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Abstract: Industry concentration has been rising in the US since 1980. Firm operating margins have also been rising. Are these signs of declining competition that call for a new antitrust policy? This paper explores the role of proprietary information technology systems (IT), which could increase industry concentration and margins by raising the productivity of top firms relative to others. Using instrumental variable estimates, this paper finds that IT system use is strongly associated with the level and growth of industry concentration and firm operating margins. The paper also finds that IT system use is associated with relatively larger establishment size and labor productivity for the top four firms in each industry. Successful IT systems appear to play a major role in the recent increases in industry concentration and in profit margins, moreso than a general decline in competition.

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

JEL codes: D4, O33, L10, L4

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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.[2] 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. If these views are right, then perhaps antitrust enforcement needs to be strengthened or other policy changes made to increase 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

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

[2] The Economist, "Too much of a good thing," March 26, 2016.

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 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 made available by the Internet or other technology. 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.[3] 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

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[3] See Autor et al. (2017) and Table A1.

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 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.[4]

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

[4] 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.

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 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 revenues and higher labor productivity.

The empirical analysis makes three 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. 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. IT systems use is strongly associated with the growth in operating profit margins of publicly listed firms from 2000 to 2014 and this effect can account for most of that growth. Once IT and intangibles are taken into account, the residual trend is not positive, weighing against a general decline in competition as the source of the increase in margins.
3. Industry use of IT systems is associated with larger revenues per establishment and higher labor productivity among the top four firms within each industry, both in absolute terms and relative to other firms in the industry.

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. Demsetz (1973) argued that high industry concentration might be a sign of superior performance rather than an indicator of insufficient competition. 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.[5] 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

[5] Their measure of concentration is a Herfindahl index based on Compustat data.

by firms purchasing custom systems or developing their own applications.[6] 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.[7] These are investments in technology that are not readily available to product market rivals, giving rise to heterogeneous firm productivity with implications for industry structure. Such investments have occurred in the past, even in the early years of computing, but the level of investment has grown dramatically over the last several decades.[8]

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 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).

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[6] 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.

[7] 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.

[8] For instance, from 1977 to 2002 the mean IT share of the workforce in manufacturing industries increased threefold (see Table 6)

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*, and fixed labor, *F*:[9]

$$L_i = V_i + F.$$

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

$$Y_i = A_i V_i^{\gamma}, \qquad 0 < \gamma < 1$$

where A_i represents the firm's heterogeneous productivity, and γ is less than one to capture decreasing returns to production.[10] 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:

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

[9] 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.

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

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,

$$\pi_i = P_i Y_i - wV_i - wF.$$

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

- Given positive fixed costs, higher productivity firms will have higher operating margins.
- Firms with higher productivity, A_i, will have greater revenues, $R_i \equiv \hat{P}_i \cdot \hat{Y}_i$. Assuming that larger firms also have larger establishments, higher productivity firms will have greater revenues per establishment.[11]
- Given positive fixed costs, higher productivity firms will have greater output per worker, R_i/L_i.

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 greater revenues, 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.

[11] It is possible, of course, that larger firms could simply have more establishments of the same size. This would be the case if the economies of scale were purely economies in the management of the number of establishments. Eckard (1994) finds evidence that industry concentration is mainly associated with larger establishment size rather than more establishments per firm. I make the assumption that a substantial portion of the increase in firm revenues caused by greater productivity arises from larger establishment size.

If the top firms within an industry have greater productivity relative to the rest, then the industry will exhibit higher concentration. That is, if, say, the top four firms have higher productivity, then they will also have relatively larger revenues, all else equal. And their share of revenues, the concentration ratio, will also be larger. From this it follows that if IT use leads to greater productivity dispersion, it will also lead to greater industry concentration.

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 1997, 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.[12] 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). I also use data from the 1977 Economic Census for the manufacturing sector.

[12] I use industry concentration by revenues rather than by value added because the revenue measure corresponds more directly with the model.

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; Guttierez 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.[13] 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.

