Declining Industrial Disruption

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Abstract: Recent research finds that markups are rising, suggesting declining competition. But does less price competition mean less Schumpeterian "creative destruction"/industry dynamism? This paper provides the first recent estimates of trends in the displacement of industry-leading firms. Displacement hazards rose since 1970 but have declined sharply since 2000. Using a production function-based model to explore the role of investments, acquisitions, and lobbying, we find that investments by dominant firms in intangibles, especially software, are associated with greater persistence and reduced leapfrogging. Software investments by top firms soared around 2000, contributing substantially to the decline. Also, higher markups are associated with *greater* displacement hazards, linking rents positively with industry dynamism. While technology is often seen as disrupting industry leaders, it also appears to sometimes suppress disruption.

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Introduction

Many economists and policymakers are concerned about declining competition in the US and in other developed economies. Studies find evidence of rising firm markups and profit shares[1] and of rising industry concentration at the national level.[2] Generally, declining competition is troubling for two very different reasons, one static and the other dynamic: 1) without sufficient competition, firms acquire market power and consequently raise prices and lower output, creating allocative inefficiencies,[3] and, 2) low competition may reflect barriers that block firms with innovative new technologies from entering, growing, and replacing firms that use older, less productive technologies; the result is a decline in industrial dynamism and productivity growth. Economists have suggested that declining competition is related to declining firm startup rates, slower labor reallocation to more productive firms, and declining investment (see for example Furman 2016, Crouzet and Eberly 2018).

However, there is considerable tension between the notion of static price competition and Schumpeterian technological competition. Markups measure price competition. Markups quantify the deviation from Bertrand competition where prices equal marginal cost. But markups may be orthogonal to technological competition. Indeed, firms with innovative new technologies may earn rents, allowing them to charge higher markups. For instance, Bessen (2017) and Criscuolo et al. (2018) find links between information technology (IT) and markups/profit margins.

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[1] De Loecker and Eeckhout, and Unger (2019), Barkai (2017), Hall (2018), Baqaee and Fahri (2017); see Basu (2019) and Syverson (2019) for reviews.

[2] Grullon et al. (2019), Autor et al. (2019), Gutierrez and Philippon (2017, 2019), Bessen (2017) but also see Rinz (2018), Hsieh and Rossi-Hansberg (2019), and Berry et al. (2019).

[3] Including, possibly, monopsony power in labor markets.

Different measures are need in order to gain a more complete understanding of competition trends in a time of technological change. This paper measures Schumpeterian competition, explores how it has changed over recent decades, and we identify what appear to be the main barriers to Schumpeterian competition. We find that markups and measures of Schumpeterian competition are quite distinct and actually counterpoised on average.

Background

Joseph Schumpeter (1942) famously criticized traditional economic analysis of industry structure that was focused on formal models of price and quantity competition in oligopolies. What matters in "capitalist reality as distinguished from its textbook picture" (p. 84) is innovation, both technological and organizational. Innovative firms are able to command a decisive cost or quality advantage that allows them to grow and to displace existing firms in a "perennial gale of creative destruction." In dynamic industries, innovative firms will enter new markets and they will grow until they displace firms using inferior technologies or business models.

While evidence on a general link between Schumpeterian competition and innovation is mixed (see Gilbert 2006), many economists see industrial dynamism as highly important for long term productivity growth—perhaps more important than static deadweight losses arising from insufficient price competition. Recognizing that Schumpeterian competition is important for at least some types of innovation, antitrust authorities include barriers to technology competition in their analysis, for example, as in the US v. Microsoft suit (see Bresnahan 2002).

A common assumption holds that rising markups and industry concentration reveal rising barriers to entry that inevitably affect industry dynamism. This view is bolstered by evidence of a concurrent decline in the rate of firm entry and in the rate of growth of startup firms (Hathaway and Litan 2014a,b; Guzman and Stern 2016). Yet it is not so clear that entry barriers have risen or what those barriers might be. Berry et al. (2019), recalling the discarded structure-conduct-performance paradigm, argue that a robust analysis is needed to infer the effects of markups on industry dynamism.

Hence, it might be helpful to obtain direct measures of "creative destruction" and see how they have changed over time. There is a literature on the persistence of dominant firms that seeks to establish the degree of persistence of industry leadership and to identify correlated industry characteristics (Caves 1998; Davies and Geroski 1997; Doi 2001; Franko 2003; Geroski and Toker 1996; Honjo et al. 2018; Kato and Honjo 2006, 2009; Sutton 2007). However, this literature has not looked at trends in the hazard of displacement for market leaders.

This paper examines these trends. To fix ideas, it is helpful to preview a result developed more completely below. Figure 1A shows the hazard that a firm with sales ranked in the top four in its industry the previous year ranks below the top four in the current year. This particular figure uses publicly listed firms in 6-digit NAICS industries.[4] The displacement hazard rose substantially from 1970 through the 1990s, but around 2000 the displacement hazard dropped sharply, indicating a substantial decline in Schumpeterian competition.[5] Below we test the robustness of this finding using alternative measures and industry definitions, some of these also shown in Figure 1.

[4] By construction, this measure includes only firms that are listed both years.

[5] The figure shows the best-fit linear trends with a break year determined by Wald supremum tests.

The displacement of market leaders is, of course, not the only measure of industrial dynamism. Some papers have studied changes in firm entry rates (Hathaway and Litan 2014a,b; Guzman and Stern 2016; Gutierrez and Philippon 2019) and others have studied the growth rates of productive firms (Decker et al. 2018). However, the displacement of incumbent market leaders by innovators is the "finish line" of Schumpeterian competition, making displacement hazards an important dimension of industrial dynamism.

We can gain some insight as to what might be driving the sharp change in displacement hazards by looking at associated firm investments. In many models of industrial organization, firms can make investments to bolster their market shares. In the classic Cournot model, firms invest in capacity. In endogenous sunk cost models (Sutton 1991), firms improve the perceived quality of their products through investments in advertising or R&D. Firms also differentiate their offerings using information technology to develop more product features, to offer greater selection (retail), or to target marketing and advertising. Firms can also acquire other companies (investment by acquisition), thereby obtaining new technologies or distribution channels not accessible to competitors. And to the extent that industries are regulated, firms can invest in lobbying and political capital that may provide them with advantageous regulation relative to rivals.

The persistence of dominance literature identifies several industry-level investments associated with persistence, including R&D and advertising (Geroski and Toker 1996). Using firm microdata, we can better identify the role of specific investments as barriers to mobility. We regress displacement hazards using a production function model that accommodates strategic interaction and imperfect competition. We estimate associations between specific investments made by dominant firms and their risk of displacement and also the probability that smaller firms will be able to "leapfrog" them. We find that investments by dominant firms in intangibles and particularly in software are significantly associated with declining disruption. Moreover, dominant firm investments in intangibles and in software specifically grew dramatically starting around 2000, providing an explanation for the reversal in displacement trends. These investments by dominant firms appear to exert a negative externality on other, smaller firms, suppressing leapfrogging probabilities. Contrary to the view that declining competition has resulted from lax antitrust merger enforcement, we find that mergers and acquisitions by top firms do not significantly reduce displacement and leapfrogging.

This paper makes three major contributions. One, we are the first to report changes in the displacement hazard for top firms in industries over time, finding a sharp reversal of trend around 2000.[6] Two, we develop a model and obtain estimates of the link between investments made by dominant firms and their risk of being leapfrogged, including the negative externalities these investments exert on other firms. Three, we explore the associations between displacement hazards of market leaders, their markups, and industry concentration. We find that the rate of displacement of industry leaders is *positively* correlated with markups, contrary to the view that assumes that markups signal reduced industry dynamism. This finding is more consistent with an interpretation that innovative firms earn rents even if they are also more likely to be displaced by greater technological competition.

This analysis is related to a literature on the persistence of firm profits across all firms within each industry (see Bennett and Gartenberg 2016 for a recent review). Beginning with Mueller (1977), a substantial literature looks at the persistence of profits for all firms

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[6] Autor et al. (2019, Figure A14), in a subsidiary analysis, report changes in the persistence of the top 500 firms in Compustat. . McKinsey consultants have tabulated a "topple rate" for firms finding a rise up to 2002 (Viguerie and Thompson 2005).

within industries. A few of these studies have looked at trends in persistence of profits over time. Examining US firms through the 1990s, Wiggins and Ruefli (2005) and Gschwandtner (2012) find a decline in persistence/increase in competition; McNamara et al. (2003) find no significant change. Only one study looks beyond the 1990s: Bennett and Gartenberg (2016) find declining persistence of return on assets until about 2000 and rising persistence after that. Moreover, they find that rising persistence/declining competition is associated with software investments. These findings are thus highly congruent with ours.

We begin by describing the diverse data sources we use. We then present alternative measures of trends in displacement and leapfrogging hazards, followed by analysis of the associations between these hazards and firm investments. We then explore the association between displacement hazards, firm markups, and industry concentration and then conclude.

