New Evidence on Market Power, Profit, Concentration, and the Role of Mega-Firms in the US Economy*

Robert E. Hall
Hoover Institution and Department of Economics
Stanford University
rehall@stanford.edu; stanford.edu/∼rehall

September 23, 2018

Abstract

Modern commentary on market power in the industries in the US economy has focused on three indicators: (1) The Lerner index—the ratio of price less marginal cost to the price—to measure of market power, (2) profit, measured relative to a benchmark based on assets, as a profit rate or as Tobin's q, (3) concentration, measured as the combined market shares of a small number of leading firms. I develop data for the 60 KLEMS industries for these measures, based on a number of conceptual improvements over existing measures. I find a typical Lerner index of 0.2. Lerner indexes grew slightly between 1988 and 2015. I find large increases in the earnings of capital, both as a ratio to the value of business assets and as q. I also find strong evidence of rising concentration in conventional 4-firm concentration ratios and in the incidence of mega-firms, defined as those with 10,000+ workers. A key finding of the paper is the low correlation of the levels and growth rates of these measures of market power.

JEL L1 D24

*This research was supported by the Hoover Institution. I am grateful to Chad Syverson, James Traina, and Hal Varian for comments. This paper supersedes an earlier version, "New Evidence on Market Power, Profit, Concentration, and the Role of Mega-Firms in the US Economy"

1 Introduction

The measurement of market power informs many branches of economics. This paper uses the Lerner index—the ratio of price minus marginal cost to price—as the measure of market power. A profit-maximizing price-taking firm equates its marginal cost to the prevailing price of output. That price is invariant to the firm's output choice. The price-taking firm's Lerner index is zero. A firm facing a constant-elastic residual demand, with elasticity ϵ, maximizes profit at the point where the Lerner index is $1/\epsilon$. In general, the Lerner index, designated $\mathcal{L}$ in this paper, is a useful way to think about market power or monopoly power. It has a simple functional relationship to an equivalent measure, the markup ratio, that is, the ratio of price to marginal cost, μ:

$$\mu = \frac{1}{1 - \mathcal{L}}, \tag{1}$$

which maps the Lerner index from $\mathcal{L} \in [0, 1]$ to $\mu \in [1, \infty]$.

The literature on measurement of marginal cost has two main branches. The demand-side approach infers the residual elasticity ϵ, typically from a differentiated-products oligopoly model. The production side-approach uses data on price and cost from firms. Thirty years ago, Hall (1988) proposed a refinement of the production-side approach that measures marginal cost rather than average cost. De Loecker and Warzynski (2012) developed a related method also focusing on empirical marginal cost, and De Loecker and Eeckhout (2017) recently captured a great deal of attention with the finding that market power has risen substantially in the US in recent decades. See Traina (2018) and Gutiérrez and Philippon (2017) for critiques of that paper. Since the publication of my 1988 paper, much improved data have become available, thanks to the efforts of US statistical agencies in developing productivity data. Their compiled data feed directly into calculations of $\mathcal{L}$. In addition, De Loecker and Eeckhout's recent paper together with a literature on the rising importance of large firms and the decline in the labor share has generated great interest in the growth of market power. This paper responds to those developments. It finds support for the conclusion that market power has risen in recent decades, though by less than in De Loecker and Eeckhout's paper.

One reason for the rise in market power may be increasing concentration. I study a conventional measure of market power, the four-firm concentration ratio, for 6-digit manufacturing product markets, using the same industry aggregates as in the measurement of the Lerner index. I confirm the finding of other recent work that concentration has risen in a substantial number of industries. Sunset industries such as apparel are prominent among those with rising concentration. The correlation of the levels of concentration and the Lerner indexes is slightly negative, while the correlation of the rates of growth is somewhat positive. The rise in market power is economically meaningful in half the industries, as judged by applying the Department of Justice's merger-screening criteria.

A related issue is the rising role of mega-firms in some US industries. Most work on this topic has used data from publicly traded firms. In data from the US Economic Census covering all firms (not establishments), which reports employment in firms by number of employees, including those with 10,000 or more, which I designate as mega-firms, increases in the mega-firm employment fraction are modest where they occur. Further, important sectors including manufacturing experienced declines in the mega-firm employment fraction. I find no systematic relation between the level mega-firm fraction and the Lerner index across 19 major sectors of the US economy. But there is moderately strong evidence that industries with growing mega-firm fraction have gained market power in the years since 1998.

This paper is self-contained and presumes no acquaintance with my earlier work or other work on this subject. Everything here is new, including a novel derivation of the basic idea of extracting marginal cost from time-series data.

The text describes the many calculations underlying this paper in general terms. The calculations are fully documented in the computer files available from my website.