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. Proprietary systems might incorporate off-the-shelf components including software (e.g., SAP software), but these components are bundled with firm-specific software. I assume that in-house 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

[13] 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.

BEA software investment measures that do include contracted software.[14] Tambe and Hitt (2012) find that a similar labor-based measure corresponds with a variety of other measures of IT.

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, and computer software developers.[15] Since the aim is to measure the use of custom IT systems, I exclude industries that are involved in creating information technology products.[16] These industries employ IT personnel in designing and producing products, not 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.[17]

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

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[14] 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.

[15] 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.

[16] 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, 3344 Semiconductor and Other Electronic Component Manufacturing, and 3345 Navigational, measuring, electromedical, and control instruments manufacturing.

[17] That is, it excludes industries with fewer than 28,748 employees.

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.[18]

I also use data for the manufacturing sector for 1977, using the 1980 Census of Population to obtain measures of the IT share per industry. The 1977 Economic Census uses 4-digit SIC codes to classify industries while the Census uses its own industry classification and the later Economic Censuses use the NAICS classification. To make the 1977 Economic Census data comparable both to the Census of Population and to the later Economic Censuses, I match the 1977 industries. Where the target data use a higher level of industry aggregation, I averaged the 1977 industry data on concentration, weighting by shipments per detailed industry.

To study the growth in firm operating margins, the main sample consists of Compustat firms traded on US exchanges in 2000 and 2014, excluding financial firms, matched to industry IT systems data, totaling 1,532 firms. 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 5 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 and advertising and marketing expenditures are computed using the perpetual inventory method.[19] Industry level IT capital is also calculated using the perpetual

[18] 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.

[19] 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

inventory method where annual investment consists of the deflated wages paid to IT personnel in the industry.[20] As a control in the operating margin regressions, I use a measure of industry regulation developed by Al-Ubaydli and McLaughlin (2015) that is based on an industry-relevance weighted count of words in the Code of Federal Regulations.[21]

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 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.

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advertising and marketing expenditures and assumes a 45% annual depreciation rate and 5% pre-sample growth rate (Villalonga 2004, p. 217).

[20] 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.

[21] 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.

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 show rising concentration.

Instrumental variable

Firm investments in information technology might be endogenous, reflecting other factors that might also be related to industry concentration. This might confound the analysis of the impact of IT on concentration or the analysis of operating margins. For example, faster growing firms might invest more in IT in order to manage their more rapid growth; they would become larger, possibly increasing industry concentration, and their growth would be correlated with IT. But in this case, growth in market share would cause IT spending rather than the reverse.

In order to correct for reverse causality and other confounding influences in the analysis of industry concentration and operating margins, I use an instrumental variable estimation. The ideal instrument should be correlated with (but independent of) IT and it would also plausibly satisfy the exclusion restriction; that is, the ideal instrument would not influence industry concentration except through IT.

To instrument the IT share of hours, I use a measure of industry sedentariness derived from the Dictionary of Occupational Titles (1977). The notion here is that it is easier to implement computer technology in industries with more sedentary employees because seated employees can more advantageously use desktop computers or terminals. These industries should therefore tend to adopt IT somewhat earlier and somewhat more intensively, all else equal.

I use a measure of sedentariness derived from the 1977 edition of the Dictionary of Occupational Titles; this was before most occupations used computers so that computers likely had little effect on the sedentariness of occupations. 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. 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.

This measure is correlated with the IT share of the workforce and the estimates show that the instrument is not weak. Table 2 shows correlation coefficients and first stage regressions. The first column, for the manufacturing sector only, is for 1977, using the sedentariness index weighted by the occupational distribution from the 1980 Census. The table shows regressions of the IT share of the workforce regressed on the sedentariness index and, in the bottom row, the simple correlation. Even though the level of IT use in 1977 was low compared to more recent years, the first stage correlation is strong (.791). The correlation coefficients for the years 2002, 2007, and 2012 range from .422 to .448 and the regression coefficients are highly significant. One concern is that the rise of mobile computing might correspond to a weakening of the instrument, which is based conceptually on desktop computing. While the regression coefficient on the sedentariness variable did decline somewhat from 2002, this difference is not statistically significant and the correlations and regression R-squared statistics did not weaken.