Data

Datasets

Our main dataset consists of Compustat firms traded in US currency with positive sales, including firms with headquarters outside the US. Because of data limitations (see below), we primarily use years 1976 – 2017. To identify industries in these data, we use the historical NAICS assignments made by Standard & Poors, projecting backwards for years before NAICS coverage. Because NAICS coding changes every five years, we map these NAICS codes to the 2012 version for continuity. Compustat primarily includes publicly listed firms and reported sales include all global operations.

A second dataset is the National Establishment Time Series (NETS), a product of Walls & Associates, derived from the Dun & Bradstreet Marketing Information File. NETS consists of establishment-level longitudinal data covering, in principle, the universe of U.S. business establishments, private and public. We aggregated the establishments from 1990 – 2014, assigning firms to 8-digit SIC codes based on the primary line of business. Robustness checks based on coarser industry categories did not find substantially different results.

Each of these datasets has limitations. Compustat misses most private firms, however, the largest firms in most industries tend to be publicly listed, so displacement rates of top four firms should still be reasonably accurate.[7] NETS is known to over-represent very small firms, but that shortcoming is not likely significant for our analysis (Barnatchez, Crane and Decker, 2017).

Finally, we also use confidential microdata from the Annual Capital Expenditures Survey (ACES) of the US Census from 2002 – 2012. This survey provides data on capital spending for new and used structures and equipment by U.S. nonfarm businesses, most importantly, spending on three types of software: pre-packaged, custom (contract), and own-developed. These microdata aggregate sales and capital expenditures of US establishments to the firm level, assigning the firm to a 4-digit NAICS code based on the largest business line.

Variables

Our basic measure of displacement hazard is the probability that a firm that was ranked among the top four firms in its industry by sales last year is ranked below the top four this year. While we test alternative definitions below and perform additional robustness checks, this basic measure excludes firms that are not included in the dataset for the current year but includes firms that change industries.

7 Tracking the 100 largest firms in the NETS database each year from 1990 – 2014, 77% of the observations are publicly listed.

We use a variety of capital stocks in our analysis. All are deflated and all are beginning-of-year stocks, that is, they are lags of the end-of-year stocks that are typically reported. For tangible capital, we use net property, plant, and equipment from firm balance sheets. Peters and Taylor (2017) have developed measures of intangible capital based on three components: knowledge capital derived from R&D spending, organizational capital derived from Sales, General, and Administrative expenditures, and balance sheet intangibles. These values are available from 1975 through 2016.[8]

We also obtained data on other detailed intangible investments and computed capital stocks using the perpetual inventory method:

- Data on advertising and marketing expenditures come from Compustat. Following Villalonga (2004), we calculate stocks using a 5% pre-sample growth rate and 45% depreciation rate.
- Data on patents come from Autor et al. (forthcoming), who use a 15% depreciation rate to compute patent stocks and who matched the data to Compustat.
- Data on lobbying expenditures since 1998 come from Center for Responsive Politics.[9] We use a 6% pre-sample growth rate and a 25% depreciation rate. We matched these data to Compustat using the company name (the client parent entity).[10]

We also wanted to measure investments that firms make in developing proprietary software for their own use. To do this, we obtained LinkedIn resume data and identified 1,791 job titles that pertained to software development jobs (see details in Bessen and Righi 2019). We tabulated the number of these employees, adjusted the numbers to account for differences in LinkedIn coverage over time, and matched the firms to Compustat from 1990

[8] Following Peters and Taylor's advice we exclude firms with less than $5 million gross PPE in 1990 dollars, firms in finance or utility industries, and we trim the 1% tails in Tobin's q.

[9] http://www.opensecrets.org/resources/create/data_doc.php accessed 2016.

[10] Of 19,359 entities (companies, unions, trade associations, other organizations), we matched 11% to Compustat firms; these firms accounted for 53% of all lobbying expenditures.

– 2012.[11] We then constructed software stocks from the software employee flows using a 33% depreciation rate and an 8% pre-sample growth rate.

We also evaluate acquisitions as a kind of investment. To the extent that acquisitions generate goodwill—that is, to the extent that acquirers pay more than the book value of assets of acquired firms—they show up as balance sheet intangibles in the Peters and Taylor accounting. We also wanted to count the number of acquisitions made by large firms because even small-value transactions might confer significant market advantage to dominant firms. We obtained a list of mergers and acquisitions from the Thomson Reuters SDC Platinum database and matched these to Compustat.[12] To create acquisition stocks, we accumulated the number of transactions assuming a 15% depreciation rate and 8% pre-sample growth rate. To check the robustness of this procedure, we also used simple lagged acquisition flows and obtained similar results.

Following common practice (see Keller and Yeaple 2009), we impute materials and value added for the productivity estimates as follows: materials is cost of goods sold plus sales, general, and administrative expense less depreciation less the wage bill. The wage bill is imputed as firm employment times the industry mean wage taken from the BEA. Value added is revenues minus materials.

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[11] The match covers firms that account for 68% of the employees in Compustat in 1990, rising to over 90% of the employees in 2012. To adjust for changes in coverage over time, we scaled the LinkedIn counts of software employees by the ratio of software employees to all employees in the Current Population Survey to the ratio of software employees to all employees in LinkedIn.

[12] These data primarily consist of announced transactions. Public companies are not required to announce all mergers and acquisitions; however, the list tends to include transactions that are materially significant or where the acquired company has customers or suppliers who need to be informed. In practice, the number of announced transactions far exceed the number of transactions reported to the FTC under the Hart-Scott-Rodino reporting requirements. We matched CUSIPs in the SDC data to permnos in CRSP to gvkeys in Compustat producing over 100,000 matched transactions.

Finally, we estimate firm markups using the method of De Loecker and Eeckhout (2017) which is based on De Loecker and Warzynski (2012) (see Appendix).

Summary statistics can be found in Appendix A1.

Empirical Findings

The persistence of dominance

The literature cited above on the persistence of dominance measures persistence by the hazard that leading firms will lose their leadership positions and by survival analysis for firms in leadership positions. Here we use large samples and estimate the hazard of changes in leadership.

Our baseline measure is the annual hazard that a firm that was in the top four firms in its primary industry (6-digit NAICS in Compustat) ranked by revenue last year is no longer in the top four firms this year (not counting firms that exit Compustat). This hazard is shown in Figure 1A. The line represents the best-fit linear trend with a single break where the break year is determined by the supremum Wald test. In this case, the estimated break year is 2000. Table 1, row 1, displays the probability value of this estimate plus the resulting regression coefficients for the baseline trend and change in trend after 2000. That is, for break year τ, we estimate the annual hazard over time t

$$h_t = \alpha \cdot t + \beta \cdot \min[0, t - \tau] + C + \epsilon_t.$$

The estimated coefficients for both the trend and the change in trend are highly significant substantial and the change is negative.

The remaining panels of Figure 1 and the additional rows in Table 1 explore a variety of alternative measures, alternative industry definitions, and alternative datasets to test the robust of this finding. The second row of Table 1 considers the displacement hazard for a firm in the top 2 within its industry and the third row considers the displacement hazard for a firm in the top 8. The fourth row measures the combined hazard of being displaced from the top 4 firms or of exiting the Compustat dataset (no longer publicly listed). The fifth row considers the hazard that a firm ranked 5-9 in the previous year enters the top 4 firms. All show a substantial change from a positive to negative trend around 2000.

One concern about these measures regards the definition of the relevant industries. Broad national industrial categories, even at the 6-digit level, do not always reflect the product markets that would be used, say, in merger analysis. It seems, however, that the change in the persistence of dominance is robust to particular industry definitions. Row 6 uses 4-digit NAICS; row 7 uses no industry definitions but looks instead at the persistence of firms within the top 100 of all firms in Compustat; row 8 uses Compustat industry segment data for multi-product firms. Top firms have remained more dominant even among groups of firms that compete only in some markets or not at all.

Compustat does not include most private firms, although most dominant firms are publicly listed. Also, firm sales in Compustat are global sales. It might be informative to measure sales just within the United States, including private firms, to understand domestic persistence of dominance. Row 9 shows results for the NETS database using 8-digit SIC industries where firm sales are calculated as the sum of sales at US establishments. While the time period for the NETS data only begins in 1990, a similar break in trend is found.

Finally, this change in trend is observed across sectors, as seen in the next five rows of the table.

In summary, across a wide range of measures, the displacement of dominant firms rose from 1970 until the late 1990s. Then, somewhere around year 2000, this trend sharply reversed with substantial declines in the displacement rate. Displacement hazards have declined roughly half a percentage point per year since then. This change represents a substantial decline in Schumpeterian competition.

