Technical Appendix

Capital Depreciation and Industry Competition:

Theory and Evidence

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This Technical Appendix provides additional material for the paper *Capital Depreciation and Industry Competition: Theory and Evidence*.

In Appendix A, we discuss the measurement of key variables. Then, in Appendix B, we present a number of robustness checks cited in the paper. Finally, in Appendix C, we present the proofs of analytical results, as well as outlining the analytical basis for the computational algorithm used in the paper. See the next page for a detailed table of contents.

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A Measurement of Variables

In this section, we describe the measurement of the key variables in the paper, including markups (Appendix A.1) and depreciation (Appendix A.2).

A.1 Markup Calculations

We calculate firm-level markups of price over marginal cost following the production approach as presented in De Loecker et al. (2020). This approach is based on the framework of De Loecker and Warzynski (2012) that integrates insights from Hall (1988). Unlike the standard approach in the Industrial Organization literature which derives markups from the first order condition of optimal pricing combined with price-elasticities of demand and assumptions on how firms compete, this approach is not conditioned on the specification of the demand system nor assumptions on firm competition.

According to this production approach, markups are backed out from the cost minimization conditions of a variable input of production. At time t, firm i minimizes costs based on a production function that transforms the vector of variable inputs $\mathbf{V}$ and capital stock K_{it} into output Q_{it}. While individual variable inputs vary and might include labor, intermediate inputs, materials... due to the nature of variable input reporting in Compustat, we treat all individual variable inputs as a *bundle*, and thus the vector $\mathbf{V}$ of variable inputs as a scalar V.

Following De Loecker et al. (2020), markup is defined as $\mu = \frac{P}{\lambda}$ where P is the price of the output good and λ is the Lagrange multiplier of the Lagrangian objective function associated with the firm's cost minimization. The Lagrange multiplier is considered a direct measure of marginal cost as it represents the value of the objective function as output constraints are loosened.

From a rearrangement of the first order condition with respect to the variable input V and plugging in the fraction that expresses λ, the formula to calculate markup can be obtained as follows:

$$\mu_{it} = \theta_{it}^{v} \frac{P_{it} Q_{it}}{P_{it}^{V} V_{it}} \tag{1}$$

where θ_{it}^{v} is the output elasticity of bundle of variable inputs V, P_{it} is the price of the output good, and P_{it}^{V} is the price of the variable input bundle V. θ_{it}^{v} measures the sensitivity of output to changes in variable inputs and can be derived from the first order condition of the Lagrangian objective function for cost minimization of the firm:

$$\theta_{it}^{v} \equiv \frac{\partial Q(.)}{\partial V_{it}} \frac{V_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^{V} V_{it}}{Q_{it}} \tag{2}$$

where $Q(.)$ represents the technology of production or the form of the production function.

We can break down equation 1 that expresses markups into two components: (i) the output elasticity of the variable input bundle θ_{it}^{v} and (ii) the ratio of revenue from selling the output good $(P_{it} Q_{it})$ to the cost of the variable input bundle $(P_{it}^{V} V_{it})$. The second component can be calculated from the Compustat database as it records both net sale (revenue) and the cost of goods sold (cost of the variable input bundle). It remains a task to estimate the first component which is θ_{it}^{v}.

There are a couple of methods to estimate the output elasticity of the variable input of production. One major method, which is more quantitatively rigorous, is to estimate θ_{it}^{v} from a parametric production function. According to this method, the output elasticity of the variable input bundle is the coefficient of the variable input bundle in the production function with this variable input bundle and capital as inputs. The estimation of the production function, at the same time, adopts standard techniques in the literature[1] to address potential endogeneity issues which arise from the presence of the determinants of production e.g. productivity shocks that are observable to the firm but not observable to an econometrician. Accordingly, the identification strategy would happen through a two-stage approach where a control function of optimal input (static) or investment (dynamic) demand is inverted to allow us to control for unobserved productivity shocks. De Loecker et al. (2020) find that results obtained using either the static or dynamic processes are very similar to each other.

While following these standard practices, De Loecker et al. (2020) consider both time-varying and sector-specific production function parameters for each of the 22 sectors at the 2 digit NAICS level. Thus, θ_{it}^{v} varies across sectors and across time under their assumptions. Multiplying this time-varying and sector-specific parameter by the ratio of revenue to cost of goods sold, we get measures of markups that varies across firms, allowing for the consideration of firm heterogeneity of markups in our analyses. The output elasticity of variable input of our interest is thus the

[1]Some well-known techniques have been proposed by Olley and Pakes (1996) Levinsohn and Petrin (2003), and Ackerberg et al. (2015)

parameter θ^V_{st} for each given industry s in the Cobb-Douglas production function that is estimated at the firm level as follows:

$$q_{it} = \theta^V_{st} v_{it} + \theta^K_{st} k_{it} + \omega_{it} + \epsilon_{it} \tag{3}$$

While this method helps overcome the potential biases in estimating the output elasticity variable, its implementation is operationally complex as it requires the identification of an optimal input decision, the inversion of which allows the econometrician to account for unobserved productivity shocks.

At the same time, the alternative method to estimate θ^v_{it} is to approximate it to the share of expenditures on the variable input bundle in total cost. This share is referred to as the "cost share" and is constructed by the ratio of cost of goods sold to the sum of cost of goods sold and cost of capital in our data. While this alternative method can be performed without the need to estimate the production function and thus circumvents the challenging identification issues, it requires time-invariant technological parameters and constant returns to scale in production.

As the main focus of our paper is to explore the role of technological characteristics of production in industry competition, we apply time-varying production function coefficients in order to better capture factor-driven technological changes and consequently the impact of variations in technological characteristics in our analyses. Thus we follow the former method to calculate the output elasticity of variable input that is backed out from the time-varying and sector-specific production function parameters, which is a major contribution of De Loecker et al. (2020). The production function method to calculate output elasticity of variable input bundle from time-varying technological parameters (which gives us the markup measure Mu_2) is used in parallel with our time-invariant measure (Mu_1) as a robustness check for our results. We also calculate another markup measure (Mu_3) with output elasticity measures backed out from a secondary production function (referred to as PF2) that includes overhead costs reported under "Selling, General and Administrative Expenses" (SG&A, denoted as XSGA in Compustat) apart from the baseline production specification 3 (PF1).

While we directly calculate the ratio of revenue to cost of goods sold using Compustat data, we use the output elasticity measures under specifications discussed above from the data published by De Loecker et al. (2020).

In addition, for our robustness checks, we also calculate an alternative markup measure ("cost share" markup) using the alternative method for calculating output elasticity of input (using cost shares). We show these results in Appendix B.6.

A.2 Measuring Depreciation

To begin, we discuss the measurement of depreciation. The Securities and Exchange Commission requires publicly traded companies to follow the Generally Accepted Accounting Principles (GAAP). Deviations from these principles are sanctionable, so we can assume that companies in Compustat do not follow significantly different approaches to measuring these variables.

The value of the capital stock in the denominator is the variable PPENT from Compustat, or Property Plant and Equipment as reported on company balance sheets. This is measured using accounting principles, not market valuations (for example, by valuing each asset based on its initial value minus depreciation). In turn, the value of depreciation is the variable DP from Compustat, which is Depreciation as reported on company income statements. Depreciation in accounting is an allocation of the value of an asset over a calculation of its expected lifetime, thus it adds up to 100 percent of the asset's initial value by construction. There is some flexibility over the exact method of allocation (e.g. "straight line" vs. "declining balance") but over the lifetime of a typical asset this will not matter so at low frequencies this measure should capture the depreciation rate regardless, provided the estimated asset lifespans are correct.

In this paper, we estimate our main specification using annual data to take advantage of the totality of the panel data available. Given that depreciation is essentially measured using estimates of asset lifetimes, this suggests that repeating the estimation using 10-year averages rather than annual data is important to check as well. These results are reported in Appendices B.4 and B.5. Nonetheless, the GAAP allow for revisions of asset lives based on events or circumstances that might impact them.

