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Abstract: It is widely held that more productive firms grow faster, thus reallocating resources and raising aggregate productivity. Yet little empirical research identifies the features of the mechanisms affecting this process. This paper develops and tests a general model encompassing several mechanisms used to overcome informational frictions to growth. We find that firm size, productivity dispersion, and large firm investments in intangibles are all significantly related to changes in firm growth in response to productivity. These factors can account for much of the decline in the response to productivity since 2000 (Decker et al. 2020). Also, industry concentration is directly related to aggregate productivity growth.

JEL codes: L13, L15, D22, D24

Keywords: information technology, productivity growth, firm growth, industry concentration

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Introduction

Schumpeter asserted that competition in the form of "creative destruction," is "the powerful lever that in the long run expands output and brings down prices" (1942, 85). Firms with new technologies or better sources of supply or superior organizations grow and displace incumbents, bringing the benefits of higher productivity. Large theoretical and empirical literatures draw on Schumpeterian ideas regarding innovation, firm growth and survival, productivity, and economic growth (for a partial review see Cohen 2010). The link between aggregate productivity growth and reallocation to more productive firms is well-established (Foster, Haltiwanger, and Krizan 2001). The dynamic impact of competition on innovation and subsequent productivity growth also features centrally in the literature on competition policy (Gilbert 2006; Shapiro 2011).

Yet relatively little empirical research has detailed the specific mechanisms by which more productive firms grow and eventually displace market incumbents. This paper presents an empirical model that identifies key factors affecting how firm growth responds to productivity and we test the role of these factors in a broad sample of firms.

Understanding just how productivity relates to firm growth is important for two reasons. First, it can help explain recent shifts in the reallocation to productive firms—Decker et al. (2020) find that firms grow more slowly in response to productivity shocks since 2000 and that this slowdown substantially contributes to the slower growth of aggregate productivity. Second, such analysis can shed light on the relationship between competition and productivity growth. A large literature looks at the link between competition and innovation incentives in industrial economies and the economics of innovation (Cohen 2010 for a review), growth theory (Aghion and Griffith 2005; Aghion et al. 2005), and policy (Gilbert 2006; Shapiro 2011). Yet incentives are only part of the story.

They have little effect on aggregate productivity unless the innovation diffuses and/or the firm grows. Evidence suggests that these things are not happening quickly or automatically.[1]

The problem is that firms do not immediately "disrupt" incumbents upon introducing a highly productive innovation, as is sometimes assumed in the literature. The reallocation literature finds that more productive firms grow *somewhat* faster than less productive firms (and are less likely to exit) but this appears to be an extended process (Caves 1998 provides a review). For instance, Foster et al. (2016) find that industry entrants have greater technical efficiency than older firms, but much smaller size of demand. Demand grows over time but this process extends for more than a decade at least (see also Dunne, Roberts, and Samuelson 1988; Cabral and Mata 2003). In studies that look separately at the effects of demand and of technical efficiency, it appears that differences in demand across producers are the dominant factors affects firm growth and survival (Foster, Haltiwanger, and Syverson 2008; 2016). It has long been recognized that demand adjusts slowly as seen, for example, by differences between long-run and short-run demand elasticity.

But what factors affect the rate of this adjustment? A variety of theoretical models attribute slow demand growth to informational frictions (Radner 2003; Rob and Fishman 2005; Bar-Isaac and Tadelis 2008; Arkolakis 2010; Dinlersoz and Yorukoglu 2012; Drozd and Nosal 2012; Perla 2013; Gourio and Rudanko 2014; Foster, Haltiwanger, and Syverson 2016).[2] Consumers lack the information they need to switch to better quality/lower priced products, but they gain that information through various communication or search

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[1] In addition to the slowdown in reallocation shown by Decker et al. (2020), Andrews et al. (2016) and Akcigit and Ates (2021) find evidence of a declining rate of diffusion with far-ranging effects.

[2] Another set of papers models firm growth as the result of firms learning about their productivities over time (Jovanovic 1982; Ericson and Pakes 1995; Hopenhayn 1992). Given the productivity realization, growth is determined, so these models do not explain factors that affect the relationship between productivity and growth.

mechanisms. Foster, Haltiwanger, and Syverson (2016) implement one of these models in microdata.[3] In their model, firm demand is a function of the firm's past customer base, but they do not model a specific mechanism.

Our model accommodates a variety of possible mechanisms—word-of-mouth, trial-and-error search, and advertising. Under some assumptions, the surplus that consumers gain from a firm's product is homomorphic to that firm's revenue productivity. This means that the consumer's choice over which firm offers greater consumer surplus (higher quality at lower price) can be recast as a choice over which firm has higher revenue productivity. This allows us to relate the level of lagged firm revenue productivity to firm sales growth. While many standard models relate the *change* in productivity—productivity shocks—to firm growth, our model relates the lagged *level* of revenue productivity and firm growth, which is critical for understanding reallocation.

Furthermore, our model identifies several factors that affect the response of firm growth to productivity, including firm market share, the overall dispersion of productivity, and firm investments in product differentiation. It is straightforward to implement our model empirically. We find that each of these factors is economically and statistically significant. Indeed, they can account for about half of the decline in the rate at which firms grow in response to high productivity since 2000. Each of these factors can be related to market competition conditions, suggesting that considerations of productive reallocation might be important in antitrust analysis. In particular, we show that under some conditions,

[3] A related literature looks at the links between productivity and firm survival (Syverson 2004; Foster, Haltiwanger, and Krizan 2006; Foster, Haltiwanger, and Syverson 2008).

industries with higher Hirschman-Herfindahl concentration indexes will tend to have slower productivity-enhancing reallocation.

This paper makes several contributions to the literature. First, we build a model of slow adjustment of demand that relates revenue productivity to subsequent firm growth. This model identifies several firm and industry characteristics that affect the rates at which firms grow. Second, we test key predictions of the model empirically, finding both statistical and economic significance. In particular, the model can account for much of the decline in reallocation identified by Decker et al. (2020). Third, the model relates industry concentration to the rate at which reallocation increases aggregate productivity. This has important implications for competition policy.

Model

Our model aims to explore how firms grow based on their productivities when demand is subject to communication or search frictions. The basic setup it this: consumers have price information on all products in the market, but they lack information on the quality of products that they have not consumed. A learning process conveys information about a new product to some, but not all, consumers each year. This learning process could take the form of word-of-mouth communication, trial-and-error search, or advertising communication. Once informed about the quality of another firm's product, consumers compare the consumer value offered by the new product relative to their current product. They switch if the new product has superior consumer surplus.

