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James Bessen
Boston University School of Law

Erich Denk
Boston University School of Law

Joowon Kim
Boston University School of Law

Cesare Righi
Boston University School of Law

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Declining Industrial Disruption

By James Bessen, Erich Denk, Joowon Kim, Cesare Righi
Technology & Policy Research Initiative, Boston University School of Law

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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 reports the first recent estimates of trends in the displacement of industry-leading firms. Displacement hazards rose for several decades 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 distinctly 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 now appears to help suppress disruption.

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Introduction

Studies find evidence of rising firm markups and profit shares[1] and of rising industry concentration at the national level.[2] Many economists and policymakers are concerned about declining competition in the US and in other developed economies. Generally, declining competition is troubling for two very different reasons, one static and the other dynamic: 1) without sufficient competition, firms acquire market power allowing them to 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. While markups measure price competition by quantifying the deviation of prices from marginal cost, markups may be orthogonal to technological competition. Firms with innovative new technologies may earn rents, allowing them to charge higher markups. For instance, Bessen (2020) and Criscuolo et al. (2018) find positive links between information technology (IT) investments and markups or profit margins.

[1] De Loecker and Eeckhout, and Unger (2020), Barkai (2017), Hall (2018), Baqaee and Fahri (2017); see Basu (2019) and Syverson (2019) for reviews.

[2] Grullon et al. (2019), Autor et al. (2020), Gutierrez and Philippon (2017, 2019), Bessen (2020) but also see Rinz (2018), Hsieh and Rossi-Hansberg (2019), and Berry et al. (2019).

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

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A complete understanding of competition requires additional metrics. This paper measures Schumpeterian competition, explores how it has changed over recent decades, and identifies what appear to be the main barriers to Schumpeterian competition. We also look at the relationship between Schumpeterian competition and other measures of competition, specifically markups and industry concentration.

We use two main measures of Schumpeterian "creative destruction": 1) the annual displacement hazard that a firm ranked top four by sales in its industry falls out of the top four, and, 2) the annual hazard that a firm ranked fifth through eighth leapfrogs into the top four. We model these probabilities using a simple extension of a standard production function. We assume that firms optimize variable inputs so that each firm's revenues are a reduced-form function of the firm's idiosyncratic productivity, the firm's capital, and—because of strategic interaction—capital stocks of rival firms. Then, under some simple assumptions, displacement and leapfrogging probabilities can be expressed as functions of firm productivity and firm investments, including those of rivals. This allows us to use regression analysis to explore the extent to which different kinds of capital affect the hazard rates and can account for the observed trends. We consider a variety of capital stocks including physical capital, intangibles, R&D, patents, organizational capital, different types of software, advertising and marketing, lobbying, and acquisitions.

Our first finding is that displacement and leapfrogging hazards exhibit a sharp break in trend: after rising robustly for many decades, they fell sharply starting around the year 2000. To fix ideas, it is helpful to preview a result developed more completely below. Figure 1 shows several annual measures of Schumpeterian turnover along with the best-fit linear trends with a single break, where the break years are determined by Wald supremum tests. Panels A, C, and D show displacement hazards; panel B shows a leapfrogging hazard. Below

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we discuss the details of these measures and also a number of alternative metrics. The picture that emerges is this: turnover of market leaders rose substantially from 1970 through the 1990s, but around 2000 the turnover rates began dropping. The change was sharp and substantial and across most sectors, suggesting a major shift in the nature of Schumpeterian competition.

Second, we explore the roles of different capital stocks in accounting for these shifts. We find that rising investments in intangibles generally and in software in particular can account for most of the drop in displacement and leapfrogging hazards since 2000. Intangible and software investments by top firms appear to impose a negative externality on second-tier firms, reducing their leapfrogging probabilities. Dominant firms increased their investment in software by an order of magnitude around 2000. Even relative to second-tier firms ranked 5-8, the top four firms more than doubled their software stocks. Moreover, using Census microdata and BEA industry data, it appears that this relationship is largely driven by own account (self-developed) software, which is substantially dominated by large firms. An instrumental variable analysis provides some support for the idea that the impact of own-account software on displacement hazards may be causal. We discuss why software might be playing this role.

We find little to support the view that declining competition has resulted from lax antitrust merger enforcement. Mergers and acquisitions by top firms do not significantly reduce displacement and acquisitions by top firms have been declining. Nor does lobbying appear to have much influence on the persistence of dominant firms.

Finally, we look at the correlations between displacement hazards and industry markups and concentration. We find that industries with higher markups actually have

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higher rates of displacement, implying that markups are not a reliable indicator of industry dynamism. Displacement hazards are negatively associated with industry concentration.

This analysis provides a richer picture of the nature of competition, including different kinds of competition. And it highlights the possibility that software technology is playing a new and different economic role recently. This paper makes three major contributions. First, we report changes in the displacement hazard for top firms ranked by sales in industries over time, for the first time in the literature, finding a sharp reversal of trend around 2000.[4] Second, we develop a model that includes strategic interaction and, using firm level data, we 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. Third, we explore the associations between displacement hazards of market leaders, their markups, and industry concentration.

Literature

Joseph Schumpeter (1942, p. 84) held that what matters in "capitalist reality" is innovation, both technological and organizational. Innovative firms can 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

[4] Autor et al. (2020, 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). Covarrubius et al. (2019) look at displacement of top firms ranked by profits or market value. While they find a similar drop in displacement hazards, their measures are noisier and less indicative of market dominance. For instance, Amazon long had a low profit ranking because it reinvested at a high level. In any case, we find that sales-based measures are more precise and show a larger and sharper break in trend.

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business models. Substantial empirical evidence supports the proposition that greater contestability of sales encourages firms to improve efficiency and invest in R&D (Shapiro 2012, but see also 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.

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, while this literature has looked at levels of displacement hazards it has not looked at time trends, as we do. Furthermore, while the literature explores correlated industry characteristics, we explore a range of firm level investments that might affect displacement hazards, including possible strategic interaction.

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. For example, in the classic Cournot model, firms invest in capacity. In endogenous sunk cost

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models (Sutton 1991), firms improve the perceived quality of their products through investments in advertising or R&D. 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. This is particularly important because firms dramatically increased their investments in some forms of capital since the 1990s, notably intangibles and software.[5]

Our 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 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. Looking beyond the 1990s, there is some evidence of a reversal. Bennett and Gartenberg (2016) find declining persistence of return on assets until about 2000 and rising persistence after that plus some evidence of a link to software. Bennett (2020), measuring production function autocorrelation finds decreasing persistence until around 2000, a reversal, and then a subsequent decline.