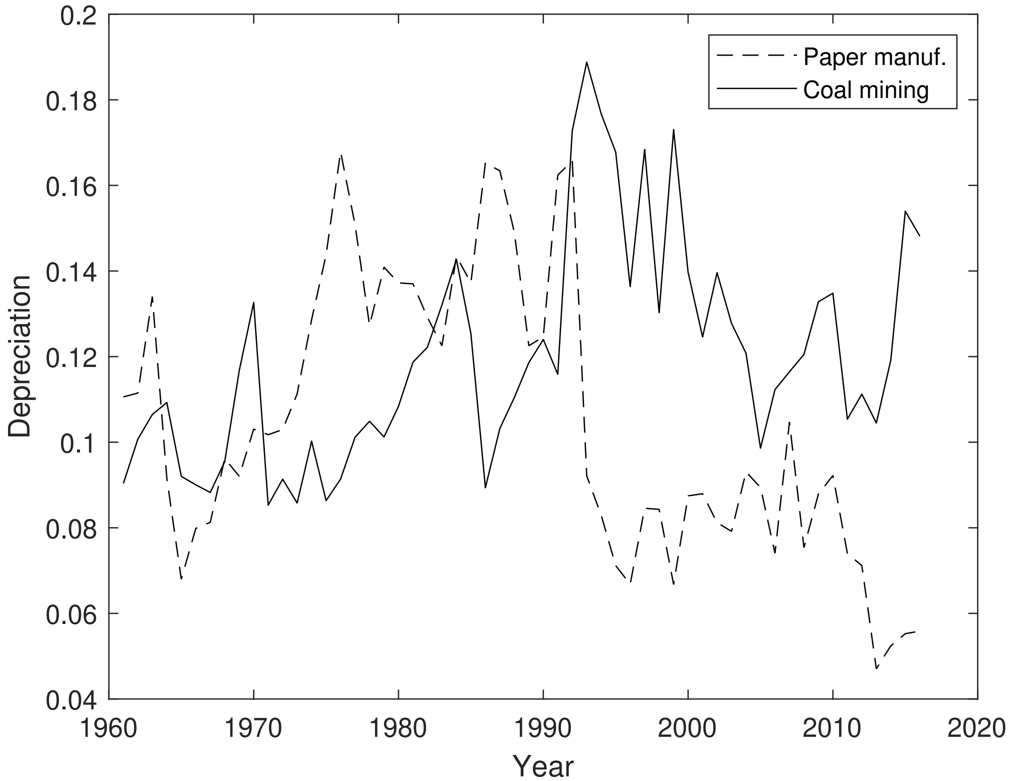
Since we make use of annual data, it is worth considering what kind of mechanisms might be behind time variation in depreciation at the firm or industry level. This could be high frequency variation, or lower frequency variation. For example, Figure S1 displays how depreciation rates change over time for a couple of industries, indicating that within industries there is indeed some variation in depreciation over time. There is a question of whether change over time is due to volatility of the numerator or the denominator. To discuss whether the numerator or the denominator is more volatile requires a measure of volatility. To measure the volatility of a variable, for each firm, we compute the standard deviation over the sample period and divide it by the mean. We find that the mean volatility of depreciation (the numerator) at the firm level is 0.65. The mean volatility of the denominator is 0.61. In this sense, it appears that the numerator and the denominator are of roughly equal importance.

Regarding the two industries in Figure S1, for Coal Mining the same statistics are 0.71 and 0.68, and for Paper Manufacturing they are 0.65 and 0.63. Thus, for these industries, it is also the case that the volatility of the numerator and the denominator are similar.

One reason depreciation might change over time is when there is a change in the use of different capital goods, which could occur at high frequency or could have secular components. In particular, it is known that IT diffused intensively starting in the mid-1970s, see Cummins and Violante (2002). In addition, the use of intangibles has also increased over time, see Corrado et al. (2009). Both IT and intangibles have relatively high depreciation rates. As a result, there is a question of whether we might be identifying industry trends in technology adoption. This is only a confounding issue if we believe that secular changes in IT or intangibles might lead to changes in competition through mechanisms other than changes in depreciation. Still, it suggests checking whether trends in depreciation are correlated with levels, and whether our results are robust to conditioning on IT adoption and intangibles intensity.

In fact, we find that the correlation between average depreciation and the average change in depreciation over the period at the 4 digit level is 19 percent. To condition

Figure S1: Examples of depreciation rates for paper manufacturing and for coal mining.



on the possibility of trends in technological variables that might affect both depreciation and competition, in Appendix B.9 we provide additional results controlling for IT investment and controlling for intangibles intensity.

Another possibility behind time variation in depreciation is natural factors. In particular, weather conditions - which range from mild to severe - are exogenous events that may affect the wear-and-tear of capital equipment, as are natural disasters - see (Strömberg 2007). In addition, power outages can also cause electronics to malfunction or fail - see Steinbuks (2012) - and these are often related to weather events such as lightning strikes - see Andersen et al. (2012). Less overt factors such as variation in humidity, tides, and other conditions could also lead to variation in the depreciation of equipment or structures. Human error, such as improper construction, could also lead to variation in the depreciation of structures or the depreciation of equipment housed in those structures,[2] or to the deterioration of equipment that is not operated properly. Improper maintenance is another possible factor of idiosyncratic depreciation. Some of these factors are location specific, but to the extent that industries vary by location, these factors could lead to industry variation in depreciation rates over time. Changes in regulation may also make particular kinds of capital obsolesce more rapidly, which might affect industries asymmetrically.

To explore the hypothesis that the weather could be an exogenous factor affecting depreciation, we compare firm level depreciation to weather-related damage in the geographic area where the firm is based. We obtain data on the cost of severe weather events (hail, wind and tornado damage) from 2016-2019 in different US

[2] A tragic reminder that this can occur is the Surfside building collapse of June 2021.

states and territories from the National Oceanic and Atmospheric Administration.[3] The summary statistics of the relevant variables are presented in Table S1 below.

Table S1: **Summary Statistics on the Data on Costs of Weather Damage**

Variable	Mean	Median	Nr Obs
Economic Cost of Hail	$33,661,963	$20,000	209
Economic Cost of Tornado	$22,257,207	$685,000	209
Economic Cost of Wind	$3,318,550	$1,370,000	209
Total Economic Cost of Weather Damage	$59,237,721	$4,504,500	209

Notes: Data are reported by the Storm Prediction Center of the National Weather Service of the National Oceanic and Atmospheric Administration.

We then regress the depreciation cost of each firm on the weather damage costs, as reported in the state where the firm is headquartered as reported in Compustat, including firm fixed effects and year dummy variables, clustering the standard errors by state. We find a positive and significant coefficient, as reported in Table S2 below.

Table S2: **Weather and Capital Depreciation**

	(1) Depreciation
Cost of Weather Damage	0.003***
	(0.001)
Year Fixed Effects	Yes
State Fixed Effects	Yes
N	17,869
R-squared	0.017

Robust standard errors in parentheses, clustered by industry
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

While the coefficient is small, there are many reasons why the magnitude of this

[3] The data are estimates of property losses. Data for earlier years exist but are not comparable. The combined data contain 17869 observations across 5646 firms in 52 US states and territories.

coefficient is not itself very informative. For example, much of the cost of weather events may be borne by infrastructure or households rather than firms, and some of the operations of firms may be located in other states. Nonetheless, the sign and significance of the coefficient offers suggestive evidence that there is a firm-level relationship between weather severe enough to have an economic impact on the one hand, and time-series variation in depreciation on the other. The broader point is that there are reasons why there might be relatively high-frequency variation in depreciation rates at the industry or firm level.

B Robustness Checks of Empirical Results

This Appendix shows the results of various robustness checks we perform that complement our main baseline results using the annual panel. Here we summarize the robustness checks.

Section B.1 presents the baseline regressions with other technological variables including R&D intensity, investment lumpiness and asset fixity instead of capital depreciation. These regressions result in statistically insignificant coefficients on these other technological variables, highlighting the robustness of the results of depreciation.

Section B.2 presents the baseline regressions with alternative control variables and with size variables in logs.

Section B.3 shows our robustness checks with datasets trimmed up to 2 percent and 3 percent of top and bottom values of the ratio of cost of goods sold to sales.

Section B.4 shows the results of the baseline regression when conducted with the decadal panel. Section B.5 shows the firm-level regression results of the baseline regression with the decadal panel. Results are robust in terms of sign but sometimes weaker in terms of statistical significance. This is not surprising, however, since the decadal panel contains only about one tenth of the observations in the annual panel.

Section B.6 presents our baseline regression with an alternative measure of markups ("cost share" markup) using the ratio of cost of goods sold to the sum of cost of goods sold and cost of capital as the approximation of the output elasticity of input - an alternative method for calculating markup according to De Loecker et al. (2020).

Sections B.7 and B.8 present further robustness checks by repeating the baseline regression with concentration measures including the Herfindahl-Hirchsman Index, and the number of firms as the dependent variable, respectively, instead of markups.

Section B.9 performs robustness checks on the baseline regression specification with additional four control variables including intangibles intensity, share of capital in sale, average wage and IT investment.