2 The Lerner Index of Market Power

2.1 Measuring marginal cost and the Lerner index

In time-series data, a natural measure of marginal cost is the change in cost divided by the change in output. More precisely, the numerator is the change in cost not associated with changes in factor prices and the denominator is the change in output not associated with the change in Hicks-neutral productivity. Cost is

$$c = \sum_i w_i \, x_i, \tag{2}$$

in obvious notation. The change in cost is

$$dc = \sum_i x_i \, dw_i + \sum_i w_i \, dx_i. \tag{3}$$

The first summation is the component associated with changes in factor prices, while the second is the desired component purged of effects from changing factor prices:

$$\sum_i w_i\, dx_i. \tag{4}$$

The technology is

$$y = A\, f(x), \tag{5}$$

so output growth is

$$dy = Adf(x) + f(x)dA = Adf(x) + y\frac{dA}{A} \tag{6}$$

The desired component purged of effects from changing productivity is

$$Adf(x) = dy - y\frac{dA}{A} \tag{7}$$

Marginal cost is the ratio of adjusted cost change to adjusted output change,

$$m = \frac{\sum_i w_i\, dx_i}{dy - y\, dA/A}. \tag{8}$$

The Lerner index is

$$\mathcal{L} = \frac{p - m}{p} = 1 - \frac{\sum_i w_i\, dx_i}{p(dy - y\, dA/A)}. \tag{9}$$

so

$$1 - \mathcal{L} = \frac{\sum_i w_i\, dx_i}{p(dy - y\, dA/A)}. \tag{10}$$

Now let

$$\alpha_i = \frac{w_i x_i}{p\, y}, \tag{11}$$

the share of factor i in revenue, $p\, y$. The equation can then be written

$$(1 - \mathcal{L})\left(dy + y\frac{dA}{A}\right) = y \sum_i \alpha_i\, \frac{dx_i}{x_i.}. \tag{12}$$

Dividing by y and rearranging yields a useful result,

$$\frac{dy}{y} - \sum_i \alpha_i \frac{dx_i}{x_i} = \mathcal{L}\,\frac{dy}{y} + (1 - \mathcal{L})\frac{dA}{A}. \tag{13}$$

With discrete time, the same equation is

$$\Delta \log y - \sum_i \alpha_i\, \Delta \log x_i = \mathcal{L}\, \Delta \log y + (1 - \mathcal{L})\Delta \log A. \tag{14}$$

This formulation is useful because the left-hand side is the Solow residual, calculated meticulously in productivity accounts. Note that if $\mathcal{L} > 0$, the Solow residual does not measure actual technical progress, because it does not adjust for market power.

This derivation of the measurement of $\mathcal{L}$ does not assume anything about optimal choice by the firm, apart from remaining on its production function. The firm is not necessarily satisfying its first-order conditions in the output market or any input market. The coefficient $\mathcal{L}$ does not necessarily describe the residual demand function facing the firm, effects of market power by sellers of inputs including labor unions, or monopsony power of the firm in those input markets.

The growth rate of productivity, $a = (1 - \mathcal{L})\Delta \log A$, is a statistical residual in equation (14). It can only be measured with knowledge of the Lerner index, $\mathcal{L}$. The most basic approach is to treat $\mathcal{L}$ as a parameter to be estimated in time-series or panel data, with suitable instrumental variables. Eligible instruments are variables that are uncorrelated with productivity growth but are correlated with output changes. Shifts in supply and demand in the output market or factor markets could be eligible. The residual based on the estimated value of $\mathcal{L}$ is the estimated rate of true productivity growth, adjusted for market power.

With a single time series, the specification for $\mathcal{L}$ may capture changes over time, with a small number of parameters. For example, an equation that considers a linear trend is

$$\Delta \log y_t - \sum_i \alpha_i \Delta \log x_i = (\phi + \psi t)\Delta \log y + a_t. \tag{15}$$

Here ϕ controls the level of the Lerner index and ψ is the per-period growth of the index. With panel data, the function multiplying $\Delta \log y$ may capture differences in market power across industries as well.

2.2 Interpretation

Here I consider whether the procedure described earlier measures the Lerner index accurately or measures it with a bias of known sign in the presence of decreasing and increasing returns to scale, market power of factor suppliers, and monopsony power in factor markets. This discussion introduces the assumption of optimization by firms, an assumption deliberately omitted from the earlier derivation of the empirical marginal cost measure.

Differentiation of the production function,

$$y = Af(x), \tag{16}$$

yields

$$\frac{dy}{y} = \frac{dA}{A} + \sum_i \frac{x_i}{f(x)} \frac{\partial f}{\partial x_i} \frac{dx_i}{x_i}. \tag{17}$$

Now assume that the firm is a price-taker in all of its input markets, and the firm equates the marginal revenue product of a factor to its price:

$$(1 - \mathcal{L}) p A \frac{\partial f}{\partial x_i} = w_i. \tag{18}$$

Use this equation to substitute out the $\frac{\partial f}{\partial x_i}$ in the previous equation and rearrange to get

$$\frac{dy}{y} - \sum_i \alpha_i \frac{dx_i}{x_i} = \mathcal{L} \frac{dy}{y} + (1 - \mathcal{L}) \frac{dA}{A}, \tag{19}$$

as before. Under the new assumptions, $\mathcal{L}$ *is* the Lerner index of market power. Notice that the assumptions do not include constant returns to scale. But the second-order condition for profit maximization requires that the Lerner index exceed $1 - 1/\gamma$, where γ is the returns-to-scale index of the production function, the elasticity of $f(\theta x)$ with respect to θ, at $\theta = 1$. A firm with strong increasing returns and weaker market power will not satisfy the second-order condition.