Specifically, there are *N* firms in an industry, each making a single competing product of differing quality. Firm *i* has product quality Q_i. We initially assume that there are identical consumers, of mass 1. Each consumer selects a firm and purchases the good of only that firm in varying quantities.

There are two periods. In period 1, consumers have been pre-assigned to a firm by some historical process so that firm *i* has a share of consumers of S_{i1}. In period 2, consumers can switch firms. We assume that while customers know the prices that all firms charge, they do not know the qualities of all firms' products. Specifically, we assume that a consumer can know the expected quality Q_{i2} for firm *i* in period 2 only if: a) the consumer purchased from firm *i* in period 1 and hence knows Q_{i1}, or b) the consumer receives some communication that lets them form expectations about period 2 consumer surplus.

Communication

However, this communication process is constrained so that not all consumers receive new information. We can model it in a variety of ways:

1. Word-of-mouth. δ pairs of consumers exchange information about their current product choices by word-of-mouth, each member of the pair selected randomly. If they currently consume different products, they will compare and the consumer with the inferior product will switch.
2. Trial-and-error search. Manufacturers sell through retail stores. On average, each retail store will stock products in proportion to the market share of the manufacturers. Each period, δ consumers choose to evaluate a new product by randomly selecting one from retail shelves (thus in proportion to that firm's market share). If the evaluation favors the trial product, the consumer switches.
3. Advertising. Firms broadcast informative advertising messages at some cost. Consumers receive multiple ad messages from different firms, but given limited attention, δ randomly chosen consumers randomly choose one message they received to select a product to evaluate. If firm *i* broadcasts m_i messages, the probability that a consumer who pays attention will evaluate its product is

$\frac{m_i}{\sum_{j=1}^{N} m_j}$. We assume, consistent with casual evidence, that a firm's share of advertising messages equals its share of period one customers, S_{i1}.[4]

These models each generate an equivalent reallocation equation. In the word-of-mouth model, δS_{i1} consumers of firm *i* communicate with other consumers of whom $1 - S_{i1}$ are customers of other firms. Thus, the number of pairs of consumers who communicate with each other where one is a customer of firm *i* and the other is not is $\delta S_{i1}(1 - S_{i1})$.[5] Note that these models make a critical assumption: once a consumer is selected to receive information, the probability that the consumer receives information on any particular firm is proportional to that firm's share of customers. This property ensures that the distribution of firms is not entirely dominated by small firms.

Consumption

Each consumer purchases a variable quantity from their chosen firm. Each consumer's demand is an isoelastic function of product quality and price, *P*,

$$D = QP^{-\epsilon}, \quad \epsilon > 1 \tag{1}$$

yielding a consumer surplus of

$$V(Q, P) = \int_P^\infty Qx^{-\epsilon}dx = \frac{QP^{-(\epsilon-1)}}{\epsilon - 1} \tag{2}$$

[4] Advertising expenditures tend to average a constant share of sales over several orders of magnitude of firm size (see, for example, Dinlersoz and Yorukoglu 2012, Table 1). In our data, regressing log advertising expenditure against log sales with controls for industry and year, using a Heckman sample selection model to correct for firm non-reporting and firm exit, the coefficient on log sales is .997 (.008).

[5] For the search and advertising models, $\delta(1 - S_i)$ consumers not currently at firm *i* consider switching and of these, S_i will consider firm *i*'s product. At the same time, δS_i consumers from firm *i* will consider switching and of these, $1 - S_i$ will compare a product from another firm.

Production

Firms produce output per consumer $Y = A \cdot K$ where A is technical efficiency and K is capital per consumer (or alternatively a constant-returns-to-scale Cobb-Douglas composite). Equating demand to output and inverting equation (1), revenue per customer

$$R = PY = e^{\omega} K^{\frac{1}{\mu}}, \quad \omega \equiv \frac{\ln Q}{\epsilon} + \frac{\ln A}{\mu}, \quad \mu \equiv \frac{\epsilon}{\epsilon - 1}$$

where ω is (log) revenue productivity. We assume that both technical efficiency, A, and product quality, Q, are pre-determined, although they likely result from past firm investments.[6] Total firm revenue $R^{TOT} \equiv S \cdot R$ is related to total capital $K^{TOT} \equiv S \cdot K$ as

$$\ln R^{TOT} = \omega + \frac{1}{\mu} \ln K^{TOT}.$$

We estimate a version of this revenue production function below.

Total profits are the profits made on each customer times the size of the customer base, $S = S(P)$,

$$\Pi = S(P) \cdot (PY - WK)$$

where W is the user cost of capital. We designate the customer base as a function of price because the price that each firm charges in period 2 will affect how many customers switch to that firm. That is, the firm faces a dynamic tradeoff between increasing the profit per customer and increasing the number of customers in period 2. The firm sets prices as a monopolist and the consumer is a price-taker. Equating demand with output and substituting equation (1), the profit maximizing price for period 2 is (see Appendix)

[6] Our model is purely a demand side model. In a more dynamic, long term model with supply-side considerations, prospects for firm growth likely affect innovation incentives.

$$\hat{P} = \frac{\mu W}{A}\left[1 - \frac{1}{1 - \frac{\partial \ln S}{\partial P} \cdot \frac{P - W/A}{\epsilon - 1}}\right]. \quad (3)$$

The term in front of the brackets is the standard result from static optimization (ignoring growth of the customer base) where μ is the average markup. The second term in brackets represents the discount that firms offer to keep current customers and to attract new ones. Evidence suggests that firms do indeed offer lower prices in order to induce growth (Foster, Haltiwanger, and Syverson 2016).

The discount makes it difficult to solve equation (3) analytically and it also implies that productivity estimates will be biased. Fortunately, some evidence suggests that these discounts are not large. In a careful study of industries with homogenous products, Foster et al. (2008, 412) find that industry entrants—firms that presumably offer the greatest discounts because they have small customer bases—offer discounts of only 0.15% on average (3.88% in a revenue-weighted regression) after controlling for productivity differences. For now, we will assume that $\hat{P} \approx \frac{\mu W}{A}$. Below we test for evidence of discounts, finding that their effect on our main estimates is small.