In section B.10, we rerun the regressions in section B.9 with fixed assets-weighted industry means of capital depreciation and markups. Section B.11 repeats the baseline regression at the firm level.

Section B.12 explores whether the markup-depreciation link is present in data for privately owned (not just publicly owned) firms. This is important not just to determine the robustness of the results on the basis of ownership status but also on the basis of size, as discussed in the main text. We focus on Scandinavia, as the requisite data are available for very few firms in other countries. It turns out that the results are robust for large firms, but not for small firms, consistent with the idea that the competitive environment of the smallest firms is different from that of the large players.

Finally, section B.13 presents the results linking the depreciation rate with the firm size as the dependent variable conditional on markups in Table 6, for the other markup measures (Mu_1 and Mu_3), with log variables for the regression of firm size measures over depreciation as well as results unconditional on markups.

B.1 Baseline Regressions with the Other Technological Variables

In this section, we examine whether replacing depreciation with other technological variables yields a significant coefficient. We look at R&D intensity (R&D), investment lumpiness (LMP) and asset fixity (FIX).

Table S3 show the regression results for each of the technological variables other than DEP (R&D, LMP, and FIX) with Mu_1 (time invariant, sector-specific, PF1), Mu_2 (time varying, sector-specific, PF1), and Mu_3 (time-varying, sector-specific, PF2) as markup measures, respectively.

Table S3: **Markups and Alternative Technological Variables**

	(1) Mu_1	(2) Mu_2	(3) Mu_3	(4) Mu_1	(5) Mu_2	(6) Mu_3	(7) Mu_1	(8) Mu_2	(9) Mu_3
R&D	0.005	0.004	0.021						
	(0.039)	(0.037)	(0.028)						
Investment lumpiness				-0.079	-0.047	-0.003			
				(0.060)	(0.058)	(0.044)			
Asset fixity							-0.128	-0.049	-0.038
							(0.116)	(0.108)	(0.082)
Advertising	0.086^{*}	0.077	0.070^{**}	0.101^{**}	0.082^{*}	0.080^{**}	0.100^{**}	0.081^{*}	0.079^{**}
	(0.052)	(0.049)	(0.034)	(0.051)	(0.048)	(0.035)	(0.051)	(0.048)	(0.035)
Employment share	-1.543	-0.525	-0.097	-1.557	-0.608	-0.344	-1.474	-0.564	-0.335
	(1.441)	(1.121)	(0.931)	(1.383)	(1.106)	(0.794)	(1.283)	(1.071)	(0.777)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9,864	9,870	9,885	11,340	11,346	11,359	11,337	11,343	11,356
R-squared	0.074	0.031	0.055	0.058	0.024	0.042	0.059	0.024	0.042

Robust standard errors in parentheses, clustered by industry

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Interestingly, despite demonstrated links between R&D intensity and competition in the literature, we do not find support for that notion, possibly indicating either no link or a non-linear link. As Aghion et al. (2005) find an inverted U-shaped relationship between innovation and competition. They measure competition using the HHI. As a result, it is not clear that their findings necessarily will be reflected in markups. We test this relationship by including the square of R&D intensity and find no supporting evidence as shown in Table S4 below.

Table S4: **Markups and the Square of R&D Intensity**

	(1) Mu_1	(2) Mu_2	(3) Mu_3
R&D	-0.068	-0.071	-0.024
	(0.055)	(0.050)	(0.037)
Square of R&D	0.018	0.018	0.011
	(0.011)	(0.011)	(0.009)
Advertising	0.087*	0.078	0.070**
	(0.052)	(0.049)	(0.034)
Employment share	-1.663	-0.648	-0.170
	(1.443)	(1.113)	(0.927)
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
N	9,864	9,870	9,885
R-squared	0.077	0.035	0.056

Robust standard errors in parentheses, clustered by industry
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.2 Alternative Controls

This section presents the baseline industry regression results with log controls and with alternative size variables in levels and logs for the annual panel.

Table S5 below presents the baseline industry results with the control variables specified in logs rather than levels:

Table S5: **Baseline Results Using Log of Advertising Expense and Log of Employment**

	(1) Mu_1	(2) Mu_2	(3) Mu_3
Depreciation	0.283***	0.183***	0.108**
	(0.067)	(0.060)	(0.046)
Log of advertising	0.015***	0.012***	0.009***
	(0.004)	(0.004)	(0.003)
Log of employment	-0.011	-0.009	-0.007
	(0.010)	(0.009)	(0.007)
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
N	11,087	11,090	11,100
R-squared	0.076	0.033	0.047

Robust standard errors in parentheses, clustered by industry
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table S6 below presents the baseline industry results using advertising expense and sale as control variables:

Table S6: **Baseline Results Using Advertising Expense and Sale**

	(1)	(2)	(3)	(4)	(5)	(6)
	Mu_1	Mu_2	Mu_3	Mu_1	Mu_2	Mu_3
Depreciation	0.284***	0.185***	0.109**	0.279***	0.179***	0.103**
	(0.067)	(0.059)	(0.046)	(0.067)	(0.059)	(0.046)
Advertising	0.122***	0.098**	0.094***			
	(0.047)	(0.047)	(0.034)			
Sale share	-2.719**	-1.812*	-1.561*			
	(1.158)	(1.028)	(0.813)			
Log of advertising				0.015***	0.013***	0.009***
				(0.004)	(0.004)	(0.003)
Log of sale				-0.014	-0.013	-0.010
				(0.014)	(0.012)	(0.009)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	11,292	11,294	11,304	11,154	11,156	11,166
R-squared	0.070	0.030	0.045	0.075	0.033	0.046

Robust standard errors in parentheses, clustered by industry

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table S7 below presents the baseline industry results using advertising expense and fixed assets as control variables:

Table S7: **Baseline Results Using Advertising Expense and Fixed Assets**

	(1) Mu_1	(2) Mu_2	(3) Mu_3	(4) Mu_1	(5) Mu_2	(6) Mu_3
Depreciation	0.282***	0.185***	0.109**	0.288***	0.186***	0.108**
	(0.067)	(0.059)	(0.046)	(0.066)	(0.058)	(0.046)
Advertising	0.109**	0.087*	0.084**			
	(0.044)	(0.046)	(0.033)			
Fixed assets share	-1.407**	-0.599	-0.452			
	(0.625)	(0.535)	(0.408)			
Log of advertising				0.011***	0.009**	0.007**
				(0.004)	(0.004)	(0.003)
Log of fixed assets				0.003	0.002	0.001
				(0.013)	(0.011)	(0.009)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	11,292	11,294	11,304	11,154	11,156	11,166
R-squared	0.070	0.030	0.044	0.074	0.032	0.045

Robust standard errors in parentheses, clustered by industry
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.3 Dataset Winsorized at 2% and 3% in terms of the Cost of Goods Sold to Sales Ratio

This section shows our robustness checks with datasets trimmed up to 2% and 3% respectively of top and bottom values of the ratio of cost of goods sold to sales. We run the same regressions for each markup measure over each of the technological variables (DEP, R&D, LMP and FIX) across four different versions of the dataset as shown below. The sign and significance of the coefficient on DEP is robust, showing that the trimming procedure is not responsible for the results.

Table S8: **Baseline Regressions on 2% Winsorized Dataset**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Mu_1	Mu_2	Mu_3	Mu_1	Mu_2	Mu_3	Mu_1	Mu_2	Mu_3	Mu_1	Mu_2	Mu_3
Depreciation	0.263***	0.180***	0.107**									
	(0.058)	(0.055)	(0.041)									
R&D				0.005	0.004	0.006						
				(0.061)	(0.058)	(0.034)						
Investment lumpiness							-0.033	0.005	0.030			
							(0.052)	(0.047)	(0.039)			
Asset fixity										-0.062	0.006	-0.008
										(0.098)	(0.093)	(0.069)
Advertising	0.099**	0.080*	0.078**	0.088*	0.077	0.069**	0.096*	0.079*	0.078**	0.096*	0.079*	0.078**
	(0.046)	(0.046)	(0.032)	(0.051)	(0.049)	(0.033)	(0.049)	(0.047)	(0.033)	(0.049)	(0.047)	(0.033)
Employment share	-1.186	-0.400	-0.285	-2.018	-1.051	-0.501	-1.771	-0.806	-0.472	-1.733	-0.811	-0.490
	(1.270)	(1.061)	(0.768)	(1.704)	(1.317)	(1.014)	(1.536)	(1.228)	(0.847)	(1.488)	(1.232)	(0.843)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11,205	11,207	11,210	9,824	9,825	9,836	11,309	11,312	11,323	11,306	11,309	11,320
R-squared	0.092	0.037	0.059	0.096	0.038	0.069	0.075	0.028	0.055	0.076	0.028	0.055