To make some further progress on these issues, consider the simple case with only one factor, labor, n, paid wage w. The production function is

$$y = n^{\gamma}. \tag{20}$$

The elasticity γ is positive but may lie in either side of 1. In changes,

$$\frac{dy}{y} = \gamma \frac{dn}{n}. \tag{21}$$

The Solow residual uses the revenue share,

$$\alpha = \frac{w\,n}{p\,y} = (1 - \mathcal{L})\gamma, \tag{22}$$

capturing the well known depressing effect of market power on the measured share of labor. The Solow residual is

$$\frac{dy}{y} - \alpha \frac{dn}{n} = \frac{dy}{y} - (1 - \mathcal{L})\gamma \frac{dn}{n}. \tag{23}$$

From above, two of the terms on the right net to zero, so

$$\frac{dy}{y} - \alpha \frac{dn}{n} = \mathcal{L} \gamma \frac{dn}{n}, \tag{24}$$

and, as before,

$$\frac{dy}{y} - \alpha\frac{dn}{n} = \mathcal{L}\frac{dy}{y} \tag{25}$$

The assumption that the firm is a price taker in its input markets does not mean that those market are competitive. That property is sufficient but not necessary. The price-taking assumption would apply if a labor union or dominant seller of another input chose to exercise its market power by sticking to a fixed non-negotiable price quote.

On the other hand, if a firm has monopsony power in an input market and perceives that increasing its purchase volume will drive up the price, a downward bias in the estimate of the firm's Lerner index will result. Suppose the elasticity of the wage with respect to the firm's level of employment is λ. Then the observed labor share is further depressed by the fact that the average wage understates the marginal wage:

$$\alpha = \frac{w\,n}{p\,y} = (1-\mathcal{L})\frac{\gamma}{1+\lambda}, \tag{26}$$

which propagates through the rest of the math to the conclusion,

$$\frac{dy}{y} - \alpha\frac{dn}{n} = \frac{\mathcal{L}-\lambda}{1+\lambda}\frac{dy}{y}. \tag{27}$$

Thus the coefficient on the right side of the equation is $\frac{\mathcal{L}-\lambda}{1+\lambda}$, which is less than $\mathcal{L}$ for any positive value of the monopsony parameter λ.

An important case deviating from the assumptions stated earlier is an omitted variable in the productivity calculation. A leading example is the firm's stock of intangible capital of a type not included in its measured capital stock. Let x_o designate the omitted factor quantity and α_o be the elasticity of the production function with respect to the omitted factor. Also let $\tilde{\alpha}_k$ designate the true elasticity of capital, on the assumtion that the measured elasticity α_k is overstated because its revenue share includes the firm's earnings from the omitted factor along with the earnings of capital. The growth of output becomes

$$\frac{dy}{y} = \sum_i \alpha_i\frac{dx_i}{x_i} + \tilde{\alpha}_k\frac{dx_k}{x_k} + \alpha_o\frac{dx_o}{x_o} + \mathcal{L}\frac{dy}{y} + (1-\mathcal{L})\frac{dA}{A}. \tag{28}$$

The estimating equation becomes

$$\frac{dy}{y} - \sum_{i \text{ not } o} \alpha_i\frac{dx_i}{x_i} = (\tilde{\alpha}_k - \alpha_k)\frac{dx_k}{x_k} + \alpha_o\frac{dx_o}{x_o} + \mathcal{L}\frac{dy}{y} + (1-\mathcal{L})\frac{dA}{A}. \tag{29}$$

The omitted variable is $(\tilde{\alpha}_k - \alpha_k)\frac{dx_k}{x_k} + \alpha_o\frac{dx_o}{x_o}$. If it is correlated with the instruments, the IV estimates will be biased. Under the hypothesis that an instrument is positively correlated with $\frac{dx_k}{x_k}$ and with $\frac{dx_o}{x_o}$, the two components will contribute offsetting effects to the bias, because, by assumption, $\tilde{\alpha}_k - \alpha_k < 0$.

2.3 Conclusions about the applicability of the approach

Increasing returns to scale. The approach is robust to increasing returns. A fixed cost of continuing operations is a commonly considered source of increasing returns. Increasing returns must be coupled with market power. A leading example of a firm with a combination of increasing returns and market power is one satisfying the assumptions of the monopolistic competition model. In that model, entry of firms with differentiated products (giving them market power) occurs to the point of zero profit. In the simplest model, increasing returns takes the particular form of a fixed cost of operation, independent of scale but avoidable by shutting down. In equilibrium, the firm makes just enough excess profit from market power to offset the fixed cost.

Decreasing returns to scale. Decreasing returns occur when factors, notably capital, involve delays, adjustment costs, or permanent restrictions on inputs. The approach is also robust to decreasing returns, which will be accompanied by profit in excess of factor costs.