Sedentariness and computer use vary substantially across sectors. Table A2 in the Appendix shows the mean sedentariness of each 1-digit NAICS sector as well as the index for the lowest and highest industry within each sector. Finance, real estate, and business services is the most sedentary sector (mean .70) while agriculture is the least sedentary (mean .14). However, the differences in the sedentariness index between the low and high industries within each sector show that there is significant variation in the index within sectors. For example, within manufacturing, Animal Slaughtering and Processing has a sedentariness index of .12, but Aerospace Products and Parts has a sedentariness index of .73. Moreover, the correlation between sedentariness and IT share of the workforce, estimated for 2002, 2007, and 2012, is substantial for all sectors except for Other Services. Thus, the link between this instrumental variable and IT share is not mainly driven by a few industries or sectors.

One concern is that sedentariness might be linked to other occupational characteristics that somehow affect industry concentration. Specifically, while sedentary occupations are more likely to use computers, they are also more likely to handle paper documents. Sedentariness is likely correlated with the use of desks, paper, and pencils. Dinardo and Pischke (1997) famously found that pencil use is correlated with higher wages, likely reflecting unobserved worker characteristics of those workers who select into pencil-using occupations. Sedentariness might well be correlated with such characteristics and also with higher wages.

These correlated variables might cause a problem for the instrument if they were *also* correlated with the outcome variable, industry concentration. Evidence in Table 3 suggests that this second correlation is not a significant problem. This table regresses several measures of industry concentration and the growth in industry concentration against three industry characteristics: the share of workers in professional and managerial occupations, the mean years of schooling of workers in the industry, and the mean log industry wage. The regressions also include dummy variables for year, industry sector, and the number of digits in the industry classification, as are used in the regressions on industry concentration below. Joint tests of the significance of these variables cannot reject the null hypothesis that they are all zero. Individually, the coefficients are not statistically significant except for weak significance (10% level) of the wage variable in the two broadest measures of industry concentration. These estimates appear to rule out the possibility that the correlation between sedentariness and industry concentration spuriously reflects the effect of professional/managerial work, education, or wages.

Further evidence in support of the validity of the exclusion restriction comes from placebo tests. The left side of Table 4 reports regressions on industry concentration using data from the 1977 Economic Census for the manufacturing sector and also from the Economic Censuses of 2002, 2007, and 2012.[22] The regressions show that the instrumental variable is not significantly correlated with the four-firm concentration ratio in 1977, but the association is highly significant for the more recent sample of manufacturing industries. The assumption in this paper is that the correlation during the recent period reflects the greater use of information technology since 1977. A similar pattern is seen in the right panel of the table which regresses firm operating margins on the instrumental variable with various controls corresponding to the analysis below. Again, the coefficient for 1977 is not significant while the coefficient for the recent period is highly significant.

[22] 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.

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 concentration or operating margins. However, it does mean that such a third factor could not have had significant influence prior to 1980 and its influence must have grown more or less concurrently with the rapid growth in IT systems use after 1980.

Empirical Findings

Basic regressions on concentration ratios

Table 5 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 if 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 A3 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 5 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% x 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.[23]

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 instrumental variables, instrumenting with the index of sedentariness. Using IV estimation, the coefficient estimates for IT share are somewhat smaller and somewhat weaker statistically, but are overall similar.[24] 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,

[23] One concern is that many firms in education and health care are nonprofit, perhaps biasing the results. Repeating these regressions but excluding those industries (results not shown) makes little difference in the coefficients.

[24] The IV sample is slightly smaller than the OLS sample because of missing values for the instrument. If the OLS estimates are repeated with the same sample as the IV analysis, the OLS coefficients are quite similar to those in the larger sample.

.098). At the sample mean, IT share is associated with an increase in the four-firm concentration ratio of 0.85 x 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.

