algorithm to probabilistically assign each section of the Code to a specific NAICS industry. They do this assignment for sets of 2-digit, 3-digit, and 4-digit NAICS industries. The result is a time series of the extent of regulation for specific industries since 1970.

Summary statistics

Table 1 provides some summary statistics on the sample of industries. On average, IT workers account for 2.2% of hours worked. The table shows the four different concentration ratios. Relatively few industries could be described as monopolies or oligopolies; the top four firms account for the majority of revenues in only 15% of the industries. But industries have been growing more concentrated. The table shows the change in mean concentration ratios from 2002 to 2007, before the recession; the mean changes from 2007 to 2012 were slightly smaller. Note that most of the increase in concentration can be attributed to the growing share of the top four firms; the increase in the share of the top 50 firms is not much larger than the increase for the top four. Also, the number of establishments in each industry grew, on average. And consistent with prior literature (Schmalensee 1989), the top firms in each industry tend to have larger plants (revenues / establishment), higher labor productivity (revenues / employee), higher pay, but lower labor share of output.

Table A1 in the Appendix displays the distribution of observations across industry sectors, defined as the first digit of the industry NAICS code. It also displays the average change in the four-firm concentration ratio for each sector from 2002 to 2007. Most sectors shows rising concentration.

Empirical Findings on Industry Concentration

Basic regressions on concentration ratios

Table 2 shows basic regressions on the different concentration ratios. The regression estimates concentration ratio j for industry i during year t :

$$C_{ijt} = \beta \cdot IT_{it} + \alpha_t + \delta_i + \gamma_n + \epsilon_{it}$$

where IT_{it} is the measure of IT systems use, δ_I is a dummy variable for industry sector (1-digit NAICS code), and γ_n is a dummy variable for the number of digits in the industry definition. The latter dummy variable is included because more narrowly defined industries are likely to have higher concentration ratios, all else equal. Table A2 in the Appendix breaks out the regression for the 4-firm concentration ratio by different industry digit levels. All show an association between IT share and industry concentration, but the estimates for more narrowly defined industries are larger and have greater statistical significance.

The top panel of Table 2 shows OLS regressions on the pooled (2002-2012) level of each concentration ratio with errors clustered by industry sector. The coefficient of the share of IT workers in the workforce is highly significant for all concentration ratios. It is also economically significant. The sample mean of IT share of hours worked is 2.2%. At this mean, IT share is associated with an increase in the revenue share of the top four firm of $2.2\% \times 1.90 = 4.2\%$. This is comparable to the increase in four-firm concentration ratios reported by Autor et al. (2017) for most sectors since 1982. Since the share of IT workers was much smaller in 1982, IT systems use appears to “explain” most of the increase in industry concentration since then, loosely speaking.

One concern with these estimates is the possibility that IT systems use might be endogenously related to the error term. Suppose, for instance, that some omitted variable caused more concentrated industries to have larger plants and larger plants used IT relatively more to administer their greater number of employees and assets. Then the coefficients on IT systems use would be biased upwards. To address this concern, the second panel reports the same regressions estimated using GMM instrumental variables. A suitable instrument should be correlated with IT systems use, but exogenous with respect to the error term. I instrument IT share using the degree to which workers in the industry were sedentary in

1977. Sedentary occupations are easier to computerize, hence it is not surprise that sedentary industries have higher IT shares. Also, since the measure of sedentariness is taken before computers were widely adopted in most industries, this measure is likely independent of subsequent IT systems use. This instrument is arguably also independent of the error term and placebo tests below provide support for this assumption. Using IV-GMM estimation, the coefficient estimates for IT share are somewhat smaller and somewhat weaker statistically, but are overall similar. The null hypothesis that the right hand variables are exogenous cannot be rejected.

The levels of industry concentration observed in the pooled sample roughly capture the increase in concentration brought about by the adoption of IT systems, occurring mainly since 1980 or so. A further test is to see whether IT is also related to the growth in concentration occurring during the sample period. The third panel makes IV estimates of the change in concentration ratios between 2002 and 2007. I exclude changes after 2007 because of possible confounding effects of the recession. The coefficient on IT systems use is again statistically significant and economically substantial. In this panel, the hypothesis that the right hand variables are exogenous is weakly rejected in the first two columns ($P = .083, .098$). At the sample mean, IT share is associated with an increase in the four firm concentration ratio of $0.85 \times 2.2\% = 1.9\%$. This is larger than the actual change in the mean four firm concentration ratio shown in Table 1.

In all three panels, it is evident that most of the increase in concentration ratios associated with IT is driven by the top four firms. That is, the coefficient for the eight firm ratio is only slightly larger than the one for the four firm ratio, implying that the market shares of firms five through eight grew relatively little. Similarly, for the other concentration

ratios. For this reason, the remainder of the paper focuses on just the role of the top four firms.

Placebo tests

The instrumental variable used here might violate the exclusion restriction. Perhaps industry sedentariness is correlated with some third factor that also influences industry concentration. Placebo tests provide some support that this is not the case. Table 3 reports regressions on industry concentration and average plant size using data from the 1977 Economic Census for the manufacturing sector. To perform comparable regressions, I first calculated the instrumental variable using the 1977 Dictionary of Occupational Titles but weighting each industry using the 1980 Census public use sample. The Economic Census reports concentration ratios for 4-digit SIC industries while the Census of the Population uses its own industry codes. Where the Population data use a higher level of industry aggregation, I averaged the industry data on concentration and plant size, weighting by shipments per detailed industry.