Robust standard errors in parentheses, clustered by industry

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table S9: **Baseline Regressions on 3% Winsorized Dataset**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Mu_1	Mu_2	Mu_3	Mu_1	Mu_2	Mu_3	Mu_1	Mu_2	Mu_3	Mu_1	Mu_2	Mu_3
Depreciation	0.237***	0.180***	0.107**									
	(0.052)	(0.055)	(0.041)									
R&D				-0.041	0.004	0.006						
				(0.077)	(0.058)	(0.034)						
Investment lumpiness							-0.016	0.005	0.030			
							(0.044)	(0.047)	(0.039)			
Asset fixity										-0.047	0.006	-0.008
										(0.082)	(0.093)	(0.069)
Advertising	0.056*	0.080*	0.078**	0.045	0.077	0.069**	0.054*	0.079*	0.078**	0.053*	0.079*	0.078**
	(0.030)	(0.046)	(0.032)	(0.030)	(0.049)	(0.033)	(0.032)	(0.047)	(0.033)	(0.032)	(0.047)	(0.033)
Employment share	-0.944	-0.400	-0.285	-1.577	-1.051	-0.501	-1.309	-0.806	-0.472	-1.287	-0.811	-0.490
	(1.114)	(1.061)	(0.768)	(1.305)	(1.317)	(1.014)	(1.242)	(1.228)	(0.847)	(1.206)	(1.232)	(0.843)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11,172	11,207	11,210	9,764	9,825	9,836	11,263	11,312	11,323	11,260	11,309	11,320
R-squared	0.101	0.037	0.059	0.108	0.038	0.069	0.082	0.028	0.055	0.082	0.028	0.055

Robust standard errors in parentheses, clustered by industry

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.4 Decadal Panel Industry Results

Table S10 below shows regression results of the baseline specification on the dedacal panel with decade and industry fixed effects rather than year and industry fixed effects.

Table S10: **Decadal Panel**

	(1) Mu_1	(2) Mu_2	(3) Mu_3
Depreciation	0.288***	0.198**	0.083
	(0.110)	(0.096)	(0.074)
Advertising	0.132*	0.097	0.101*
	(0.071)	(0.064)	(0.052)
Employment share	0.064	0.806	0.592
	(1.456)	(1.213)	(0.944)
Decade Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
N	1,494	1,493	1,496
R-squared	0.086	0.033	0.058

Robust standard errors in parentheses, clustered by industry
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.5 Decadal Panel Firm-level Results

In this section, we repeat our baseline analysis using firm level rather than industry level data. Here we perform the firm level estimation again, this time using the decadal panel. Results are robust for all three markup measures. It should be mentioned that the decadal results involve losing roughly an order of magnitude of observations, so the fact that the results are this robust is noteworthy.

Table S11: **Firm-level Results - Decadal Panel**

	(1) Mu_1	(2) Mu_2	(3) Mu_3
Depreciation	0.188***	0.175***	0.113***
	(0.058)	(0.054)	(0.042)
Advertising	0.066**	0.055**	0.053**
	(0.030)	(0.028)	(0.024)
Employment (Rescaled)	-0.228**	-0.198*	-0.151
	(0.113)	(0.110)	(0.110)
Decade Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
N	19,766	19,813	19,855
R-squared	0.021	0.012	0.009

Robust standard errors in parentheses, clustered by firm

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Employment has been divided by 1000 for ease of interpretation of the coefficients

B.6 Alternative Markup Measure ("Cost Share" Markup)

This section presents our baseline regression with an alternative measure of markups using the ratio of cost of goods sold to the sum of cost of goods sold and cost of capital as the approximation of output elasticity - the alternative method used for robustness in De Loecker et al. (2020). This regression also returns a positive and significant coefficient on capital depreciation with similar magnitude (0.29) to the regression with the markup measures presented in the main text (Table 4).

Table S12: **Baseline Regression with Alternative Markup Measure**

	(1) Costshare Markup Measure
Depreciation	0.297***
	(0.054)
Advertising	0.072*
	(0.042)
Employment share	-0.578
	(1.277)
Year Fixed Effects	Yes
Industry Fixed Effects	Yes
N	11,205
R-squared	0.113

Robust standard errors in parentheses, clustered by industry
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.7 Concentration Measures

In this section, we perform robustness checks using concentration measures instead of markups as a measure of competition. A common proxy for industry concentration is the Herfindahl-Hirchsman Index (HHI) of the market share of the largest 50 firms in terms of value added. In addition, we also examine the shares of value added of the largest 50, 20, 8 and 4 firms in an industry respectively as alternative concentration measures. These concentration ratios are calculated using Economic Census data that are available every five years, and are publicly available on the website of the Census Bureau.[4]

[4] https://www.census.gov/programs-surveys/economic-census/data/tables.html

HHI is calculated according to the following formula:

$$HHI = \sum_{i=1}^{N} s_i^2 \tag{4}$$

where s_i is the market share of firm i in the market, and N is the number of firms. For example, if there are two firms in an industry and each firm has 50% share of the market, the HHI would be equal to 2500. A higher value of HHI reflects a smaller number of firms i.e. a more concentrated industry. The maximum HHI value is $10,000$.

Our panel is constructed using data from three years (2002, 2007 and 2012) based on the availability of the Economic Census data. These data are then merged with the Compustat data of the same years to form a three-period panel dataset that contains all the required variables for our baseline specification, replacing markups with HHIs. Table S13 presents the summary statistics on the concentration measures.

Table S13: **Summary Statistics on Concentration Measures**

Variable	Acronym	Mean	Median	Nr Obs
HHI in terms of value added	HHI	442.74	300.20	247
Share of value added of largest 50 firms	Share of VA_50	66.97	69.7	247
Share of value added of largest 20 firms	Share of VA_20	54.71	55.05	250
Share of value added of largest 8 firms	Share of VA_8	40.97	40.40	250
Share of value added of largest 4 firms	Share of VA_4	30.55	28.70	250

We repeat the baseline regression with each of the five concentration measures instead of markups as the dependent variable. Note that these data are available for the manufacturing sector only, which limits the sample size of our analysis. For this regression, we use industry value added share as a control variable to condition on industry size, as value added is reported alongside concentration ratios in the Census data and are thus measured consistently.

First, results for HHIs are displayed in Table S14. The coefficient is positive and statistically significant, confirming the robustness of our results. Results for the other concentration measures are displayed in Table S15 below. We obtain robustly significant and positive results for these measures as well.

Table S14: **Baseline Regression with HHI as Dependent Variable**

	(1) HHI
Depreciation	488.853*
	(292.982)
Advertising	0.022
	(0.090)
Industry's share of value added	8204.014**
	(3398.398)
Year Fixed Effects	Yes
Industry Fixed Effects	Yes
N	226
R-squared	0.099

Robust standard errors in parentheses, clustered by industry
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table S15: **Baseline Regression with Share of Value Added (VA) of the Largest 50, 20, 8 and 4 Firms Respectively as Dependent Variable**

	(1) Share of VA_50	(2) Share of VA_20	(3) Share of VA_8	(4) Share of VA_4
Depreciation	15.140**	17.991**	19.113**	19.526**
	(6.502)	(7.634)	(8.887)	(9.765)
Advertising	0.001	0.001	0.002	0.001
	(0.002)	(0.001)	(0.002)	(0.002)
Industry's share of value added	249.968***	359.073***	411.424***	303.103**
	(71.917)	(89.242)	(91.493)	(133.660)
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
N	226	226	226	226
R-squared	0.238	0.258	0.241	0.132

Robust standard errors in parentheses, clustered by industry

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.8 Firm Number instead of Markup as Dependent Variable

In this section, we perform a robustness check with the *number of firms* in each industry at the NAICS 4-digit level instead of average markup as the dependent variable. Data tables on the number of firms in each industry at the NAICS 6-digit level were downloaded from the Statistics of U.S. Businesses (SUSB) section of the Census Bureau's website.[5] Data are available starting from 1998 so when we merge them with the Compustat data we obtain a panel dataset that covers years from 1998 to 2016. Then we re-run the baseline regression with the number of firms in each industry as the dependent variable instead of markups. We repeat this procedure with the number of firms in three different size bins: firms of all sizes (No. All Firms), firms with 20 or fewer employees (No. Firms < 20), and firms with 500 or

[5] https://www.census.gov/programs-surveys/susb.html

more employees (No. Firms 500+).