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

[5] Byrne, Oliner, Sichel (2013); Corrado, Hulten, Sichel (2009); BEA, "National Income and Product Accounts," Table 9.4u, Software Investment and Prices.

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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.[6] NETS is known to over-represent very

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

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small firms, but that shortcoming should not affect our analyses on dominant firms that tend to be large (Barnatchez, Crane and Decker, 2017).

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 3 or 4-digit NAICS code based on the largest business line.

Finally, we used industry level data from the Bureau of Economic Analysis (BEA) that also includes measures of software investment by type. We supplement these data with measures of investment, including software investment, in EU countries from EU KLEMS. We use these latter data in an instrumental variable analysis.

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.

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

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derived from Sales, General, and Administrative expenditures, and balance sheet intangibles. These values are available from 1975 through 2016.[7]

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.[8] 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).[9]

We also wanted to measure investments that firms make in developing proprietary software for their internal 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 – 2012.[10] We then constructed software stocks treating the employment of software

[7] 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.

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

[9] 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.

[10] 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.

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developers as an investment, 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. While goodwill captures the values of acquisitions, we also wanted to count the number of acquisitions made by large firms because even small-value transactions might confer significant technological advantage to dominant firms. We obtained a list of mergers and acquisitions from the Thomson Reuters SDC Platinum database and matched these to Compustat.[11] 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.

To compute firm productivity, we follow common practice (see Keller and Yeaple 2009), imputing 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. Where the wage bill is not reported, we impute it as firm employment times the industry mean wage taken from the BEA. Value added is revenues minus materials.

Finally, we estimate firm markups using the method of De Loecker, Eeckhout, and Unger (2020) which is based on De Loecker and Warzynski (2012) (see Appendix).

Summary statistics can be found in Appendix A1.

[11] 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.

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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. In this paper, we use large samples, we estimate changing trends in the hazard of changes in leadership, and we relate these to a variety of firm investments.

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.[12] 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 resulting regression coefficients for the baseline trend and change in trend after the break year. That is, for break year τ, we estimate the annual hazard over time t

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

where C is a constant. The estimated coefficients for both the trend and the change in trend are substantial, the change is negative, and the coefficients are significant at the 1% level.

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

[12] Note that while the number of firms listed in Compustat has declined substantially since 2000, the number of large firms (e.g., those with over $1 billion in sales in 2009 $) has not. The rankings of the top firms should therefore not be significantly affected by the decline in total firms listed.

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robustness 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, we find a similar break in trend.

Finally, this change in trend is observed across sectors. Table A2 in the Appendix shows regression results for a variety of sectors in both Compustat and NETS data, all showing a similar pattern, although not always statistically significant and with breaks

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occurring in different years. Furthermore, the pattern is similar if firms are weighted by real sales in the calculation of annual hazards (not shown, available on request).

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 and implies a marked and rapid change in industrial structure.

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, only limited inferences can be drawn using industry level data because firm behavior may differ significantly—dominant firms may behave differently than their rivals and those differences might be key to understanding their persistence. For this reason, it is important 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 $t-1$. We

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assume a Cobb Douglas revenue production function with an additional term for rival's capital. Let the log revenue of firm *i* at time *t*, designating the other firm as *-i*, be

(1)

$$y_{it} = \alpha^0 l_{it} + \beta^0 k_{it} + \gamma^0 k_{-it} + \omega_{it} + \nu_{it}$$

where *l* is log labor, *k* is log of beginning-of-year capital, ω_{it} is firm productivity, and ν_{it} is an error term of mean zero and independent of the right-hand side variables. The variable k_{-it} captures the notion that firm investments can exert an externality on other firms' revenues. For example, in a classic Cournot duopoly one firm's investment in capacity shifts the other firm's demand curve.

Allowing the firm to optimize labor in each period given capital stocks and productivity yields a reduced form equation

(2)

$$y_{it} = \beta^1 k_{it} + \gamma^1 k_{-it} + \delta^1 \omega_{it} + \mu_{it}$$

Sutton (2007) finds that the shocks to firm's market shares are independent of each other, so, without significant loss of generality we can model the errors as a normal distribution, $\mu_{it} \sim N(0, \sigma_t)$.[13] Then the probability of a change in market leadership at time *t* is

(3)

$$P[y_{-it} < y_{it}] = 1 - \Phi\left(\frac{y_{it} - y_{-it}}{\sqrt{2}\sigma_t}\right) = \Phi\left(-\frac{y_{-it} - y_{it}}{\sqrt{2}\sigma_t}\right)$$

[13] This assumes that both firms have the same error distribution. Allowing different variances does not significantly alter the specification.

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where Φ is the standard normal distribution function. Taking a linear approximation of Φ, and capturing differences in σ with fixed effects for year and industry *j*, we get a linear probability model,[14]

(4)

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

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 $\gamma, \beta_1 > 0, \beta_2 < 0.$

Empirical implementation

Equation (4) can be readily extended to accommodate more than two firms. To explore the displacement hazard of top firms, we use a sample consisting of firms ranked in the top four by sales the previous year. In this case, we include capital stocks, k_{-it}, for firms ranked 5 – 8 or an average of these. These are the firms most likely to displace the subject firm. To explore leapfrogging hazards, the sample consists of firm ranked 5 – 8 and we include capital stocks of firms ranked 1 – 4.

Also, equation (4) can include multiple capital stocks. Our base specification includes tangible capital (property, plant, and equipment) and intangible capital. We also decompose intangible capital into a range of component stocks.

[14] In this specification, ω_{-it} is included in the error term, although this is not necessary. Also note that this specification accommodates differences in coefficients between dominant and other firms.

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In our data the capital stocks are observed, but firm productivity is not. Obtaining 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 in intangible capital, then omitting the productivity measure, will bias the coefficient for intangible capital. To obtain measures of productivity, we use a two-step procedure. First, we estimate equation (1) for the sample of all firms, obtaining firm-year productivity estimates, $\widehat{\omega}_{it}$. Then we regress equation (4) for the limited sample of subject firms (top four or second four), using our productivity estimates as a control variable. Because we are using an estimated variable in our second step, we bootstrap to obtain standard errors.