With this assumption, using the static optimal price, we can write customer surplus from equation (2) as

$$V = \frac{e^{\epsilon \omega}}{(\epsilon - 1)(\mu W)^{\epsilon - 1}}.$$

This means that consumer surplus maps 1:1 to revenue productivity. That is, comparing two firms, consumers will choose to purchase from the one with higher revenue productivity.

Reallocation

We can now model customer switching. As above, $\delta S_{i1}(1 - S_{i1})$ pairs of consumers exchange information on the quality of products they consumed in period 1. Based on this information, they will choose the firm that has the highest expected consumer surplus/productivity in period 2. To implement this comparison, we assume as a first order approximation that $E[\omega_{i2}]$ is distributed uniformly in the range $\overline{\omega} \geq E[\omega_{i2}] \geq \underline{\omega}$ so that the probability density is $\frac{1}{Z}$, $Z \equiv \overline{\omega} - \underline{\omega}$. Variable Z represents the dispersion of consumer surplus. This distribution is common knowledge.

We can then calculate the growth of firm *i*'s customer base as follows. On average, of the consumers of firm *i* who communicate with consumers from other firms, $\frac{\overline{\omega} - E[\omega_{i2}]}{Z}$ will find better value at the other firm and these firm *i* consumers will switch; $\frac{E[\omega_{i2}] - \underline{\omega}}{Z}$ will find lower value at the other firm, so those other consumers will switch to firm *i*. The expected change in firm *i*'s customer base from period 1 to period 2 is then

$$\Delta S_i = \delta S_{i1}(1 - S_{i1}) \frac{E[\omega_{i2}] - \underline{\omega} - (\overline{\omega} - E[\omega_{i2}])}{Z}$$

Defining the mean productivity $\widetilde{\omega} = \frac{\overline{\omega} + \underline{\omega}}{2}$,

$$\Delta S_i = 2\delta S_{i1}(1 - S_{i1}) \frac{E[\omega_{i2}] - \widetilde{\omega}}{Z} \tag{4}$$

and the expected growth rate is

$$g \equiv \frac{\Delta S_i}{S_{i1}} = 2\delta(1 - S_{i1}) \frac{E[\omega_{i2}] - \widetilde{\omega}}{Z}. \tag{5}$$

The customer bases of high-productivity firms grow while those of low-productivity firms shrink. This equation thus describes reallocation to higher productivity firms. The absolute increase in market share for productive firms will be an inverted-U, that is, low for firms with small market shares, high for large firms (~50% market shares) and low again for extremely large firms (close to monopoly). The growth rate, *g*, of productive firms will be smaller for firms with large market share, S, and slower when productivity levels of firms are more widely dispersed (Z). There are two intuitions behind this behavior: first, a firm with large market share has relatively fewer prospective customers it can hope to acquire, so it grows relatively slower in response to productivity. Generally, of course, firm growth rates are seen to decline with firm size (see, for example, Jovanovic 1982; Evans 1987). Second, when productivity levels are dispersed, a firm must have relatively higher productivity in order to attract the same number of new customers.

Heterogeneous consumers

We now relax the assumption that consumers are identical. When consumers have heterogeneous needs, firms can make investments that differentiate their products and services. Firms can invest in R&D to make distinctive product characteristics, they can invest in information technology to increase the variety of goods or product features to meet disparate wants, they can advertise to appeal to certain consumers' distinctive identities, or they can add locations closer to consumers, shortening travel distance. Since Hotelling (1929), travel costs are a useful way to model consumer heterogeneity.

In the context of our model, consumers now choose between firms based on both the consumer surplus they derive from their purchases *and* on their travel costs. Suppose that firm *j* has made an investment that places them "closer" to consumers so that travel costs are *x* less to firm *j*. Then a consumer will choose firm *j* over firm *i* if $E[\omega_{i1}] < E[\omega_{j1}] + x$. Because consumer utility now has two dimensions—the consumption of goods and travel costs—consumers might actually prefer to consume less at firm *j* if the savings in travel costs are large enough. Revenue productivity is no longer a sufficient indicator of switching decisions.

Suppose the share of firms investing in locating closer to consumers is λ. These firms are randomly drawn from the original productivity distribution and their *effective* productivity increases by *x*. Then, if the firms offering inducements are randomly selected, the growth equation for firm *i* that doesn't offer the inducement is

$$\Delta S_i = 2\delta S_{i1}(1 - S_{i1})\frac{E[\omega_{i2}] - \widetilde{\omega} - 2\lambda x}{Z}$$

Not surprisingly, these investments slow the growth of other firms. To the extent that large firms have an advantage in this regard, these investments will tend to slow the grow of smaller firms. To the extent that these investments do not change productivity, they are sometimes called "business stealing" activities. Below we will test for evidence of firm investments altering consumer choices of firms.

Empirical implementation

We estimate a version of (5) in two steps. First, we obtain estimates of firm productivity each year, $\widehat{\omega}_{it}$, with the method of Ackerberg, Caves, and Frazer (2015) using a value-added production function with labor, net tangible capital, and intangible capital as factor inputs. Second, using the growth in total revenues as a proxy for the growth in customer base and assuming an AR1 process for productivity, $E[\omega_{i2}] = \rho \cdot \omega_{i1}$, equation (5) can be transformed to

$$\Delta \ln R_{it}^{TOT} \approx g_{it} = \alpha_{jt} + \beta^1 \widehat{\omega}_{it-1} - \beta^2 S_{it} \widehat{\omega}_{it-1} + \beta^3 S_{it} + \varepsilon_{it}. \qquad (6)$$

where *j* is industry. This equation expresses the response, in terms of firm revenue growth, to the level of lagged productivity. Additional terms can be added to capture product-differentiating investments.