Before turning to the results, there are reasons why the number of firms is likely to be problematic for our purposes. The Census Bureau reports that there are several million firms active in the United States, the vast majority having few if any employees other than the business owner. For example, according to the Census Bureau, in 2018 there were $6,075,937$ firms in the United States, of which 61 percent have 4 or fewer employees and of which 89 percent have 19 or fewer employees. Thus, the total number of firms includes large numbers of tiny firms that likely provide some sort of services for larger entities in the industry or even in other industries. These entities are unlikely to be capital intensive due to financing constraints (see Beck et al. (2005)), so depreciation is not likely to be very important for them, and other considerations likely determine their numbers. These businesses are also unlikely to have any significant market power, and are also likely distributed unevenly across industries. As a result, the number of firms could vary across industries and over time for reasons unrelated to the factors that drive variation in competition and markups, which are determined by the major players. Indeed, it is possible that the determinants of competition that might lower the number of large players could in fact provide openings for small players to enter and pick up the crumbs. In addition, the larger firms are more likely to operate in many industries, making industry classification more noisy.[6] This was one of the reasons why we used unweighted (rather than size-weighted) depreciation rates in our baseline analysis.

[6] See https://www.bls.gov/opub/mlr/2016/article/establishment-firm-or-enterprise.htm

Table S16: **Firm Number Regression**

	(1) No. All Firms	(2) No. Firms < 20	(3) No. Firms 500+	(4) Log No. All Firms	(5) Log No. Firms < 20	(6) Log No. Firms 500+
Depreciation	2902.737**	2757.459**	22.292**	0.040	0.043	0.060
	(1241.616)	(1149.687)	(10.118)	(0.049)	(0.059)	(0.051)
Advertising	-1129.069	-994.846	-5.534	-0.159**	-0.148*	-0.048
	(1190.968)	(1073.141)	(10.614)	(0.079)	(0.077)	(0.124)
Employment share	15981.439	31100.349	-83.689	13.335	13.279	4.663
	(144729.778)	(125644.833)	(1425.922)	(8.269)	(10.111)	(5.879)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	3,821	3,820	3,821	3,821	3,820	3,821
R-squared	0.038	0.037	0.018	0.065	0.051	0.084

Robust standard errors in parentheses, clustered by industry

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As shown in Table S16 above, we find a significant and *positive* coefficient on capital depreciation rates when we use the number of firms in the industry as a dependent variable. This is the opposite of what we might expect if higher depreciation makes it harder to enter. It is consistent with our hypothesis that the number of firms is a channel through which depreciation might affect markups, but that the actual number of firms as reflected in the data is not suitable for measuring this directly due to the large number of small firms that swamp the number of large players in any given industry, as well as possibly making the classification of such firms to individual industries harder. We verify this by repeating the regression with the number of firms with under 20 employees, finding the same result. We also try with firms with 500+ employees, again finding the same result - which is not surprising since 500 is an arbitrary number which likely does not identify the firms in the industry with market power. This suggests that the competitive environment for the majority of (small) firms is quite different from that of market leaders, something that would be interesting to explore in future research.[7] Later in Appendix B.12, we will see further evidence that the competitive environment for smaller firms is very different from that affecting larger, more dominant firms.

[7] We also performed the same robustness checks with the number of establishments as the dependent variable and obtained similar results.

B.9 Additional Controls

We perform robustness checks on the baseline regression specification with additional four control variables including intangibles intensity, capital intensity (measured using the share of capital in sales), average wages (as an indicator of human capital intensity) and IT investment intensity. As discussed in the text, some of these variables are thought to be related to fixed costs, while the use of relatively rapidly-increasing intangibles and IT investments has increased over time, and these might be correlates of depreciation.

Data on IT intensity (i.e. amount of investment) by industry are obtained from the US Bureau of Economic Analysis (BEA) fixed asset tables. We define IT investment as the sum of expenditure on Mainframes, Personal Computers, Direct Access Storage Devices, Printers, Terminals, Tape drives, Storage devices, System integrators, Communications equipment, Office and accounting equipment, Computer systems, and Software. We define IT intensity as expenditure on IT investment divided by total investment.

The data to calculate intangibles intensity, capital intensity and average wage are taken from the Compustat database. The level of intangible intensity is calculated by taking the ratio of intangible assets to total assets (INTAN/AT) for each firm. The average wage is calculated by taking the ratio of staff expense (XLR - a proxy for labor cost) to total employment (EMP) at each firm. The share of labor cost in sale is calculated by dividing labor cost by sale (XLR/SALE), then capital intensity is calculated by subtracting 1 by the share of labor. After calculating the variables at the firm level, we take the mean value of each variable across all the firms in each 4-digit NAICS industry for each year from 1961 to 2016, and merge these with the IT intensity data. We repeat the baseline regression specification with these additional control variables.

Table S17 below shows summary statistics for these additional control variables. The summary statistics for the variables used to calculate them are presented in Table 1.

Table S17: **Summary Statistics of Additional Control Variables (1961-2016)**

Variable	Mean	Median	Nr Obs
Intangibles Intensity	.08	.04	16,981
Capital Intensity	0.52	0.72	9,471
Average Wage (Per Worker)	$64,197	$26,716	9,019
IT Intensity	0.13	0.08	17,686

Notes: Industry means and medians are reported.

Cross-industry correlations between depreciation, markup measures and additional control variables, as shown in Table S18 below are slightly different (e.g. correlation correlations between depreciation and markup variables are a bit higher) from those shown in Table 2 due to the fact that IT intensity was taken from the BEA dataset, which uses BEA industry groupings. BEA industry groupings largely follow NAICS but in some cases multiple NAICS correspond to one BEA industry code. This results in fewer industries in the merged dataset, resulting in slightly different cross-industry correlations. Still, broad patterns of relationships between our key variables of interest stay robust.

Table S18: **Cross-Industry Correlations of Markup, Technological Variables and Additional Control Variables**

	Mu_1	Mu_2	Mu_3	DEP	INT	CAP	AVW	ITI
Mu_1	1							
Mu_2	0.9529***	1						
Mu_3	0.9022***	0.9444***	1					
DEP	0.4639***	0.3833***	0.2618**	1				
Intangible Share (INT)	0.1046	0.0883	-0.0309	0.5857***	1			
Capital Intensity (CAP)	0.0997	0.1298	0.1607	-0.0204	-0.0243	1		
Average Wage (AVW)	0.1485	0.1233	0.0499	0.0917	0.1864	0.0335	1	
IT Intensity (ITI)	0.3584***	0.2859**	0.2234*	0.6582***	0.3047**	0.1323	0.4919***	1

** $p<0.1$, ** $p<0.05$, *** $p<0.01$*

The regressions are presented in Table S19 in the next page. As we can see, the coefficient on capital depreciation remains positive and significant with additional control variables, demonstrating the robustness of our results.

Table S19: **Baseline Regression with Additional Controls**

	(1) Mu_2	(2) Mu_2	(3) Mu_2	(4) Mu_2
Depreciation	0.237***			
	(0.064)			
R&D		0.017		
		(0.034)		
Investment lumpiness			-0.170	
			(0.126)	
Asset fixity				-0.248*
				(0.135)
Advertising	0.096**	0.082*	0.095**	0.095**
	(0.038)	(0.044)	(0.042)	(0.042)
Employment share	1.258	0.960	0.727	0.802
	(1.049)	(1.562)	(1.012)	(0.885)
Intangible share	0.107	0.365***	0.262**	0.166
	(0.119)	(0.131)	(0.107)	(0.131)
Capital intensity (Rescaled)	0.710*	0.742*	0.603*	0.593*
	(0.374)	(0.388)	(0.317)	(0.335)
Average wage (Rescaled)	-0.011***	-0.009***	-0.009***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
IT intensity	0.017	0.100	0.072	0.072
	(0.133)	(0.167)	(0.151)	(0.147)
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
N	6,226	5,786	6,275	6,275
R-squared	0.047	0.048	0.042	0.042

Robust standard errors in parentheses, clustered by industry

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Capital intensity and average wage variables have been divided by 1,000 and 1,000,000 respectively for ease of interpretation of the coefficients

It is interesting to observe that the coefficient on average wages is *negative*. If one thought that simply having higher marginal costs would decrease competition in the same manner as depreciation, this would suggest the opposite finding should be expected. However, to understand how labor costs might impact competition, consider that generally higher wages are awarded to agents who have higher human capital, so that a higher wage does not necessarily mean that a firm is paying more for the same labor services - whereas a higher depreciation rate does mean that the firm is paying a higher gross interest rate for essentially the same capital services, as shown in the model. For example, in an efficiency wage framework, a person who is paid \$20 delivers twice as much efficiency units of labor as someone paid \$10. As a result, firms paying higher wages would hire correspondingly fewer workers as all they need is a certain amount of efficiency units of labor: their total costs would be identical even though their wages were higher. In such a world, the average wage would have no link with competition.