Omitted input. As noted earlier, if the effect of the instrument on the growth of the omitted factor has the same sign as its effect on capital growth, there are two biases in opposite directions. In the best case, the net effect would be zero.

Market power held by a seller of an input. The leading example is unionized labor. If a seller of an input exercises its market power by setting a higher price that reflects that power, the calculation described in this paper takes account of the true marginal cost associated with that input, and the calculation uncovers the true Lerner index of the firm. Notice that such an arrangement is bilaterally inefficient. If the firm and the input seller use efficient two-part pricing, the average price paid exceeds the underlying marginal price. In that case, the calculation overstates $\mathcal{L}$.

Monopsony power in an input market. The leading example is a firm whose employment level is a substantial fraction of total employment in its labor market. The average price paid for the input understates the effective marginal price. The employment share is understated and the estimate of $\mathcal{L}$ is correspondingly understated.

2.4 Data for measuring the Lerner index

The data in the Solow productivity framework come from klemscombinedbymeasure.xlsx, available at bls.gov/mfp/mprdload.htm#Multifactor%20Productivity%20Tables. See bls.gov/mfp/#technotes for extensive technical descriptions of the data. The data are annual starting in 1987. I use the version of the data for 60 distinct non-overlapping industries. Some of the advantages of the data relative to data in earlier work on production-side measurement of the price/marginal cost literature are:

- Rigorous adherence to proper measurement of output—no reliance on value added
- Uniform use of the modern NAICS industry definitions
- Breakdown of inputs into 5 categories: capital, labor, energy, materials, and services
- Aggregation of capital and labor inputs from detailed underlying data using appropriate methods
- Use of Tørnqvist's refinement of the weights applied to log-changes in factor inputs

For instrumental variables, I follow the identification strategy of Hall (1988), which treats an industry's productivity growth as orthogonal to government purchases of military goods and services and to movements of the oil price. NIPA table 3.11.3 breaks down real military purchases into a variety of categories. I use FRED series ACOILWTICO, the market price of west Texas intermediate crude, as a measure of the oil price. The instruments are:

- Military purchases of equipment
- Military purchases of ships
- Military purchases of software
- Military expenditure on research and development
- The oil price

All of these enter as log differences.

Data on the fraction of employment by industry of very high employment firms (10,000 or more employees) come from the SUSB database compiled from business census data. See

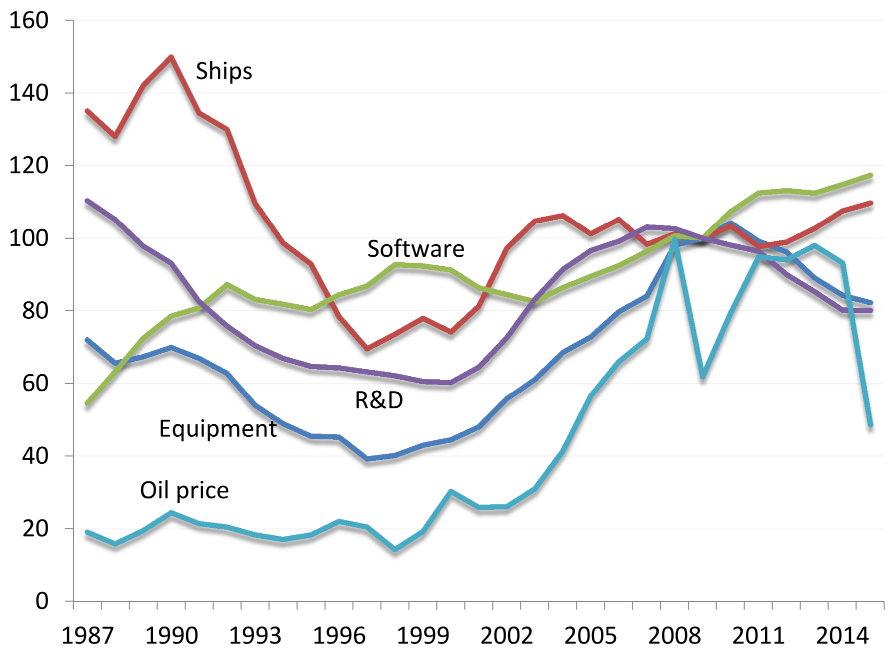

Figure 1: Instrumental Variables

census.gov/data/tables/2015/econ/susb/2015-susb-annual.html, link to "U.S., NAICS sectors, larger employment sizes up to 10,000+" and similar for years back to 1998. These data are for 19 NAICS sectors and begin in 1998. Data on the distribution of firm employment at more detailed industry levels is available, but not including the employment at mega-firms, because of disclosure restrictions. Apparently many more detailed industries have only one or a small number of mega-firms, so publication of the data would violate the anonymity of census data.