Investments in dominance

A model of leapfrogging

What might be behind this sharp decline? Some papers on the persistence of dominance have explored industry characteristics that are associated with the displacement of market leaders, including industry growth, industry concentration, and R&D intensity. However, this literature does not provide causal analysis and the link between general industry characteristics and the displacement of leaders can be complicated and can work in both directions. For instance, the relationship between industry growth and displacement of leaders appears to be complex, with higher displacement in both growing and declining industries relative to stable industries (Honjo, Doi, and Kudo 2018).

Another avenue is to explore how firm investments are related to the displacement of leaders. It might be informative to understand which specific investments by dominant firms are most associated with their persistence and also, possibly, which investments by smaller firms are most associated with the occurrence of leapfrogging. Such analysis can provide important clues as to the mechanisms underlying the recent decline of disruption.

We conduct this inquiry in the context of an extended production function. Initially, consider a duopoly consisting of firm 1 and 2, where 1 has smaller revenue at time $t-1$. Let the revenue of firm i at time t, designating the other firm as $-i$, be

(1)

$$R_{it} = A_{it} G(\,K_{it},\ K_{-it}),\ \ i = 1{,}2$$

where A captures stochastic productivity and demand shocks and K is beginning-of-year capital. This is a reduced form revenue production function where the variable factors have been optimized in each period. The other firm's capital enters the revenue function because the other firm's investments exert an externality on the subject firm's demand. For example, in a classic Cournot duopoly one firm's investment in capacity shifts the other firm's demand curve.

Sutton (2007) finds that the shocks to firm's market shares are independent, so, without significant loss of generality we can model the shocks as a lognormal distribution, $\ln A_{it} \sim N(\omega_{it}, \sigma_t),\ \ i = 1{,}2,$ where ω_{it} is the mean log productivity of firm *i* at time *t*. Then the probability of a change in market leadership is

(2)

$$P[R_{2t} < R_{1t}] = -\Phi\left(\frac{\omega_{2t} - \omega_{1t} + \ln G(K_{2t}, K_{1t}) - \ln G(K_{1t}, K_{2t})}{\sqrt{2}\sigma_t}\right)$$

where Φ is the standard normal function. Giving G a Cobb-Douglas form, taking a linear approximation of Φ, and capturing differences in σ with fixed effects for year and industry *j*, we get an estimable linear probability model,

(3)

$$P_{it} = \alpha_j + \delta_t + \gamma\omega_{it} + \beta_1 \ln K_{it} + \beta_2 \ln K_{-it} + \epsilon_{it}.$$

where ω_{-it} is included in the error term. This equation can represent either the probability that a leader firm becomes a follower or the probability that a follower firm leapfrogs into leadership. When the dependent variable is the displacement hazard of a leading firm, we expect $\gamma, \beta_1 < 0, \beta_2 > 0$. When the dependent variable is a leapfrogging probability, we expect $\gamma, \beta_1 > 0, \beta_2 < 0$.

In our data the capital stocks are observed, but firm productivity is not. Obtaining unbiased estimates of productivity for each firm each year is important to avoid biasing the capital stock estimates. For example, if better managers made the firm more productive and less likely to be displaced and if better managers also invested relatively more or less in intangible capital, then omitting the productivity measure (or using a biased one), will bias the coefficient for intangible capital. To obtain unbiased measures of productivity, we estimate a standard production function using the method of Wooldridge (2009) and we obtain firm-year productivity estimates as the residual.[13] This procedure uses a control function to proxy for unobserved productivity in a GMM estimation.

Equation (3) can also be readily extended to consider multiple leaders or multiple followers and to consider multiple capital stocks.

Displacement hazard

Table 2 shows basic estimates of (3) for the top four firms in each 6-digit NAICS industry in Compustat, using stocks for tangible and intangible capital and omitting the terms for other firms. The sample includes only firms that were in the top four last year and the dependent variable is 1 for those that are ranked out of the top four in the current year and 0 otherwise. Column 1 shows that productivity and both capital stocks have a significant

[13] Our production function is for log value-added as a function of labor, tangible capital, and intangible capital. We use log materials as the proxy in the control function and we include lagged polynomials in the capital and materials variables as instruments. For robustness checks we also performed simple OLS estimation as well as Arellano-Bond "GMM system" estimates. We also bootstrapped errors but found little change.

influence on the displacement hazard. The coefficients for tangible and intangible capital are quite similar.

It is possible that the coefficient estimates might be biased for a number of reasons. First, independent changes in industry characteristics might affect both the dependent variable and firm's decisions to invest in capital stocks. For instance, a decline in industry volatility might reduce displacement hazards and also provide more favorable conditions for firms to invest. To control for changing industry conditions, Column 2 includes separate year fixed effects for each industry. With these additional controls, the coefficients are larger in absolute magnitude.

Another bias might arise if firms anticipate changes in volatility in advance, investing or disinvesting prior to the disruption. In this case, the capital stocks might be correlated with the error term. Column 3 conducts an instrumental variable regression with fixed effects, using the five-year lags of the capital stocks as instruments. Firms are much less likely to anticipate changes in volatility five years in advance. The coefficients are quite similar to the OLS estimates and the null hypothesis that the capital stocks are exogenous cannot be rejected (probability value of .221).

Columns 4 and 5 repeat the regression in Column 1 over different time periods. It appears that after 2000 the coefficient on tangible capital fell. This shift suggests that dominant firms received a relatively greater payoff to intangible investments in terms of persistence after 2000. That view is supported by the relative capital stocks of top four firms shown in Figure 2. Both stocks have grown substantially since the mid-1990s. But around 2000, relative investment in intangibles grew much more rapidly, more than doubling intangible stocks relative to tangible capital. Both this shift in investment and the shift in coefficients suggests that the relative rise of intangibles is important in understanding the reversal in displacement hazards following 2000.

Externalities

The regressions in Table 2 omit the terms in equation (3) for the capital of rival firms. The omitted terms might be correlated with the error term, biasing the coefficients. Table 3 explores interactions between the top four firms in each industry with the second four firms, those ranked 5 – 8. Column 1 adds the capital stocks of the second-tier firms to the regression in Table 2, column 1. The coefficients for the subject firm are indeed larger. The main interaction appears to involve the firm ranked fifth. This is, of course, the firm closest to the fourth firm and thus most likely to displace one of the top four. The joint probabilities that second-tier firms' investments affect the displacement hazard of the top firms (the bottom two rows of the table) are not significant.

The second column of Table 3 shows the corresponding regression for the second-tier firms. The dependent variable is now the probability that a firm that was ranked 5 – 8 last year leapfrogs into the top four firms. Here, the investments made by the top four firms significantly affect the leapfrog probability, both individually and jointly. The tangible capital investments of the third and fourth ranked firms reduces the leapfrog probability. In effect, these investments increase the revenues of the third and fourth ranked firms and thus raise the hurdle that second-tier firms need to overcome.

The pattern for investments made by the top four firms in intangibles, however, exhibits a markedly different pattern. Here, it is the *largest* firm's investment that has the biggest coefficient. This suggests that intangibles play a different role—they don't so much raise the hurdle to leapfrogging as they depress the revenues of second-tier firms. Recall that in equation (1), investments play a dual role: they raise the revenue of the subject firm and they also exert a negative externality on demand for other firms. These intangible investments may exert a negative externality on smaller firms as occurs, for instance, in the Shaked and Sutton models of vertical differentiation where the intangible investments are endogenous sunk costs (1982, 1983, 1987). That is, this pattern suggests that intangibles play a role in "business stealing." Given the dramatic shift towards intangible investment by the top four firms seen in Figure 2, these externalities may represent important "barriers to mobility" that appear to play a major role in the decline in displacement and leapfrogging.

Decomposing intangibles

Which specific intangibles are involved in these interactions? It is interesting to decompose the aggregate firm intangible stocks into components. To explore the relative influence of different types of intangibles, it is helpful to simplify the regression in Table 3, column 2. Specifically, we aggregate the intangible stocks of the top four firms and only include the tangible stocks of the firms ranked third and fourth the previous year. A likelihood ratio test does not reject these restrictions (probability value of .663).[14]

Column 1 of Table 4 shows the components of Peters and Taylor's (2016) intangible capital: a stock of R&D investments, a stock of organizational capital (derived from Sales, General, and Administrative expenditures), and balance sheet intangibles, which consist substantially of goodwill accumulated from firm mergers and acquisitions. Organizational capital and other intangibles are important for the subject firm's probability of leapfrogging.

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[14] To minimize problems of firms with missing or zero stocks, we use the logs of average stocks of the top four firms rather than the sum of individual log stocks in Table 4.