Thinking about human capital raises the question of whether the rate of depreciation of *human* capital might be a factor of competition. If human capital intensity, i.e. the average wage, is related to more rapid human capital depreciation, we might expect a *positive* coefficient on the average wage. Since we do not find such a coefficient, this suggests several possibilities. One is that these two variables are simply not related. Another is that, if they are related, the link between human capital depreciation and competition is weakened by several factors. For example, since human capital is inalienable (see Hart and Moore (1994)), it is not an asset that the firms own, and it takes a long time to create as it is embodied in humans who may have several decades of training. Also, a lot of evidence indicates that labor markets have many frictions that might create wedges between the price of labor and its productivity, including search delays, informational frictions about worker and job properties, bargaining frictions, and so on. At the same time, this is ultimately an empirical question. This would be difficult to show without detailed data at the individual level suitable for measuring human capital and its depreciation. The recent study of Dinerstein et al. (2022) provides for the first time estimates of the depreciation rate of human capital on average, so the profession has yet to develop depreciation rates of human capital by sector, field or occupation, all of which would be of value to the literature.

The following two tables present robustness checks with Mu_1 and Mu_3:

Table S20: **Baseline Regression with Additional Controls - Robustness check with** Mu_1

	(1)	(2)	(3)	(4)
	Mu_1	Mu_1	Mu_1	Mu_1
Depreciation	0.324***			
	(0.068)			
R&D		0.024		
		(0.036)		
Investment lumpiness			-0.227	
			(0.139)	
Asset fixity				-0.290*
				(0.147)
Advertising	0.113***	0.097*	0.112**	0.112**
	(0.040)	(0.050)	(0.047)	(0.046)
Employment share	0.758	0.351	-0.020	0.086
	(1.188)	(1.893)	(1.221)	(1.011)
Intangible share	0.266*	0.599***	0.471***	0.357**
	(0.143)	(0.161)	(0.137)	(0.158)
Capital intensity (Rescaled)	0.922**	0.963**	0.781**	0.775**
	(0.441)	(0.439)	(0.358)	(0.383)
Average wage (Rescaled)	-0.010***	-0.008***	-0.008***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
IT intensity	-0.003	0.123	0.079	0.083
	(0.147)	(0.198)	(0.176)	(0.173)
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
N	6,223	5,780	6,268	6,268
R-squared	0.103	0.109	0.096	0.095

Robust standard errors in parentheses, clustered by industry

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Capital intensity and average wage variables have been divided by 1,000 and 1,000,000 respectively for ease of interpretation of the coefficients

Table S21: **Baseline Regression with Additional Controls - Robustness check with** Mu_3

	(1) Mu_3	(2) Mu_3	(3) Mu_3	(4) Mu_3
Depreciation	0.120**			
	(0.050)			
R&D		0.043*		
		(0.023)		
Investment lumpiness			-0.083	
			(0.091)	
Asset fixity				-0.155
				(0.110)
Advertising	0.081***	0.074***	0.081***	0.082***
	(0.026)	(0.025)	(0.029)	(0.028)
Employment share	0.696	1.215	0.472	0.503
	(0.873)	(1.413)	(0.874)	(0.821)
Intangible share	0.088	0.286***	0.177*	0.118
	(0.103)	(0.107)	(0.098)	(0.118)
Capital intensity (Rescaled)	0.490*	0.635**	0.372	0.363
	(0.261)	(0.286)	(0.261)	(0.269)
Average wage (Rescaled)	-0.009***	-0.008***	-0.008***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
IT intensity	-0.104	-0.068	-0.077	-0.078
	(0.110)	(0.128)	(0.116)	(0.114)
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
N	6,234	5,796	6,286	6,286
R-squared	0.055	0.067	0.056	0.057

Robust standard errors in parentheses, clustered by industry

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Capital intensity and average wage variables have been divided by 1,000 and 1,000,000 respectively for ease of interpretation of the coefficients

B.10 *Additional Controls with Fixed Assets-Weighted Means of Markups and Capital Depreciation*

In our baseline results, we report results using unweighted measures of markups and depreciation. This section repeats the regressions from section B.9 with fixed assets-weighted means of markup measures and capital depreciation - so, in a sense, we are looking at the average unit of capital rather than the average firm in the dataset. We first trimmed the top and bottom 1% values of the size variable to avoid having outliers drive the results, then we weighted firm measures of capital depreciation and markups by its share of assets out of total sales in each industry before taking the means for each four NAICS digit industry. Then, we repeat the regressions from section B.9 with these fixed assets-weighted means instead of the regular means at the industry level. Data in use are from 1961 to 2016. Table S22 below shows summary statistics on these fixed assets-weighted variables.

Table S22: **Summary Statistics of Fixed Assets-Weighted Variables - Industry Panel**

Variable	Acronym	Mean	Median	Nr Obs
Weighted Capital Depreciation Rate	DEP	.1417	.1197	17,232
Weighted Firm Markup (Time-Invariant, PF1)	Mu_1	1.4413	1.2955	17,232
Weighted Firm Markup (Time-Varying, PF1)	Mu_2	1.3770	1.2386	17,232
Weighted Firm Markup (Time-Varying, PF2)	Mu_3	1.1177	1.0122	17,232

Notes: Industry-level statistics are reported. Data are from 1961 to 2016.

Regression results are presented in Table S23 below, which shows positive and significant results for all three measures of markup. Thus, our results are robust to using both weighted and unweighted measures.

Table S23: **Baseline Regression with Additional Controls and Fixed Assets-Weighted Means**

	(1) Weighted Mu_1	(2) Weighted Mu_2	(3) Weighted Mu_3
Weighted capital depreciation	0.678**	0.564**	0.428*
	(0.290)	(0.282)	(0.225)
Advertising	0.155**	0.131*	0.102
	(0.077)	(0.071)	(0.065)
Employment share	-16.641	-10.879	-10.132
	(18.930)	(17.989)	(13.094)
Intangible share	0.200	0.036	-0.003
	(0.240)	(0.225)	(0.170)
Capital intensity (Rescaled)	0.283	-0.013	-0.045
	(0.365)	(0.486)	(0.412)
Average wage (Rescaled)	-0.001	-0.003***	-0.004***
	(0.001)	(0.001)	(0.001)
IT intensity	0.025	0.127	-0.047
	(0.283)	(0.264)	(0.203)
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
N	6,229	6,241	6,254
R-squared	0.108	0.059	0.079

Robust standard errors in parentheses, clustered by industry

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Capital intensity and average wage variables have been divided by 1,000 and 1,000,000 respectively for ease of interpretation of the coefficients

B.11 Firm-level Regression

In this subsection, we rerun the baseline regression at the *firm* level instead of industry level as a robustness check.[8] We use firm employment to replace industry's employment share out of total of all industries as a control variable. Summary statistics for key variables at the firm level have been provided in Table 1. According to the regression results presented in Table S24 below, the coefficient on capital depreciation is positive and significant at the 5% level for both Mu_1 and Mu_2 which is our main markup measure while it remains positive for Mu_3, demonstrating the overall robustness of our results.

Table S24: **Baseline Regression at the Firm Level**

	(1) Mu_1	(2) Mu_2	(3) Mu_3
Depreciation	0.055**	0.042**	0.026
	(0.023)	(0.020)	(0.017)
Advertising	0.082***	0.075***	0.061***
	(0.025)	(0.023)	(0.019)
Employment (Rescaled)	-0.232**	-0.182**	-0.134
	(0.094)	(0.083)	(0.084)
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
N	85,965	86,294	86,573
R-squared	0.031	0.027	0.023

Robust standard errors in parentheses, clustered by firm

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Employment has been divided by 1000 for ease of interpretation of the coefficients

[8] For firm-level regressions, we use a 5% cutoff threshold for the markup variables as there are many outliers.

B.12 Robustness Checks Using the Orbis Dataset

Our baseline data are drawn from Compustat. A concern regarding the generality of our results arises from the fact that Compustat focuses on publicly traded firms, which are also likely to be large. There is also a question of whether the results are US-specific.