2.5 Results for the Lerner index

My earlier work measured market power with the ratio of price to marginal cost, μ. Estimation occurred in a specification where μ^{-1} was estimated and then inverted for interpretation. In principle, in an instrumental variables setting, the choice between estimation of a coefficient and estimation of its inverse, followed by calculating its reciprocal, is arbitrary. With a single instrumental variable, the results of the two approaches are numerically identical. In the KLEMS data using the 5 instruments in this paper, the reciprocity principle comes close to holding. But for the reason discussed in Hall (1988), it is better to estimate μ^{-1}, which is effectively what is done in this paper, in the Lerner-index framework. As noted earlier, μ ranges from 1 to infinity. Very high values will occur in cases where variable inputs are

Instrument	*Percent of first-stage t-statistics > 2*
Military purchases of equipment	38
Military purchases of ships	7
Military purchases of software	60
Military expenditure on research and development	17
Oil price	35
Average	31

Table 1: Metrics for the Power of the Instruments

unimportant—software and proprietary pharmaceuticals are examples. The reported standard error for these cases will be high. The results in those cases make more sense where μ^{-1} or $\mathcal{L}$ is estimated, and the high and uncertain values of μ are mapped into a small region around 1 for μ^{-1} or zero for $\mathcal{L}$.

2.5.1 First-stage results

The first-stage regressions have output growth on the left and the five instruments, as log-changes, on the right. The KLEMS data form a panel with 60 industries and 28 years when stated as log differences. Because the instruments are all time series, cross-section regressions in single years, or in small groups of years, are not identified. I focus on the 60 first-stage regressions where each industry contributes a time-series OLS regression. The question at hand is whether the instruments have adequate power to support instrumental-variables estimation.

Table 1 describes the power of the instruments in terms of the ratios of the first-stage coefficients to their standard errors. The first column gives the percent of the 60 ratios that exceed two in absolute value. These numbers would be about 5 percent if the data were purely random. All 5 of the instruments outperform that standard, by a considerable margin in all cases but one.

2.5.2 Estimates of the ratio of the Lerner index, $\mathcal{L}$, by industry

The results for the 60 industries are too extensive to digest in a single table. Table 2 summarizes them in aggregates at the level of 19 NAICS sectors, sorted by the estimate of the estimated Lerner index, which I denote L. The table presents averages across the industries contained in the sectors. The standard errors of the coefficients are summarized as averages and should not be confused with the standard errors that would result from aggregating the underlying data and estimating a single coefficient. The indexes for four sectors—information, utilities, finance–insurance, and agriculture–fishing–hunting—are sufficiently large to render the estimates questionable. In these cases, the instruments lack the power to identify the markup ratio with usable accuracy.

2.6 Inference about the sources of dispersion of the measured Lerner index across industries

From Table 2, it is clear that the estimates specific to the industries have a good deal of noise. In particular, 30 percent of the industries have negative values of L_i despite the fact that the true value of $\mathcal{L}$ cannot be negative. To disentangle the distribution of the true values of the Lerner index across industries from the distribution of the sampling error, I consider a simple statistical model that exploits the fact that sampling error must have a role sufficient to explain the 30 percent of values of the ratio that are estimated to be negative. The statistical model is

$$L = \mathcal{L} + \eta, \tag{30}$$

where $\mathcal{L}$ is distributed as beta(ν, β), with density proportional to $\mathcal{L}^{\nu-1}(1-\mathcal{L})^{\beta-1}$. The measurement error η_i accounts for the residual distribution of the measured index.

Four assumptions identify the model:

1. The true value of the Lerner index obeys the beta distribution, so it is between zero and one: $\mathcal{L} \in [0, 1]$
2. The second shape parameter of the beta distribution of the true Lerner index is $\beta = 8$
3. The two components are statistically independent
4. The mean of the measurement error η is zero

Independence and zero mean of measurement error are standard assumptions in models of this type. The restriction $\beta = 8$ defines a reasonable family indexed by the first shape parameter, ν. Figure 2 shows several members of the family.

The following result establishes the principle that the desired untangling is possible:

Weighted averages across industries				
Lerner index	*Standard error*	*Percent of value added in sector*	*Number of industries in sector*	*Sector name*
-0.13	(0.11)	5.1	3	Health Care and Social Assistance
-0.05	(0.10)	0.2	1	Educational Services
-0.02	(0.15)	6.5	1	Construction
0.03	(0.07)	3.9	2	Administrative and Support and Waste Management and Remediation Services
0.07	(0.12)	6.0	2	Real Estate and Rental and Leasing
0.08	(0.21)	5.2	4	Information
0.09	(0.39)	1.4	3	Mining, Quarrying, and Oil and Gas Extraction
0.10	(0.43)	2.7	1	Utilities
0.16	(0.26)	2.4	1	Management of Companies and Enterprises
0.19	(0.09)	4.1	8	Transportation and Warehousing
0.21	(0.06)	21.3	18	Manufacturing
0.21	(0.10)	7.0	1	Wholesale Trade
0.23	(0.10)	9.0	3	Professional, Scientific, and Technical Services
0.25	(0.17)	2.8	1	Other Services (except Public Administration)
0.28	(0.28)	8.5	4	Finance and Insurance
0.29	(0.17)	1.0	2	Arts, Entertainment, and Recreation
0.31	(0.15)	8.0	1	Retail Trade
0.35	(0.09)	3.1	2	Accommodation and Food Services
0.46	(0.64)	1.7	2	Agriculture, Forestry, Fishing and Hunting