We estimate equation (1) using log value added as the dependent variable and log labor, log tangible capital, and log intangible capital as the independent variables. We also experimented with different measures of k_{-it}, but these made little difference to the coefficients obtained.[15]

To obtain estimates of productivity, ω_{it}, independently of the error term, ν_{it}, we use the Ackerberg, Caves, and Frazer (2015) control function method. Note that control function methods of estimating production functions—Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2015)— are two step procedures that generate estimates of ω_{it} in their first stages. Using OLS or other techniques for estimating production functions, a rough measure of productivity might also be obtained by taking the residual of the estimated equation. However, that residual equals $\omega_{it} + \nu_{it}$ and, since ν_{it} is

[15] Our base specification calculates it as the log of the sum of capital for all firms in the industry excluding the subject firm. While this term has a statistically significant coefficient, it made little difference in the productivity estimates. The correlation between productivity including it and excluding it altogether is .9974.

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correlated with the error in our second stage regression, ϵ_{it}, by construction, using these residuals will lead to biased estimates.

To check the robustness of our estimation choice, Table A3 in the Appendix compares estimates of equation (4) using different productivity measures. The results differ little, especially across the different control function methods.

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 outcome 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 are significantly associated with the displacement hazard. The coefficient for intangible capital is somewhat larger in absolute magnitude than the coefficient for tangible capital, but the difference is not statistically significant. To gauge the economic significance of these estimates, from 1995 to 2017 the sample mean hazard rate declined 7.7% while the mean of log tangible capital increased 1.55 and the mean of log intangible capital increased 2.03. Intangible capital is associated with a larger contribution to declining turnover by virtue of its greater growth and higher coefficient.

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

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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, so these lagged stocks should not be much influenced by expectations of future volatility yet they are correlated with subsequent capital stocks by construction.[16] 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 .153).

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 substantially while the coefficient on intangible capital rose. This shift suggests that intangibles are associated with larger decreases in turnover after 2000, perhaps because firms received a greater payoff to these investments. 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 rise of intangibles is important in understanding the reversal in displacement hazards following 2000.

[16] The first stage regression indicates that the instrument is not weak; an F-test of the joint significance of the explanatory variables has a statistics of 405.6.

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Finally, note that the decline in turnover of market leaders is not the result of declining volatility in markets, σ_t. Both the variance of the residual in (1) and of productivity, ω_{it}, have been rising.[17] The rising persistence of market leaders has been occurring *despite* a general increase in market turbulence.

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. But neither the second-tier firms' investments in tangible capital or intangible capital appear to have a significant effect on the top tier firms. Also, 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,

[17] The variance of the change in ω_{it} rises from .083 up through 2000 to .117 after 2000; the variance in the change in the total residual rises from .092 to .124.

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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 relative revenues of second-tier firms. That is, to the extent that intangibles raise the hurdle that second tier firms need to overcome, that effect should mostly appear in the coefficients of the fourth and third ranked firms, the firms that are most at risk of being leapfrogged. The large coefficient for the biggest firm suggests that the role of intangibles may be in the negative externality these investments exert on smaller firms rather than their role in raising firm revenues and thus raising the leapfrogging hurdle. 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. Intangibles may 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 since these

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are the stocks that significantly affect leapfrogging. A likelihood ratio test does not reject these restrictions (probability value of .703).[18]

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. Of the investments made by top four firms, only investments in organizational capital are economically and statistically significant.[19]

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.[20] 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

[18] 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.

[19] 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).

[20] 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.

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years 1999 – 2014 when lobbying data are available. Of the detailed investments made by top firms, only software and patent stocks have statistically 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.[21] 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). To estimate the combined impact of the growth in software capital, multiply the change in the log software capital stock in Figure 3 (about 2) times the coefficient of top firm software from column 3 (-.014) to get a 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 1B, the increase in software investment by top four firms accounts for most 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.

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

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Different types of software investment

The software stock measure used above is built from employment flows of software developers. These flows represent firm investment in developing their own software. Firms also purchase software services (custom programming) and pre-packaged software. We can look at the relative roles of different types of software investment in the US using data from the Census ACES survey and also using industry level data from the Bureau of Economic Analysis (BEA). The industry level data also permit us to perform instrumental variable estimation.

[ACES results are awaiting Census disclosure]

The BEA provides a longer time series on software investments at the industry level. We calculate annual displacement hazards from the NETS data aggregated to BEA industry classifications for the US from 1990 through 2014. Since software investment is dominated by the largest firms in each industry,[22] we use the share of software capital in total capital as an independent variable. We scale other capital stocks similarly. Table 5 reports regression results the annual displacement hazard using all software (column 1) and different types of software (column 2), both with controls for stocks of equipment and structures as well. All regressions have industry and year fixed effects, they are weighted by the number of firms in each industry to reduce heteroscedasticity arising from sampling variance,[23] and standard

[22] Using CPS data from 2000-2014, 38% of software developers work at firms with more than 1000 employees. The ACES data show that the largest firms spend dramatically more on own-account software in proportion to their total investments.

[23] The number of firms per industry vary by two orders of magnitude, creating substantial differences in sampling variance.

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errors are clustered by industry. Software in general and own-account software in particular have significant negative coefficients.

Some scholars suggest that competition has declined in the US relative to Europe because of lax antitrust enforcement or corporate lobbying.[24] Perhaps software investment endogenously responds to these exogenous changes in competition, creating a spurious correlation. To correct for possible endogeneity, columns 3 and 4 report an instrumental variable estimation. We instrument the software share (column 3) and the own-account software share (column 4) using the software share of capital for European countries obtained from the EU KLEMS database. Since European businesses likely respond to similar technological opportunities as do US businesses, software investment should exhibit similar variation across industries.[25] But European software investment is plausibly independent of factors that might influence the displacement of leaders in US markets. The IV regression coefficients have the same signs, are larger in magnitude, but are less precise.[26]

Thus, both at the firm and industry levels, the rate of displacement of dominant firms is negatively related to investments in own-account software and this relationship appears to be independent of US political economic factors.

[24] Grullon et al. (2019); Philippon (2019).

[25] Our first stage regressions are highly significant.

[26] The first stage regression indicates that the instrument is not weak with an F-test of joint significance of the explanatory variables of 705.1. An overidentification test for covariate balance cannot reject the null hypothesis that the covariates are balanced (χ_2=4.386; p<0.986).

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Discussion: Why software?

Large firm investments in all types of intangibles have 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. It is helpful to speculate why this might be.