Aggregate productivity growth

Because larger firms grow relatively less than smaller firms of comparable productivity, an industry dominated by large firms might perform worse in aggregate. We can, in fact, show this to be the situation for a base case. Let $\Omega \equiv \sum S_i \omega_i$ be aggregate (weighted average) productivity. Then the change in aggregate productivity from period 1 to period 2 can be decomposed as

$$\Delta\Omega \equiv \Omega_2 - \Omega_1 = \sum_{i=1}^{N} \Delta S_i \omega_{i1} + \sum_{i=1}^{N} \Delta\omega_i S_{i2}.$$

The first term represents the contribution of between-firm changes; the second term represents the within-firm changes in productivity. The second term depends on the correlation between firm productivity growth and firm size. A substantial literature looks at whether large firms are more or less innovative than small firms (see for example Cohen 2010) with somewhat mixed results. The first term captures the reallocation process we study here. Using equation (4) we have,

$$\sum_{i=1}^{N} \Delta S_i \omega_{i1} = \frac{2\delta\rho}{Z} \sum_{i=1}^{N} S_{i1}(1 - S_{i1})(\omega_{i1} - \widetilde{\omega}_1)\omega_{i1}$$

Assuming that productivity and customer base size are uncorrelated, ($\mathrm{cov}(S, \omega) = 0$) and that sample means correspond to expectations, suppressing subscripts,

$$E\left[\sum \Delta S\omega\right] = \frac{2\delta\rho N}{Z} E[S\omega^2 - S\,\widetilde{\omega}\omega - S^2\omega^2 + S^2\widetilde{\omega}\omega] \tag{7}$$

$$= \frac{2\delta\rho}{Z} \cdot \mathrm{var}(\omega) \cdot (1 - H), \qquad H \equiv \sum S^2$$

$$= \frac{\delta\rho}{\sqrt{3}} \cdot \mathrm{stdev}(\omega) \cdot (1 - H)$$

where H is the Hirschman-Herfindahl index.[7] Reallocation contributes less to aggregate productivity growth in more concentrated markets (ranked by size of customer base).

This finding, of course, is not general; it is based on the strong assumption that firm size and productivity are uncorrelated. If large firms become large because they are more productive (Demsetz 1973), then productivity might be correlated with firm market share. In that case, more concentrated industries might not have slower reallocation. Evidence shows that *labor* productivity tends to be correlated with firm size. Bartelsman, Haltiwanger, and Scarpetta (2013), surveying data from eight countries, find the covariance between firm labor productivity and firm share of employment tends to be positive, ranging from -.03 to .51, the latter figure for the United States (see also Leung, Meh, and Terajima 2008). However, labor productivity overstates the covariance between total factor productivity because larger firms tend to be relatively more capital intensive. In our data, the covariance between firm revenue size and labor productivity (revenue per employee) is .51, but that declines to .02 when productivity is estimated with tangible capital and it further declines to -.07 when intangible capital is included. This suggests that at the very least equation (7) applies in some industries, although the covariance assumption must be determined on a case-by-case basis.

[7] The last equation using the variance of a uniform distribution, $Z^2/12$.

Data and Variables

Our main dataset consists of Compustat firms traded in US currency with positive sales, including firms with headquarters outside the US. The Compustat sample is, of course, highly selected. However, by using Compustat, we gain rich data on firms, including intangibles, that help test and validate our model, providing a foundation for research using more comprehensive data. We use years 1976 – 2018. To identify industries in these data, we use the historical NAICS (6 digit) 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. Revenues are deflated using BEA gross output deflators for each two-digit industry. Our basic sample covers 15,616 firms and 172,551 observations. See summary statistics in the Appendix.

We use two capital stocks in our analysis. Both are deflated and all are beginning-of-year stocks. For tangible capital, we use deflated net property, plant, and equipment from firm balance sheets. Peters and Taylor (2017) have developed measures of intangible capital based on three components: knowledge capital derived from R&D spending, organizational capital derived from Sales, General, and Administrative expenditures, and balance sheet intangibles. Our results depend critically on including intangibles in the production function. While the measure we use has been validated by multiple researchers (Eisfeldt and Papanikolaou 2013; 2014; Peters and Taylor 2017), we also test other measures for robustness (Appendix Table A4).

To compute firm productivity, we follow common practice (see Keller and Yeaple 2009), imputing intermediates and value added for the productivity estimates as follows: intermediates 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 intermediates.

Our preferred productivity measure uses value added as the dependent variable in the method developed by Ackerberg, Caves, and Frazer (2015). This method corrects for bias arising when firms adjust variable factors after observing their productivity. The Appendix shows alternative estimation methods (Table A2) and results for our basic regression relating sales growth to lagged productivity using these different estimates (Table A3). While the magnitude of the estimated effect changes with productivity measures, all are significant. Note that inclusion of both tangible and intangible capital is important for our estimates. We also obtained data on mergers and acquisitions from Thomson Reuters SDC Platinum database and matched these to Compustat.

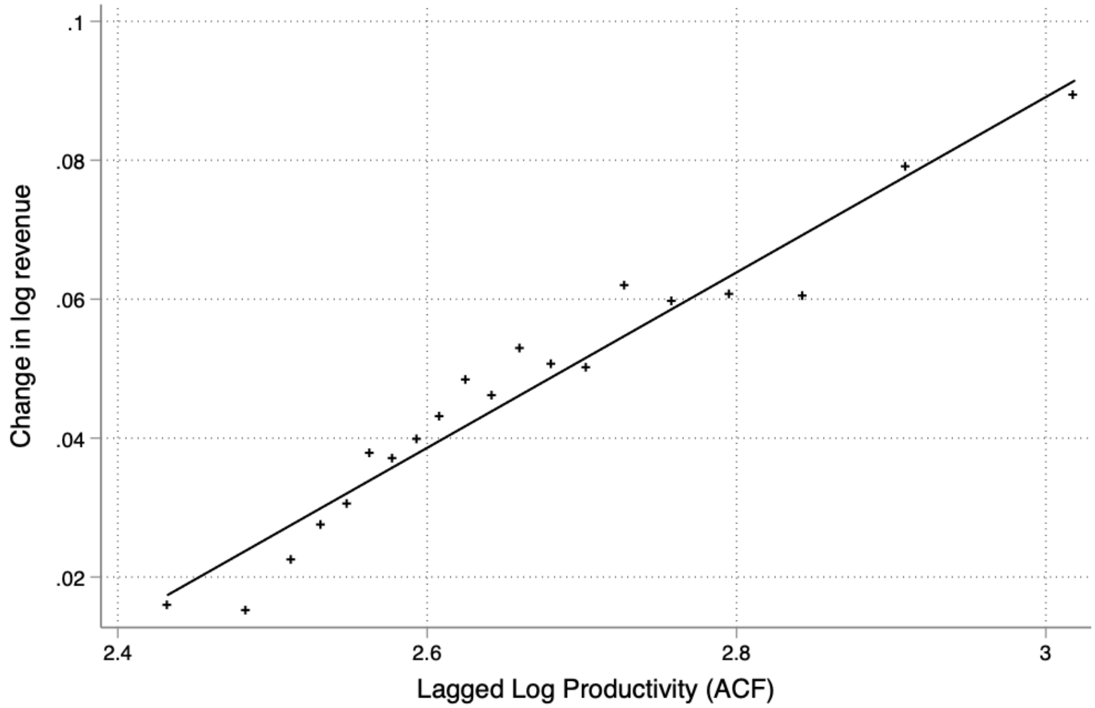

Figure 1. Binned Scatterplot of Firm Growth and Lagged Productivity. Controls for industry and year.

