

Industry Concentration and Information Technology

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Abstract

Industry concentration has been rising in the United States since 1980. Does this signal declining competition and the need for a new antitrust policy? Or are other factors causing concentration to increase? This paper explores the role of proprietary information technology (IT), which could increase the productivity of top firms relative to others and raise their market share. Instrumental variable estimates find a strong link between proprietary IT and rising industry concentration, accounting for most of its growth. Moreover, the top four firms in each industry benefit disproportionately. Large investments in proprietary software—\$250 billion per year—appear to significantly impact industry structure.

1. Introduction

Industry concentration at the national level has been rising across sectors in the United States 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 manufacturing industries grew 4.5 percent, with similar increases in most other major sectors.¹ At the same time, evidence shows a concomitant rise in profit margins and mark-ups (Rognlie 2015; Barkai, forthcoming; De Loecker and Eeckhout 2017). 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).² Grullon, Larkin, and Michaely (2017) attribute the rise in industry

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¹ See also White and Yang (2017) on trends in aggregate concentration. Rinz (2018) and Rossi-Hansberg, Sarte, and Trachter (2018) find that local concentration ratios have been falling.

² National markets identified in the economic census do not correspond to the relevant markets used in antitrust analysis; however, the general rise in national concentration ratios might reflect important changes nevertheless.

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concentration partly to lax antitrust enforcement of mergers and acquisitions (M&A). Gutiérrez and Philippon (2017, 2018) suggest that growing federal regulation, weakened antitrust, and corporate lobbying might be reducing competition specifically in the United States. If these views are right, then perhaps antitrust enforcement needs to be strengthened or other policy changes made to increase competition.

However, these views are controversial (*Journal of Economic Perspectives* 2019). Rising industry concentration does not necessarily imply declining competition. As Demsetz (1973) argues, concentration can also increase when some firms grow faster because they are more efficient. In this case, rising concentration would reflect greater innovation and social benefit. The policy implications from rising industry concentration depend very much on what is causing the increase.

This paper explores the role of one possible cause: the large investments that firms are making in proprietary information technology (IT). Firms, especially large firms, have dramatically increased their spending on proprietary software. According to estimates from the Bureau of Economic Analysis (BEA 2017, table 5.6.5), in 2016, firms invested \$250 billion in proprietary software development (self-developed and contracted). That is nearly as much as all private nonresidential investment in equipment and structures, net of depreciation.

Figure 1 shows that this investment in IT is, in fact, strongly correlated with industrial concentration.³ Its binned scatterplot relates the market share of the top four firms in industries (excluding industries in which software is a major part of the product) to the share of software developers in the industry workforce. Below I show that this correlation holds for several different specifications, is robust to a number of controls including M&A activity and international trade, and, using several instrumental variable (IV) regressions, is plausibly causal.

Moreover, this relationship is economically significant. I find that proprietary software explains most of the rise in industrial concentration. Evaluated at the sample means, proprietary software accounts for a 3–5 percent increase in the four-firm concentration ratio since 1980. This is roughly the rise in concentration ratios found by Autor et al. (2017) since 1982. Looking at the change in concentration ratios between 2002 and 2007, I find that proprietary software accounts for a 1.2 percent increase, compared with a 1.4 percent average increase in the sample. In contrast, measures of M&A activity are not positively associated with changes in concentration.

In addition, some evidence suggests that the role of proprietary software is related to differences in efficiency between the top firms and the rest. Industry use of proprietary IT is associated with larger revenues per establishment and higher labor productivity among the top four firms in each industry, both in absolute terms and relative to other firms in the industry. This finding is congruent with evidence of a productivity gap between the top-performing firms and the

³ Figure 1 is for 254 industries, excluding industries producing information technology (IT) in 1997, 2002, 2007, and 2012.

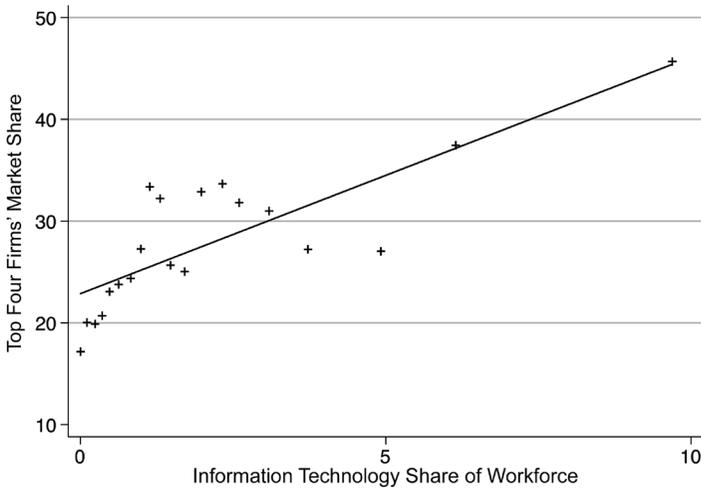


Figure 1. Four-firm concentration ratio and the information technology workforce

rest (see Andrews, Criscuolo, and Gal 2016; Berlingieri, Blanchenay, and Criscuolo 2017).⁴ In addition, rising productivity gaps and rising markups are observed across developed economies (De Loecker and Eeckhout 2018; Diez, Leigh, and Tambunlertchai 2018; Calligaris, Criscuolo, and Marcolin 2018), which undercuts the notion that specific US domestic policies are the main causal culprit.

Thus, the contribution of this paper is to show that proprietary software is responsible for a substantial part of the observed rise in national levels of industry concentration in the United States and that this effect appears to be related to efficiency advantages of the largest firms. While these findings by themselves provide little support for a change in antitrust policy, they do indicate that large and rising investment in proprietary IT systems is affecting industry structure and is an important phenomenon to study that may have important implications for policy. Moreover, these changes are occurring across all sectors; they are not just about Big Tech.

2. Background: Why Information Technology?

But why might IT increase industry concentration? Rapidly falling prices for computer hardware and strong growth of prepackaged software suggest to some that IT might, instead, level the playing field, allowing small firms to compete with larger rivals (see, for instance, Schafer 1995). In this view, investments in generally available computer technology should not increase industry concentra-

⁴ Calligaris, Criscuolo, and Marcolin (2018) find a rising dispersion in markups that is greater in IT-intensive industries; Dunne et al. (2004) associate growing productivity differences to IT; Peltzman (2018) finds that, in manufacturing, growing concentration is associated with higher productivity.

tion. Indeed, Brynjolfsson et al. (2008) find that industry concentration did not grow faster in IT-intensive industries than in other industries from 1987 to 2006.⁵

But beginning in the mid-1990s, the nature of nonresidential investment in IT changed. It not only grew sharply, but the investments switched from consisting primarily of generally available technology—prepackaged software and off-the-shelf computer hardware—to proprietary technology, especially custom-written software that was either developed by firms themselves or contracted by them. According to BEA statistics, in 2016 proprietary software accounted for 55 percent (\$250 billion) of the total private investment in software, computers, and peripherals (\$452 billion).⁶ In 1985, proprietary software accounted for only 33 percent of a much smaller total (\$58 billion); by 1995 this share was still only 37 percent (of \$141 billion), with most of the increase in magnitude and share coming since then.