To get a sense of why software might have a similar impact on competition across a wide range of industries, it is helpful to look at some examples. Many of the large IT systems used by dominant firms share a common purpose: they allow firms to improve the quality of products and services by managing complexity. Consider:

- Retailers such as Amazon and Walmart are able to use logistics and inventory management systems to offer customers much greater selection and to respond to demand changes much more rapidly despite the larger number of items for sale.
- Large manufacturers are able to design products such as airplanes and automobiles with many more features using expensive custom CAD/CAM

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systems and software components. Modern cars have over 100 computers and over 100 million lines of software code.

- Using large amounts of data, online 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, managing both marketing and risk.

All of these systems in diverse industries allow market leaders to manage a higher degree of complexity than their rivals, thus delivering better quality products and services.

Why might complex systems provide greater advantage to dominant firms? Some researchers, such as Bauer and Lashkari (2018) find evidence of economies of scale in the use of IT.[27] Software has large fixed costs and low marginal cost, giving an advantage to those firms who use it more widely.

However, economies of scale are nothing new. Other technologies exhibit well-known scale economies, such as steelmaking or electric power generation. Nor is it clear why second-tier firms cannot also realize scale advantages from software, as they do in the steel and electricity industries. There is a critical difference. Steel and electricity generation derive size advantages because of exogenous factors related to the physics of heat generation. In contrast, the advantages brought by the systems in the above examples derive from their ability to improve quality and to thereby differentiate the firm from its rivals. The advantages of these large software systems derive not from absolute size but from an advantage *relative* to the size rivals' systems. Firms *endogenously* choose the scale of complexity they manage relative to rivals.

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

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In other words, investments in these large software systems appear to be endogenous sunk costs as described by (Sutton 1991).[28] Sutton argues that leading firms in vertically differentiated markets can sink large investments in advertising or R&D to improve product quality and thereby achieve a large stable market share, creating a "natural oligopoly." In equilibrium, firms invest at different levels, they differ in quality and in the prices they charge. Effectively, the quality investments made by leading firms increase the revenue gap to follower firms, decreasing the likelihood of leapfrogging. Large investments in own-account software can also differentiate firms by quality, perhaps at a larger scale. For example, Ellickson (2007) shows evidence that supermarket distribution systems create a Sutton-type market structure. Technology that provides greater differentiation at scale generates industry structures very different from technologies that generate exogenous cost savings at scale.

These endogenous scale economies provide a succinct explanation for the observed trends. The emergence of IT systems to manage highly complex environments 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 hence declining displacement.

Other factors may amplify these trends. 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. To the extent that these systems depend on complementary organizations and are tailored to specific organizations, some firms will have

[28] See also Shaked and Sutton (1982, 1983, 1987).

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greater benefit than others and these advantages will not easily diffuse. Also, 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).

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, Eeckhout, and Unger (2020) 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 A4 on the Appendix reports a series of regressions along the lines of Table 2, adding the firm markup lagged one year. 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

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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 Table A5) 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.[29] 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 2020). 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. 2020). Also, note that falling industrial concentration at the local level has accompanied rising concentration at the national level.[30]

Conclusion

Using multiple measures of the turnover of dominant firms, we find evidence of a substantial and abrupt change in the nature of competition across most sectors of the US

[29] 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%.

[30] Rinz (2018), Hsieh and Rossi-Hansberg (2019).

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economy beginning in the late 1990s. Schumpeterian competition rose substantially over previous decades but dropped sharply in a relatively short time since the late 1990s.

This pattern seems quite distinct from the evolution of markups and industry concentration which have grown steadily since about 1980 (De Loecker, Eeckhout, and Unger 2020, Autor et al. 2020). Our analysis suggests that these metrics capture different things. In particular, markups are perhaps a better measure of static price competition than they are of dynamic technological competition. We find, in fact, that higher markups are associated with *greater* industrial dynamism reflected by the displacement of industry leaders.

Furthermore, we analyze the relationship between displacement rates of dominant firms and a wide array of investments they make, including investments in intangibles, R&D, organizational capital, acquisitions, software, advertising, and lobbying expenditures. 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. We find that software stocks are significantly related to lower displacement rates across a variety of datasets and measures. Moreover, investments by large firms in self-developed software increased by an order of magnitude beginning in the late 1990s. This surge can account for most of the decline in leapfrogging rates and an instrumental variable analysis suggests the relationship is causal. Viewing these investments as endogenous sunk costs (Sutton 1991) provides a parsimonious explanation for the decline in Schumpeterian competition. Enabled by new technology, leading firms made large

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investments in managing complexity to improve the quality of their products and services, differentiating themselves from rivals and creating a "natural oligopoly."

Thus, it seems 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 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	Break year	Trend (α)	Change in trend (β)
Compustat data				
Displacement from top 4 firms	6-digit NAICS primary industry	2000	0.0017 (0.0004)***	-0.0046 (0.0009)***
Displacement from top 2 firms	6-digit NAICS primary industry	2000	0.0027 (0.0005)***	-0.0062 (0.0010)***
Displacement from top 8 firms	6-digit NAICS primary industry	2000	0.0010 (0.0004)**	-0.0032 (0.0007)***
Displacement from top 4 firms + Exit	6-digit NAICS primary industry	2000	0.0024 (0.0004)***	-0.0061 (0.0010)***
Leapfrog into top 4 firms (rank 5-9)	6-digit NAICS primary industry	2001	0.0013 (0.0002)***	-0.0029 (0.0007)***
Displacement from top 4 firms	4-digit NAICS primary industry	2000	0.0022 (0.0003)***	-0.0055 (0.0008)***
Displacement from top 100 firms	All industries	2003	0.0014 (0.0004)***	-0.0048 (0.0013)***
Displacement from top 4 firm segments	4-digit SIC industry segments	1998	0.0012 (0.0011)	-0.0047 (0.0019)**
NETS data				
Displacement from top 4 firms	8-digit SIC industries	1997	0.0057 (0.0028)*	-0.0079 (0.0033)**

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).

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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	-0.019	-0.066**	-0.099***	-0.102***	-0.032
	(0.018)	(0.028)	(0.009)	(0.031)	(0.023)
Net PPE	-0.029***	-0.037***	-0.027***	-0.043***	-0.023***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
Intangibles	-0.026***	-0.033***	-0.030***	-0.030***	-0.032***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
Industry FE	x		x	x	x
Year FE	x		x	x	x
Industry x year FE		x			
Observations	26471	26471	22159	15936	10535
Adjusted R-squared	0.091	0.067	0.077	0.109	0.091

Note: Bootstrapped standard errors clustered by firm in parentheses, * p<.1, ** p<.05, *** p<.01. Independent variables are in logs. Productivity is estimated by the ACF method. Column 3 instruments capital stocks using 5-year lagged values.