Of the investments made by top four firms, only investments in organizational capital are economically and statistically significant.[15]

Organizational capital includes spending on advertising and marketing, lobbying, and software development where software is not part of the product. Columns 2 – 4 include measures of specific intangible stocks including software, acquisitions, advertising and marketing, lobbying expenditures, and patents. Because we want to focus on organizational capital, columns 2 and 3 exclude industries where software is a major part of the product.[16] This restriction isolates the general effect of own-developed software on competition across all sectors, aside from the role that software plays as a cost of goods sold. These regressions cover 1991 – 2012 because of data limitations. Column 4 includes all industries, but only years 1999 – 2014 when lobbying data are available. Of the detailed investments, only software and patent stocks have significant coefficients, both for the subject firm and for the investments of top-four firms.

The importance of information technology is also seen in Figure 3. Top four firms dramatically increased their software investments since around 2000 compared to the other intangible stocks.[17] This difference is seen both in the level capital stocks for the top four firms (top panel) and also in the stocks of top four firms compared to the second-tier firms ranked 5-8 (bottom panel). The combined impact of these shifts in software capital and the software coefficients in columns 2 and 3 of Table 4 implies that software can account for a

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[15] When the regression is run using just the organizational capital of the largest firm in each industry, the coefficient on organizational capital is highly significant, -.016 (.006).

[16] These industries are 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] The software line in the figure also excludes industries where software is a major part of the product.

reduction in the leapfrog probability of about 2.5 – 3 percent (2 x -.014). Looking at the decline in the aggregate leapfrog hazard in Figure 1, the increase in software investment by top four firms can account for much of it. Software spending by dominant firms might present a substantial barrier to mobility.

Some researchers have suggested that a decline in competition has resulted from mergers and acquisitions that have been permitted by overly lax antitrust enforcement (Grullon et al. 2019). Acquisitions do not appear to play much role in the increased persistence of market-leading firms. Figure 3 shows that the stock of acquisitions by top firms remained flat since 2000. Figure 4 shows the mean acquisitions per year for top four firms. These have declined since the late 1990s, making it difficult to attribute a decline in competition to excessive acquisitions since then.

Different types of software investment

Our software stock measure is built from employment flows of software developers. We can look at the relative roles of different types of software investment using data from the Census ACES survey, which measures separate firm investment in pre-packaged software, custom contracted software, and self-developed software.

[TK]

Discussion: Why software?

Large firm investments in all types of intangibles has risen since 2000. But investment in software has risen dramatically more in proportion, software investment by top four firms has risen sharply even relative to large second-tier firms, and software investments by top firms appear to play a unique role in suppressing leapfrogging by second tier firms. Moreover, the reversal in trend of the displacement hazard occurred just as investment in software by top four firms surged starting in the late 1990s. Of course, other developments affected some industries around this time, such as the China Shock and the dotcom bubble, but both the decline in displacement hazards and the surge in software investment happened across all sectors, not just those directly affected by China trade or dotcom firms. The decline of Schumpeterian competition appears to be more than a general story just about the rise of intangibles. Both large and small firms in many industries now invest more in intangibles generally, but information technology appears to play a particular asymmetric role, advantaging large firms at the expense of smaller ones.

We can identify several overlapping reasons why information technology might play a distinct role. First, Bauer and Lashkari (2018) find evidence of economies of scale in the use of IT.[18] Software has large fixed costs and low marginal cost, giving an advantage to those firms who use it more widely. However, other technologies also have substantial scale economies and it is not clear why large second tier firms might not also benefit from scale economies.

A related possibility is that large investments in software are endogenous sunk costs that alter industry structure (Sutton 1991). Sutton argues that leading firms in differentiated markets can sink large investments in advertising or R&D to improve product quality and thereby achieve a large stable market share. Geroski and Toker (1996) find that industries with higher advertising or R&D levels tend to have lower displacement rates of leading firms. Large investments in own-account software and custom software can also differentiate firms by quality and these investments appear to be quite extensive in many industries. This is because software allows firms to improve quality by managing complexity. Retailers such

[18] Aghion et al. (2019) and de Ridder (2019) provide growth models featuring IT scale economies.

as Amazon and Walmart are able to use IT logistics and inventory management systems to offer customers much greater selection and lower costs, thereby achieving larger market shares. Ellickson's (2007) empirical analysis concludes that supermarket distribution systems create a Sutton-type market structure. Large manufacturers are able to design products such as airplanes and automobiles with more and more features using expensive custom CAD/CAM systems. Because of this feature inflation, major new aircraft requires design costs of $25-30 billion and new automobile models cost $5-6 billion, both beyond the capabilities of small or medium-sized competitors. Online IT systems of platform advertising companies like Google and Facebook are able to target prospective consumers with highly tailored ads, delivering better quality to advertisers. Financial institutions use large software systems to similarly target credit offers. The emergence of these systems in the 1990s might have created new opportunities for firms to compete via large sunk investments in software, leading to a growing gap between first and second tier firms and declining displacement.

To the extent that implementation of these systems depends on particularly skilled managers and/or software developers, some firms may have unique advantages. Bloom et al. (2012) find that firms with US managers have a distinct advantage at implementing IT systems. The knowledge and skills of certain firms may have provided them with hard-to-imitate advantages, allowing them to distance themselves from disruptive competition.

Finally, some of the knowledge needed to implement these systems may be blockaded from rivals by intellectual property restrictions or other means. Andrews et al. (2016) suggest that the diffusion of new knowledge has slowed (see also Akcigit and Ates 2019). This interpretation is bolstered by evidence that dominant firm patent stocks have a modest negative impact on leapfrogging (Table 4).

Some combination of these four factors might have allowed large investments in firm-specific information technology to enhance the dominance of leading firms well beyond the advantages brought to leading firms by their investments in advertising or R&D.

Markups and Industry Concentration

Economists sometimes speak as if there were a unitary level of "competition" for each industry. As we noted in the introduction, price competition might be different from or even counter to technological or Schumpeterian competition. In this section, we explore how firm markups and industry concentration—generally taken as measures of competition—relate to our measure of industry leadership displacement, a measure of Schumpeterian competition.

We calculate firm markups using the method of De Loecker and Eeckhout (2017) with Compustat data (see Appendix). Figure 5 shows a binned scatterplot of the mean displacement hazard for top-four firms in each industry-year plotted against the mean lagged markup of firms in the industry, after controlling for year fixed effects. The plot shows a modestly upward sloping relationship except at the tails. Table 5 repeats the firm level regression of Table 2, column 1, adding the firm markup lagged one year. The coefficient on markup is substantial, positive, and statistically significant. To rule out possible mean reversion effects, column 2 uses the five-year lag. Columns 3 and 4 interact lagged markups with a dummy variable that is 1 if the year is after 2000 (column 3) or if the firm's R&D spending exceeds 2 percent of revenues (column 4). Neither of these interactions are significant. Column 5 interacts markups with industry sector. Markups have a significant positive relationship with the displacement of leader firms across all sectors.

To study industry concentration, we calculate the top four firms' share of sales in 8-digit SIC industries using NETS data for national industries. Figure 6A shows a tight negative relationship between industry concentration and the displacement hazard for top four firms. Figure 6B shows the displacement hazard declining with the Herfindahl-Hirschman index until the index reaches a value of about 0.25, corresponding to the threshold for what the Department of Justice considers "highly concentrated." Regressions of the displacement hazard against interactions of industry concentration (see Appendix) show a highly significant negative relationship with little difference across industry sectors and with an increase in magnitude after the year 2000. In these data, industry concentration rose modestly after 2000, corresponding to the parallel decline in displacement hazards.[19] These correlations suggest that rising industry concentration might reflect the same factors driving a decline in Schumpeterian competition. This association is bolstered by evidence that the increase in industry concentration at the national level is substantially driven by the increase in proprietary software spending (Bessen 2017). And it is consistent with the view that growing endogenous sunk software costs might lead to both higher concentration and greater persistence of dominant firms (Shaked and Sutton, 1982, 1983, 1987). On the other hand, it appears that industry concentration has been rising since well before 2000 (Autor et al. 2019).

[19] Using a balanced panel, mean unweighted four-firm industry concentration rose from 72.6% in 2990 to 73.3% in 2014; weighted by industry sales, four-firm concentration rose from 75.2% to 79.4%.

Conclusion

Economists have documented a rise in firm markups and some have proposed that this increase marks a decline in industrial dynamism. While the rise in markups does indicate a decrease in price competition, it does not indicate a decrease in Schumpeterian competition or industry dynamism generally. Indeed, we find that Schumpeterian competition is associated with *higher* firm markups. This is consistent with an interpretation that firms are able to earn rents on their innovations in dynamic industries, but they might also have greater risk of being displaced by rivals' innovations.

Measuring the displacement hazard for the largest firms within industries, we find that displacement hazards rose from the 1970s to the 1990s, but that after 2000 the trend sharply reversed. The displacement of leading firms has indeed declined sharply, but this appears to be *despite* rising markups rather than because of them.