Proprietary IT, as opposed to off-the-shelf products, can affect industry concentration by providing competitive advantages unavailable to rivals. If large firms invest more in proprietary software, then they may grow faster, increase their market shares, and thus increase industry concentration.

For example, since the 1970s, off-the-shelf bar code scanners and associated computer programs have been available to retail stores both large and small. These systems provide proven productivity advantages. However, the advantages are available to relatively small firms, so it is unlikely that the barcode scanner itself increased concentration in retail industries. But Walmart integrated scanners into a complex proprietary system. In 1990, Walmart introduced a system that linked suppliers and stores and headquarters, providing suppliers with detailed inventory data for each store. The technology, combined with complementary changes in the organization of distribution centers and stores, allowed Walmart to adjust rapidly to changes in demand, for instance, to identify hot-selling items and to get them on store shelves quickly. The system sped the delivery of goods, reduced inventory requirements, increased the number and variety of items sold in each store, reduced prices, and delivered dramatically faster productivity growth. Few rivals could match Walmart's technology. Basker (2007) suggests that Walmart alone accounts for most of the growth in productivity in general merchandise retailing from 1982 to 2002, and this explains its growing market share. In 1982, Walmart accounted for 3 percent of the sales of US general merchandise retailers; 30 years later, Walmart's US sales constituted 52 percent of industry sales.

Such investments in proprietary IT are being made by large firms across all major sectors, not just by big-tech companies or a few companies like Walmart. Big banks developed IT systems to handle credit card operations; Boeing devel-

⁵ Their measure of concentration is a Herfindahl-Hirschman index based on Compustat data. Brynjolfsson et al. (2008) also find that industry concentration in IT-intensive industries grew faster after 1995 than before then.

⁶ Bureau of Economic Analysis, Prices and Output for Information and Communication Technologies, Software Investment and Prices by Type (<https://www.bea.gov/prices-and-output-information-and-communication-technologies>).

oped systems to design large aircraft. Large firms invest disproportionately more in proprietary software. Software developers make up 4.1 percent of the workforce at firms with over 1,000 employees but only 1.3 percent of the workforce at firms with 50 or fewer employees (US Census Bureau 2010–17). Prepackaged software as a share of investment declines sharply with firm size, while own-developed software increases with firm size, dramatically so for the largest firms (Unger 2019).

Why might large firms disproportionately invest in proprietary software? One reason is that these may be the firms that are best able to implement large and risky IT projects. For instance, Bloom, Sadun, and Van Reenen (2012) find that well-managed US multinationals achieve greater productivity from their IT investments. Companies with the right talent and management may be able to grow faster, becoming dominant in their industries and raising industry concentration. In addition, IT systems might exhibit economies of scale—they have large fixed costs—that advantage large firms.

Another reason large firms might dominate investment in proprietary software is that they receive greater benefits from these investments. Large IT systems can improve service quality or facilitate targeting or price discrimination.⁷ These investments might constitute an endogenous fixed cost in the sense of Shaked and Sutton (1983, 1987), leading to a natural oligopolistic industry structure. For instance, Ellickson (2006) finds evidence that retail industries are such natural oligopolies, and Crouzet and Eberly (2018) attribute the growth in retail industry concentration to rising investment in intangibles, including IT.

3. Identification

Of course, proprietary software is not the only factor affecting industry concentration. Activity in M&A might be responsible for increased consolidation. And greater exposure to global competition could increase the market share of the most productive firms and force less efficient producers to drop out (Melitz 2003). Below I test the robustness of my main findings with controls for these and other possibly confounding variables. These factors do not appear significantly related to industry concentration.

In addition, proprietary software might be endogenous. For example, if firms with better managers are better able to implement IT systems, and if these managers independently cause firms to grow faster, then IT variables might be correlated with the error term. Also, large firms in concentrated industries might use greater IT resources to manage their enterprises, which raises the possibility of reverse causality. To achieve identification, I instrument industry IT share with a measure of the share of jobs in each industry that are sedentary. The motivation for this instrument is that computers are more readily adopted in sedentary occupations, yet industry concentration is not likely to influence the sedentariness of occupations as measured in 1977, the source year of the data. Placebo tests pro-

⁷ I thank a referee for pointing out the potential role of price discrimination.

vide some support for this assumption. In addition, I use two other instruments that should be independent of changes in US competition policy, especially since 1980: the IT share of the workforce in 1980 and the IT share of investment in 18 European countries.

Several papers are related to this one. This paper goes beyond Brynjolfsson et al. (2008) by using a more detailed set of industries and census-based concentration measures and using IVs. Tambe and Hitt (2012) and Harrigan, Reshef, and Toubal (2016) also use the employment share of IT workers as an independent variable to explore firms' productivity and job polarization, respectively.

4. Data

4.1. *Industrial Concentration*

The concentration data are for 1997–2012 and come from the quinquennial economic census reports that use the North American Industry Classification System (NAICS). The census reports the share of industry revenues (or shipments) going to the top four, eight, 20, and 50 firms in each NAICS industry at the two-, three-, four-, five-, and six-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 in the industry (the latter data are missing for manufacturing industries). I also use data from the 1977 economic census for the manufacturing sector, using the Standard Industrial Classification (SIC) to NAICS crosswalk to find the corresponding industry codes (see below).

Census industry definitions, even at the six-digit level, do not necessarily correspond to the market definitions needed for competition analysis (Shapiro 2018). For example, the airline industry shows increased concentration by these measures, but detailed analysis of the number of competitors for different routes shows that competition at the route level has not declined. Moreover, rising concentration at the national level appears to be accompanied by increased competition at the local level (Rinz 2018; Rossi-Hansberg, Sarte, and Trachter 2018). Nevertheless, rising concentration ratios from the economic census have been used to argue that competition is decreasing, and, in any case, they do signal an important trend that something affecting industry structure is changing, even if it is not the level of price competition.

Note that I exclude some industries in which software is a major part of their products, for reasons related to the IT variable discussed below. While some of the public concern about competition has focused on large tech firms, the focus here is on the many industries in diverse sectors experiencing rising concentration. Large tech firms might have special characteristics, such as network effects, that raise distinct concerns not shared by other sectors.

The economic census data have the advantage that they count all firms and establishments in each industry. Some studies use concentration ratios computed for public firms listed in Compustat (Grullon, Larkin, and Michaely 2017; Gutiérrez and Philippon 2017). Those data have the advantage of being available an-

nually 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 one wants 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.⁸ To avoid conflating issues of concentration with issues of firms' changing preferences about being publicly listed and firms' changing international exposure, I employ the economic census data.