Findings

Growth Response to Productivity

If most firms have small market shares, then we can estimate an approximate version of equation (6) as

$$\Delta \ln R^{TOT} = \alpha_{jt} + \beta^1 \widehat{\omega}_{it-1} + \varepsilon_{it}.$$

This simple relationship can be seen in a binned scatterplot in Figure 1 and is presented in the regression in the first two columns of Table 1 with firm and industry fixed effects, respectively. The third column of the table adds individual year effects for each industry to control for common industry shocks.[8] These additional fixed effects improve the fit but have only a small effect on the slope of the response curve.

One concern noted above is that dynamically optimizing firms may offer prices less than the static optimizing price, tending to underestimate revenue productivity and to overstate the slope of firm growth relative to productivity. However, we know that these discounts decrease as firms build customer bases as they age (Foster, Haltiwanger, and Syverson 2016). To test for distortions related to age, column 4 adds a term interacting firm age with lagged productivity.[9] The slope of firm growth relative to productivity does, indeed, decrease with firm age, but the effect is not large, decreasing the baseline slope from .098 to .092. This suggests that discounting does not have a major effect.

Acquisition might distort our estimates. The model concerns firm "organic" growth realized by acquiring customers. To the extent that firms grow by acquiring other firms, instead, our dependent variable is measured in error. Column 5 adds two measures of acquisitions, the number of publicly announced mergers and acquisitions and balance sheet goodwill, which captures the value of acquisitions net of book value. Both have significant coefficients, but the slope coefficient increases slightly, as we would expect with measurement error.

Another concern is sample selection bias. Firm survival might be correlated with productivity, possibly biasing the productivity coefficient. To test this, we employ a Heckman sample selection model basing selection on the ratio of long-term debt to the sum of debt plus common equity and also on the independent regression variables. Presumably,

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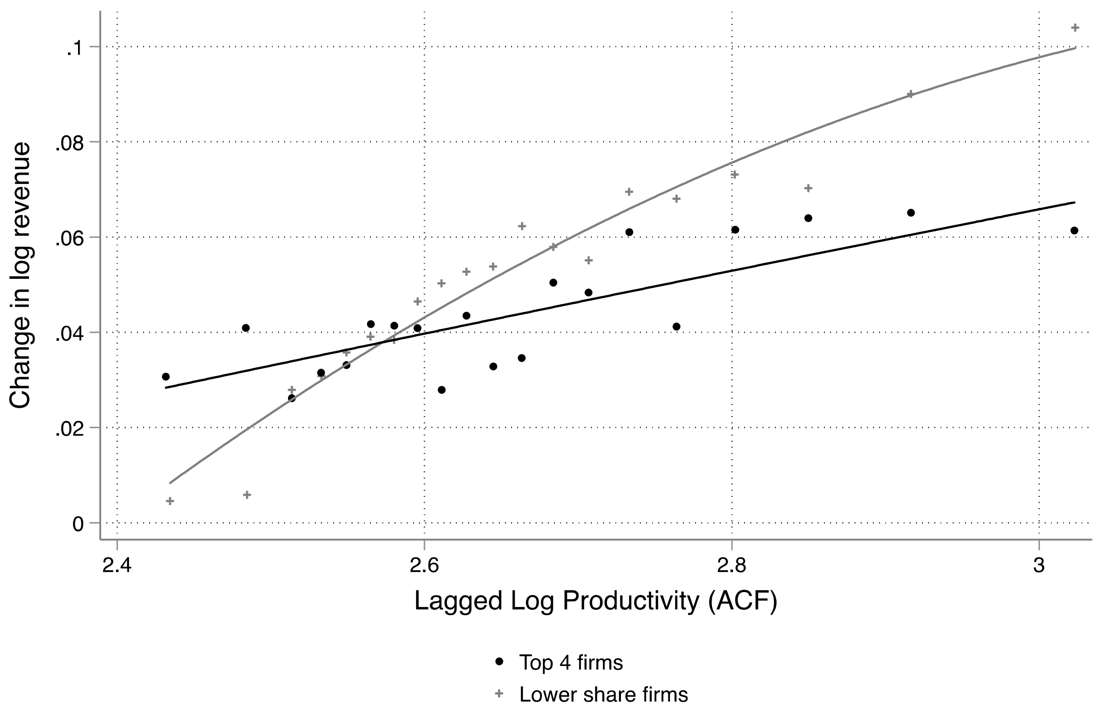
[8] Equation (5) includes industry average productivity, which will change year-to-year.

[9] Age is calculated, with some measurement error, as the number of years the firm has data in Compustat.

firm growth is independent of the debt ratio (Modigliani and Miller 1958), hence meeting an exclusion restriction. The Heckman correction increases the slope coefficient slightly (see Appendix Table A5).[10] We ignore sample selection in the remainder of the paper.

Figure 2. Binned Scatterplot of Firm Growth and Lagged Productivity by Top Four Firms in Each Industry and the Rest. Controls for industry and year.



Factors affecting the growth response

Equation (5) suggests three factors that might influence how firm growth responds to productivity: firm market share, the dispersion of productivity, and δ, roughly the rate of communication. The last is, perhaps, the most difficult to quantify. Broadly conceived, it

[10] The sample selection regression is slightly different from the regressions in Table 1 because it analyzes forward firm growth (next year – current year) against current productivity. Also, for tractability, we use 3-digit industries rather than 6-digit. Sample size is different because not all observations have debt data.

might capture switching costs, the extent of word-of-mouth marketing, or other factors that are hard to measure. We do obtain proxies for the first two variables.

Although we do not have accurate market shares for each firm, we can identify firms that have higher market shares than others, namely, those firms ranked in the top four by sales within their Compustat industry. Compustat excludes most private firms and Compustat industries might not correspond to the real industry one might want to use to analyze firm behavior, but nevertheless, top four ranking should generally correspond to higher market share. Figure 2 and Column 1 of Table 2 show, consistent with our model, that the slope of the response curve is sharply lower for top-ranked firms.