We further investigate which investments made by dominant firms are associated with decreased displacement, including tangible capital, intangibles, R&D, patents, advertising and marketing, own-developed software, and lobbying expenditures. Intangible investments and especially software investments are most strongly associated with declining displacement hazards and dominant firms have dramatically increased investments in intangibles and software starting around 2000. In a model that includes firm interactions, these investments appear to create barriers to mobility to second tier firms and these barriers can account for most of the decline in the probability that second tier firms will leapfrog into the top four. Investments in intangibles by dominant firms appear to exert a negative "business stealing" externality on second tier firms.

Contrary to a view that attributes declining competition to lax antitrust merger enforcement (Grullon et al. 2017), we find that acquisitions by top firms are not significantly associated with decreased leapfrogging and, in any case, top firms have reduced the number of acquisitions they make each year since 2000. Nor do we find a substantial role for corporate lobbying by top firms (Gutierrez and Philippon 2017). Instead, the evidence is most consistent with an explanation that emphasizes the role of proprietary software.

More generally, the evidence suggests that technology has begun to play a new and different role in the economy. New technologies have been generally associated with increased disruption of industries and technology continues to disrupt industries and business models in general (newspapers, music). But now, it seems, information technology allows dominant firms to suppress their own "creative destruction," decreasing disruption in this particular dimension. The social welfare implications might be ambiguous: while dominant firms use information technology to improve the quality of their products and services (more features, greater selection, greater targeting), these firms might use technology to differentiate their products excessively with an eye toward "business stealing." Moreover, while this technology may deliver productivity benefits to the top firms today, it is not clear that it will diffuse through the rest of the economy or that future innovators will face restrictions to their growth.

The decline in displacement hazards is not a conventional antitrust problem and it will not likely be best addressed by simply reinvigorating conventional antitrust policy. This paper provides methods to measure and analyze changes in displacement hazards, providing tools for future research on how the persistence of dominant firms affects innovation and productivity growth and what that means for policy.

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Tables and Figures

Table 1. Best-fit trends with single break for various hazard measures.

Hazard measure	Industry measure	Data	Break year	Prob. value	Trend	Change in trend
Displacement from top 4 firms	6-digit NAICS primary industry	Compustat	2000	(0.000)	0.0017 (0.0004)***	-0.0046 (0.0009)***
Displacement from top 2 firms	6-digit NAICS primary industry	Compustat	2000	(0.000)	0.0027 (0.0005)***	-0.0062 (0.0010)***
Displacement from top 8 firms	6-digit NAICS primary industry	Compustat	2000	(0.000)	0.001 (0.0004)**	-0.0032 (0.0007)***
Displacement from top 4 firms + Exit	6-digit NAICS primary industry	Compustat	2000	(0.000)	0.0024 (0.0004)***	-0.0061 (0.0010)***
Leapfrog into top 4 firms (rank 5-9)	6-digit NAICS primary industry	Compustat	2001	(0.000)	0.0013 (0.0002)***	-0.0029 (0.0007)***
Displacement from top 4 firms	4-digit NAICS primary industry	Compustat	2000	(0.000)	0.0022 (0.0003)***	-0.0055 (0.0008)***
Displacement from top 100 firms	All industries	Compustat	2003	(0.000)	0.0014 (0.0004)***	-0.0048 (0.0013)***
Displacement from top 4 firm segments	4-digit SIC industry segments	Compustat	1998	(0.016)	0.0012 (0.0011)	-0.0047 (0.0019)**
Displacement from top 4 firms	8-digit SIC industries	NETS	1997	(0.034)	0.0057 (0.0028)*	-0.0079 (0.0033)**
		Compustat Sector				
Displacement from top 4 firms	6-digit NAICS primary industry	Nondurable mfg.	2000	(0.002)	0.0017 (0.0008)**	-0.0052 (0.0016)***
Displacement from top 4 firms	6-digit NAICS primary industry	Durable mfg.	1997	(0.000)	0.0032 (0.0007)***	-0.0059 (0.0011)***
Displacement from top 4 firms	6-digit NAICS primary industry	Transport, utilities	2003	(0.002)	0.0012 (0.0009)	-0.0059 (0.0021)***
Displacement from top 4 firms	6-digit NAICS primary industry	Trade, services	1998	(0.000)	0.0017 (0.0009)*	-0.0052 (0.0015)***
Displacement from top 4 firms	6-digit NAICS primary industry	Finance	1999	(0.009)	0.0029 (0.0014)**	-0.0046 (0.0026)*

Note: Standard errors in parentheses, * p<.1, ** p<.05, *** p<.01. Break years are estimated using the supremum Wald test. The trend and change in trend after the break are determined from a simple OLS regression of the annual hazard rates on these two terms (see text).

Table 2. Displacement Hazard and Tangible/Intangible Capital

	1	2	3	4	5
	Base	Ind-year FE	IV	<=2000	>2000
	1976-2017	1976-2017	1980-2017	1976-2000	2001-2017
Productivity	-0.0956***	-0.1334***	-0.1015***	-0.1173***	-0.1025***
	(0.0077)	(0.0107)	(0.0084)	(0.0114)	(0.0124)
Net PPE	-0.0268***	-0.0320***	-0.0287***	-0.0333***	-0.0230***
	(0.0026)	(0.0033)	(0.0040)	(0.0035)	(0.0042)
Intangibles	-0.0284***	-0.0385***	-0.0274***	-0.0355***	-0.0338***
	(0.0028)	(0.0033)	(0.0041)	(0.0035)	(0.0044)
Industry FE	x		x	x	x
Year FE	x		x	x	x
Industry x year FE		x			
Observations	27097	26048	22159	16646	10445
Adjusted R-squared	0.093	0.074	0.079	0.113	0.096

Note: Standard errors clustered by industry in parentheses, * p<.1, ** p<.05, *** p<.01. Independent variables are in logs. Productivity is estimated using the Wooldridge (2009) GMM method. Column 3 instruments capital stocks using 5-year lagged values.

Table 3. Hazard estimates with external interactions

Hazard:	Top 4 firm moves down		Second 4 firm moves up
Subject firm			
Productivity	-0.1112***		0.0936***
	(0.0068)		(0.0065)
Net PPE	-0.0336***		0.0348***
	(0.0027)		(0.0031)
Intangibles	-0.0384***		0.0390***
	(0.0029)		(0.0032)
Tangible Capital			
Firm 5	0.0058**	Firm 1	0.001
	(0.0026)		(0.0038)
Firm 6	0.0011	Firm 2	0.0001
	(0.0026)		(0.0037)
Firm 7	-0.0006	Firm 3	-0.0096***
	(0.0024)		(0.0035)
Firm 8	-0.0016	Firm 4	-0.0162***
	(0.0021)		(0.0033)
Intangible Capital			
Firm 5	0.0006	Firm 1	-0.0159***
	(0.0028)		(0.0039)
Firm 6	0.003	Firm 2	-0.0071*
	(0.0029)		(0.0037)
Firm 7	0.0018	Firm 3	-0.0092**
	(0.0026)		(0.0036)
Firm 8	0.0053**	Firm 4	-0.0096***
	(0.0025)		(0.0035)
Observations	15128		14260
R-squared	0.120		0.091
Other firms (probability values)			
Joint test of tangibles	.220		.000
Joint test of intangibles	.106		.000

Note: Standard errors in parentheses, * p<.1, ** p<.05, *** p<.01. All regressions have industry and year fixed effects. Independent variables are in logs. Productivity is estimated using the Wooldridge (2009) GMM method.

Table 4. Decomposing Intangibles, Leapfrog hazard

Subject firm	1	2	3	4
Productivity	0.0885***	0.1108***	0.0989***	0.0962***
	(0.0085)	(0.0115)	(0.0101)	(0.0143)
Net PPE	0.0400***	0.0694***	0.0651***	0.0615***
	(0.0041)	(0.0058)	(0.0049)	(0.0073)
R&D	0.0024			
	(0.0017)			
Org. capital	0.0263***			
	(0.0048)			
Other intangibles	0.0030**			
	(0.0012)			
Software Stock		-0.0008	0.0044	
		(0.0046)	(0.0043)	
Acquisitions		0.0105		0.0133
		(0.0067)		(0.0089)
Advertising		0.0060*		0.002
		(0.0035)		(0.0038)
Patents				0.0134***
				(0.0045)
Lobbying				-0.0082
				(0.0115)
Top 4 firms (average)				
PPE, firm #3	-0.0173***	-0.0059	-0.005	-0.01
	(0.0037)	(0.0055)	(0.0049)	(0.0073)
PPE, firm #4	-0.0214***	-0.0208***	-0.0198***	-0.0246***
	(0.0037)	(0.0056)	(0.0046)	(0.0062)
R&D	-0.0042			
	(0.0027)			
Org. capital	-0.0174**			
	(0.0078)			
Other intangibles	0.0011			
	(0.0015)			
Software Stock		-0.0122**	-0.0136**	
		(0.0052)	(0.0054)	
Acquisitions		0.0015		-0.0088
		(0.0074)		(0.0124)
Advertising		0.0030**		0.0034
		(0.0015)		(0.0021)
Patents				-0.0143**
				(0.0063)
Lobbying				0.0072
				(0.0065)
Observations	13262	6670	7911	3649
R-squared	0.090	0.123	0.110	0.138