4.2. *Proprietary Information Technology*

This paper seeks to capture the extent to which firms use proprietary IT systems. Firms building proprietary systems typically hire software developers and systems analysts to design, build, and maintain these systems. General computer use for common office applications does not require such personnel. Proprietary systems might incorporate off-the-shelf components including software (such as SAP software), but those components tend to be bundled with firm-specific software.

For each industry, I measure proprietary IT as the software share of the workforce, specifically, the share of hours worked by IT personnel, identified as people working as computer systems analysts and computer scientists, operations and systems researchers and analysts, and computer software developers.⁹ Since the aim is to measure the use of custom proprietary IT, I exclude industries that are involved in creating IT products,¹⁰ which employ IT personnel in designing and producing products, not just in building systems for their internal use. To reduce measurement error in small industries, the sample also excludes the smallest 5 percent of industries by number of employees.¹¹

Some proprietary IT is contracted rather than developed in-house. I assume that firms building proprietary systems typically hire software developers and systems analysts to design, build, and maintain the systems even if much of the work is done by outside contractors. In fact, the software share of the workforce

⁸ I ran several tests. For example, I calculated the Compustat four-firm concentration ratios for 2012 for three-digit North American Industry Classification System (NAICS) industries. The correlation coefficient between these data and the corresponding four-firm ratios from the economic census is .196. See also Keil (2017), who warns about the use of Compustat concentration ratios.

⁹ Hours worked is calculated as weeks worked last year times 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. Note that these occupations constitute about 83 percent of all IT employees, excluding managers.

¹⁰ The industries 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.

¹¹ The sample excludes industries with fewer than 28,748 employees.

is correlated with BEA software investment measures that do include contracted software.¹² 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 Microdata Samples of the American Community Surveys (ACS) (Ruggles et al. 2015). These data are not available for 1997, so some of the analysis is restricted to 2002, 2007, and 2012.¹³ The ACS uses modified NAICS industry codes, which are reported at different levels of aggregation. Some industries are identified at the six-digit level, while others are identified only at the three-digit level. I match the reported industries to the corresponding industries in the economic census to obtain a sample of 730 industry-year observations over 3 years at different (nonoverlapping) levels of industry classification.¹⁴

I also use data for the manufacturing sector for 1977, using the 1980 Census of Population to obtain measures of the software share per industry. 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 average the 1977 industry data on concentration, weighting by shipments per detailed industry.

4.3. Operating Margins

As a robustness check, I also look at the relationship between proprietary IT and the growth of firms' operating margins. For this analysis, 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.¹⁵ As a

¹² The Bureau of Economic Analysis/Bureau of Labor Statistics Integrated Gross Domestic Product Productivity accounts report the capital income of software investment by year for 61 private industries (see Bureau of Economic Analysis, Article Collection: Industry Economic Accounts, Integrated Industry-Level Production Account [available from the author on request]). I aggregated my data to match the BEA/BLS industries (my data have nearly four times as many industries) and compared the share of IT workers in the industry workforce with the share of software compensation in total gross output. The association is highly significant, with a correlation coefficient of .42.

¹³ While workforce data are available for other sources for 1997, such as the Current Population Survey, the sample sizes of those sources are far smaller than those of the American Community Surveys (ACS), which makes detailed industry analysis infeasible.

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

¹⁵ I exclude firms that are missing data on market value, sales, and assets; firms for which research and development (R&D) exceeds half of revenues (start-up mode); and the 5 percent tails of the dependent variable (operating margin, that is, operating income after depreciation before taxes, R&D, and advertising expenses, all divided by revenues) to counter measurement error at the extremes. I use the method of Lewellen and Badrinath (1997) with the national income and product accounts investment deflator to calculate the net capital stocks. Stocks of R&D and advertising and marketing expenditures are computed using the perpetual inventory method. The R&D stock is calculated assuming a 15 percent annual depreciation rate and an 8 percent presample 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 percent annual depreciation rate and 5 percent presample growth rate (Villalonga 2004, p. 217). Industry-level IT capital is also calculated using the perpetual inventory method in which annual investment consists of the deflated wages paid to IT

control in the operating-margin regressions, I use a measure of industry regulation developed by Al-Ubaydli and McLaughlin (2017) that is based on an industry-relevance-weighted count of words in the Code of Federal Regulations.¹⁶

4.4. Summary Statistics

Tables 1 and 2 provide some summary statistics for the sample of industries. On average, IT workers account for 2.2 percent of hours worked. Table 1 shows the four 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 percent of the industries. But industries have been growing more concentrated. Table 1 shows the mean 5-year change in concentration ratios from 1997 to 2002 and 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. Consistent with prior literature (Schmalensee 1989), Table 2 shows that the top firms in each industry tend to have larger plants (revenues/establishment), higher labor productivity (revenues/employee), and higher pay but lower labor share of output.

Table OA1 in the Online Appendix displays the distribution of observations across industry sectors, defined as the first digit of the industry's 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, except for education and health, which have a high nonprofit component.

5. Empirical Findings

5.1. Basic Ordinary Least Squares Regressions on Concentration Ratios

I begin exploring the relationship between industry concentration and IT using simple ordinary least squares (OLS) regressions on the four-firm concentration ratio. The main hypothesis holds that proprietary IT allows the largest firms to increase their market shares, which increases industry concentration. Since investments in proprietary software development are highly persistent (Bessen and Righi 2019), both the level and rate of change in industry concentration should be associated with proprietary software investment.

I begin with level regressions because they have less measurement error than difference regressions. The concentration ratio for industry i during year t is

$$C_{it} = \beta \times IT_{it} + \alpha_i + \delta_t + \gamma_n + \varepsilon_{it},$$

personnel in the industry. I assume a 15 percent depreciation rate and a 2 percent presample growth rate based on the average growth rate from 2000 to 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.

¹⁶ Al-Ubaydli and McLaughlin (2017) use an algorithm to probabilistically assign each section of the code to a NAICS industry for sets of two-digit, three-digit, and four-digit NAICS industries. The result is a time series of the extent of regulation for specific industries since 1970.

Table 1
Summary Statistics

	%
Information technology work hours	2.2
Industries in which top four firms have >50 percent of revenues	15.1
Share of industry revenue:	
Top four firms	27.8
Top eight firms	36.0
Top 20 firms	46.6
Top 50 firms	55.9
Change in market share, mean from 1997–2002 and 2002–7:	
Top four firms	1.43
Top eight firms	1.60
Top 20 firms	1.67
Top 50 firms	1.70

Note. The sample includes 808 industries with data on the information technology share in 1997, 2002, 2007, and 2012. Changes in industry revenue are 5-year averages.