Other factors might make large firms less responsive to productivity such as diseconomies of scale. Column 2 interacts lagged productivity with beginning-of-year log total capital (tangible plus intangible). Again, the slope of the productivity response is distinctly lower and the intercept is higher for large firms. Column 3 add a measure of the annual standard deviation of estimated log revenue productivity calculated for the entire sample each year. This, too, is associated with a decrease in the productivity response. Column 4 uses, instead, the standard deviation of each two-digit NAICS industry each year.[11] The result is similar.

These results are all consistent with our model although the analysis is not causal. Nevertheless, the effect magnitudes are substantial, suggesting that market share and productivity dispersion are important factors for understanding firm growth in response to productivity. In particular, both factors have increased substantially since the year 2000,

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[11] Because the number of observations varies dramatically across industries, we weight this regression by the number of observations to reduce sampling error.

possibly contributing to the decline in reallocation observed by Decker et al. (2020). From the Economic Censuses, the market share of the top four firms ranked by sales in US 6-digit industries grew from 26.2% in 1997 to 33.5% in 2012 (weighted by shipments). In our sample, the standard deviation of productivity grew from .22 averaged over 2000 and earlier years to .31 after 2000.

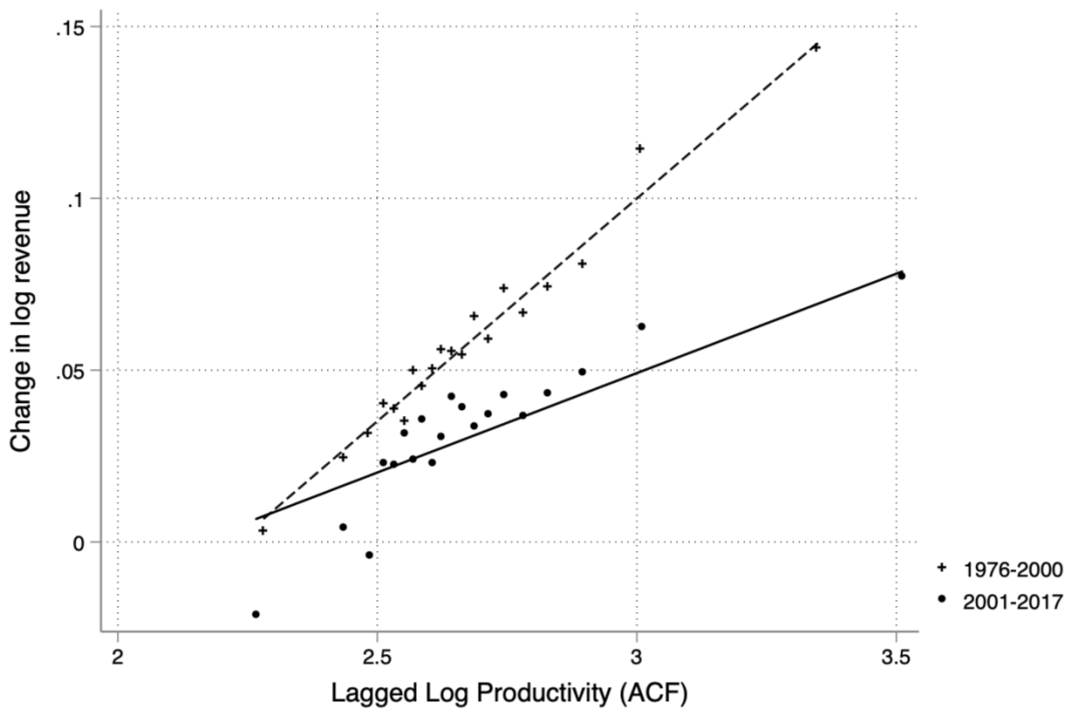

Figure 3. Binned Scatterplot of Firm Growth and Lagged Productivity by time period. Controls for industry and year.

Column 5 of Table 2, using a dummy variable for years after 2000, shows a decline in the productivity response of .086. Figure 3 shows the equivalent decline in slope. How much of this can be accounted for by increases in market concentration and dispersion? The bottom row of the table sums the coefficient for each interaction variable times the change in the sample mean of that variable before and after 2000. Combined, firm size and dispersion account for between .033 and .049 of the decline. In other words, these variables can account for about half of the decline in the response to productivity.

We also tentatively explore the relationship between industry concentration, dispersion, and aggregate productivity growth in equation (7). We calculate the productivity for each industry each year as the revenue-weighted mean of firm productivities. We obtain four-firm concentration ratios from 1997-2012 from the Economic Censuses, interpolating intervening years.[12] Leaving within-firm productivity change to the error term, we estimate

$$\Delta\Omega_{jt} = \alpha_j^1 + \alpha_t^2 + \beta^1 \text{stdev}\left(\omega_{jt}\right) - \beta^2 \cdot H_{jt} \cdot \text{stdev}\left(\omega_{jt}\right) + \epsilon_{jt}.$$

in Table 3, with and without fixed effects. The β coefficients have the right signs and are not significantly different in magnitude. While our data do not include all firms and the right-hand side variables are likely endogenous, the estimates are consistent with equation (7), providing some preliminary support.

Product differentiation investments

When consumers have heterogeneous preferences, the model suggests that firms may make investments in differentiating their products and services. These investments may lead to "business stealing" that reduces the growth rate of other firms.

Table 4 explores the role of investments made by the largest four firms in each industry on the smaller firms within that industry. The first two columns add means of top-four capital stocks to our response regressions. The last two columns breakout intangible capital measures into R&D, organizational capital, and balance sheet intangibles (largely goodwill). Investments by top firms in intangibles have a significant negative effect on the growth of smaller firms. In particular, this effect appears to be dominated by investments in

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[12] This measure has some shortcomings. The Economic Censuses cover US domestic producers while the Compustat data record global sales and we assign concentration data by the firm's primary industry. Nevertheless, we might expect the US domestic industry concentration to be correlated with firms' actual market concentrations.

organizational capital, which includes advertising, marketing, and most information technology investments. Large firms tend to dominate investing in these intangibles, especially in information technology, and these investments have increased sharply since 2000 (Bessen et al. 2020). While firm size and productivity dispersion are linked to changes in the slope of the productivity response curve, investments in differentiation are related to the level. The bottom row of the table estimates how much these investments contribute to the decline in growth of smaller firms by taking the difference in the mean intangible stocks of the top four firms before and after 2000 and multiplying it by the corresponding regression coefficient. Intangibles generally can account for a 3% decline in growth after 2000 and organizational capital a 1-2% decline.