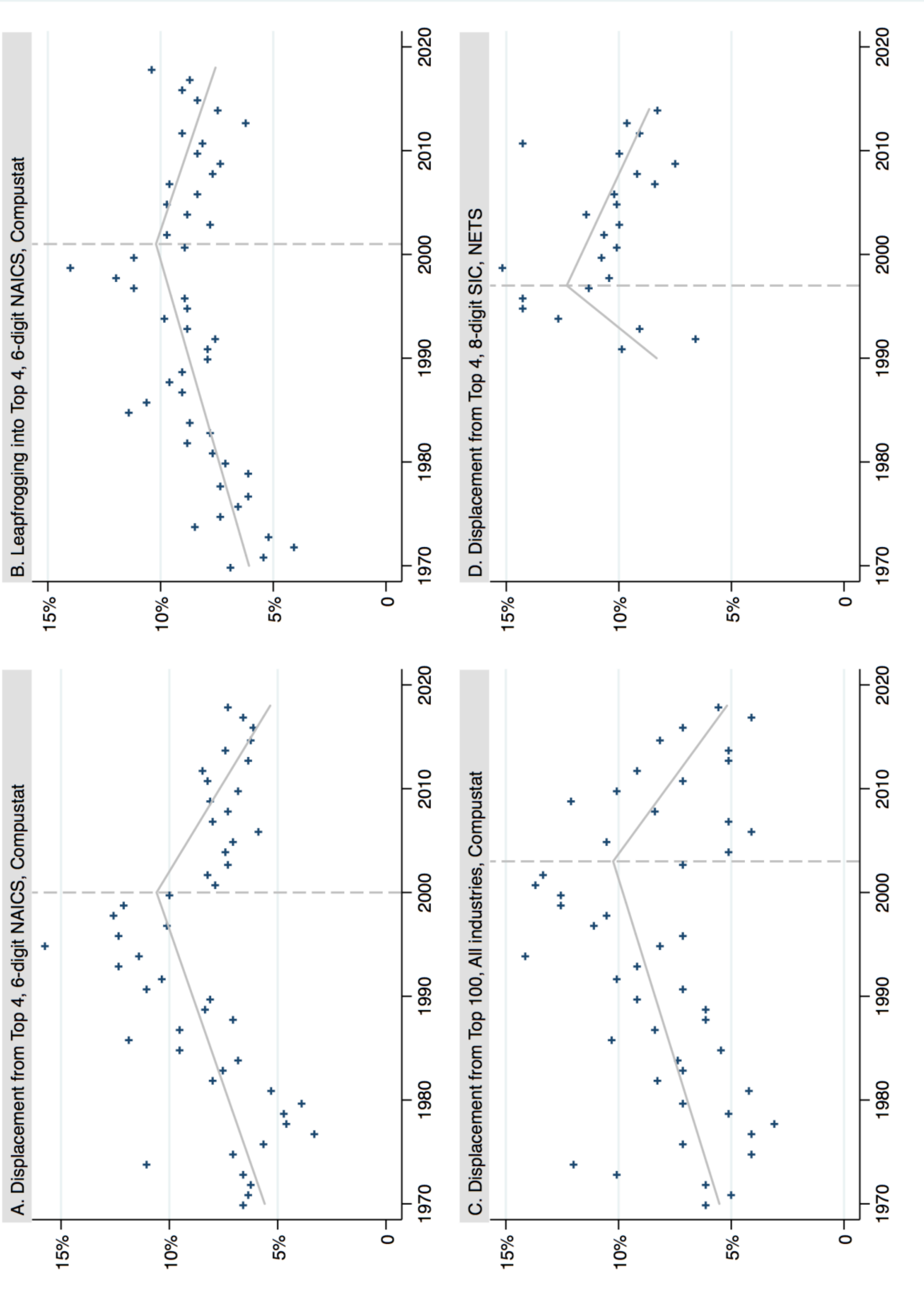
Note: Standard errors clustered by industry in parentheses, * p<.1, ** p<.05, *** p<.01. Industry and year fixed effects. Columns 2 and 3 exclude firms in industries where software is a major portion of the product.

Table 5. Displacement Hazards and Markups

	1	2	3	4	5
Net PPE	-0.0494***	-0.0454***	-0.0494***	-0.0494***	-0.0497***
	(0.0025)	(0.0027)	(0.0025)	(0.0025)	(0.0025)
Intangibles	-0.0066***	-0.0070***	-0.0066***	-0.0067***	-0.0062***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Lagged markup	0.0905***		0.0935***	0.0898***	
	(0.0112)		(0.0175)	(0.0112)	
Lag 5 markup		0.0678***			
		(0.0117)			
L.markup x after 2000			-0.0046		
			(0.0183)		
L.markup x High R&D				0.0039	
				(0.0047)	
<u>Lag markup x sector</u>					
Nondurable mfg.					0.0999***
					(0.0188)
Durable mfg.					0.1136***
					(0.0140)
Transportation, utilities					0.0872***
					(0.0250)
Wholesale, retail					0.0996***
					(0.0227)
Finance					0.0610***
					(0.0114)
Services					0.1050***
					(0.0116)
Other					0.1334***
					(0.0201)
Observations	30189	25603	30189	30189	30189
R-squared	0.112	0.108	0.112	0.112	0.113

Note: Standard errors clustered by industry in parentheses, * p<.1, ** p<.05, *** p<.01. Industry and year fixed effects. Markups are calculated by the method of De Loecker and Eeckhout (2017).

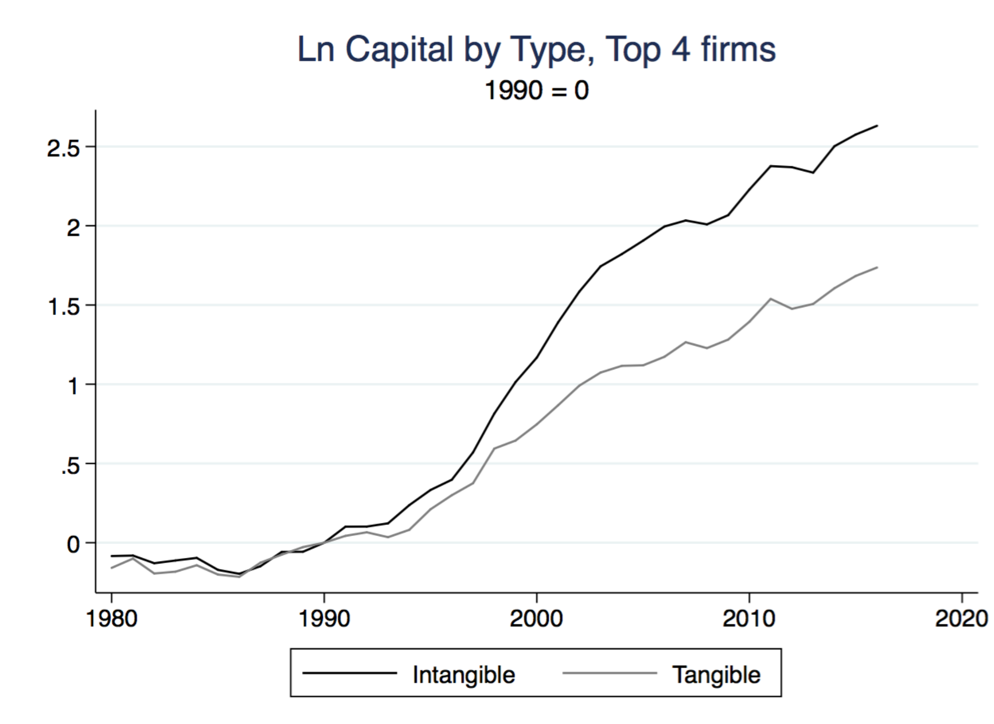
Figure 1. Displacement Hazards



Note: Break years are estimated using the supremum Wald test. The trend and change in trend after the break are determined from a simple OLS regression of the annual hazard rates on these two terms.