The regressions show that the instrumental variable is not significantly correlated with the four-firm concentration ratio or the average industry plant size in 1977. Similar regressions using the 2002-2012 sample for just the manufacturing sector—effectively a first stage regression for the IV analysis—show a significant correlation. The assumption in this paper is that the correlation during the recent period reflects the greater use of information technology since 1977.¹⁹ This finding does not definitively eliminate the possibility that some third factor could be responsible for a spurious link between IT systems use and industry

¹⁹ This instrumental variable also turns out to be uncorrelated with the growth rate of occupational employment during the 1960s and 1970s, but correlated since 1980, further supporting the view that the widespread adoption of IT after 1980 may have changed the covariates of sedentariness (Bessen 2017).

concentration and plant size. However, it means that the third factor could not have had significant influence prior to 1980 and its influence must have grown more or less along with the rapid growth in IT systems use after 1980.

Other variables

A variety of other variables might confound the analysis, possibly being correlated with IT systems use and also with industry concentration. Table 4 considers some possibly confounding variables: the number of establishments, merger and acquisition activity, exposure to imports, wages, and industry growth. As Schmalensee (1989) notes, these variables may well be endogenous. For example, IT-based economies of scale might encourage firms acquire other firms or to merge. Nevertheless, including these variables in regressions along with the measure of IT systems use provides a robustness check on the IT coefficient.

Column 1 includes the number of industry establishments. The more firms or establishments in an industry, the harder it might be for a few firms to capture a large market share. Also, rising entry barriers would tend to reduce the number of establishments, driving concentration up. Including this variable does not significantly change the coefficient on IT systems use and the coefficient on the number of establishments is weakly significant ($P = .092$), negative, and small. A supplementary regression (not shown) on the change in industry concentration from 2002 to 2007 against the change in industry establishments shows no significant relationship. Thus entry barriers do not seem to be a first order cause of the recent rise in industry concentration nor does the number of establishments confound the IT relationship.

Column 2 includes a measure of merger and acquisition activity. Grullon et al. (2017) argue that mergers and acquisitions are a major reason industry concentration is rising, which they attribute to lax antitrust enforcement. To measure industry M&A activity, I use data from Thomson Reuters SDC database of M&A transactions. Since acquisitions by large firms are those most likely to affect industry concentration and since large firms are more likely to be publicly listed, I extracted those acquisitions made by publicly listed firms. Excluding transactions where the acquirer did not obtain majority ownership, I matched these data with Compustat data for publicly listed firms, resulting in a list of 33,942 acquisitions from 1985 through 2001. I use these data to construct an index of M&A activity prior to 2002. Using the Compustat historical NAICS assignments for each firm, I tabulated the number of acquisitions and the number of active publicly listed firms for each industry. I then calculated the index of M&A activity as the aggregate number of acquisitions per public firm for each industry over the entire period. The regression finds a negative coefficient on M&A activity that is not statistically different from zero. The coefficient on IT systems use changes only slightly. Using this measure, mergers and acquisitions do not seem to account for rising concentration nor do they confound the estimates of the effects of IT systems use.

Exposure to global trade might also confound the estimation. Autor et al. (2017) suggest that globalization might increase competition thus increasing industry concentration. Column 3 includes a measure of industry import penetration ($(\text{imports} - \text{exports}) / \text{shipments}$) for NAICS manufacturing industries (Schott 2011) for 2002 through 2005. For non-manufacturing industries, I set import penetration to zero. This measure of import penetration has no effect on the coefficient of IT systems use and is not significantly correlated with industry concentration.

Industry wages might also confound the effect of IT. Since high wage occupations are more likely to use computers, wages might be correlated with IT systems use. If wages are also somehow related to industry concentration, then they might confound the analysis. Column 3 also includes the average industry wage in 2009 dollars. It appears to be uncorrelated with industry concentration.

Column 4 adds the average annual growth rate for real shipments from 1980 to 2002 for manufacturing industries.²⁰ It might be harder to maintain market share in a rapidly growing industry and rapidly growing industries might have greater need of IT. The coefficient on industry growth is negative and weakly significant ($P = .077$). The coefficient on IT systems use is larger, suggesting that, if anything, the omission of industry growth biases the coefficient downwards.

IT and Productivity

The Productivity Gap

The above data support the link between IT systems and industry concentration. If the paper's hypothesis is correct, IT systems should increase industry concentration by increasing the productivity gap between the top firms and the rest. From the model, the link between IT and a productivity gap should show up as a link between IT and plant size and also as a link between IT and labor productivity.

Table 5 explores the relationship between the IT share of the workforce and average plant size, comparing the relationship for the top four firms in each industry with the relationship for the remaining firms. Because the Economic Census does not provide

²⁰ Data from the NBER-CES Manufacturing Productivity database.

complete data for the manufacturing sector, that sector is necessarily excluded from the analysis that follows.

The table reports regressions on the log of deflated revenues per establishment for each group of firms (Top 4 and the rest) separately. I use a log specification because plant revenues are highly skewed. The basic results hold even more strongly for a simple linear specification, but these might be unduly influenced by a few large outliers. The bottom row of the table shows a comparison of the IT coefficients, reporting the probability value of the null hypothesis that the coefficient for the top four firms is not greater than the coefficient for the remaining firms.²¹

Industry IT systems use is associated with substantially larger plant size for both groups, but especially for plants owned by the top four firms. In the OLS estimates at the sample mean, IT systems use is associated with an average plant size among the top four firms that is 63% larger and is 31% larger for the remaining firms. The difference between the IT coefficients of the two groups, about 0.11, is also highly significant and the null hypothesis is rejected. The instrumental variable estimates are statistically weaker, but similar. Both support the view that industry IT systems use is associated with a greater productivity gap between the top firms and the rest.