Table 2
Industry Characteristics

	Industry	Top Four Firms
Revenues per establishment	1,664	7,200
Revenues per employee	146.4	194.8
Average annual pay	32.3	36.7
Wage bill per revenues	23.5	19.4

Note. The sample excludes manufacturing. Values are in thousands of dollars and are deflated by the gross domestic product deflator, which equals 1 for 2009. $N = 355$.

where IT_{it} is the measure of proprietary IT use, δ_i is a dummy variable for industry sector (one-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 OA3 in the Online Appendix breaks out the regression for the four-firm concentration ratio by 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.

Table 3 presents results of basic regressions on the four-firm concentration ratio. (Corresponding regressions on the eight-firm, 20-firm, and 50-firm concentration ratios can be found in Table OA2 in the Online Appendix.) Column 1 shows OLS regressions on the pooled (2002–12) concentration ratios with heteroskedasticity-robust standard errors without the industry-sector dummy δ_i . The coefficient of the share of IT workers in the workforce is both economically and statistically significant. The sample mean of the software share of hours

Table 3
Regressions on Four-Firm Concentration Ratios

	2002–12		1997–2012	Δ CR4: 1997–2007	1997–2012
	(1)	(2)	(3)	(4)	(5)
Information technology share	2.14** (.32)	1.99** (.31)	1.27** (.35)		
Scaled coefficient				3.17	.56
Sedentariness				19.81** (7.48)	3.49+ (2.07)
1980 Information technology share					
Industry-digit dummies	Yes	Yes	Yes	Yes	Yes
Sector dummies	No	Yes	Yes	No	No
N	725	725	720	1,829	844
R ²	.184	.257	.222	.163	
Within R ²		.179	.128		

Note. The dependent variable is the share of revenues accounted for by the top four firms. Heteroskedasticity-robust standard errors are in parentheses. All regressions include year dummies, level regressions include industry-digit dummies, and fixed-effects regressions include one-digit North American Industry Classification System (NAICS) controls. Column 3 weights results by shipment or revenues. The reduced-form instrumental variable (IV) regressions in columns 4 and 5 regress the dependent variable on sedentariness using occupational measures from 1977 apportioned to industries in the 1980 census. Column 6 regresses industry concentration against the information technology (IT) share of the workforce from the 1980 census, using the walkway to NAICS industries. Column 7 uses the share of IT in investment for 18 European Union countries as an instrument in a two-stage least squares regression. The IV regressions in columns 4–7 are weighted by shipments or revenues using instruments not available for the sample of industries used in the ordinary least squares estimates in columns 1 and 2. The scaled coefficient for the reduced-form IV regressions is determined by dividing the regression coefficient by that obtained by regressing the IT share of the workforce on the instrument with year and sector fixed effects for industries with both measures. The scaling factor is 6.24 for sedentariness and 2.43 for the 1980 IT share of the workforce.

+ Significant at the 10 percent level.

* Significant at the 5 percent level.

** Significant at the 1 percent level.

worked is 2.2 percent. At this mean, the software share is associated with an increase in the revenue share of the top four firms of $2.2 \text{ percent} \times 2.14 = 4.7$ percent. 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 only .4 percent in 1980, proprietary IT use appears to account for most of the increase in industry concentration since then, loosely speaking.¹⁷

Since the panel is largely cross-sectional—the time dimension is at most three observations—estimates with full industry fixed effects may not be consistent, and measurement error attenuation of coefficients could be severe. Adding industry-sector fixed effects δ_i provides a degree of control for omitted variables associated with industry characteristics. Column 2 shows this estimate, which is slightly smaller. The within R^2 -values are substantial, which suggests that even in this short panel, time variation provides significant identification.

One concern is that these estimates are unrepresentative because the sample does not accurately reflect business activity. The industries defined by the census vary substantially by size. Column 3 repeats the analysis of column 2 but weights observations by industry shipments or revenues.¹⁸ The coefficient is somewhat smaller.

5.2. Instrumental Variable Estimates

Firms' investments in IT might be endogenous, reflecting other factors that could also be related to industry concentration. To correct for endogeneity, I estimate the relationships using three instrumental variables. 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.

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. Thus, to instrument the software share of hours, my main IV is a measure of industry sedentariness derived from the *Dictionary of Occupational Titles* (US Department of Labor 1977). The US Department of Labor has sought to define aspects of some 14,000 jobs, including a measure of how sedentary the job is, publishing the fourth edition of this work in 1977.¹⁹ This was before most occupations used computers, so

¹⁷ One concern is that many firms in education and health care are nonprofit, which perhaps biases the results. Repeating these regressions but excluding those industries (results not shown) makes little difference in the coefficients.

¹⁸ The weighted regression should also reduce measurement error in the software share—some small industries likely suffer from sampling variance because of limited data in the ACS.

¹⁹ The *Dictionary of Occupational Titles* reports a job characteristic called strength, which rates the physical demands of the job on a scale of 1, for sedentary occupations, to 5, for very heavy work. Only the first category relates to sedentariness; the other categories relate to level of exertion required. Since the England and Kilbourne (2013) data report averages for an occupation, I flag an occupation as being sedentary if its strength rating is less than 2.

computers likely had little effect on the sedentariness of occupations. England and Kilbourne (2013) map the *Dictionary of Occupational Titles* occupations to detailed occupation census codes, averaging them to this higher level of aggregation. Using those occupations, I calculate the distribution of sedentary occupations across industries using the 1980 census Public-Use Microdata Sample.²⁰

The endogenous variable, the software share of the workforce, derives from the ACS. However, the ACS was not conducted in 1997. For this reason, rather than estimating a two-stage least squares regression for 1997–2012, I estimate a reduced-form IV regression, directly regressing industry concentration on the IV sedentariness.²¹ This instrument should be correlated with the endogenous variable. Table OA4 in the Online Appendix shows correlation coefficients and first-stage regressions indicating that the instrument is strong.²²

Sedentariness and computer use vary substantially across sectors. Table OA5 in the Online Appendix shows the mean sedentariness of each one-digit NAICS sector and the index for the lowest and highest industry scores in each sector. The link between this IV and the software share is not driven mainly by a few industries or sectors.²³

One concern is that sedentariness might be linked to other occupational characteristics that somehow affect industry concentration. In particular, while sedentary occupations are more likely to involve the use of computers, they are also more likely to involve handling paper documents. Sedentariness is likely correlated with the use of desks, paper, and pencils. DiNardo and Pischke (1997) famously find that pencil use is correlated with higher wages, which likely reflects unobserved characteristics of workers who select into pencil-using occupations. Sedentariness might well be correlated with such characteristics and with higher wages.

These correlated variables might cause a problem for the estimation if they are also correlated with the outcome variable, industry concentration. Evidence in

²⁰ To use sedentariness as an instrument, I need to map it to the same industry categories used for the dependent variable, industrial concentration. For the analysis of concentration from 1997 through 2012, I develop a walkway to map the 1980 census industries to the NAICS categories used in the economic censuses, using the most disaggregated classifications possible.