Long differences

Table 6 extends this analysis by looking at the change in the four-firm concentration ratio from 1977 to 2002. This sample is for the manufacturing sector only, due to limitations in the available public data.[25] The first column uses the 1980 estimate of IT share and the second column measures the difference between IT shares in 1980 and 2002. The third column repeats the regression of column 1 using IV estimations. In all of these regressions, the coefficient on IT share is significant. The bottom of the table shows the sample means of the IT measures and product of these means and the IT share coefficient. In each estimation, IT share accounts for a 3 – 5% rise in industry concentration, roughly corresponding to the actual increase found by Autor et al. (2017). In other words, IT use appears to account for much of the rise in industry concentration.

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[25] The sample also excludes industries where software development is part of the product and it excludes the 1% tails in the dependent variable (1 observation each) in order to limit measurement error.

Other variables

A variety of other variables might confound the analysis, possibly being correlated with IT systems use and also with industry concentration. Table 7 considers some possibly confounding variables: the number of establishments, merger and acquisition activity, exposure to imports, 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 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 or where ownership percentage was not reported, I matched these data with Compustat data for publicly listed firms, resulting in a list of 33,942 acquisitions by publicly listed firms from 1985 through 2001.[26] 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 ((imports–exports)/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.

Columns 4 adds the average annual growth rate for real shipments from 1980 to 2002 for manufacturing industries.[27] It might be harder to maintain market share in a rapidly growing industry and rapidly growing industries might have greater need of IT. The

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[26] These are acquisitions by publicly listed firms of private and publicly listed firms. In aggregate, private firms do more acquisitions—85% of them in these data.

[27] Data from the NBER-CES Manufacturing Productivity database.

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.[28]

Column 5 includes all of the right-hand side variable tested in columns 1-3 for the whole sample. The coefficient on the number of establishments in the industry is now statistically significant, but the coefficient on IT share remains roughly the same, suggesting that none of these additional variables confound the analysis of the role of IT.

Growth in Operating Margins

Table 8 provides an analysis of the growth in operating margins. The sample in this case consists of publicly listed US firms that reported in both 2000 and 2014, excluding firms in the finance sector.[29] The dependent variable is the change in operating margin between 2000 and 2014 where operating margin is defined as operating income after depreciation but before taxes, R&D, advertising and marketing expenditures all divided by revenues. I exclude R&D, advertising and marketing from income because I treat these as intangible investments on the right-hand side of the regression equations. That is, operating profits should reflect the returns on investments in capital as well as returns to stocks of intangibles. The model above finds that operating margins should be greater with firm productivity and IT use, but the model does not explicitly incorporate capital measures. The model can be readily extended so that the operating margin for firm *i* at time *t* is

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

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[28] If I include the growth in the industry capital stock, that has a significant negative coefficient and the coefficient for the IT share is even larger.

[29] In addition, the sample excludes the 5% tails in the dependent variable and firms where R&D spending exceeds 50% of revenues.

where $K_i^1, K_i^2, \ldots$ represent stocks of capital assets as well as stocks of intangible assets, R&D and advertising and marketing. The β_j represent the rental rates for each type of capital. α represents the effect of IT and, by hypothesis, $\alpha > 0$. δ represents a time trend rate; if a general decline in competition were causing a rise in margins, then we should find $\delta > 0$. Because we are interested mainly in the growth of margins over this period (2000-2014) and because there are also likely significant firm fixed effects, I estimate the differenced equation over this interval:

$$\Delta M_i = \alpha \cdot \Delta IT_i + \delta + \beta_1 \Delta \frac{K_i^1}{R_i} + \beta_2 \Delta \frac{K_i^2}{R_i} + \cdots + \Delta \epsilon_i.$$

Table 8 reports some basic estimates. Column 1 reports a simple OLS regression and Column 2 reports the instrumental variable regression. Note that the IT measure is an industry-level measure. Both are highly significant, but the IV estimate is substantially larger. At the sample mean for the change in IT share (.007), these coefficients represent an increase in operating margins of 0.9% and 3.5% respectively. By comparison, the actual increase in operating margins for this sample is 3.2%, suggesting that IT can account for a major portion of the observed increase.