Table 6 performs a similar comparative analysis for the log of revenue per employee. Because the dependent variable involves a ratio, measurement error might be extreme for industries with few employees. In these regressions I trim the sample to exclude the lowest five percent of industries ranked by the number of employees in the top four firms.²²

²¹ This is a one-tailed t-test.

²² That is, I exclude industries where the top four firms jointly have fewer than 1420 employees.

IT systems use is also associated with greater output per worker for both groups. At the sample mean, IT systems use is associated with 37% greater output per worker among the top four firms and about 25% greater output per worker among the remaining firms using the OLS estimates. The difference is also highly significant. The IV estimates are much noisier and the difference in these coefficients is only weakly significant. Nevertheless, the overall pattern from Tables 5 and 6 suggests that IT systems use is, indeed, associated with a greater gap in productivity between the top firms and the rest and this implies higher industry concentration.

Operating Margins

Plant operating margins can be written (see Appendix)

$$M_i \equiv \frac{\hat{P}_i \cdot \hat{Y}_i - w\hat{L}_i}{\hat{P}_i \cdot \hat{Y}_i} = 1 - \gamma\sigma - \frac{wF}{\hat{P}_i \cdot \hat{Y}_i}.$$

The term $1 - \gamma\sigma$ is implicitly a measure of competition or market power in this setting. For example, if demand for each variety is highly elastic ($\gamma\sigma \rightarrow 1$), operating margins will be small, all else equal. The last term captures the role of fixed costs on margins. For empirical analysis, it is helpful to consider these fixed costs as the sum of various rental rates associated with different capital stocks, K_i^1, K_i^2, \dots , including physical capital assets but also intangibles such as investments in R&D, in advertising and marketing, and in IT systems. In addition, entry barriers can be represented as fixed costs.

Using the firm as the unit of observation (firm margins are an average of plant margins), the following equation can be estimated for the operating margin of firm i at time t :

$$M_{it} = \delta \cdot t + \beta_1 \frac{K_{it}^1}{R_{it}} + \beta_2 \frac{K_{it}^2}{R_{it}} + \dots + \epsilon_{it}$$

where R is revenues as above and the K variables are beginning-of-year capital stocks. The first term captures the trend of changes in competition or market power over time, including changes in unmeasured entry barriers. The β coefficients capture the rental rates of the various capital stocks plus, including any rents (supra-normal returns) that might accrue to those assets. Proprietary IT systems might well earn rents because they are assets that are not available to firm rivals.

The top panel of Table 7 shows weighted least squares regressions using this equation, weighting firms by deflated revenues to reflect their contribution to aggregate operating margins as shown in Figure 1. Column 1 includes just a measure of net assets derived from the firm's balance sheet (see data section for details) from 1980 through 2014. In this regression, the time trend is positive and highly significant. Multiplying the coefficient (.0009) times 34 years yields a 3.0% increase in operating margins attributable to the time trend. This is roughly the increase observed in Figure 1, so, accounting only for conventionally measured assets, there does seem to be an overall increase in margins aside from changing investment intensity.

Column 2 adds three measures of intangibles: the R&D stock,²³ a stock of advertising and marketing expenditures, and a term for IT capital stock. Note that while the other assets are scaled by revenues, because of data limitations, the IT variable is scaled by the number of workers for the industry. Implicitly, the coefficient on this term includes the number of workers / revenues.²⁴ All three intangible measures have highly significant coefficients. And now the time trend is negative, suggesting a possible *increase* in competition.

²³ Adding a patent stock or a citation-weighted patent stock contributes little, so I have left that out here.

²⁴ Compustat contains employment data for most firms, however, this represents global employment while the IT measure captures only domestic IT investment. Because the US share of IT investment likely changes substantially from industry to industry, multiplying IT capital / worker times Compustat employment / sales

Column 3 tests the robustness of this regression in two ways. First, there is a possible problem with simultaneity. Because positive demand shocks might increase operating margins and also increase investment, the error term might be correlated with capital stocks. The capital stocks in Column 2 include investment from the prior year, not the current year, however, if demand shocks are serially correlated, then the coefficients on the capital stocks might be biased upwards. Second, because the IT capital stock is an industry measure, it might capture some other industry characteristic with which it is correlated. Column 3 uses lagged measures of the capital stock and includes 2-digit industry dummies. In this regression, the coefficient for conventional assets is no longer statistically significant and the coefficient for IT capital is smaller, but still significant both statistically and economically. The coefficients on the other intangible assets are only slight diminished. Additional regressions with 2-4 year lags on the capital stocks (not shown) find that the coefficient for IT capital remains substantial and statistically significant.²⁵ The substantial role of IT capital in accounting for operating margins appears to be robust to concerns about simultaneity or other industry effects.

Column 4 repeats the regression in Column 2, but interacts the IT share variable with a dummy variable that is one if the firm is among the top 4 firms by sales in the industry in the Compustat sample and zero otherwise. Consistent with the main hypothesis, the coefficient on IT systems use is significantly larger for the largest firms.²⁶

may introduce substantial noise. This is what I find running such regressions. The IT term is still statistically significant, but the t-statistics are nearly three times larger, suggesting inefficient estimates. Future research will attempt to construct IT capital at the firm level rather than at the industry level.