²¹ For the analysis from 1977 to 2002, I aggregate the data to industry categories that correspond to the ACS, so a full two-stage least squares regression is possible. Aggregation dilutes the concentration measures, so a disaggregated approach is preferred for the main analysis.

²² The correlation coefficients for 2002, 2007, and 2012 range from .307 to .328, and the regression coefficients are highly significant. One concern is that the increase in 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 does decline somewhat after 2002, this difference is not statistically significant, and the correlations and regression R^2 -statistics do not weaken.

²³ Finance, real estate, and business services is the most sedentary sector (mean .70), while agriculture is the least sedentary (mean of .14). However, the differences in the sedentariness index between the low and high scores in each sector show that there is significant variation in the index within sectors. For example, in 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 other services.

Table 4
Placebo Tests

	Manufacturing Industries Four-Firm Concentration Ratio		Compustat Firms Operating Margin	
	1977	1997–2012	1977	2000–2014
Sedentariness	.19 (.21)	1.06** (.20)	.07 (.05)	.27** (.02)
Year dummies	No	Yes	No	Yes
SIC two-digit industry dummies	No	No	Yes	Yes
Capital and intangible stocks	No	No	Yes	Yes
<i>N</i>	79	185	1,179	31,346
<i>R</i> ²	.012	.200	.651	.625

Note. Robust standard errors are in parentheses. The sedentariness index is assigned to firms via the North American Industry Classification System (NAICS) classification assigned by the census; consequently, the firms in the 1977 sample also appear in 1998 or later when NAICS codes were assigned. The 1 percent tails of the dependent variable are excluded. The firm regression is weighted by real sales. SIC = Standard Industrial Classification.

** Significant at the 1 percent level.

Table OA6 in the Online Appendix suggests that this second correlation is not a significant problem. Table OA6 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.²⁴ These estimates appear to rule out the possibility that the correlation between sedentariness and industry concentration spuriously reflects the effect of professional or managerial work, education, or wages.

Further evidence in support of the validity of the exclusion restriction comes from placebo tests. Table 4 reports regressions on industry concentration in the manufacturing sector using data from the 1977 economic census and the economic censuses of 1997, 2002, 2007, and 2012. The regressions show that the IV 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 IT since 1977. A similar pattern is seen in the regressions of firms' operating margins on the IV 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.

This finding does not definitively eliminate the possibility that some third factor could be responsible for a spurious link between proprietary IT use and in-

²⁴ 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. Joint tests of the significance of these variables cannot reject the null hypothesis that they are all 0. Individually, the coefficients are not statistically significant except for weak significance (10 percent level) of the wage variable in the two broadest measures of industry concentration.

dustry concentration or operating margins. However, it does mean that 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 the use of IT systems after 1980.

To bolster the validity of this IV analysis, I use two other instruments directed to the concern that rising concentration might reflect changes in US competition policy, especially after the 1980s. The first instrument uses the share of software developers in each industry's workforce with data from the 1980 census Public-Use Microdata Sample. This should be independent of subsequent policy changes.

The second instrument measures the share of software investment in total investment of the industries of 18 European countries obtained from the EU KLEMS database (Jäger 2018).²⁵ These data are grouped into far fewer industrial categories (24 that match the economic census), so for each European industry I calculate a weighted average (by shipments or revenues) of the US industry concentration and software share variables. To the extent that competition policy differs between the US and Europe, this instrument should be independent of US policy yet still be correlated with US IT use. Industry concentration in Europe reflects factors such as the formation of EU common markets. Empirical studies differ as to whether industry concentration is rising or falling in Europe since 2000, but competition policy is seen to differ significantly (Gutiérrez and Philippon 2017; Bajgar et al. 2019). Both supplementary instruments should be independent of US policy since the 1980s, although they might be correlated with some third factor associated with industry concentration other than IT.

In Table 3, column 4 shows the level regression using the sedentariness measure in a reduced-form IV model. The coefficient on sedentariness is highly significant. To compare this estimate with the OLS estimates, it is necessary to scale them. I estimate a scaling factor by regressing the software share of the workforce on sedentariness with controls for year and sector for industries where both data items are available. The scaled coefficient is 3.17, which is somewhat higher than the OLS coefficients.

The levels of industry concentration observed in the pooled sample roughly capture the increase in concentration brought about by the adoption of proprietary IT 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. Column 5 of Table 3 shows reduced-form IV estimates of a 5-year change in concentration ratios. I exclude changes after 2007 because of possible confounding effects of the recession. The coefficient on sedentariness is marginally significant, and the scaled coefficient estimate is smaller, perhaps because of measurement error issues. At the sample mean, the software share is associated with a 5-year increase in the four-firm concentration ratio of $.56 \times 2.2$ percent = 1.2 percent.

²⁵ The countries, determined by data availability, are Austria, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Luxembourg, the Netherlands, Portugal, Slovenia, Spain, and Sweden.

This is slightly smaller than the actual change in the mean four-firm concentration ratio from 2002 to 2007 shown in Table 1, 1.43 percent.

To further bolster the analysis, column 6 shows results using the 1980 software share of the workforce in a reduced-form IV estimation. The coefficient is highly significant, and the scaled version is slightly smaller than in column 4. Column 7 shows a full two-stage least squares estimation using the aggregated industry categories of the EU KLEMS data set. The coefficient is significant at the 5 percent level; it is smaller, but that is not surprising given that the industries are more highly aggregated.

5.3. Long Differences

Table 5 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 because of limitations in the available public data.²⁶ The first column uses the 1980 estimate of the software share, and the second column measures the difference between the software shares in 1980 and 2002. The third column repeats the regression in column 1 using IV estimations. In all of the regressions, the coefficient on the software share is significant. The table also shows the sample means of the IT measures and product of the means and the software share coefficient. In each estimation, the software share accounts for a 3–5 percent 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.

5.4. Other Variables

Other factors likely affect industry concentration in some sectors as well. These factors might confound the analysis if they are correlated with proprietary IT use and industry concentration. Table 6 considers some possibly confounding variables: the number of establishments, M&A activity, exposure to imports, and industry growth. Including these variables in regressions along with the measure of proprietary IT 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. In addition, rising entry barriers would tend to reduce the number of establishments, which would drive up concentration. Including this variable does not significantly change the coefficient on proprietary IT 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

²⁶ The sample also excludes industries in which software development is part of the product, and it excludes the 1 percent tails in the dependent variable (one observation each) to limit measurement error.

Table 5
Long Difference in Four-Firm Concentration Ratio

	Ordinary Least Squares		Instrumental Variable (3)
	(1)	(2)	
1980 Information technology share	8.98** (1.43)		7.59** (2.67)
Change		1.76+ (1.05)	
R ²	.154	.053	.15
Mean	.55	1.55	.55
Average effect	4.90	2.74	4.14

Note. The dependent variable is the change in the share of revenues accounted for by top-four firms in manufacturing industries. Heteroskedasticity-robust standard errors are in parentheses. The information technology (IT) share is instrumented with sedentariness using occupational measures from 1977 apportioned to industries in the 1980 census. The 1 percent tails of the dependent variable are excluded. The null hypothesis that the IT share is exogenous in the instrumental variable regression cannot be rejected ($P = .352$). $N = 71$.