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Table 3. Hazard estimates with external interactions

Hazard:	Top 4 firm moves down		Second 4 firm moves up
Subject firm			
Productivity	-0.006		0.090***
	(0.021)		(0.022)
Net PPE	-0.033***		0.039***
	(0.004)		(0.003)
Intangibles	-0.035***		0.032***
	(0.004)		(0.003)
Tangible Capital			
Firm 5	0.004	Firm 1	-0.001
	(0.003)		(0.004)
Firm 6	0.001	Firm 2	-0.002
	(0.002)		(0.004)
Firm 7	-0.001	Firm 3	-0.011***
	(0.003)		(0.004)
Firm 8	-0.002	Firm 4	-0.014***
	(0.002)		(0.004)
Intangible Capital			
Firm 5	-0.001	Firm 1	-0.014***
	(0.002)		(0.004)
Firm 6	0.003	Firm 2	-0.004
	(0.003)		(0.004)
Firm 7	0.002	Firm 3	-0.005
	(0.003)		(0.005)
Firm 8	0.004	Firm 4	-0.006
	(0.003)		(0.004)
Observations	14924		13765
R-squared	0.118		0.087
Other firms (probability values)			
Joint test of tangibles	.261		.000
Joint test of intangibles	.164		.000

Note: Bootstrapped standard errors in parentheses, clustered by firm, * p<.1, ** p<.05, *** p<.01. All regressions have industry and year fixed effects. Independent variables are in logs. Productivity is estimated using the ACF method.

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Table 4. Decomposing Intangibles, Leapfrog hazard

Subject firm	1	2	3	4
Productivity	0.093***	0.085***	0.056***	0.105***
	(0.023)	(0.023)	(0.017)	(0.035)
Net PPE	0.043***	0.053***	0.051***	0.052***
	(0.004)	(0.004)	(0.004)	(0.006)
R&D	0.001			
	(0.002)			
Org. capital	0.022***			
	(0.004)			
Other intangibles	0.002*			
	(0.001)			
Software Stock		0.003	0.008	
		(0.004)	(0.005)	
Acquisitions		0.009		0.012
		(0.006)		(0.009)
Advertising		0.006**		0.002
		(0.003)		(0.004)
Patents				0.012***
				(0.004)
Lobbying				-0.006
				(0.014)
Top 4 firms (average)				
PPE, firm #3	-0.016***	-0.003	-0.001	-0.008
	(0.004)	(0.006)	(0.004)	(0.007)
PPE, firm #4	-0.019***	-0.012***	-0.013***	-0.018***
	(0.004)	(0.004)	(0.004)	(0.007)
R&D	-0.003			
	(0.003)			
Org. capital	-0.015***			
	(0.006)			
Other intangibles	0.001			
	(0.002)			
Software Stock		-0.014**	-0.014**	
		(0.007)	(0.006)	
Acquisitions		0.002		-0.003
		(0.007)		(0.012)
Advertising		0.003*		0.002
		(0.002)		(0.002)
Patents				0.009
				(0.007)
Lobbying				-0.012**
				(0.006)
Observations	12964	7706	9140	4088
R-squared	0.086	0.118	0.106	0.133

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

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Table 5. Displacement hazard at industry level, US
Dependent variable: Displacement of top four firm ranked by sales in US market

	(1) OLS	(2) OLS	(3) IV	(4) IV
All software share	-0.412*** (0.120)		-0.911*** (0.219)	
Own-account software share		-0.669** (0.324)		-2.850* (1.545)
Prepackaged software share		-0.595 (0.640)		0.455 (2.404)
Custom software share		-0.127 (0.272)		0.283 (0.501)
All equipment share	-0.097 (0.076)	-0.070 (0.097)	-0.235*** (0.083)	-0.158 (0.106)
All structures share	0.072 (0.079)	0.093 (0.095)	0.044 (0.091)	0.110 (0.097)
Observations	1,440	1,440	1,440	1,440
R-squared	0.373	0.374		

Note: Standard errors clustered by industry in parentheses, * $p<.1$, ** $p<.05$, *** $p<.01$. All regressions have industry and year fixed effects and industries are weighted by firm counts. Independent variables are in logs. Software share (column 3) and own-account share (column 4) are instrumented using the log software share of capital for European countries. First stage regressions are highly significant.

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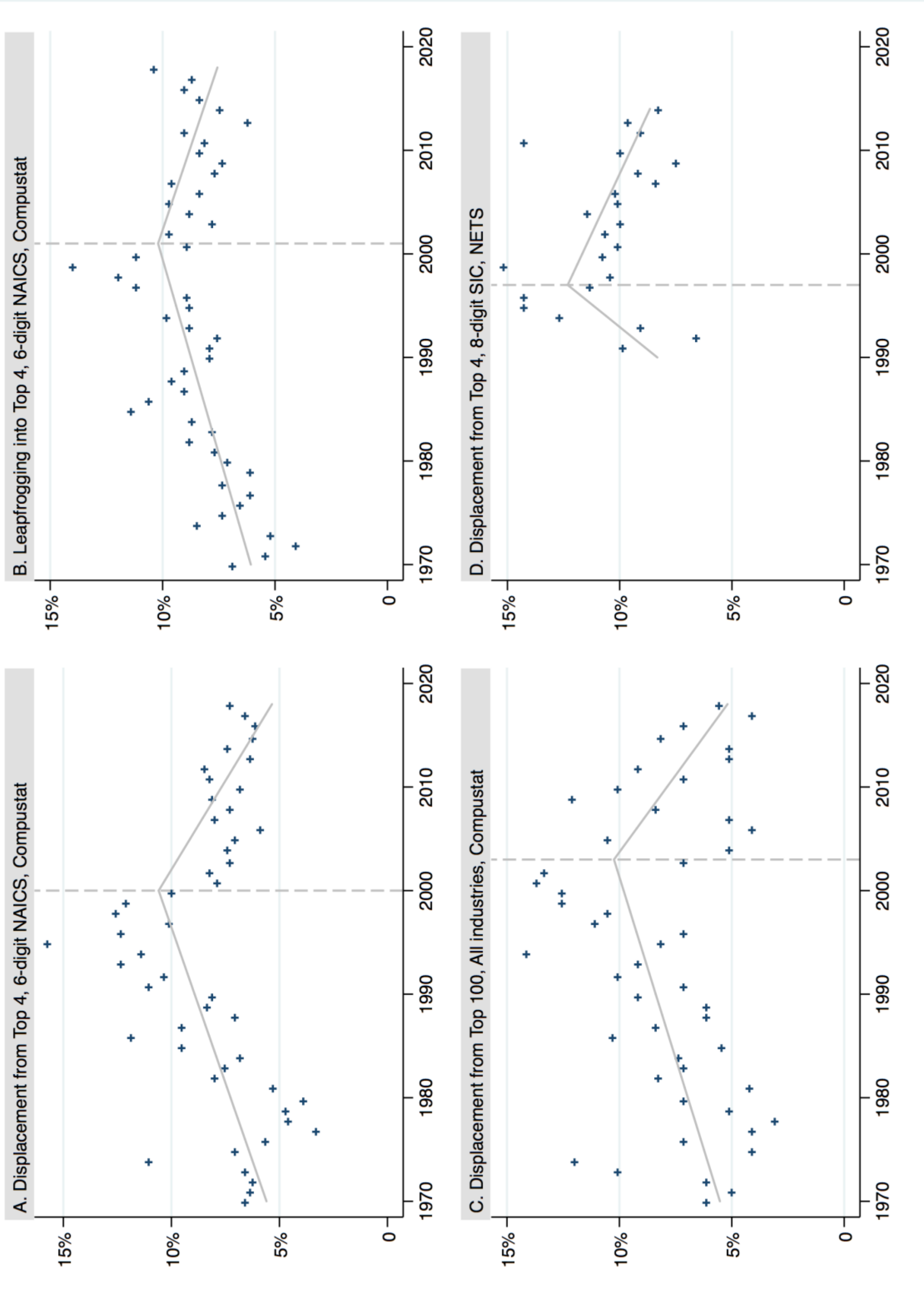
Figure 1. Displacement Hazards