Table 2: Estimates of the Lerner Index by Industry, Stated as Sector Averages

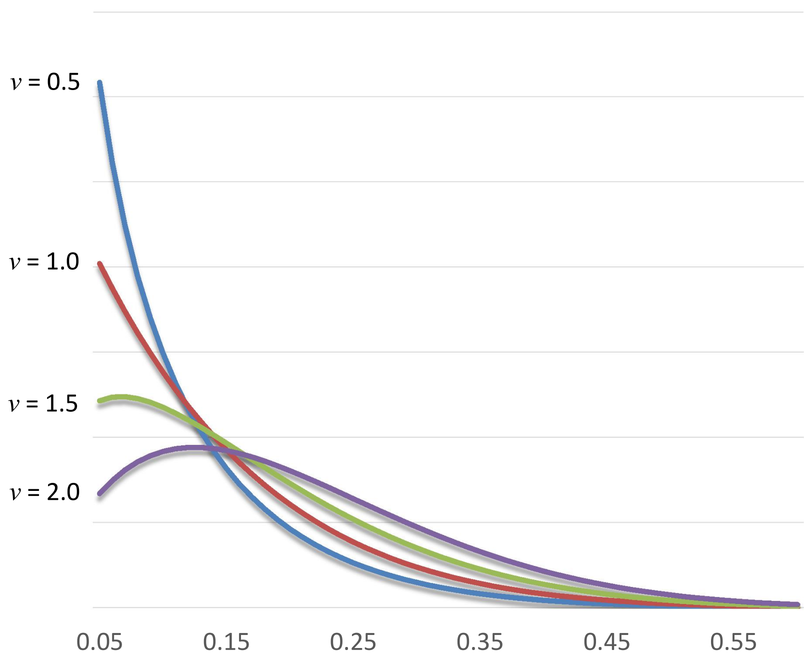

Figure 2: The Family of Beta Distributions with Second Shape Parameter = 8

Identification Theorem: The mean of the measured Lerner index identifies the first shape parameter of the beta distribution of the true Lerner index; the distribution of the measurement error η is identified by solving a convolution problem.

Proof: By assumption 4, the mean of the estimated Lerner index is the mean of the true index. That mean is the mean of the beta distribution,

$$M = \frac{\nu}{\nu + \beta}. \tag{31}$$

Thus

$$\nu = \frac{\beta M}{1 - M}. \tag{32}$$

The distribution of the estimates of the Lerner index is the convolution of the distributions of $\mathcal{L}$ and η. By the convolution theorem—see Cramér and Wold (1936)—the characteristic function of the convolution of two random variables is the product of the two characteristic functions. Thus the characteristic function of η is the ratio of the characteristic function of the observed random variable L to the characteristic function of the random variable $\mathcal{L}$. Distributions are one-to-one with characteristic functions, so the distribution of η is identified. $\square$

Although manipulating characteristic functions might seem to be the natural way to calculate the distribution of η, it appears to be unworkable in this application, so I proceeded by a direct solution—representing the distribution in a flexible parametric form and solving the convolution by minimizing the distance between the actual distribution of the estimates L and the distribution calculated as the convolution of the parametric distribution and the known distribution of the true Lerner index $\mathcal{L}$. I use a discrete 32-point support η_j so the probabilities π_j serve as the parameters, subject to the natural restrictions $\sum_j \pi_j = 1$ and $\pi_j \geq 0$ and small penalties encouraging smoothness of the π_js. The problem becomes

$$\min_{\pi_j} \left[\sum_j \pi_j \int_0^{\text{plus}(L-\eta_j)} f(\mathcal{L}) d\mathcal{L} + \left(1 - \sum_j \pi_j\right)^2 + \sum_j \text{minus}(\pi_j)^2 + \omega \sum_2^j (\pi_j - \pi_{j-1})^2 \right].$$

Here plus$(\cdot)$ is the positive part function and minus$(\cdot)$ is the negative part function. The weight ω on the smoothness term is taken as 0.01, so the much higher weight on the matching conditions results in values of π_j that come close to satisfying the matching conditions.

Table 3 shows the inputs to and results of these calculations based on the distribution of estimates of the estimated Lerner index L. The upper panel shows the moments of the 60 estimates of L. The next lower panel reports the value of the first shape parameter of the beta distribution assumed to describe the distribution of the true, $\nu = 1.36$. The third panel down gives the implied mean and standard deviation of the level of the true Lerner index, $\mathcal{L}$. The mean is 0.15 and the standard deviation is 0.11. The distribution of the true Lerner index is fairly tightly contained in the range between 0 and 0.4. As Figure 2 indicates, the distribution is skewed to the right, win a skewness coefficient of 1.14. The bottom panel gives moments of the solved distribution of the measurement errors. The mean is zero by assumption The standard deviation of the implied distribution of the sampling error, η, is 0.29. The main feature of the distribution of the estimated Lerner index that supports this finding is that 31 percent of the estimates are negative, which can only arise from the left tail of the distribution of the sampling error.