Column 3 uses the level of IT share rather than the change in that variable. Column 4 repeats the regression in Column 2, but adds an additional variable, a measure of the change in industry regulation based on word counts in the Federal Code. If Federal regulation imposes substantial fixed compliance costs, then this might serve as an entry barrier, raising margins (Bessen 2016, Guttierez and Philippon 2017). There does seem to be a significant association between regulation and margins; at the sample mean, the increase in regulation may have contributed 1.6% to the growth in operating margins. But inclusion of this variable does not significantly alter the coefficient on IT share.

Finally, the constant term represents the background trend. This term is either not significantly different from zero or significant and negative. It appears that once IT and intangibles are accounted for, the trend is not positive, contrary to the notion that a general decline in competition has led to rising firm margins.

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 establishment size and also as a link between IT and labor productivity.

Table 9 explores the relationship between the IT share of the workforce and average establishment 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 complete data for the manufacturing sector, that sector is necessarily excluded from the analysis that follows.

The table reports joint estimates using Zellner's "Seemingly Unrelated Regression" of equations relating the log of deflated revenues per establishment for each group of firms (Top 4 and the rest) separately:

$$\ln R_{it}^{top\ 4} = \alpha^{top\ 4} \cdot IT_{it} + \mu_i + \delta_t + \epsilon_{it}$$

$$\ln R_{it}^{rem} = \alpha^{rem} \cdot IT_{it} + {\mu'}_i + {\delta'}_t + {\epsilon'}_{it}$$

I use a log specification because establishment revenues are highly skewed. The first column shows the unrestricted regressions with controls for industry sector and year. The second column shows the regression where the coefficients for the industry sector and year dummies are constrained to be equal across equations. The bottom row reports a Wald test of the null hypothesis that $\alpha^{top\ 4} = \alpha^{rem}$.

In both columns, estimates of $\alpha^{top\ 4}$ and α^{rem} are both highly significant and the Wald test strongly rejects the null hypothesis. IT is strongly associated with greater revenue per establishment and the association is substantially stronger for the larger, presumably more productive, firms.

Columns 3 and 4 repeat the analysis using log revenues per employee as the dependent variable. The results are broadly similar. Although this is not a causal analysis, these findings support the notion that IT may be implicated in the rising productivity gap between the top firms and the rest.

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, instead, 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.[30] 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

[30] Some recent evidence suggests that cloud computing might be altering the relationship in favor of small firms (Jin and McElheran 2017).

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; IT does not appear to generate a natural monopoly in most markets. 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.[31]

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 not positive once intangible investments are taken

[31] Shapiro (2017) questions the relevance of Economic Census of concentration as reliable indicators of competition.

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.

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Appendix

Solving the first order condition, the optimal level of variable labor for firm *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 and revenue per employee are

(A2)

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

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

Firm 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	
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	
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. First stage regressions

Dependent variable: IT share of workforce				
Year	1977	2002	2007	2012
Sedentariness	5.13 (0.48)**	6.52 (0.78)**	4.97 (0.57)**	4.85 (0.60)**
Sector dummies		✓	✓	✓
No. of observations	71	236	227	208
Adjusted R-squared	0.621	0.269	0.356	0.392
Simple correlation	0.791	.463	.422	.448

Note: Standard errors in parentheses, * = significant at 5% level; ** = significant at 1% level. Sectors are 1-digit NAICS sectors. The 1977 data are for the manufacturing sector only and the sedentariness index is calculated using occupational weights from the 1980 Census. The other columns are for all sectors and the index is calculated using occupational weights from the 2000 Census. Samples correspond to those used in the analysis below.

Table 3. Do industry worker characteristics affect concentration ratios?