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.

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Figure 2. Mean difference in capital stock by type of top four firms

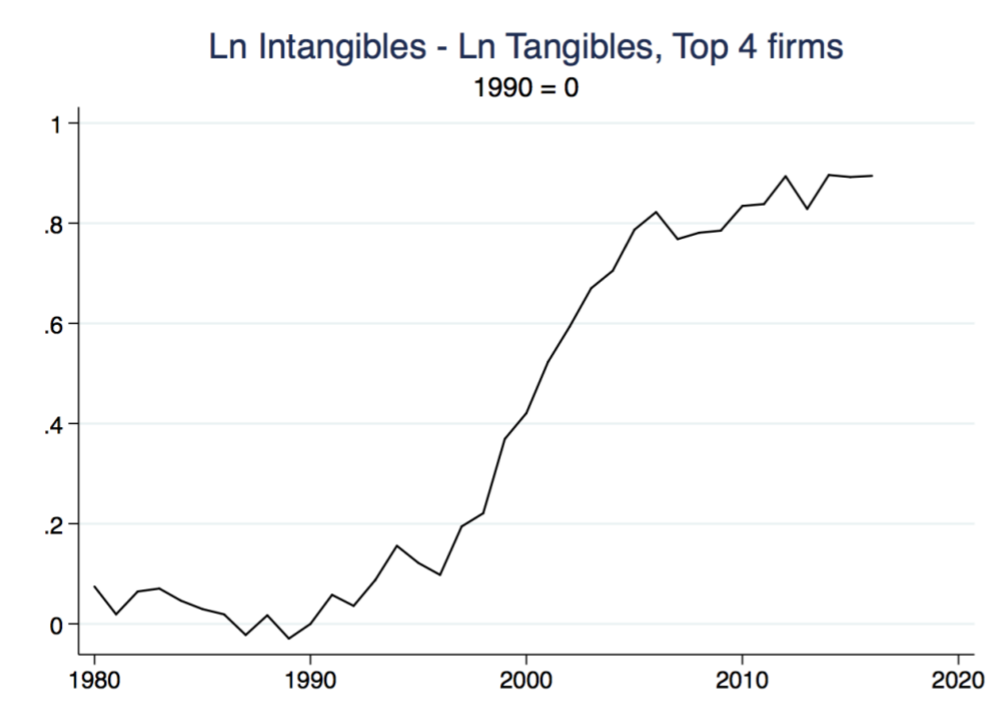

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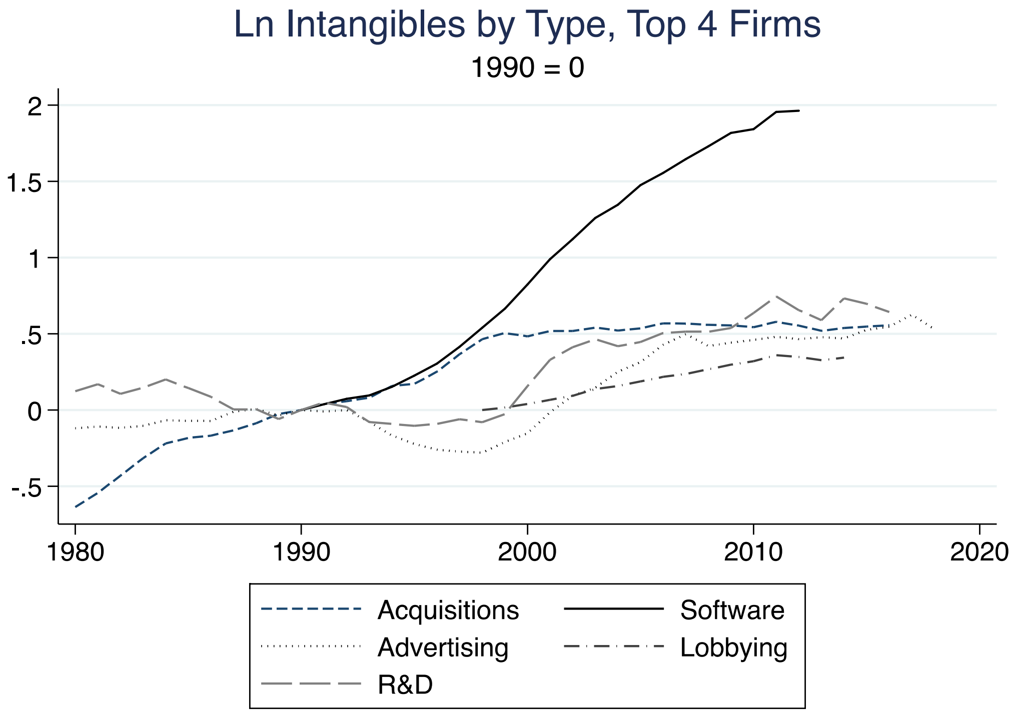
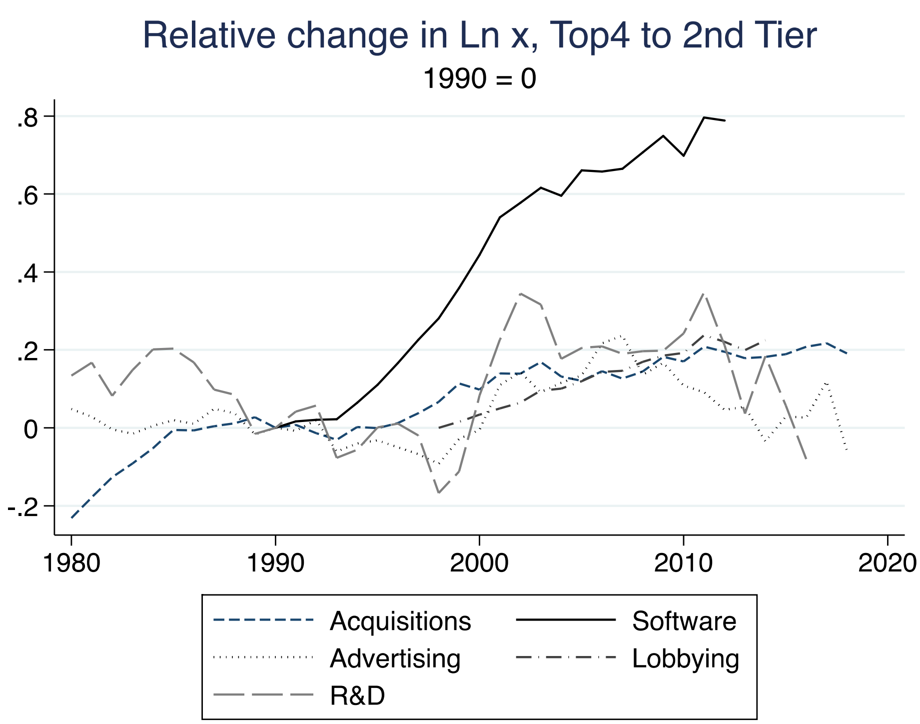
Figure 3. Trends in Intangible Stocks of Top Four Firms