Conclusion

This paper details mechanisms that helps explain how firms grow in response to their level of productivity and how this response influences aggregate productivity growth. We identify several firm and industry characteristics that affect the way firms grow in response to productivity. While our empirical analysis is not causal, we find that these characteristics have statistically and economically significant associations with firm growth. Indeed, they can account for much of the decline in the response to productivity that has occurred since 2000. This validation makes application of our model to comprehensive longitudinal firm data a candidate for further research.

A broader implication of this analysis is that the rate of reallocation of resources to more productive firms should be an important topic for policy, especially antitrust policy. We show that firm size and industry concentration affect reallocation. While competition authorities have focused on how competition affects innovation incentives, this paper shows that the translation of innovations into aggregate productivity growth is neither automatic nor quick in many cases. We need to understand how policy can affect this process.

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Tables

Table 1. Firm Growth and Lagged Productivity
Dependent variable: Change in log revenue

	(1)	(2)	(3)	(4)	(5)
Lagged log productivity	0.121***	0.107***	0.098***	0.092***	0.116***
	(0.012)	(0.007)	(0.007)	(0.007)	(0.007)
Age x lagged log productivity				-0.001***	
				(0.000)	
Acquisitions					0.026***
					(0.002)
Goodwill					0.009***
					(0.000)
Observations	170,799	172,551	163,351	163,351	150,111
R-squared	0.203	0.037	0.162	0.165	0.176
Firm FE	Yes	No	No	No	No
Industry FE	No	Yes	No	No	No
Year FE	Yes	Yes	No	No	No
Industry x Year FE	No	No	Yes	Yes	Yes

Standard errors clustered by firm in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Table shows the response of firm sales growth in response to lagged productivity. Productivity is calculated using the Ackerberg, Caves, Frazer method (2015). Acquisitions is the number of firm mergers and acquisitions obtained from SDC. [13]

[13] 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.

Table 2. Firm Growth and Productivity by Firm Size and Productivity Dispersion
Dependent variable: Change in log revenue

	(1)	(2)	(3)	(4)	(5)
Lagged log productivity	0.112***	0.195***	0.280***	0.298***	0.143***
	(0.008)	(0.015)	(0.032)	(0.023)	(0.010)
Year > 2000 x lagged log productivity					-0.086***
					(0.013)
Lagged log productivity x …					
x Top 4 firm	-0.068***				
	(0.013)				
x Log Total Capital		-0.020***	-0.017***	-0.021***	
		(0.002)	(0.002)	(0.003)	
x Std. dev. of productivity			-0.352***		
			(0.112)		
x Std. dev. of industry productivity				-0.225***	
				(0.042)	
Base effects					
Top 4 firm	0.179***				
	(0.033)				
Log Total Capital		0.054***	0.047***	0.058***	
		(0.006)	(0.006)	(0.008)	
Std. dev. of industry productivity				0.821**	
				(0.319)	
Observations	139,387	163,318	163,318	163,302	163,351
R-squared	0.132	0.163	0.163	0.172	0.162
Implied decrease in slope after 2000					
Change in response		-0.022	-0.049	-0.033	-0.086

Standard errors clustered by firm in parentheses. All regressions include industry (6-digit) by year fixed effects. *** p<0.01, ** p<0.05, * p<0.1. Table shows the response of firm sales growth in response to lagged productivity interacted with several other variables. Top 4 firms rank in the top of their Compustat industries by sales. Total capital is the sum of real tangible and intangible capital. Column 3 uses the annual standard deviation of productivity for the entire sample; column 4 calculates the standard deviation for each two-digit industry and weights the regression by the number of industry-year observations. Productivity is calculated using the Ackerberg, Caves, Frazer method (2015). The implied decrease in slope after 2000 is calculated by multiplying the regression coefficient by difference in the mean values of the interacted variables before and after 2000.

Table 3. Industry Productivity, Industry Concentration, and Dispersion
Dependent variable: Change in share-weighted mean log industry productivity

	(1)	(2)
Standard deviation of industry productivity	0.248***	0.567***
	(0.050)	(0.090)
Industry four-firm concentration x standard deviation of industry productivity	-0.130*	-0.461***
	(0.075)	(0.158)
Observations	7,124	7,038
R-squared	0.053	0.156
Industry FE	No	Yes
Year FE	No	Yes

Standard errors clustered by industry in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The data are Compustat firm-year data aggregated to NAICS 6-digit industries by year from 1997-2012. The dependent variable is the one-year difference in mean log productivity weighted by firm revenue shares. Four firm concentration for 6-digit NAICS industries comes from Economic Censuses from 1997 through 2012, with intermediate years interpolated.

Table 4. "Business-Stealing" Investments by Top 4 Firms
Dependent variable: Change in log revenue

	(1)	(2)	(3)	(4)
Mean capital of Top 4 Firms in Industry				
Physical capital	0.005	0.003	0.003	-0.001
	(0.003)	(0.003)	(0.003)	(0.004)
Intangible capital	-0.015***	-0.015***		
	(0.003)	(0.003)		
R&D capital			-0.001	-0.000
			(0.002)	(0.002)
Organizational capital			-0.011***	-0.009**
			(0.004)	(0.004)
Goodwill			0.000	-0.000
			(0.001)	(0.001)
Subject firm				
Lagged log productivity	0.255***	0.235***	0.270***	0.254***
	(0.034)	(0.036)	(0.042)	(0.043)
Log total capital x productivity	-0.015***	-0.013***	-0.015***	-0.014***
	(0.003)	(0.003)	(0.004)	(0.004)
Dispersion x productivity	-0.220*	-0.163	-0.212	-0.142
	(0.128)	(0.135)	(0.155)	(0.161)
Log total capital	0.041***	0.016*	0.044***	0.019*
	(0.009)	(0.009)	(0.010)	(0.011)
Acquisitions		0.046***		0.048***
		(0.002)		(0.002)
Goodwill		0.017***		0.019***
		(0.001)		(0.001)
Observations	105,629	98,185	75,957	70,152
R-squared	0.035	0.061	0.038	0.066
Effect at sample means:	Intangible capital		Organizational capital	
Change in firm growth after 2000	-0.0334	-0.0317	-0.0155	-0.0121

Standard errors clustered by firm in parentheses. All regressions include industry (6-digit) and year fixed effects. *** p<0.01, ** p<0.05, * p<0.1. The sample excludes firms ranked four or less by sales within their industries. Table shows the response of firm sales growth in response to lagged productivity interacted with several other variables with controls for investments made by top 4 firms. Top 4 firms rank in the top of their Compustat industries by sales. Total capital is the sum of real tangible and intangible capital. The bottom row shows mean effects for top 4 intangible and organizational capital as indicated. The effect is the relevant coefficient time the difference in means before and after 2000.