Figure 2. Average capital of top four firms by type

A. Levels



B. Difference

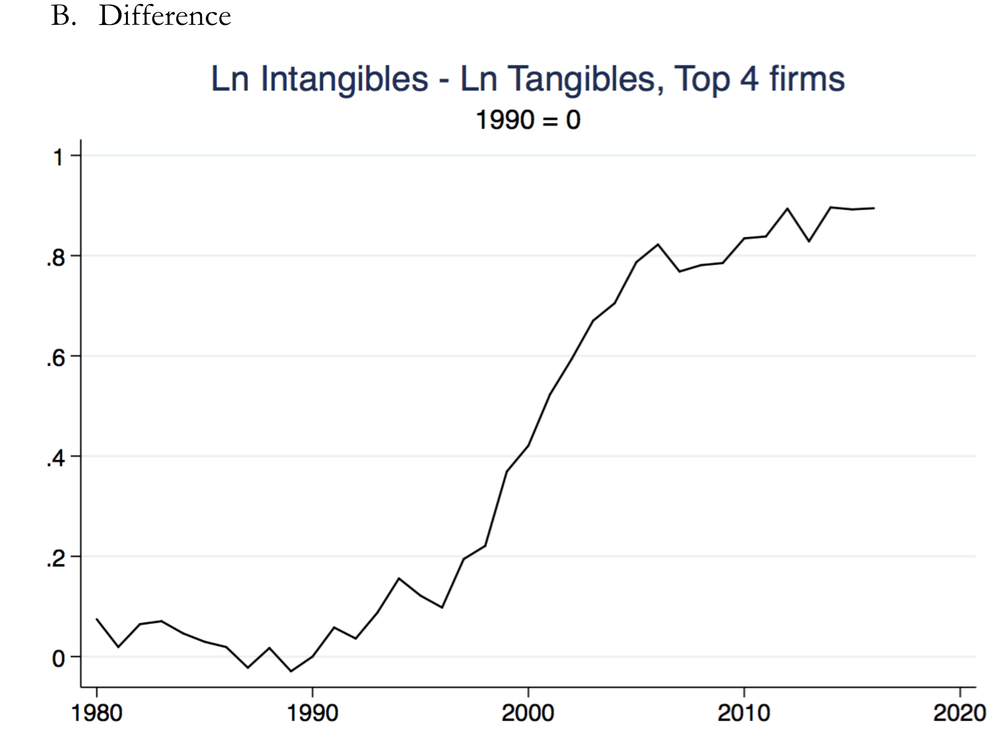
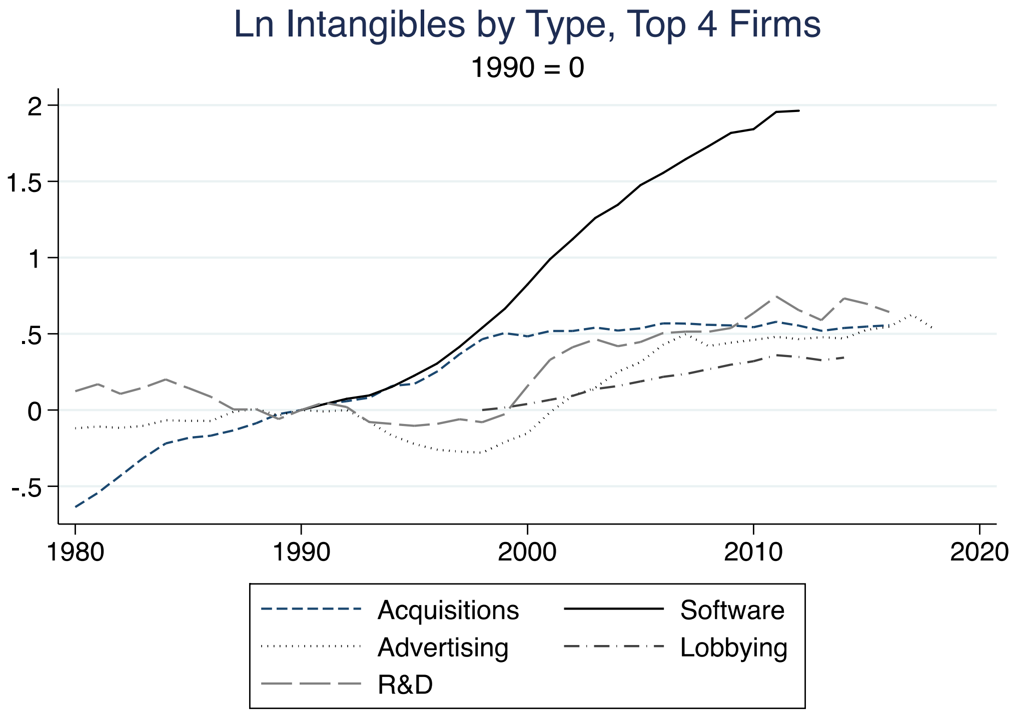
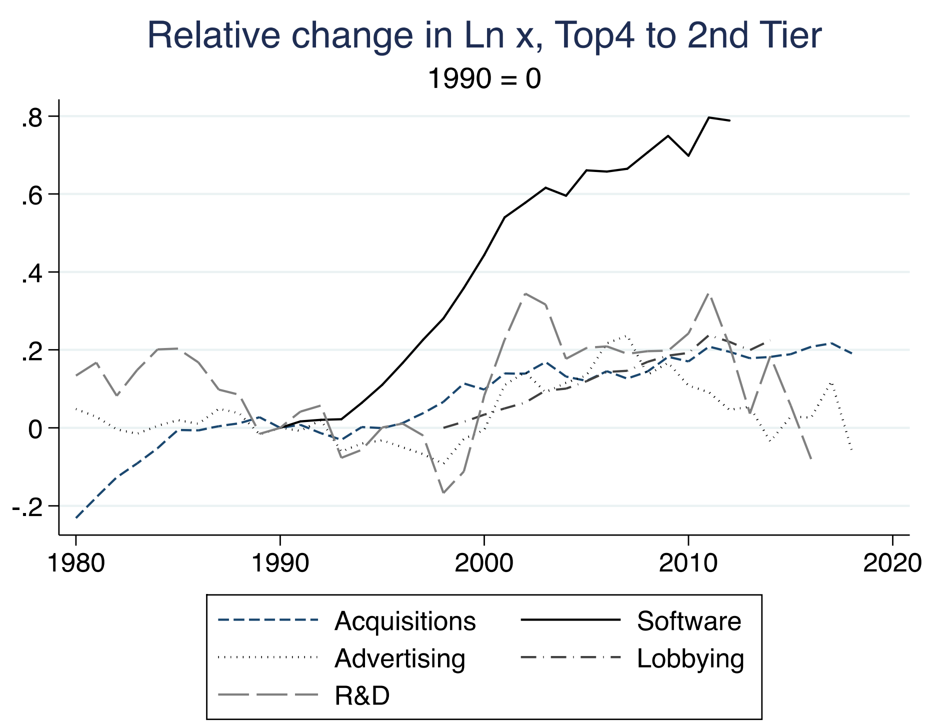


Figure 3. Trends in Intangible Stocks of Top Four Firms

A. Levels, Top four firms



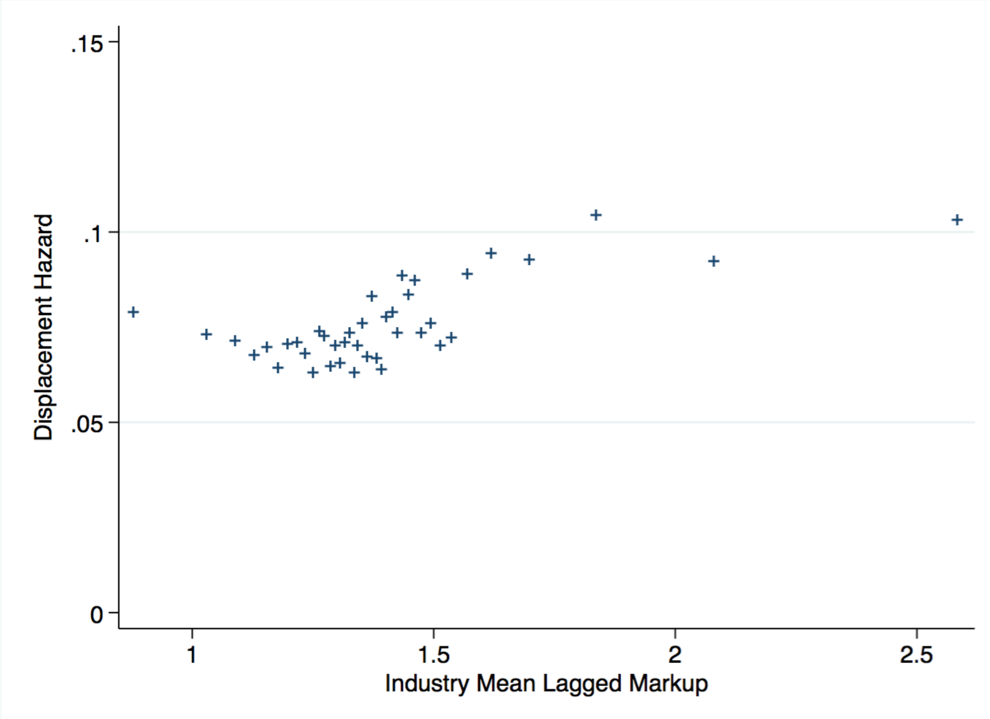
B. Difference, top four firms relative to firms ranked 5-9



Note: software line excludes firms in industries where software is a major part of the product.