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.

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Figure 4. Mean acquisitions by top four firms

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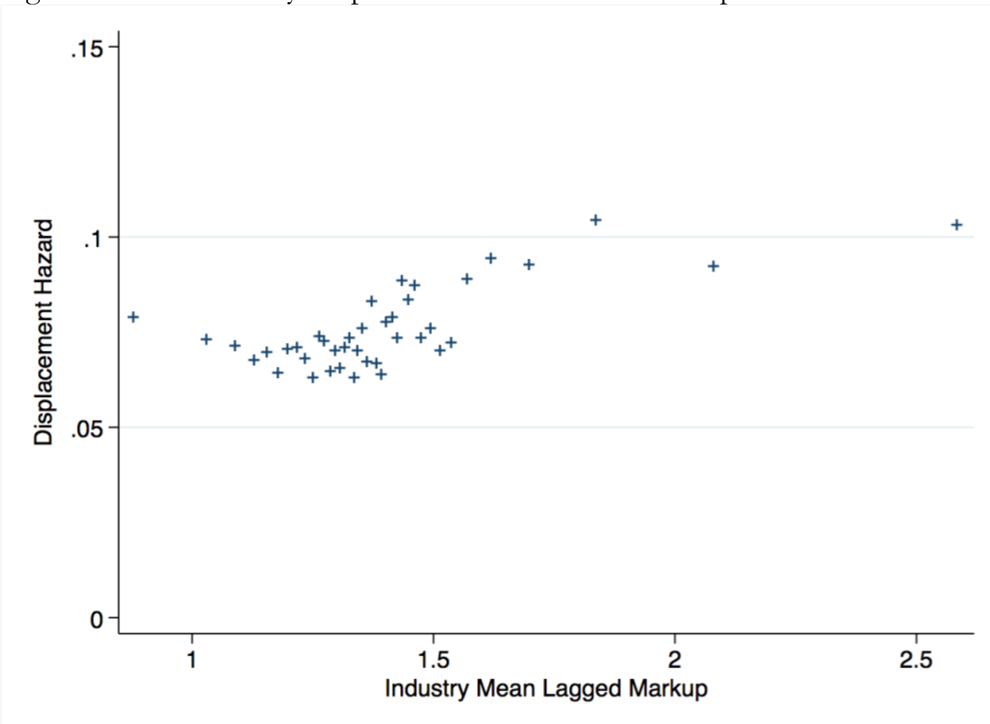
Figure 5. Mean Industry Displacement Hazard and Markups



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, Eeckhout, and Unger 2020.