+ Significant at the 10 percent level.

** Significant at the 1 percent level.

Table 6
Possible Confounding Variables

	(1)	(2)	(3)	(4)	(5)
Information technology share	1.88** (.31)	1.80** (.35)	2.00** (.32)	3.15** (.64)	1.70** (.33)
Establishments (1,000s)	-.00 (.00)*				-.00** (.00)
Mergers and acquisitions index, 1985–2001		-2.79 (2.78)			-3.01 (2.53)
Import penetration			-1.85 (3.99)		-1.34 (3.76)
Output growth, 1980–2002				.05 (1.06)	
N	724	661	725	276	660
R ²	.287	.274	.257	.401	.302

Note. Results are for ordinary least squares regressions on pooled industries for 2002, 2007, and 2012. The dependent variable is the four-firm concentration ratio. Robust standard errors are in parentheses. All regressions include industry-digit, year, and sector dummies.

* Significant at the 5 percent level.

** Significant at the 1 percent level.

shows no significant relationship. Thus, the number of establishments does not confound the IT relationship.

Column 2 includes a measure of M&A activity. Grullon, Larkin, and Michaely (2017) argue that M&As are a major reason that industry concentration is rising, which they attribute to lax antitrust enforcement. To measure industry M&A activity, I used an index of M&A activity calculated as the aggregate number of

acquisitions per public firm for each industry over the entire period.²⁷ The regression finds a negative coefficient on M&A activity that is not statistically different from 0. The coefficient on proprietary IT use changes only slightly. Using this measure, I find that M&A do not seem to account for rising concentration, nor do they confound the estimates of the effects of proprietary IT use.

Exposure to global trade might also confound the estimation (Melitz 2003; Autor et al. 2017). Column 3 includes a measure of industry import penetration ((imports – exports)/shipments) for NAICS manufacturing industries (Schott 2011) for 2002–5. For nonmanufacturing industries, I set import penetration to 0. This measure of import penetration has no effect on the coefficient of proprietary IT use and is not significantly correlated with industry concentration.

Column 4 adds the average annual growth rate for real shipments from 1980 to 2002 for manufacturing industries.²⁸ 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 not significant. The coefficient on proprietary IT use is larger, which suggests that, if anything, the omission of industry growth biases the coefficient downward.²⁹

In column 5, the coefficient on the number of establishments in the industry is statistically significant, but the coefficient on the software share remains roughly the same, which suggests that none of the additional variables confound the analysis of the role of IT.

5.5. *The Productivity Gap*

The above data support the link between proprietary IT and industry concentration. If my hypothesis is correct, proprietary IT should increase industry concentration by increasing the productivity gap between the top firms and the rest. The link between IT and a productivity gap should show up as a link between IT and labor productivity and, in many industries such as retail, as a link between IT and establishment size.

Table 7 explores the relationship between the software 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, it is necessarily excluded from the analysis that follows.

²⁷ I use data from the Thomson Reuters Securities Data Company database of mergers and acquisitions (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 acquisitions made by publicly listed firms. Excluding transactions in which the acquirer did not obtain majority ownership or ownership percentage was not reported, I matched these data with Compustat data for publicly listed firms, which resulted in a list of 33,942 acquisitions by publicly listed firms from 1985 through 2001. I use these data to construct an index of industry 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.

²⁸ Data are from the Manufacturing Productivity Database by the National Bureau of Economic Research and the Census Bureau's Center for Economic Studies.

²⁹ If I include the growth in the industry capital stock, it has a significant negative coefficient, and the coefficient for the software share is even larger.

Table 7
Establishment Size, Labor Productivity, and Information Technology

	Revenues/Establishment		Revenues/Employee	
	Unrestricted	Restricted	Unrestricted	Restricted
Top four firms:				
Information technology share	.25** (.03)	.48** (.03)	.15** (.02)	.25** (.02)
R ²	.256	.025	.296	.212
Remaining firms:				
Information technology share	.14** (.02)	.07** (.03)	.11** (.02)	.13** (.02)
R ²	.292	.245	.359	.353
Wald test	.000	.000	.001	.000

Note. Estimates use the seemingly unrelated regression model. The sample excludes manufacturing industries. The restricted estimates constrain the coefficients of the dummy variables to be equal across the equations. Revenues are log values in 2009 dollars. The Wald test reports the probability of the null hypothesis that $\alpha^{\text{Top 4}} = \alpha^{\text{REM}}$.

All regressions include year and sector dummies. $N = 439$.

** Significant at the 1 percent level.

Table 7 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 four and the rest) separately:

$$\ln R_{it}^{\text{Top 4}} = \alpha^{\text{Top 4}} \times \text{IT}_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

and

$$\ln R_{it}^{\text{REM}} = \alpha^{\text{REM}} \times \text{IT}_{it} + \mu'_i + \delta'_t + \varepsilon'_{it}.$$

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 in which the coefficients of the industry-sector and year dummies are constrained to be equal across equations.

In both columns, estimates of $\alpha^{\text{Top 4}}$ and α^{REM} are both highly significant, and the Wald test strongly rejects the null hypothesis. Information technology is strongly associated with greater revenue per establishment, and the association is substantially stronger for the larger, presumably more productive, firms. These findings are consistent with the idea that IT brings scale economies to many industries.

Table 7 also reports 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 labor productivity gap between the top firms and the rest.³⁰

³⁰Note that the calculation for revenues per employee includes the level of markups, so this is not a pure productivity measure.

5.6. Growth in Operating Margins

Some observers see rising profit margins as evidence that competition has declined. How do these findings for rising concentration relate to the analysis of profits and markups? In theory, in long-run equilibrium in a competitive market with homogenous productivity, firms' operating margins should reflect only the returns needed to pay fixed capital costs. If margins are higher than that, new firms could profitably enter. Barkai (2016) presents evidence that firms' margins have increased above and beyond payments to capital, concluding that this represents a decline in competition. These findings suggest some tension with the evidence found here regarding industry concentration.

However, if proprietary IT allows some firms to become more productive than others in the same industry, then the more productive firms can earn quasi rents. These would also be reflected in higher operating margins. Even in a competitive market, more productive firms could sell at the market price but profit from lower costs.

Some empirical analysis can help disentangle these effects. Table 8 provides an analysis of the growth in operating margins. The sample consists of publicly listed US firms that reported in 2000 and 2014, excluding firms in the finance sector.³¹ 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, research and development (R&D), advertising, and marketing expenditures all divided by revenues. I exclude R&D, advertising, and marketing from income because I treat them as intangible investments on the right-hand side of the regression equations. That is, operating profits should reflect the returns on investments in capital and returns to stocks of intangibles.