²⁵ For lags 2 through 4, the estimated coefficients are .0015 (.0001), .0015 (.0002), .0015 (.0002) respectively.

²⁶ A one-tailed t-test of the difference in coefficients has a probability value of .027.

Column 5 repeats the regression in Column 2, but includes two measures that might be related to market power: an index of industry regulation and a stock of lobbying expenditures.²⁷ If Federal regulation imposes substantial fixed compliance costs, then this might serve as an entry barrier, raising margins (Bessen 2016, Guttierrez and Philippon 2017). The coefficients for industry regulation and lobbying are positive and significant. Lobbying and regulation might create entry barriers or provide other sorts of transfers to firms that raise margins. The time trend is still negative.

In order to gain a sense of the economic significance of the various coefficients, Panel B of Table 7 shows the coefficients for the regressions multiplied by the sample mean for 2014 (weighted by deflated sales). Generally, intangible assets appear to account for a substantial part of average operating margins. In each case, IT capital appears to be the most economically significant contributor to operating margins (tied in Column 3). Regulation and lobbying also play a significant role that is somewhat smaller. Overall, Table 7 suggests that IT is a major contributor to the rise in aggregate operating margins observed in Figure 1. IT capital was small in the 1980s but can now account for 3% of margins, roughly equivalent to the rise in margins since the 1980s. A decline in competition might also contribute, perhaps related to industry regulation, but it is not clear that general changes in competition have necessarily increased margins, as indicated by the negative time trend coefficients in the regressions.

²⁷ I also performed regressions using a stock of campaign finance expenditures, but did not include it here because the sample is only every two years and hence is not directly comparable to the other regressions in the table. The coefficient on election spending is positive and significant.

Conclusion

It is sometimes argued that information technology “levels the playing field” by providing inexpensive tools to small and young firms. This paper finds that much of the impact of IT may be to tilt the playing field in favor of those firms who are able to use it most effectively. The use of IT systems is strongly associated with industry concentration across a wide range of sectors. Moreover, the magnitude of the link between industry IT systems use and concentration is large enough to account for much of the recent rise in industry concentration. Instrumental variable regressions provide some support for the notion that this relationship is causal, consistent with a view that IT generates a growing gap between the most productive firms and the rest. This view is further supported by evidence that IT systems use is associated with enhanced performance of the top firms within each industry. IT systems use is associated with relatively greater plant size among the top four firms, with relatively greater revenue per employee at these firms, and with higher firm operating margins, especially for the largest firms. These findings suggest that IT contributes to a widening productivity gap between the top firms and the rest, driving an increase in industry concentration.

On the other hand, the observed increases in concentration are fairly modest. There are, of course, well known examples where IT facilitates highly concentrated markets as with Amazon’s dominance in e-commerce. These cases may be described as “winner-take-all” markets. But the markets in this study show much lower levels of concentration and relatively small increases. While economies of scale or network effects might be at play in the markets studied here, it appears that there are limits to such scale effects. These are “winner-take-a-bit-more” markets. Perhaps more narrowly defined markets would be more likely to exhibit “winner-take-all” competition, but the market definitions used here from the

Economic Census (at the 6-digit NAICS and higher level of aggregation) are the markets that have raised concern about growing concentration.

The findings of this paper suggest that much of the recent rise in industry concentration and much of the rise in firm operating margins can be attributed to the deployment of proprietary IT systems. A general decline in competition might also play a role in rising concentration and profits, but the evidence found here regarding competition is mixed. Merger and acquisition activity seems unrelated to industry concentration and the residual time trend in operating margins is negative once intangible investments are taken into account. On the other hand, greater Federal regulation is associated with higher operating margins, although this effect is substantially smaller than the role of IT systems. Overall, the analysis here suggests that the recent overall rise in industry concentration is not mainly the result of anticompetitive activity that should worry antitrust authorities. Indeed, IT systems use appears to bring real social economic benefits in terms of greater output per worker even if it does raise industry concentration. While there may be other reasons to question antitrust policies (see, for instance, Kwoka 2012), the general rise in industry concentration does not appear to raise troubling issues for antitrust enforcement at this point by itself.

However, the evidence about the role of IT in raising industry concentration does broach another concern. Why aren't the productivity gains from IT shared more broadly beyond the top firms? Increasingly, it seems, top performing firms utilize new technologies productively while their rivals do not. Concentration appears to be rising because of "barriers to technology" if not actually barriers to entry. More research is needed to understand exactly how IT is related to the growing productivity gap. Top firms might be able to use patents and trade secrets to prevent the spread of new knowledge. Or perhaps,

instead, top firms are better able to recruit and develop talented managers and workers skilled at working with the new systems. Whatever the cause, the issue is important because the slow diffusion of new technologies might be related to sluggish aggregate productivity growth (Decker et al. 2017). Also, growing disparity in firm productivity might be related to growing inter-firm wage inequality. But the policies to address these issues, whether antitrust or other, depend very much on the diagnosis.