Dependent variable	Share of revenues, 2002, 2007, 2012				Change in revenue share, 1977-2002 Top 4 firms, manufacturing
	Top 4 firms	Top 8 firms	Top 20 firms	Top 50 firms	
Industry characteristics:					
Share professional & managers	0.07 (0.18)	0.09 (0.21)	0.12 (0.24)	0.07 (0.25)	0.10 (0.44)
Mean years school	-2.44 (3.87)	-3.04 (4.79)	-4.22 (5.04)	-4.94 (4.82)	9.99 (11.79)
Log wage	24.95 (14.89)	29.27 (16.83)	34.31 (16.65)°	32.21 (14.87)°	-32.49 (43.97)
Industry digit dummies	✓	✓	✓	✓	
Year dummies	✓	✓	✓	✓	
Sector dummies	✓	✓	✓	✓	
Observations	669	669	671	666	69
R-squared	0.241	0.259	0.303	0.324	0.071
Joint test (P value)	0.455	0.441	0.303	0.157	0.170

Note: Robust standard errors in parentheses, ° = significant at 10% level; * = significant at 5% level; ** = significant at 1% level. Details of the variables and samples described below.

Table 4. Placebo tests

Sample	Manufacturing industries		Compustat firms	
Dependent variable	4-firm concentration ratio		Operating margin	
	1977	2002, 2007, 2012	1977	2000-2014
Sedentariness	0.19 (0.21)	0.80 (0.12)**	-0.03 (0.08)	0.15 (0.02)**
Year dummies		✓		✓
SIC2 dummies			✓	✓
Capital and intangible stocks			✓	✓
Observations	79	273	890	64,189
R-squared	0.012	0.177	0.46	0.095

Note: Robust standard errors in parentheses, * = significant at 5% level; ** = significant at 1% level. 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. The sedentariness index is assigned to firms via the Census NAICS classification; consequently, the firms in the 1977 sample also appear in year 1998 or later when NAICS codes were assigned. As in the analysis below, the 1% tails of the dependent variable were excluded.

Table 5. Regressions on Concentration Ratios

Dependent Variable: Concentration Ratio				
A. OLS	Top 4 firms	Top 8 firms	Top 20 firms	Top 50 firms
IT share	1.99 (0.56)*	2.39 (0.55)**	2.71 (0.39)**	2.40 (0.26)**
Industry digit dummies	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
Sector dummies	✓	✓	✓	✓
No. of observations	725	725	727	722
R-squared	0.257	0.281	0.326	0.337
B. IV				
IT share	1.53 (0.71)*	1.76 (0.77)*	1.77 (0.81)*	0.99 (0.92)
Industry digit dummies	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
Sector dummies	✓	✓	✓	✓
No. of observations	669	669	671	666
R-squared	0.264	0.285	0.328	0.336
Prob. variables are exogenous	0.420	0.352	0.221	0.102

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	0.83 (0.17)**	0.77 (0.06)**	0.66 (0.06)**	0.70 (0.12)**
No. of observations	227	227	227	224
Prob. variables are exogenous	0.082	0.098	0.137	0.139

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 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 a measure of the sedentariness of the industry workforce, using occupational measures from 1977 apportioned to industries using the 2000 Census.

Table 6. Long Difference in Four-firm Concentration Ratio

Dependent Variable: Change in Four Firm Concentration Ratio			
	Manufacturing only, 1977 - 2002		
	OLS	OLS	IV
IT share, 1980	8.98 (1.43)**		7.59 (3.09)*
Change in IT share		1.76 (1.05)°	
No. of observations	71	71	71
R-squared	0.154	0.053	0.15
Mean IT variable	0.55	1.55	0.55
Average effect	4.90	2.74	4.14

Note: Standard errors in parentheses, ° = significant at 10% level; * = significant at 5% level; ** = significant at 1% level. OLS errors are robust to heteroscedasticity; IV errors are bootstrapped. Dependent variable is the change in share of revenues accounted for by top 4 firms. IT share is instrumented using a measure of the sedentariness of the industry workforce, using occupational measures from 1977 apportioned to industries using the 1980 Census. Excludes the 1% tails of the dependent variable. The null hypothesis that IT share is exogenous in the IV regression cannot be rejected (P = .352)