The operating margin for firm i at time t can be written

$$M_{it} = \alpha \times IT_{it} + \delta \times t + \beta_1 \frac{K_{it}^1}{R_{it}} + \beta_2 \frac{K_{it}^2}{R_{it}} + \dots + \varepsilon_{it},$$

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

$$\Delta M_i = \alpha \times \Delta IT_i + \delta + \beta_1 \Delta \frac{K_i^1}{R_i} + \beta_2 \Delta \frac{K_i^2}{R_i} + \dots + \Delta \varepsilon_i.$$

Table 8 reports some basic estimates. Note that the IT measure is an industry-level measure, while the other variables are for individual firms. In column 1, the

³¹In addition, the sample excludes the 5 percent tails in the dependent variable and firms in which R&D spending exceeds 50 percent of revenues.

Table 8
Change in Operating Margins, 2000–2014

	Ordinary	Instrumental Variable	
	Least Squares	(2)	(3)
	(1)		
Δ Information technology share	2.71* (1.34)	6.71 (5.81)	6.59** (2.38)
Δ Capital stock	.01** (.00)	.00 (.01)	.00 (.00)
Δ Research and development stock	.06* (.02)	−.04** (.00)	−.04** (.00)
Δ Advertising stock	.47** (.05)	.51** (.08)	.52** (.04)
Δ Regulation			.07* (.03)
Constant	−.01 (.01)	−.02 (.01)	−.03** (.01)
N	912	1,000	840
R ²	.255	.188	.207

Note. The dependent variable is the change in operating income after depreciation and before taxes, research and development, and advertising all divided by revenues. Standard errors are clustered by industry. The sample is all US Compustat firms excluding 5 percent tails of the dependent variable and firms for which research and development is more than 50 percent of revenues. The instrumental variable regressions use the sedentariness index as an instrument.

* Significant at the 5 percent level.

** Significant at the 1 percent level.

coefficient for software share is significant; the IV estimate is substantially larger but not significant. At the sample mean for the change in software share (.007), these coefficients represent an increase in operating margins of .9 percent and 3.5 percent, respectively. By comparison, the actual increase in operating margins for this sample is 3.2 percent, which suggests that IT can account for a major portion of the observed increase.

Column 3 repeats the regression in column 2 but adds 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 by raising margins (Bessen 2016; Gutiérrez and Philippon 2017). There seems to be a significant association between regulation and margins; at the sample mean, the increase in regulation may have contributed 1.6 percent 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. The term is negative in all three specifications, significantly so in the third. 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 led to rising margins for firms. In any case, the evidence on operating margins does not seem to conflict with the findings above on industry concentration.

6. Conclusion

Firms are making large investments in proprietary IT. The evidence in this paper suggests that those investments are changing industry structure and production. It is sometimes argued that IT 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 firms that are able to use it most effectively.³² The use of proprietary IT is strongly associated with industry concentration across a wide range of sectors, and the link 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. This view is further supported by evidence that the use of proprietary IT is associated with greater labor productivity, especially among the top four firms in each industry. Proprietary IT is associated with a widening productivity gap between the top firms and the rest.

The observed increases in concentration, however, are fairly modest. There are, of course, well-known examples in which IT facilitates highly concentrated markets as with Amazon's dominance in e-commerce. These cases may be winner-takes-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-takes-a-bit-more markets, consistent with the natural oligopoly models of Shaked and Sutton (1983, 1987).

In addition to the role of IT, a general decline in competition might also play a role in rising concentration and profits, but the evidence found here regarding competition is mixed. Activity in M&A seems unrelated to industry concentration, and the residual time trend in operating margins is not positive once intangible investments are taken into account. Overall, the analysis here suggests that the recent general rise in industry concentration is not mainly the result of anticompetitive activity that should worry antitrust authorities. While there may be other reasons to question antitrust policies (see, for instance, Kwoka 2013), the general rise in industry concentration does not appear to be a direct result of lax antitrust enforcement.

However, the effect of proprietary IT on industry structure does broach another concern: these changes in industry structure may dampen economic dynamism. For example, why are the productivity gains from IT not 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 barriers to entry. More research is needed to understand exactly how IT is related to the growing productivity gap. Whatever the cause, the issue is important because the slow diffusion

³² Some recent evidence suggests that cloud computing might be altering the relationship in favor of small firms (Jin and McElheran 2017).

of new technologies might be related to sluggish aggregate productivity growth or to growing interfirm wage inequality. But the policies to address these issues, whether antitrust or other, depend very much on the diagnosis.

References

- Al-Ubaydli, Omar, and Patrick A. McLaughlin. 2017. RegData: A Numerical Database on Industry-Specific Regulations for All United States Industries and Federal Regulations, 1997–2012. *Regulation and Governance* 11:109–23.
- Andrews, Dan, Chiara Criscuolo, and Peter N. Gal. 2016. The Best versus the Rest: The Global Productivity Slowdown, Divergence across Firms, and the Role of Public Policy. Productivity Working Paper No. 5. Organisation for Economic Co-operation and Development, Paris.
- Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen. 2017. The Fall of the Labor Share and the Rise of Superstar Firms. Working Paper No. 23396. National Bureau of Economic Research, Cambridge, MA.
- Bajgar, Matej, Giuseppe Berlingieri, Sara Calligaris, Chiara Criscuolo, and Jonathan Timmis. 2019. Industry Concentration in Europe and North America. Productivity Working Paper No. 18. Organisation for Economic Co-operation and Development, Paris.
- Barkai, Simcha. 2016. Declining Labor and Capital Shares. *Journal of Finance* 75:2421–63.
- Basker, Emek. 2007. The Causes and Consequences of Wal-Mart's Growth. *Journal of Economic Perspectives* 21(3):177–98.
- BEA (Bureau of Economic Analysis). 2017. *National Income and Product Accounts* (computer file). Suitland, MD: BEA.
- Berlingieri, Giuseppe, Patrick Blanchenay, and Chiara Criscuolo. 2017. The Great Divergence(s). Science, Technology, and Industry Policy Working Paper No. 39. Organisation for Economic Co-operation and Development, Paris.
- Bessen, James. 2016. How Computer Automation Affects Occupations: Technology, Jobs, and Skills. Law and Economics Research Paper No. 15-49. Boston University School of Law, Boston.
- Bessen, James, and Cesare Righi. 2019. Shocking Technology: What Happens When Firms Make Large IT Investments? Law and Economics Research Working Paper No. 19-6. Boston University School of Law, Boston.
- Bloom, Nicholas, Raffaella Sadun, and John Van Reenen. 2012. Americans Do IT Better: US Multinationals and the Productivity Miracle. *American Economic Review* 102:167–201.
- Brynjolfsson, Erik, Andrew McAfee, Michael Sorell, and Feng Zhu. 2008. Scale without Mass: Business Process Replication and Industry Dynamics. Working Paper No. 07-016. Harvard Business School, Boston.
- Calligaris, Sara, Chiara Criscuolo, and Luca Marcolin. 2018. Mark-ups in the Digital Era. Working Paper No. 2018/10. Organisation for Economic Co-operation and Development, Paris.
- Crouzet, Nicolas, and Janice Eberly. 2018. Intangibles, Investment, and Efficiency. *American Economic Association: Papers and Proceedings* 108:426–31.
- De Loecker, Jan, and Jan Eeckhout. 2017. The Rise of Market Power and the Macroeconomic Implications. Working Paper No. 23687. National Bureau of Economic Research, Cambridge, MA.