Figure 4. Mean acquisitions by top four firms

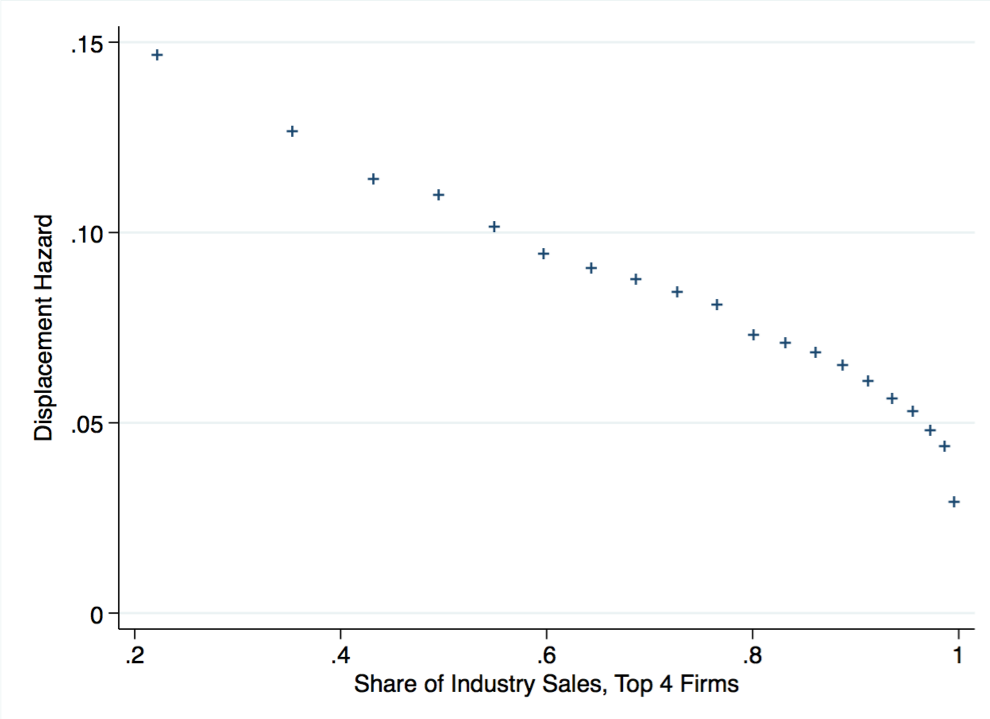
Figure 5. Mean Industry Displacement Hazard and Markups



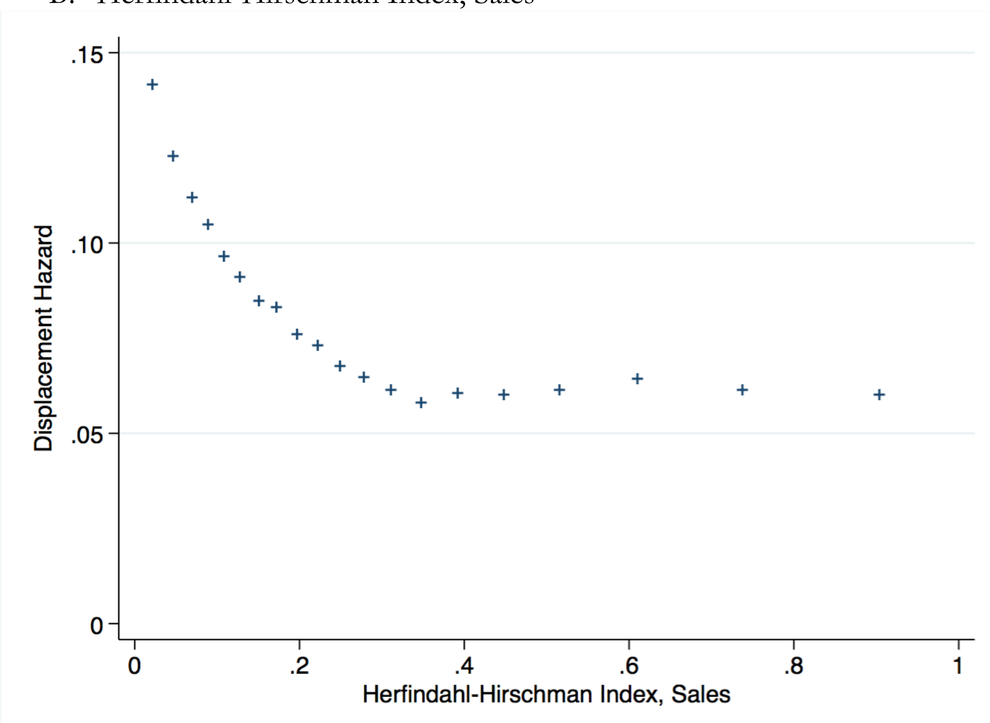
Note: Binned scatter plot from Compustat data 1980-2014, showing mean annual displacement hazard for 6-digit NAICS industries after controlling for year plotted against mean industry markup, calculated by the method of De Loecker and Eeckhout (2017).

Figure 6. Mean Industry Displacement Hazard and Industry Concentration

A. Four-firm share of sales, NETS data



B. Herfindahl-Hirschman Index, Sales



Note: Binned scatter plot from NETS data 1990-2014, showing mean annual displacement hazard for 8-digit SIC industries after controlling for year plotted against industry concentration measures.

Appendix

Supplementary Tables

Summary Statistics

Table A1. Mean Log Values, Year 2000

	Firm rank 1 – 4	Firm rank 5 - 8
Net Property, Plant, and Equipment	5.37	4.33
Intangibles	5.63	4.76
R&D	0.74	0.34
Organizational Capital	4.63	3.78
Balance Sheet Intangibles	2.83	1.71
software Stock	1.07	0.59
Patent Stock	1.26	0.86
Acquisition Stock	1.03	0.82
Advertising/Marketing Stock	1.02	0.66
Lobbying Stock	0.16	0.07
Markup	1.35	1.37

Industry Concentration

Table A2. Displacement Hazards and Industry Four-firm Concentration Ratio

	1	2	3
Concentration Ratio	-0.1284***	-0.1196***	
	(0.0015)	(0.0017)	
After 2000 x concentration		-0.0149***	
		(0.0008)	
Sector x concentration			
Mining, construction			-0.1262***
			(0.0023)
Non-durable manufacturing			-0.1297***
			(0.0017)
Durable manufacturing			-0.1282***
			(0.0017)
Transportation, utilities			-0.1292***
			(0.0027)
Trade			-0.1306***
			(0.0017)
Finance			-0.1278***
			(0.0030)
Services			-0.1260***
			(0.0018)
Other			-0.1196***
			(0.0078)
Observations	151,896	151,896	151,896
R-squared	0.063	0.050	0.063

Note: Standard errors clustered by industry in parentheses, * p<.1, ** p<.05, *** p<.01. Industry and year fixed effects. Concentration is industry share of revenues of the top 4 firms in NETS 8-digit SIC industries.

Markups

De Loecker and Eeckhout (2017) assume a revenue production function,

(A1)

$$q_{it} = \beta v_{it} + \gamma k_{it} + \omega_{it} + \epsilon_{it}$$

where q_{it} is log deflated revenues for firm *i* at time *t*, v_{it} is log deflated cost of goods sold, k_{it} is log deflated capital, ω_{it} is unobserved productivity, and ϵ_{it} is an error term capturing unanticipated shocks and measurement error. They further assume an AR(1) process so that

(A2)

$$\omega_{it} = \rho\omega_{it-1} + \xi_{it}.$$

They use a two-stage estimation, first regressing

(A3)

$$q_{it} = \beta v_{it} + \gamma k_{it} + h(v_{it}, k_{it}) + \epsilon_{it}$$

where $h(v_{it}, k_{it})$ is a non-parametric polynomial (we use a quadratic form). This regression gives us an estimate of predicted output, $\hat{q}_{it}$, purged of unanticipated shocks and measurement error. We can then define

(A4)

$$\hat{\xi}_{it}(\beta, \gamma, \rho) \equiv (\hat{q}_{it} - \beta v_{it} - \gamma k_{it}) - \rho(\hat{q}_{it-1} - \beta v_{it-1} - \gamma k_{it-1}).$$

Following De Loecker and Warzynski (2012) then have moment conditions

(A5)

$$E\left[\hat{\xi}_{it}(\beta, \gamma, \rho)\begin{pmatrix} v_{it-1} \\ k_{it-1} \end{pmatrix}\right] = 0.$$

Using GMM, we obtain estimates of β and calculate markups as

(A6)

$$\mu_{it} \equiv \hat{\beta} e^{(q_{it}-\hat{\epsilon}_{it})}/v_{it}$$

where $\hat{\epsilon}_{it}$ is the residual from (A3).