Table 7. Possibly Confounding Variables

Dependent Variable: Four Firm Concentration Ratio	1	2	3	4	5
IT share	1.80 (0.53)*	1.70 (0.63)*	2.00 (0.57)*	2.24 (0.53)**	1.70 (0.33)**
Number of establishments (1000s)	-0.08 (0.04)°				-0.08 (0.01)**
M&A index, 1985-2001		-2.82 (4.41)			-3.01 (2.53)
Import penetration			-1.85 (1.93)		-1.34 (3.76)
Output growth, 1980-2002				-1.24 (.70)°	
Industry digit dummies	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓
Sector dummies	✓	✓	✓	✓	✓
No. of observations	727	664	725	279	660
R-squared	0.284	0.271	0.257	0.373	.286

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

Table 8. Change in Operating Margins, 2000 – 2014

Dependent Variable: Δ Operating income after depreciation before taxes, R&D, advert. / Revenues	OLS	IV	IV	IV
IT share			0.85 (0.19)**	
Δ IT share	1.26 (0.30)**	5.11 (1.13)**		5.10 (1.21)**
Δ Capital stock	0.01 (0.00)**	0.01 (0.00)**	0.01 (0.00)**	0.00 (0.00)**
Δ R&D stock	-0.04 (0.01)**	-0.05 (0.01)**	-0.04 (0.01)**	-0.05 (0.02)**
Δ Advertising stock	0.15 (0.05)**	0.15 (0.08)	0.16 (0.07)*	0.16 (0.09)
Δ Regulation				0.06 (0.01)**
Constant	0.00 (0.00)	-0.02 (0.01)	-0.02 (0.01)**	-0.03 (0.01)**
No. observations	1531	1531	1532	1267
Adjusted R-Squared	0.18	0.093	0.184	0.137

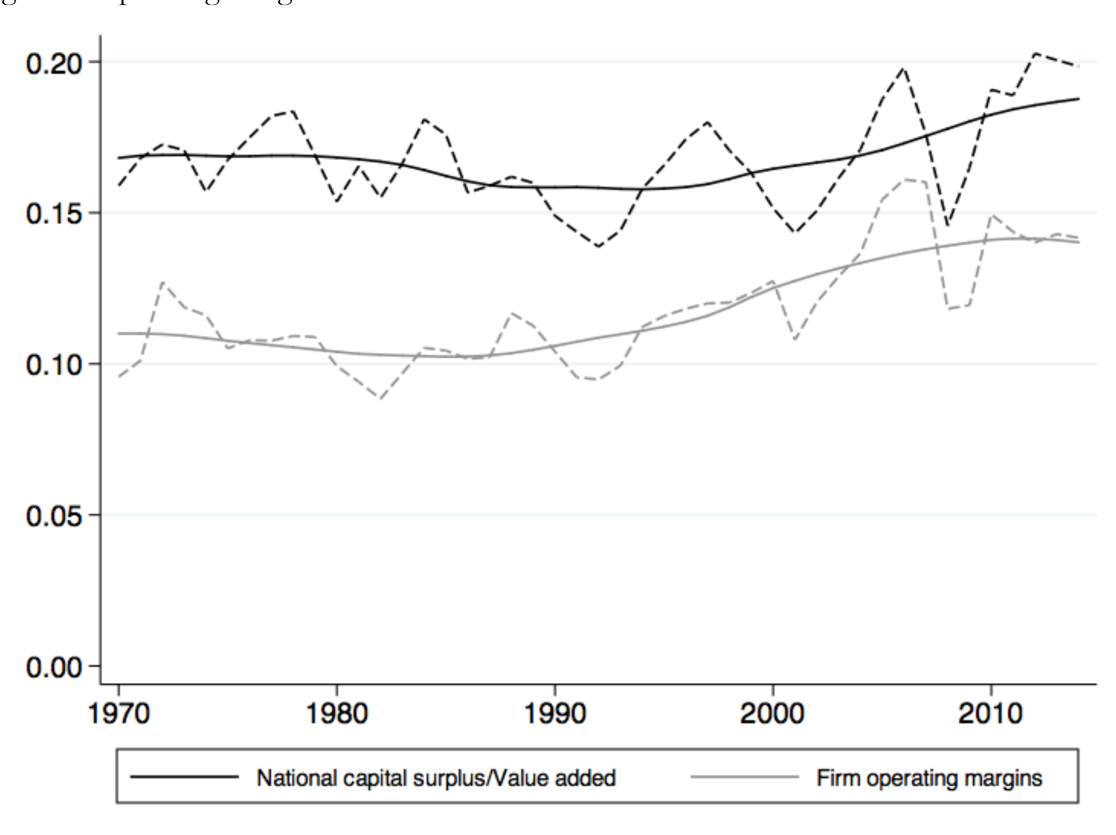
Note: **=significant at 1% level; *=significant at 5% level. Sample is all US Compustat firms excluding 5% tails of operating margin and firms where R&D > .5*sales; long difference regression trims the 5% tails of the dependent variable. IV uses sedentariness index as instrument; null hypothesis that IT share is exogenous is rejected (P = .000, .052, .000) in columns 2-4 respectively.