To examine whether the industry correlation between depreciation and markups persists outside our baseline context, we draw on Orbis, a database published by the Bureau van Dijk which surveys large numbers of firms around the World. The use of Orbis is not straightforward since coverage varies significantly by country and, even for countries with many firm observations, the number of firms reporting the data required to compute both depreciation and markups is not necessarily sufficient. For example, given that we have a few hundred industries, we would want at least two orders of magnitude more firms in order to have confidence that our industry measures are reasonably well identified, yet even large economies such as Germany, France, Italy and the UK reported fewer than $10,000$ firm-year observations with the requisite data. We settled on using data for the Scandinavian countries (Denmark, Norway and Sweden), where a large number of firms report the necessary data ($22,877$ firms, for a total of $251,647$ firm-year observations for the years 2012-2022).[9].

First of all, we find that the overall correlation between depreciation and markups in these data is 0.147, which is positive and significant at the 5% level. Second, since

[9]The output elasticity of inputs we use is the measure that varies across industries but not across time from De Loecker et al. (2020) (so the measure is analogous to Mu_1)

the objective is to see whether the depreciation-markup link varies by size, we sort the firms into quartiles by size (measured using assets). We use each quartile to construct industry measures by size. We find that there is a statistically significant correlation between depreciation and markups when these variables are measured among the largest quartile. However, interestingly, this relationship is not seen in the other quartiles. This is consistent with the idea that smaller firms may be fundamentally different from large firms, either because they provide services to the larger ones (i.e. there is vertical disintegration among smaller firms) or because they use fundamentally different technology, as argued by Holmes and Stevens (2014). It is also consistent with the idea that smaller firms are more likely to be credit-constrained, as in Beck et al. (2005), and might thus be less capital-intensive, in which case depreciation would matter less for them. The bottom line is that our finding applies to larger more dominant firms that account for the bulk of output - whether publicly traded or not - but not to smaller firms, for whom the competitive environment appears different in ways that would be interesting to explore in future research. Finally, it is interesting to note that, at the firm level, the depreciation-markup link is the opposite when we look at the smallest firms. Like Appendix B.8, this suggests that the competitive environment for the smallest firms is very different from that of dominant firms, something that would be interesting to explore in future work.

Table S25: **Correlations of Markup and Depreciation - Orbis**

	Overall	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Industry Correlation	0.1542**	-0.0112	-0.0055	0.0888	0.1796***
Industry P-value	0.0123	0.8710	0.9344	0.1769	0.0054
Firm Correlation	-0.0308***	-0.0668***	-0.0709***	0.0080	0.0542***
Firm P-value	0.0000	0.0000	0.0000	0.5550	0.0004

** p<0.1, ** p<0.05, *** p<0.01*

B.13 Firm Size and Depreciation Regressions: Robustness Checks

In Table 6, we discuss how a depreciation-driven model of competition implies that, conditional on markups, higher depreciation results in smaller firms. We did so in the main text using the markup measure Mu_2, to show a prediction of a depreciation-based model of competition that is distinct from one driven by fixed costs. Specifically, conditional on markups, we would expect higher depreciation to be related to smaller firms if it is related to marginal costs, but not if it is related to fixed costs.

Here, we show that the result is robust to using other markup measures. We also report regression results with the level of the size variables specified in logs for both the results unconditonally on markups and those conditionally on each markup measure (see Tables S26, S27 and S28 in the following two pages). This is also consistent with the model, since firm size declines with depreciation in general until the point where a new dominant player finds it profitable to enter, as in Figure 2.

Table S26: **Impact of Capital Depreciation on Log of Firm Size Variables Unconditionally on Markups and Conditionally on Mu_2 Respectively**

	(1)	(2)	(3)	(4)	(5)	(6)
	Log of employment	Log of sale	Log of fixed assets	Log of employment	Log of sale	Log of fixed assets
Depreciation	-0.333***	0.130***	-2.156***	-0.368***	0.092***	-2.214***
	(0.032)	(0.033)	(0.041)	(0.033)	(0.034)	(0.042)
Mu_2				-0.020	0.170***	0.134***
				(0.013)	(0.015)	(0.013)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	270,566	312,692	312,692	258,601	298,195	298,195
R-squared	0.102	0.463	0.433	0.098	0.471	0.438

Robust standard errors in parentheses, clustered by firm

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table S27: **Impact of Capital Depreciation on Firm Size - Conditionally on** Mu_1

	(1)	(2)	(3)	(4)	(5)	(6)
	Employment	Sale	Fixed Assets	Log of Employment	Log of Sale	Log of Fixed Assets
Depreciation	-1.848**	-805141.522***	-1132635.220***	-0.371***	0.090***	-2.225***
	(0.810)	(208781.205)	(94889.277)	(0.033)	(0.034)	(0.042)
Mu_1	-0.361*	-233087.973***	-142336.930***	-0.016	0.167***	0.128***
	(0.191)	(82021.165)	(45139.716)	(0.012)	(0.014)	(0.012)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	260,831	298,612	298,612	258,814	298,612	298,612
R-squared	0.023	0.067	0.065	0.099	0.474	0.441

Robust standard errors in parentheses, clustered by firm

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table S28: **Impact of Capital Depreciation on Firm Size - Conditionally on** Mu_3

	(1) Employment	(2) Sale	(3) Fixed Assets	(4) Log of Employment	(5) Log of Sale	(6) Log of Fixed Assets
Depreciation	-1.801**	-797001.382***	-1128076.388***	-0.368***	0.094***	-2.212***
	(0.809)	(209421.833)	(94878.078)	(0.033)	(0.034)	(0.042)
Mu_3	-0.362	-216225.169**	-112637.471*	-0.018	0.230***	0.179***
	(0.274)	(104783.056)	(60269.415)	(0.016)	(0.018)	(0.016)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	260,565	298,195	298,195	258,601	298,195	298,195
R-squared	0.023	0.067	0.064	0.098	0.472	0.438

Robust standard errors in parentheses, clustered by firm

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C Analytical Results

The following material substantiates the analytical results in the paper, and also provides additional results that are useful for the computation algorithm.

C.1 Proofs

The household solves the static problem

$$\max_{\{c_{j,n}\}} \left(\int y_j^{\frac{\sigma-1}{\sigma}} dj\right)^{\frac{\sigma}{\sigma-1}},$$
$$s.t. \int p_j y_j dj = I,$$

where p_j is the price of good j and I the income of the household. Optimality requires that the following first order condition hold almost everywhere:

$$y_j^{\frac{\sigma-1}{\sigma}-1}\left(\int y_j^{\frac{\sigma-1}{\sigma}} dj\right)^{\frac{\sigma}{\sigma-1}-1} = \lambda p_j$$

or

$$y_j^{\frac{-1}{\sigma}} \mathbf{y}^{\frac{1}{\sigma}} = \lambda p_j$$

Raising both sides to the power of $1-\sigma$ we obtain that

$$y_j^{\frac{\sigma-1}{\sigma}} \mathbf{y}^{\frac{1-\sigma}{\sigma}} = \lambda^{1-\sigma} p_j^{1-\sigma}.$$

Integrating both sides over j we obtain

$$\lambda^{1-\sigma} \int p_j^{1-\sigma} dj = 1.$$

Finally defining the price index for consumption as P (i.e. the shadow price of consumption in terms of income), we obtain that

$$P \equiv 1/\lambda = \left(\int p_j^{1-\sigma} dj \right)^{\frac{1}{1-\sigma}}.$$

The first order condition can then be rearranged as

$$y_j = \left(\frac{p_j}{P} \right)^{-\sigma} \mathbf{y} \tag{5}$$

Finally to see that this is the correct interpretation of P as a price index for the aggregate good $\mathbf{y}$, observe that local non-satiation implies that

$$\int p_j y_j dj = I,$$

or, using (5),

$$\int p_j \mathbf{y} \left(\frac{p_j}{P} \right)^{-\sigma} dj = I.$$

Rearranging, we obtain

$$\begin{aligned} \mathbf{y} \left(\frac{1}{P} \right)^{-\sigma} \int p_j^{1-\sigma} dj &= I \\ \mathbf{y} P^{\sigma} P^{1-\sigma} &= I \\ \mathbf{y} P &= I. \end{aligned}$$

Proof of Proposition 1. The first order condition for investment is

$$u'(\mathbf{c}_t) = \beta u'(\mathbf{c}_{t+1}) \left[r_{j,t+1} + 1 - \delta_j \right].$$

Since in equilibrium consumption is constant over time the result follows immediately.