References

- Abowd, John M., John Haltiwanger, Julia Lane, Kevin L. McKinney, and Kristin Sandusky. Technology and the demand for skill: an analysis of within and between firm differences. No. w13043. National Bureau of Economic Research, 2007.
- Abowd, John M., Francis Kramarz, and David N. Margolis. "High wage workers and high wage firms." *Econometrica* 67.2 (1999): 251-333.
- Al-Ubaydli, O. and McLaughlin, P.A., 2015. RegData: A numerical database on industry-specific regulations for all United States industries and federal regulations, 1997–2012. *Regulation & Governance*.
- Andrews, Dan, Chiara Criscuolo, and Peter N. Gal. *The Best versus the Rest: The Global Productivity Slowdown, Divergence across Firms and the Role of Public Policy*. No. 5. OECD Publishing, 2016.
- Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen. The Fall of the Labor Share and the Rise of Superstar Firms. No. 23396. National Bureau of Economic Research, Inc, 2017.
- Bain, Joe Staten. Barriers to new competition, their character and consequences in manufacturing industries. Cambridge: Harvard University Press (1956).
- Barkai, Simcha. "Declining labor and capital shares." Stigler Center for the Study of the Economy and the State New Working Paper Series 2 (2016).
- Bartel, Ann, Casey Ichniowski, and Kathryn Shaw. "How does information technology affect productivity? Plant-level comparisons of product innovation, process improvement, and worker skills." *The Quarterly Journal of Economics* 122, no. 4 (2007): 1721-1758.
- Bartelsman, Eric, John Haltiwanger, and Stefano Scarpetta. "Cross-country differences in productivity: The role of allocation and selection." *The American Economic Review* 103, no. 1 (2013): 305-334.
- Barth, Erling, Alex Bryson, James C. Davis, and Richard Freeman. "It's where you work: Increases in the dispersion of earnings across establishments and individuals in the United States." *Journal of Labor Economics* 34, no. S2 (2016): S67-S97.
- Berlingieri, Giuseppe, Patrick Blanchenay, and Chiara Criscuolo. "The great divergence." OECD working paper (2017).
- Bessen, James. Learning by doing: the real connection between innovation, wages, and wealth. Yale University Press, 2015.
- Bessen, James. "Information Technology and Learning On-the-Job" working paper, (2016), <https://ssrn.com/abstract=2867134>.
- Bessen, James. "Automation and Jobs: When Technology Boosts Employment," working paper, (2017) <https://ssrn.com/abstract=2935003>.
- Black, Sandra E., and Lisa M. Lynch. "How to compete: the impact of workplace practices and information technology on productivity." *The Review of Economics and Statistics* 83, no. 3 (2001): 434-445.

- Bloom, Nicholas, Erik Brynjolfsson, Lucia Foster, Ron S. Jarmin, Megha Patnaik, Itay Saporta Eksten, and John Van Reenen. "IT and Management in America." (2014).
- Bloom, Nicholas, Erik Brynjolfsson, Lucia Foster, Ron S. Jarmin, Megha Patnaik, Itay Saporta-Eksten, and John Van Reenen. "What drives differences in management?" No. w23300. National Bureau of Economic Research, 2017.
- Bloom, Nicholas, Raffaella Sadun, and John Van Reenen. "Americans do IT better: US multinationals and the productivity miracle." *The American Economic Review* 102, no. 1 (2012): 167-201.
- Bresnahan, Timothy F., Erik Brynjolfsson, and Lorin M. Hitt. "Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence." *The Quarterly Journal of Economics* 117, no. 1 (2002): 339-376.
- Brynjolfsson, Erik, Andrew McAfee, Michael Sorell, and Feng Zhu. "Scale without mass: business process replication and industry dynamics." (2008).
- Caroli, Eve, and John Van Reenen. "Skill-biased organizational change? Evidence from a panel of British and French establishments." *The Quarterly Journal of Economics* 116, no. 4 (2001): 1449-1492.
- Comanor, William S., and Thomas A. Wilson. "Advertising Market Structure and Performance." *The Review of Economics and Statistics* (1967): 423-440.
- Crespi, Gustavo, Chiara Criscuolo and Jonathan Haskel "Information Technology, Organisational Change and Productivity Growth: Evidence from UK Firms" CEP Discussion Paper 783 (2017).
- Curry, Bruce, and Kenneth D. George. "Industrial concentration: a survey." *The Journal of Industrial Economics* (1983): 203-255.
- Decker, Ryan A., John Haltiwanger, Ron S. Jarmin, and Javier Miranda. "Declining Dynamism, Allocative Efficiency, and the Productivity Slowdown." *American Economic Review* 107, no. 5 (2017): 322-26.
- De Loecker, Jan, and Jan Eeckhout. *The Rise of Market Power and the Macroeconomic Implications*. No. w23687. National Bureau of Economic Research, 2017.
- Doms, Mark, Timothy Dunne, and Kenneth R. Troske. "Workers, wages, and technology." *The Quarterly Journal of Economics* (1997): 253-290.
- Dunne, Timothy, Lucia Foster, John Haltiwanger, and Kenneth R. Troske. "Wage and Productivity Dispersion in United States Manufacturing: The Role of Computer Investment." *Journal of Labor Economics* 22.2 (2004): 397-429.
- Eckard, E. Woodrow. "Plant-level scale economies and industrial concentration." *The Quarterly Review of Economics and Finance* 34, no. 2 (1994): 173-182.
- England, Paula, and Barbara Kilbourne. *Occupational Measures from the Dictionary of Occupational Titles for 1980 Census Detailed Occupations*. Ann Arbor, MI: Inter-university Consortium for Political and Social Research, 2013.
- Furman, Jason, and Peter Orszag. "A firm-level perspective on the role of rents in the rise in inequality." *Presentation at "A Just Society" Centennial Event in Honor of Joseph Stiglitz Columbia University* (2015).