Figure 3 plots the inferred distribution of the true value of the Lerner index $\mathcal{L}$. The density of the beta distribution is

$$Bx^{\nu-1}(1-x)^{\beta-1}. \tag{33}$$

Figure 4 is a bar chart summarizing the inferred distribution of the measurement error η. The actual distribution over the 32 points of its support is quite jagged, reflecting the

Moments of estimated Lerner indexes across industries	Mean	0.15
	Stan. dev.	0.31
	Skewness	-1.84
Shape parameter of true Lerner index	α	1.36
Moments of true Lerner indexes across industries	Mean	0.15
	Stan. dev.	0.11
	Skewness	1.14
Moments of measurement errors	Mean	0.00
	Stan. dev.	0.29
	Skewness	-2.30

Table 3: Moments of the Distribution of the Estimated Lerner Index, and Inferred Properties of the Distributions of the True Index and the Error in Measurement

randomness in the 60 draws of the underlying data on the observed Lerner index L. Because the assumed distribution of $\mathcal{L}$ is smooth, all of the randomness in the observed index maps into corresponding randomness in the inferred measurement error.

All of the distribution of the measured value L below zero is the result of the sampling error, and a fair amount of the distribution above 0.5. Figure 5 compares the calculated cumulative distribution—the convolution of the distributions of $\mathcal{L}$ and η—to the cumulative distribution of the 60 estimates. The fit is pretty good. Its imperfections arise entirely from the assumption that the distribution of η has the assumed 32 discrete points in its support, rather than being a continuous distribution.

2.7 The change in the markup coefficient over time

To study the widely discussed hypothesis of growth in market power, I extend the specification to include an industry-specific linear time trend over the sample period from 1988 through 2015:

$$\Delta \log y_t - \sum_i \alpha_{i,t}\, \Delta x_{i,t} = (\phi_i + \psi_i t)\Delta \log y_t - a_t. \tag{34}$$

Here t advances by one each year and crosses zero in the middle of the sample period, 2001. The implied functional form for the Lerner index is