■

Proof of Proposition 2. We begin by showing that, in equilibrium, $N(\delta_j)$ is a lower-hemicontinuous step function that is weakly decreasing in δ_j. This proof follows from the fact that V is decreasing in N and decreasing in δ_j. Hence, given δ, the highest N that satisfies the free entry condition $V_h((N-1)y_h) \geq c_e w_t$ must be weakly decreasing in δ_j. V is continuous in parameters, so that there must exist a value of δ_j such that the entry cost is satisfied with equality. Call this δ_N. This implies that for sufficiently small $\varepsilon > 0$ we have that $N(\delta_N - \varepsilon) = N(\delta_N)$: on the other hand, for any $\varepsilon > 0$, $N(\delta_N + \varepsilon) < N(\delta_N)$.

The result follows from the fact that the markup equals $\frac{1}{1-1/\varepsilon_j} = \frac{\sigma N_j}{\sigma N_j - 1}$. ■

C.2 Computational Algorithm Outline

First, take w and I as given. Using equation (7) the firm's static profits $\pi\left(\widehat{Y}_{-h}|j\right)$ can be written

$$\pi\left(\widehat{Y}_{-h}|j\right) = \max_{k,l}\left\{zk^{\alpha}l^{1-\alpha}\left(\frac{zk^{\alpha}l^{1-\alpha}+\widehat{Y}_{-h}}{I}\right)^{\frac{-1}{\sigma}} - wl - r_j k - w\kappa\right\}. \tag{6}$$

The first order conditions are:

$$p(l)y_l + yp'(y)y_l = w, \tag{7}$$

and

$$p(l)y_k + yp'(y)y_k = r_j. \tag{8}$$

Further derivations show that

$$p'(y) = \frac{-1}{\sigma}\frac{1}{I}\left(\frac{y+\widehat{Y}_{-k}}{I}\right)^{\frac{-1-\sigma}{\sigma}},$$

and

$$y_l = (1-\alpha)\,y/l,\; y_k = \alpha y/k.$$

Now suppose that in the industry there are $N_j \in \mathbb{N}^*$ firms. If within industries all firms are identical then (7) and (8) respectively imply that

$$(1-\alpha)\,(y)^{\frac{\sigma-1}{\sigma}}\left[\left(\frac{N}{I}\right)^{\frac{-1}{\sigma}} - \frac{1}{\sigma}\frac{1}{I}\left(\frac{N}{I}\right)^{\frac{-1-\sigma}{\sigma}}\right] = wl, \tag{9}$$

and

$$\alpha\left(y\right)^{\frac{\sigma-1}{\sigma}}\left[\left(\frac{N}{I}\right)^{\frac{-1}{\sigma}}-\frac{1}{\sigma}\frac{1}{I}\left(\frac{N}{I}\right)^{\frac{-1-\sigma}{\sigma}}\right]=r_{j}k. \tag{10}$$

These combine to determine the optimal capital-labor ratio $\tilde{k}$:

$$\tilde{k}_{j}\equiv\frac{k_{j}^{*}}{l_{j}^{*}}=\frac{w\alpha}{r_{j(1-\alpha)}}. \tag{11}$$

Replacing this into (9) we obtain

$$l_{j}^{*}=w^{-\sigma}\left[z^{\frac{\sigma-1}{\sigma}}\left(1-\alpha\right)\left(\frac{w\alpha}{r_{j(1-\alpha)}}\right)^{\alpha\frac{\sigma-1}{\sigma}}\left[\left(\frac{N}{I}\right)^{\frac{-1}{\sigma}}-\frac{1}{\sigma}\frac{1}{I}\left(\frac{N}{I}\right)^{\frac{-1-\sigma}{\sigma}}\right]\right]^{\sigma} \tag{12}$$

Thus, given values of w and I and N, we can compute l_{j}^{*} and k_{j}^{*}. Then, if $y^{*}\left(N\right)$ is the output produced by a firm when there are N firms present, then

$$\pi\left(\widehat{Y}_{-h}|j\right)=\pi\left(\left(N-1\right)y^{*}\left(N\right)|j\right)-w_{t}\kappa$$

and

$$V_{h}\left(\widehat{Y}_{-h,t+1}|j\right)=\pi\left(\left(N-1\right)y^{*}\left(N\right)|j\right)\div\left(1-\beta\left(1-\delta_{f}\right)\right)$$

Using this, in each industry we find the optimal number of firms using:

$$N^{*}\left(\delta_{j}\right)=\max\left\{N\in\mathbb{N}^{*}:V_{h}\left(\left(N-1\right)y^{*}\left(N\right)|j\right)\geq c_{e}w\right\}.$$

Define

$$\mathbf{N}=\left\{N\in\mathbb{N}^{*}:\exists\delta\in\left[\underline{\delta},\bar{\delta}\right]\text{ with }N=N\left(\delta_{j}\right)\right\}.$$

Proposition 1 (Supplemental)**.** *In equilibrium, there exists a decreasing function* $\Delta^* : \mathbf{N} \to \mathbb{R}^+$ *such that the number of firms in the industry is at least* $N \in \mathbb{N}^*$ *if* $\delta \leq \Delta^*(N)$*. For values of* $\Delta^*(N)$ *in the interior of* $\left[\underline{\delta}, \overline{\delta}\right]$*,* $\Delta^*(N)$ *is continuous in* w*.*

Proof of Proposition 1. (Supplemental) We are assuming an equilibrium exists, so $\mathbf{N} \neq \varnothing$. For each $N \in \mathbf{N}$ define

$$\Delta^*(N) = \sup\left\{\delta_j \in \left[\underline{\delta}, \overline{\delta}\right] : V_h\left((N-1)\, y^*(N)\,|j\right) = c_e w\right\}.$$

The first result follows from the fact that $N(\delta_j)$ is decreasing and lower hemicontinuous. The second result follows from the continuity of decision rules in the wage.

■

So far we have assumed a value for w, and a guess of income I. We assume capital markets clear using Walras' law: given $N^*(\delta_j)$ and k_j^* we can compute the total capital of each tyle. Then, it should be clear that l_j^* is strictly decreasing in w in all industries and that N is weakly decreasing in w. Thus labor demand is strictly decreasing in w. To see this, note that labor demand is

$$\begin{aligned} L_d &= \int l_j^* N^*(\delta_j)\, dF(\delta) \\ &= \sum_{N \in \mathbf{N}} \int l_j^* N \times \mathbf{1}\left[\Delta^*(N+1) < \delta \leq \Delta^*(N)\right] dF(\delta) \end{aligned}$$

where $\mathbf{1}$ is the indicator function. In equilibrium L_d must be continuous in the wage as $\Delta^*(N)$ is continuous in the wage. Labor supply is

$$L_s = 1 - c_e \epsilon - \kappa \mu.$$

The total mass of firms is

$$\begin{aligned}\int d\mu_t &= \int N^*(\delta_j)\, dF(\delta_j) \\ &= \sum_{N \in \mathbf{N}} \int N \times \mathbf{1}\left[\Delta^*(N+1) < \delta \leq \Delta^*(N)\right] dF(\delta)\end{aligned}$$

so that

$$\epsilon = \delta_f \mu.$$

As we raise w we lower the labor demand of each firm, and also lower the number of firms, so L_d is strictly decreasing in w between zero and infinity. Lowering the number of firms lowers ϵ, also between zero and infinity, so the labor supply is weakly increasing, so given I there must be a wage that clears the labor market. This could be a candidate wage as long as c_e is not so high that entry is not profitable in the first place: then there would be no firms (the L_d curve should be truncated at some point where entry is not profitable).

Finally, let I_n be our initial guess of income I. Having used it to derive the model decision rules, we can compute income implied by this guess, which is

$$I_{n+1} = w_t (1 - c_e \epsilon - \kappa \mu) + \int r_{jt} k_{jt} dj + \Pi(\mu_t).$$

We solve for equilibrium by using I_{n+1} as a new guess, and iterating on the above procedure until $\|I_{n+1} - I_n\| < \varepsilon$ for some tolerance level ε.

Finally, assuming we have found an equilibrium, we can show that

Proposition 2 (Suppemental)**.** *If $\Delta^* (N)$ is in the interior of $\left[\underline{\delta}, \bar{\delta}\right]$, the value of $\Delta^* (N)$ is continuous in parameters.*

Proof of Proposition 2. (Supplemental) The result follows from the fact that $N(\delta_j)$ is decreasing and lower hemicontinuous, and the continuity of decision rules in the relevant parameters. ■

This implies that the equilibrium value of I will be continuous in parameters as well. The model thus allows us to have an integer number of firms in each industry and endogenous rents while having a continuous response of aggregates to policy variables. This is a useful result as it implies that the model framework is suitable for policy experiments.

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