Table 9. Establishment size, labor productivity, and IT

Dependent variable:	Log Revenues / establishment ($2009)		Log Revenues / employee ($2009)	
	Unrestricted	Restricted	Unrestricted	Restricted
Top 4 firms				
IT share	0.25 (0.03)**	0.48 (0.03)**	0.15 (0.02)**	0.25 (0.02)**
Year dummies	✓	✓	✓	✓
Sector dummies	✓	✓	✓	✓
No. of observations	439	439	439	439
R-squared	0.256	0.025	0.296	0.212
Remaining firms				
IT share	0.14 (0.02)**	0.07 (0.03)**	0.11 (0.02)**	0.13 (0.02)**
Year dummies	✓	✓	✓	✓
Sector dummies	✓	✓	✓	✓
No. of observations	439	439	439	439
R-squared	0.292	0.245	0.359	0.353
Test equality of IT share coefficients (Prob. value)	0.000	0.000	0.001	0.000

Note: **=significant at 1% level; *=significant at 5% level. Estimates use the Seemingly Unrelated Regression model for separate equations for the top 4 firms in each industry and for the remaining firms in each industry. The sample excludes manufacturing industries (data was not reported). The restricted estimates constrain the coefficients of the dummy variables to be equal across the two equations. The bottom row reports the probability of the null hypothesis in a Wald test that the coefficients of IT share are equal across the two equations.

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
Wholesale, retail, transportation, ware	25.9	2.23
Finance, real estate, business services	17.0	1.84
Education, health	8.6	-0.77
Recreation, hotel, food services	3.7	1.13
Other services	4.5	-0.15

Table A2. Sedentariness across sectors

Sector	Lowest and Highest Industry	Sedentariness	Correlation with IT share
Agriculture		0.14	--
	Animal production	0.04	
	Forestry, except logging	0.39	
Mining, utilities, construction		0.36	0.847
	Coal mining	0.12	
	Not specified utilities	0.58	
Manufacturing		0.30	0.876
	Animal slaughtering and processing	0.12	
	Aerospace products and parts	0.73	
Wholesale, retail, transportation, warehousing		0.51	0.245
	Pipeline transportation	0.13	
	Jewelry, luggage, and leather goods stores	0.94	
Finance, real estate, business services		0.70	0.663
	Other administrative, and other support services	0.08	
	Architectural, engineering, and related services	0.98	
Education, health		0.49	0.164
	Child care	0.09	
	Office of chiropractors	0.96	
Recreation, hotel, food service		0.30	0.761
	Drinking places, alcohol beverages	0.06	
	Independent artists	0.74	
Other services		0.36	0.007
	Beauty salons	0.08	
	Nail salons and other personal care services	0.92	

Table A3. 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.