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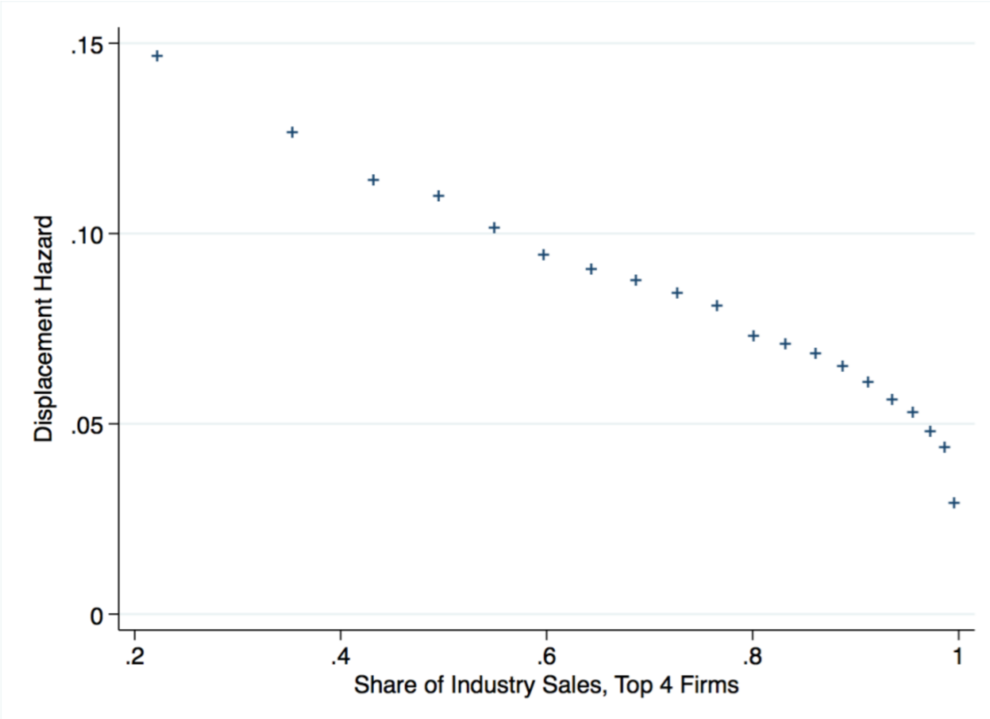
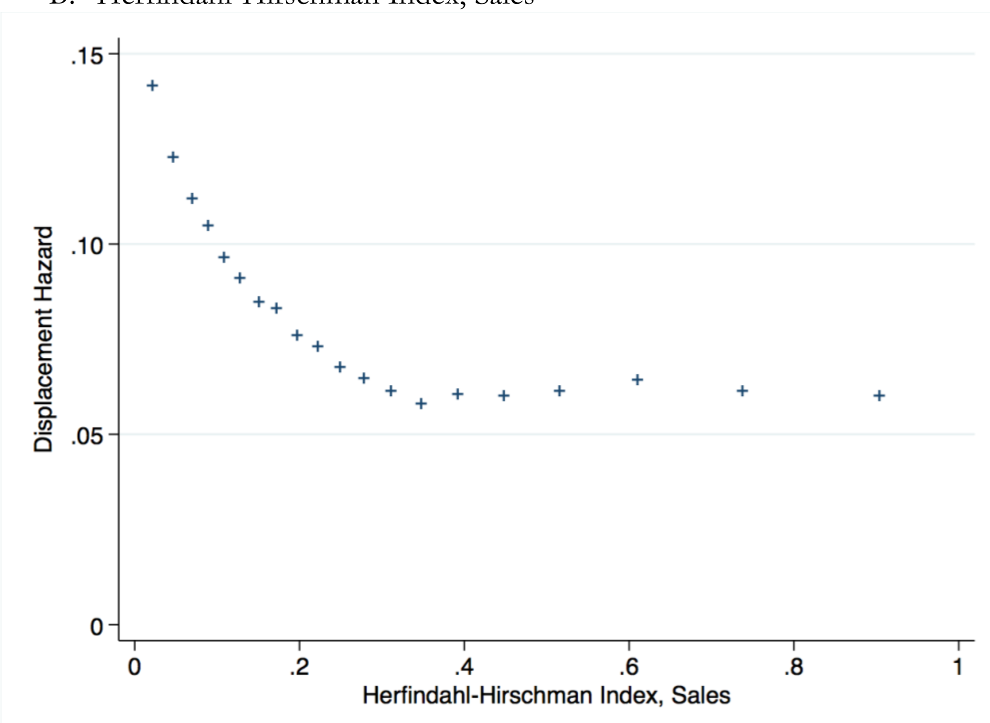
Figure 6. Mean Industry Displacement Hazard and Industry Concentration

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.

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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

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Sector displacement hazards

Table A2. Displacement Hazard from Top 4 Firms, Best-fit trend with single break

Data	Break year	Trend (α)	Change in trend (β)
Compustat Sector, (6-digit NAICS industries)			
Nondurable mfg.	2000	0.0017 (0.0008)**	-0.0052 (0.0016)***
Durable mfg.	1997	0.0032 (0.0007)***	-0.0059 (0.0011)***
Transport, utilities	2003	0.0012 (0.0009)	-0.0059 (0.0021)***
Trade, services	1998	0.0017 (0.0009)*	-0.0052 (0.0015)***
Finance	1999	0.0029 (0.0014)**	-0.0046 (0.0026)*
NETS Sector (8-digit SIC industries			
Farms	2007	0.0014 (0.0010)	-0.0068 (0.0034)*
Oil and gas extraction	2007	0.0010 (0.0020)	-0.0116 (0.0066)*
Mining, except oil and gas	1998	0.0019 (0.0020)	-0.0056 (0.0026)**
Support activities for mining	2000	0.0033 (0.0029)	-0.0063 (0.0041)
Construction	2002	0.0001 (0.0011)	-0.0022 (0.0019)
Transportation equipment	1998	0.0051 (0.0042)	-0.0084 (0.0053)
Retail trade	1995	0.0064 (0.0026)**	-0.0080 (0.0028)***
Broadcasting and telecommunications	2005	0.0031 (0.0014)**	-0.0084 (0.0035)**
Securities, commodity contracts, and investments	2001	0.0035 (0.0021)*	-0.0069 (0.0033)**
Real estate	1997	0.0010 (0.0045)	-0.0040 (0.0054)
Management of companies and enterprises - Administrative and support services	2000	0.0015 (0.0019)	-0.0035 (0.0027)
Waste management and remediation services	2005	0.0004 (0.0015)	-0.0060 (0.0041)
Ambulatory health care services	1996	0.0055 (0.0049)	-0.0084 (0.0056)

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).

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Different production function estimations

Table A3. Displacement hazard using different productivity estimates

	Labor productivity	OLS	Ackerberg, Caves, Frazer	Levinsohn, Petrin	Olley, Pakes
Net PPE	-0.0366***	-0.0302***	-0.0253***	-0.0280***	-0.0284***
	(0.0023)	(0.0027)	(0.0027)	(0.0027)	(0.0027)
Intangibles	-0.0152***	-0.0262***	-0.0295***	-0.0273***	-0.0268***
	(0.0020)	(0.0028)	(0.0029)	(0.0029)	(0.0028)
Productivity	-0.0143***	-0.0945***	-0.0915***	-0.0889***	-0.0784***
	(0.0039)	(0.0078)	(0.0079)	(0.0081)	(0.0089)
Observations	29571	27097	27097	27097	26996
Adj. R-squared	0.082	0.093	0.091	0.091	0.087

Note: Dependent variable is displacement from top 4 firms ranked by sales. Standard errors clustered by firm in parentheses, * p<.1, ** p<.05, *** p<.01. Includes industry and year fixed effects. Independent variables are in logs.

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Markups and Industry Concentration

Table A4. 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)	
Lag markup x sector					
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, Eeckhout, and Unger 2020.

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Table A5. 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.

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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).

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