Appendix

Table A1. Summary Statistics

VARIABLES	(1) mean	(2) sd	(3) p10	(4) p50	(5) p90
Log Sales	5.313	2.278	2.492	5.241	8.320
Change in log sales	0.047	0.373	-0.218	0.046	0.342
Log productivity	2.672	0.248	2.468	2.629	2.923
Firm age	15.677	12.710	3.000	12.000	34.000
Log Net PPE	3.564	2.647	0.266	3.476	7.077
Log Intangibles	4.423	2.217	1.708	4.233	7.456
Acquisitions / year	0.442	1.248	0.000	0.000	1.000
<u>Means for Top 4 Firms</u>					
Log Net PPE	8.393	1.916	5.876	8.427	10.806
Log Intangibles	8.958	1.978	6.377	8.879	11.621

Dollar values in $2009. Age is years since first listing in Compustat.

Table A2. Alternative Production Function Estimates

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Log Value Added				Log Revenue
Method	Ackerberg, Caves, Frazer	Levinsohn, Petrin	Olley, Pakes	OLS	OLS
Log employees (1000s)	0.564***	0.560***	0.545***	0.552***	0.405***
	(0.001)	(0.001)	(0.004)	(0.006)	(0.005)
Log Net Property, Plant, Equipment	0.267***	0.311***	0.152***	0.290***	0.227***
	(0.010)	(0.013)	(0.007)	(0.004)	(0.004)
Log Intangible Capital	0.196***	0.242***	0.303***	0.173***	0.183***
	(0.002)	(0.006)	(0.006)	(0.003)	(0.004)
Log Intermediates					0.182***
					(0.004)
Observations	188,539	188,539	174,130	188,539	188,539
R-squared				0.925	0.941
Number of groups	18,387	18,387	16,845		

Standard errors are bootstrapped for columns 1-3 and clustered by firm for columns 4-5. *** p<0.01, ** p<0.05, * p<0.1. The first three columns correct for simultaneity bias using control functions and productivity is estimated directly in the first stage. The last two columns do not control for simultaneous adjustment of variable factors and the productivity measure is taken as a simple residual that includes optimization errors and other errors.

Table A3. Tests of Basic Response Equation Using Alternative Productivity Measures
Dependent variable: Change in log revenue

	(1)	(2)	(3)	(4)	(5)	(6)
Productivity measure	Ackerberg, Caves, Frazer	Levinsohn, Petrin	Olley, Pakes	OLS, value added	OLS, Revenue	Value added/ employee
Lagged log productivity	0.108***	0.069***	0.188***	0.105***	0.019***	0.002
	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Observations	172,539	172,539	159,672	155,905	165,492	168,373
R-squared	0.038	0.036	0.052	0.049	0.034	0.037

Standard errors clustered by firm in parentheses. All regressions include industry (6-digit) and year fixed effects. *** p<0.01, ** p<0.05, * p<0.1. Table shows the response of firm sales growth in response to lagged productivity. Productivity is directly estimated in the first three columns but is calculated as a residual in 4 and 5. Residual measures combine productivity with optimization and other errors, possibly attenuating the coefficient estimates. To limit the effect of extreme outliers, we trimmed productivity of the 5% tails in the last three columns.

Table A4. Tests of Different Intangible Measures

	(1)	(2)	(3)	(4)	(5)
Estimation	Production Function		Response Equation		
Dependent variable	Log Value Added		Change in Log Revenue		
Intangible measure	Composite	Separate	Peters & Taylor	Composite	Separate
Log employees (1000s)	0.598***	0.607***			
	(0.009)	(0.003)			
Log Property, Plant, Equipment	0.287***	0.309***			
	(0.008)	(0.002)			
Log Composite Intangibles	0.123***				
	(0.016)				
Log R&D Stock		0.011***			
		(0.003)			
Log Goodwill & other		0.034***			
		(0.000)			
Log Advertising Stock		0.001			
		(0.001)			
Log Software Stock		0.086***			
		(0.007)			
Lagged Productivity			0.120***	0.062***	0.045***
			(0.009)	(0.007)	(0.006)
Observations	113,084	113,084	104,933	104,933	104,933
R-squared			0.049	0.045	0.045
Number of groups	13,604	13,604			

Standard errors are bootstrapped for columns 1-2 and clustered by industry for columns 3-5. *** p<0.01, ** p<0.05, * p<0.1. Columns 1-2 estimate productivity using the Ackerberg, Caves, and Frazer method. The composite intangibles measure is constructed by first regressing Peters and Taylor's log organizational capital on log stocks of advertising expenditures, software developers, and patents. The exponential of the prediction of this regression is then added to R&D stocks and balance sheet intangibles. Column 2 includes separate stocks in the production function. For details on the construction of these stock variables see Bessen et al. (2020). Columns 3-5 repeat the basic firm growth response equation with productivity estimates using different intangible measures and controls for industry and year. The Peters and Taylor measure fits the data better and has a somewhat larger response coefficient, but results are qualitatively similar.

Table A5. Heckman Sample Selection Model
Dependent variable: Forward change in log revenue (t+1)

	(1)	(2)
Estimation	OLS	Heckman
Main Equation		
Log productivity	0.090***	0.094***
	(0.006)	(0.006)
Observations	161,683	173,161
Censored observations		11,478
R-squared	0.025	
Industry FE (3-digit NAICS)	Yes	Yes
Year FE	Yes	Yes
Selection Equation		
Debt ratio		-0.467***
		(0.024)
Log productivity		-0.039*
		(0.022)
Industry FE (3-digit NAICS)		Yes
Year FE		Yes
atanh ρ		-0.534***
		(0.030)

Heckman estimation uses maximum likelihood. Standard errors clustered by firm in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is forward change in log revenue. Debt ratio is long term debt/(long term debt + common equity). ρ is the correlation of errors between the two equations.