- Grullon, Gustavo, Yelena Larkin and Roni Michaely. "Are US Industries Becoming More Concentrated?" working paper (2017).
- Gutiérrez, Germán and Thomas Philippon. "Declining Competition and Investment in the U.S." NBER Working Paper (2017).
- Hajiha, Fatemeh. "Employment by Occupational Group and Establishment Size." Bureau of Labor Statistics (2003), <https://www.bls.gov/oes/employment.pdf>.
- Hall, B.H., Berndt, E. and Levin, R.C., 1990. The Impact of Corporate Restructuring on Industrial Research and Development. *Brookings Papers on Economic Activity. Microeconomics, 1990*, pp.85-135.
- Harrigan, James, Ariell Reshef, and Farid Toubal. *The march of the techies: Technology, trade, and job polarization in France, 1994-2007*. No. w22110. National Bureau of Economic Research, 2016.
- Kurz, Mordecai. "On the Formation of Capital and Wealth." Working paper 2017.
- Kwoka Jr, John E. "Does Merger Control Work: A Retrospective on US Enforcement Actions and Merger Outcomes." *Antitrust LJ* 78 (2012): 619.
- Lewellen, W.G. and Badrinath, S.G., 1997. On the measurement of Tobin's q. *Journal Of Financial Economics*, 44(1), pp.77-122.
- Mueller, Holger M., Paige P. Ouimet, and Elena Simintzi. *Wage inequality and firm growth*. No. w20876. National Bureau of Economic Research, 2015.
- Rognlie, Matthew. "Deciphering the fall and rise in the net capital share: accumulation or scarcity?." *Brookings papers on economic activity* 2015.1 (2016): 1-69.
- Ruggles, Steven, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek. Integrated Public Use Microdata Series: Version 6.0 [Machine-readable database]. Minneapolis: University of Minnesota, 2015.
- Schott, Peter K. "U.S. Manufacturing Exports and Imports by SIC or NAICS Category and Partner Country, 1972 to 2005," (2011) http://faculty.som.yale.edu/peterschott/sub_international.htm.
- Song, Jae, David J. Price, Fatih Guvenen, and Nicholas Bloom. *Firming Up Inequality*. No. w21199. National Bureau of Economic Research, 2015.
- Tambe, Prasanna, and Lorin M. Hitt. "The productivity of information technology investments: New evidence from IT labor data." *Information Systems Research* 23.3-part-1 (2012): 599-617.
- U.S. Department of Labor. *Dictionary of Occupational Titles*, fourth edition. Government Printing Office, 1977.
- Villalonga, B., 2004. Intangible resources, Tobin's q, and sustainability of performance differences. *Journal of Economic Behavior & Organization*, 54(2), pp.205-230.
- White, Lawrence and Jasper Yang. 2017. "What Has Been Happening to Aggregate Concentration in the U.S. Economy in the 21st Century?" working paper.

Appendix

Solving the first order condition, the optimal level of variable labor for plant i is

(A1)

$$\hat{V}_i = A_i^{\sigma/(1-\gamma\sigma)} \left(\frac{\gamma\sigma}{w} \right)^{1/(1-\gamma\sigma)}.$$

And from this it follows that the revenue per plant and revenue per employee are

(A2)

$$R_i \equiv \hat{P}_i \cdot \hat{Y}_i = \frac{w}{\gamma\sigma} \hat{V}_i, \quad \frac{R_i}{\hat{L}_i} = \frac{w}{\gamma\sigma} \cdot \frac{1}{1 + F/\hat{V}_i}.$$

Given that γ and σ are both positive and less than one, plant revenue size and gross labor productivity both increase with firm productivity, A_i as long as $F > 0$. More productive plants will have larger market share.

Plant operating margin is

(A3)

$$M_i \equiv \frac{\hat{P}_i \cdot \hat{Y}_i - w\hat{L}_i}{\hat{P}_i \cdot \hat{Y}_i} = 1 - \gamma\sigma \left(1 + \frac{F}{\hat{V}_i} \right)$$

Again, given $F > 0$, margins increase with A_i .

Tables

Table 1. Summary Statistics

IT occupations, share of hours worked	2.2%	
Percent of industries where top 4 firms > 50% of revenues	15.3%	
Share of industry revenue going to:		
Top 4 firms	27.9%	
Top 8 firms	36.2%	
Top 20 firms	46.7%	
Top 50 firms	55.9%	
Number of establishments	25,045	
<hr/>		
Average change, 2002-2007:		
Change in share of industry revenue going to:		
Top 4 firms	0.97%	
Top 8 firms	1.14%	
Top 20 firms	1.33%	
Top 50 firms	1.44%	
Change in number of establishments	1,789	
<hr/>		
Median Characteristics (excludes mfg.)	Industry	Top 4 firms
Revenues / establishment (1000s \$2009)	\$1,706.6	\$7,247.9
Revenues / employee (1000s \$2009)	\$146.4	\$194.8
Average annual pay (1000s \$2009)	\$32.3	\$36.7
Wage bill / revenues	23.5%	19.4%

Note: Sample for levels includes 730 observations over the years 2002, 2007, and 2012; sample for changes in concentration ratios is 439; sample for industry characteristics excludes manufacturing because Economic Census does not report number of establishments for top 4 firms. Dollar figures are deflated by the GDP Deflator for 2009 = 1.