- . 2018. Global Market Power. Working Paper No. 24768. National Bureau of Economic Research, Cambridge, MA.
- Demsetz, Harold. 1973. Industry Structure, Market Rivalry, and Public Policy. *Journal of Law and Economics* 16:1–9.
- Diez, Federico J., Daniel Leigh, and Suchanan Tambunlertchai. 2018. Global Market Power and Its Macroeconomic Implications. Working Paper No. 18/137. International Monetary Fund, Washington, DC.
- DiNardo, John E., and Jörn-Steffen Pischke. 1997. The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure Too? *Quarterly Journal of Economics* 112:291–303.
- Dunne, Timothy, Lucia Foster, John Haltiwanger, and Kenneth R. Troske. 2004. Wage and Productivity Dispersion in United States Manufacturing: The Role of Computer Investment. *Journal of Labor Economics* 22:397–429.
- Economist*. 2016. Too Much of a Good Thing. March 26.
- Ellickson, Paul B. 2006. Quality Competition in Retailing: A Structural Analysis. *International Journal of Industrial Organization* 24:521–40.
- England, Paula, and Barbara Kilbourne. 2013. *Occupational Measures from the Dictionary of Occupational Titles for 1980 Census Detailed Occupations* (computer file). Ann Arbor, MI: Inter-university Consortium for Political and Social Research.
- Grullon, Gustavo, Yelena Larkin, and Roni Michaely. 2017. Are US Industries Becoming More Concentrated? Research Paper No. 19-41. Swiss Finance Institute, Geneva.
- Gutiérrez, Germán, and Thomas Philippon. 2017. Declining Competition and Investment in the U.S. Working Paper No. 23583. National Bureau of Economic Research, Cambridge, MA.
- . 2018. How EU Markets Became More Competitive than US Markets: A Study of Institutional Drift. Working Paper No. 24700. National Bureau of Economic Research, Cambridge, MA.
- Hall, Bronwyn H. 1990. The Impact of Corporate Restructuring on Industrial Research and Development. *Brookings Papers: Microeconomics*, pp. 85–135.
- Harrigan, James, Ariell Reshef, and Farid Toubal. 2016. The March of the Techies: Technology, Trade, and Job Polarization in France, 1994–2007. Working Paper No. 22110. National Bureau of Economic Research, Cambridge, MA.
- Jäger, Kirsten. 2018. EU KLEMS Growth and Productivity Accounts 2017 Release, Statistical Module. Brussels: European Commission. http://www.euklems.net/TCB/2018/Methology_EUKLEMS_2017_revised.pdf.
- Jin, Wang, and Kristina McElheran. 2017. Economies before Scale: Survival and Performance of Young Plants in the Age of Cloud Computing. Working Paper No. 3112901. University of Toronto, Rotman School of Management, Toronto.
- Journal of Economic Perspectives*. 2019. Symposium: Markups. 33(suppl.):1–256.
- Keil, Jan. 2017. The Trouble with Approximating Industry Concentration from Computat. *Journal of Corporate Finance* 45:467–79.
- Kwoka, John E., Jr. 2013. Does Merger Control Work?: A Retrospective on U.S. Enforcement Actions and Merger Outcomes. *Antitrust Law Journal* 78:619–50.
- Lewellen, Wilbur G., and S. G. Badrinath. 1997. On the Measurement of Tobin's q . *Journal of Financial Economics* 44:77–122.
- Melitz, Marc J. 2003. The Impact of Trade on Intra-industry Reallocations and Aggregate Industry Productivity. *Econometrica* 71:1695–1725.
- Peltzman, Sam. 2018. Productivity and Prices in Manufacturing during an Era of Rising

- Concentration. Working paper. University of Chicago, Booth School of Business, Chicago.
- Rinz, Kevin. 2018. Labor Market Concentration, Earnings Inequality, and Earnings Mobility. Working Paper No. 2018-10. US Census Bureau, Center for Administrative Records Research and Applications, Washington, DC.
- Rognlie, Matthew. 2015. Deciphering the Fall and Rise in the Net Capital Share: Accumulation or Scarcity? *Brookings Papers on Economic Activity*, pp. 1–69.
- Rossi-Hansberg, Esteban, Pierre-Daniel G. Sarte, and Nicholas Trachter. 2018. Diverging Trends in National and Local Concentration. Working Paper No. 25066. National Bureau of Economic Research, Cambridge, MA.
- Ruggles, Steven, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek. 2015. *Integrated Public Use Microdata Series: Version 6.0* (computer file). Minneapolis: University of Minnesota.
- Schafer, Sarah. 1995. How Information Technology Is Leveling the Playing Field. *Inc.*, December 15.
- Schmalensee, Richard. 1989. Inter-industry Studies of Structure and Performance. Pp. 2:951–1009 in *Handbook of Industrial Organization*, edited by Richard Schmalensee and Robert Willig. Amsterdam: North-Holland.
- Schott, Peter K. 2011. *US SIC87-Level Imports and Exports, 1972 to 2005* (computer file). New Haven, CT: Yale University School of Management.
- Shaked, Avner, and John Sutton. 1983. Natural Oligopolies. *Econometrica* 51:1469–83.
- . 1987. Product Differentiation and Industrial Structure. *Journal of Industrial Economics* 36:131–46.
- Shapiro, Carl. 2018. Antitrust in a Time of Populism. *International Journal of Industrial Organization* 61:714–48.
- Tambe, Prasanna, and Lorin M. Hitt. 2012. The Productivity of Information Technology Investments: New Evidence from IT Labor Data. *Information Systems Research* 23:599–617.
- Unger, Gabriel. 2019. Scale-Biased Technological Change. Working paper. Harvard University, Department of Economics, Cambridge, MA.
- US Census Bureau. 2010–17. *Current Population Survey* (computer file). Suitland, MD: US Census Bureau.
- US Department of Labor. 1977. *Dictionary of Occupational Titles*. 4th ed. Washington, DC: Government Printing Office.
- Villalonga, Belén. 2004. Intangible Resources, Tobin's q , and Sustainability of Performance Differences. *Journal of Economic Behavior and Organization* 54:205–30.
- White, Lawrence J., and Jasper Yang. 2017. What Has Been Happening to Aggregate Concentration in the U.S. Economy in the 21st Century? Working paper. New York University, Stern School of Business, New York.