Table 2. Regressions on Concentration Ratios

Dependent Variable: Concentration Ratio				
A. OLS	Top 4 firms	Top 8 firms	Top 20 firms	Top 50 firms
IT share	1.90 (0.48)**	2.28 (0.47)**	2.60 (0.33)**	2.37 (0.25)**
Industry digit dummies	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
Sector dummies	✓	✓	✓	✓
No. of observations	728	728	730	725
R-squared	0.254	0.277	0.322	0.337
B. IV				
IT share	1.41 (0.69)*	1.64 (0.75)*	1.67 (0.79)*	0.93 (0.88)
Industry digit dummies	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
Sector dummies	✓	✓	✓	✓
No. of observations	672	672	674	669
R-squared	0.260	0.280	0.324	0.335
Prob. variables are exogenous	0.397	0.342	0.220	0.082
Dependent Variable: Change in Concentration Ratio (2002-2007)				
C. IV	Top 4 firms	Top 8 firms	Top 20 firms	Top 50 firms
Lagged IT share	0.85 (0.18)**	0.79 (0.06)**	0.68 (0.07)**	0.71 (0.13)**
No. of observations	228	228	228	225
Prob. variables are exogenous	0.083	0.098	0.134	0.137

Note: Standard errors in parentheses, * = significant at 5% level; ** = significant at 1% level. Standard errors are clustered by sector except in panel B, where heteroskedastic-robust errors are reported; with the full set of instruments, the IV-GMM regression with clustered errors has too many clusters to compute the weighting matrix. Regressions are on pooled industries for 2002, 2007, 2012. Dependent variable is share of revenues accounted for by top firms (varying number). IT share is instrumented using the share of the workforce that was sedentary in 1977.

Table 3. Placebo tests, manufacturing industries

	1977		2002-2012	
	Four-firm concentration ratio	Shipments/ establishment (mill. \$2009)	Four-firm concentration ratio	Shipments/ establishment (mill. \$2009)
Percent sedentary	0.19 (0.21)	1.40 (1.50)	0.80 (0.12)**	6.49 (2.60)*
Year dummies			✓	✓
Observations	79	79	273	273
R-squared	0.012	0.023	0.177	0.038

Note: Robust standard errors in parentheses, * = significant at 5% level; ** = significant at 1% level. Right column regressions on pooled industries for 2002, 2007, and 2012. For the 1977 regressions, the percent of sedentary workers by industry is calculated from the occupation-industry distribution of the 1980 Census public use sample; for the recent regressions, it is calculated from the 2000 Census public use sample. Shipments in million \$2009.

Table 4. Possibly Confounding Variables

Dependent Variable: Four Firm Concentration Ratio				
	1	2	3	4
IT share	1.80 (0.53)*	1.70 (0.63)*	1.58 (0.36)**	2.24 (0.53)**
Number of establishments (1000s)	-0.08 (0.04) ^o			
M&A index, 1985-2001		-2.82 (4.41)		
Import penetration			-0.23 (3.91)	
Average hourly wage			0.07 (0.16)	
Output growth, 1980-2002				-1.24 (.70) ^o
Industry digit dummies	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
Sector dummies	✓	✓	✓	✓
No. of observations	727	664	723	279
R-squared	0.284	0.271	0.256	0.373

Note: Standard errors, clustered by sector, in parentheses, ^o = significant at 10% level; * = significant at 5% level; ** = significant at 1% level. OLS regressions on pooled industries for 2002, 2007, 2012.

Table 5. Establishment size and IT

Dependent Variable: Log Revenues / Establishment (million \$2009)				
	OLS		IV	
	Top 4 Firms	Remaining Firms	Top 4 Firms	Remaining Firms
IT share	.24 (.02)**	.14 (.04)*	.29 (.06)**	.15 (.05)**
Year dummies	✓	✓		
Sector dummies	✓	✓		
No. of observations	440	439	393	392
R-squared	0.247	0.287	0.175	0.001
$\beta_4 - \beta_{rem}$.11 (.04)** P = .008		.14 (.08)* P = .047	

Note: Standard errors clustered by sector in parentheses, ° = significant at 10% level; * = significant at 5% level; ** = significant at 1% level. Regressions on pooled industries for 2002, 2007, 2012. Samples exclude the manufacturing sector because data are unavailable. Probability values are for the null hypothesis that $\beta_4 \leq \beta_{rem}$.

Table 6. Labor Productivity and IT

Dependent Variable: Log Revenues / Employee (1000 \$2009)				
	OLS		IV	
	Top 4 Firms	Remaining Firms	Top 4 Firms	Remaining Firms
IT share	.15 (.01)**	.11 (.01)**	.35 (.04)**	.28 (.03)**
Year dummies	✓	✓		
Sector dummies	✓	✓		
No. of observations	418	417	371	370
R-squared	0.304	0.350		
$\beta_4 - \beta_{rem}$.045 (.016)** P = .003		.068 (.052)° P = .094	

Note: Standard errors clustered by sector in parentheses, ° = significant at 10% level; * = significant at 5% level; ** = significant at 1% level. Regressions on pooled industries for 2002, 2007, 2012. Samples exclude the manufacturing sector because data are unavailable. Samples also excludes industries in the lowest 5% ranked by the number of employees in the top four firms. Probability values are for the null hypothesis that $\beta_4 \leq \beta_{rem}$.

Table 7. Operating Margins

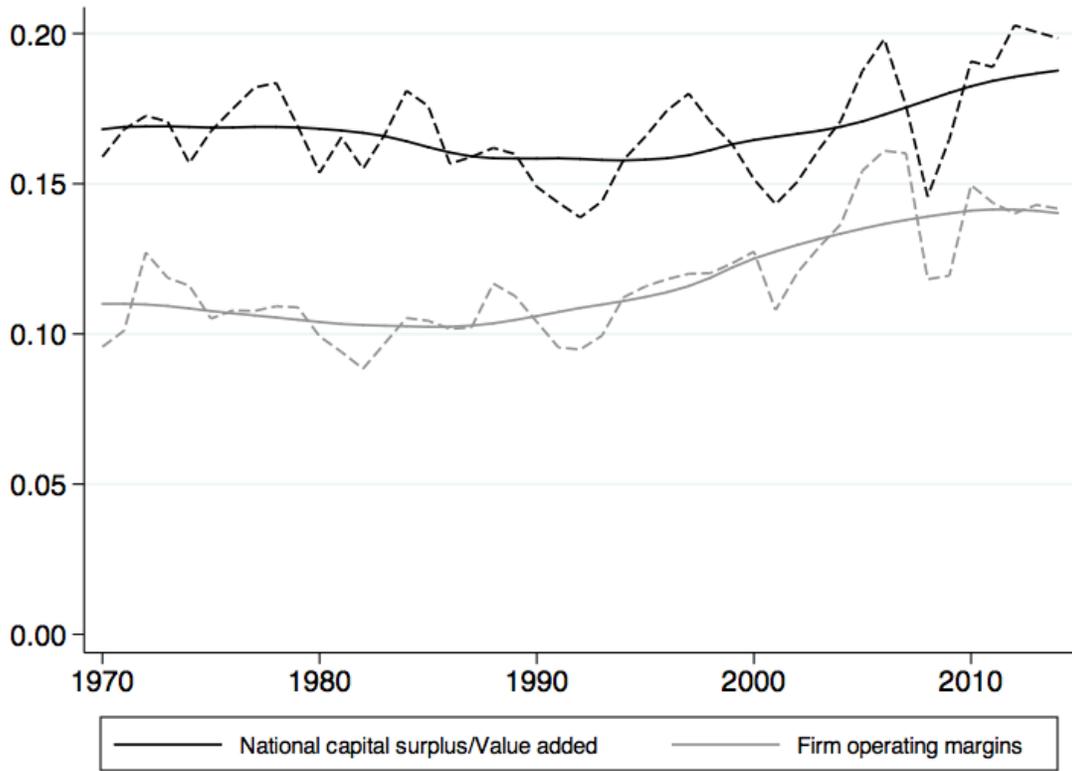
A. Dependent Variable: Operating income after depreciation before taxes, R&D, advert. / Revenues					
	1	2	3	4	5
	1980-2014	2000-2014	2000-2014 RHS lagged	2000-2014	2000-2014
Net assets / sales	.0084 (.0005)**	.0091 (.0005)**	-.0008 (.0008)	.0088 (.0006)**	.0090 (.0005)**
IT capital / worker		.0020 (.0001)**	.0009 (.0001)**		.0021 (.0001)**
IT capital x top 4 / worker				.0021 (.0002)**	
IT capital x remaining / worker				.0017 (.0001)**	
Top 4				-.0215 (.0042)**	
R&D stock / sales		.2346 (.0099)**	.2023 (.0093)**	.2321 (.0102)**	.1883 (.0101)**
Advertising stock / sales		.4648 (.0654)**	.3624 (.0584)**	.4592 (.0712)**	.3598 (.0643)**
Industry regulation					.0045 (.0004)**
Lobbying stock / sales					9.750 (2.757)**
Year	.0009 (.0001)**	-.0017 (.0004)**	-.0005 (.0003)	-.0019 (.0004)**	-.0027 (.0004)**
2-digit industry dummies			✓		
Adjusted R-squared	0.112	0.306	0.518	0.305	0.316
No. of observations	160,785	57,804	57,804	51,179	46,701
B. Contribution of fixed costs by type					
	1	2	3	4	5
Net assets / sales	2.4%	2.9%	-0.3%		3.2%
IT capital / worker		3.6%	1.6%		4.0%
R&D stock / sales		1.8%	1.6%		1.6%
Advertising stock / sales		0.9%	0.7%		0.6%
Industry regulation					2.0%
Lobbying stock / sales					0.2%
Operating margin	16.1%	15.3%	15.3%		15.5%

Note: Panel A: WLS estimations weighted by real revenues. Robust standard errors in parentheses.

**=significant at 1% level; *=significant at 5% level. Sample is all US Compustat firms excluding 1% tails of operating margin and firms where R&D > .5*sales.

Panel B: For asset type j , this table shows $\hat{\beta}_j$ times the weighted (by real revenues) mean of K^j for 2014.

Figure 1. Operating Margins



Note: Solid lines are kernel smoothed. Black line is from the System of National Accounts, Bureau of Economic Analysis. It shows the ratio of the net operating surplus to gross value added for the corporate sector (nonfinancial and financial). The gray line is the ratio of aggregate operating income after depreciation before taxes to revenues for firms publicly listed in the US.

Table A1. Distribution of observations across sectors

Sector	Percent of sample	Change in four-firm concentration ratio, 2002-2007
Mining, utilities, construction	1.6	0.00
Manufacturing	38.6	0.17
Trade, transportation, warehousing	25.9	2.23
FIRE, prof. services	17.0	1.84
Education, health	8.6	-0.77
Recreation, hotel, food	3.7	1.13
Other services	4.5	-0.15

Table A2. Four-firm concentration ratio by industry level

	3 digit	4 digit	5 digit	6 digit
IT share	2.28 (1.24) [°]	0.54 (0.33) [°]	2.40 (0.99)*	6.30 (0.98)**
Year dummies				
No. of observations	75	458	150	45
R-squared	0.046	0.006	0.047	0.679

Note: Robust standard errors in parentheses, [°] = significant at 10% level; * = significant at 5% level; ** = significant at 1% level.