$$\mathcal{L}_{i,t} = \phi_i + \psi_i t. \tag{35}$$

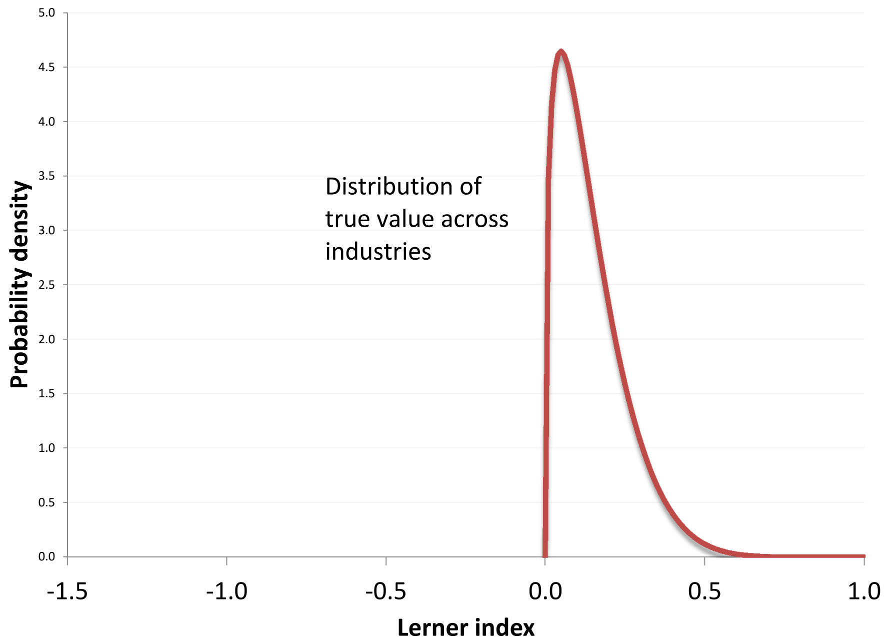

Figure 3: Inferred Distributions of True Lerner Index across Industries

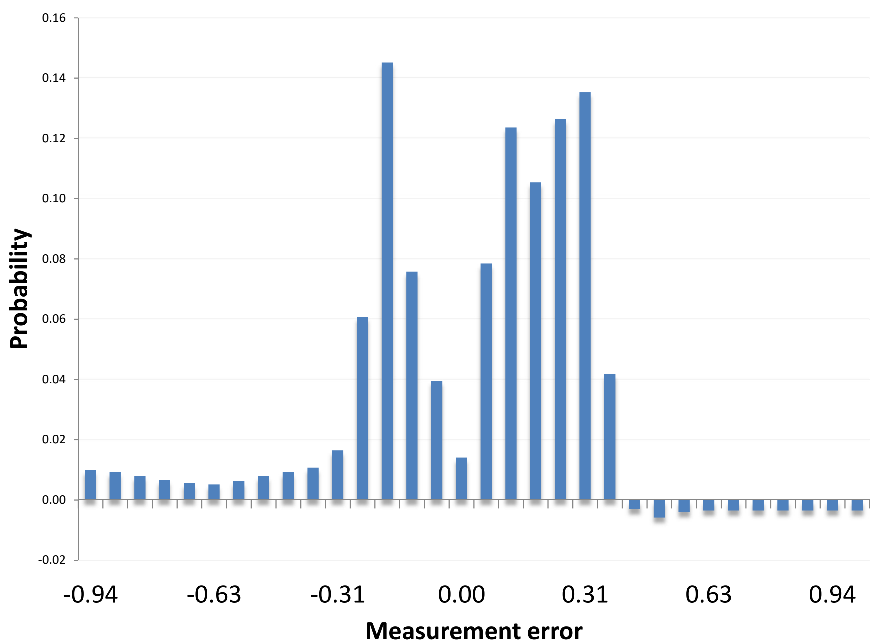

Figure 4: Distribution of the Measurement Error

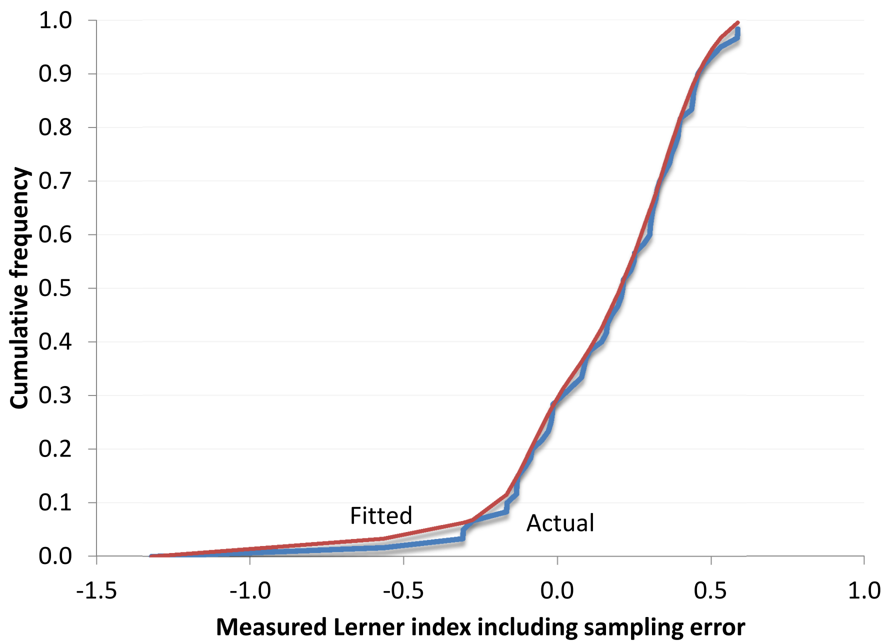

Figure 5: Actual Cumulative Frequencies of Estimates and Calculated Cumulative Distribution Functions from the Statistical Model

I extend the set of instruments to include the product of the log-changes and the time-trend variable, so there are 10 instruments.

Table 4 shows the growth coefficients ψ_i in the same sector groupings as in Table 2 earlier. They are sorted from highest to lowest. Though the ranking is plausible—for example, the information sector has relatively rapid growth in market power—there is substantial sampling error. There is no neat way to separate sampling variation from heterogeneity in the true coefficients. There are indications that sampling variation dominates the observed heterogeneity of the estimates. For example, if there were substantial variation in the true values, the t-statistics would have more dispersion across industries than the standard t distribution has. In fact, the average of the squared t-statistics is 0.97, whereas it would be 1.13 for a t distribution with 15 degrees of freedom.

Despite the preponderance of sampling variation, the estimates give reasonable support to the hypothesis that the overall price/marginal-cost ratio rose over the period from 1998 through 2015. Table 5 shows the weighted average of the 60 estimates of ψ, which is 0.0061 increase in $\mathcal{L}$ per year. The weights are the shares of the industries in total value-added. The t-statistic for the hypothesis that ψ is actually zero, and that sampling error accounts for

Weighted averages across industries		
Growth coefficient, ψ	*Standard error*	*Sector name*
-0.111	(0.061)	Mining, Quarrying, and Oil and Gas Extraction
-0.021	(0.011)	Retail Trade
-0.021	(0.011)	Wholesale Trade
-0.010	(0.011)	Professional, Scientific, and Technical Services
-0.001	(0.010)	Educational Services
0.001	(0.009)	Transportation and Warehousing
0.001	(0.007)	Manufacturing
0.001	(0.008)	Accommodation and Food Services
0.004	(0.028)	Agriculture, Forestry, Fishing and Hunting
0.006	(0.015)	Other Services (except Public Administration)
0.006	(0.007)	Administrative and Support and Waste Management and Remediation Services
0.013	(0.014)	Arts, Entertainment, and Recreation
0.015	(0.024)	Management of Companies and Enterprises
0.017	(0.016)	Construction
0.017	(0.016)	Information
0.018	(0.010)	Real Estate and Rental and Leasing
0.019	(0.007)	Health Care and Social Assistance
0.036	(0.109)	Utilities
0.064	(0.035)	Finance and Insurance

Table 4: Estimates of the Growth in the Lerner Index by Industry, Stated as Sector Averages

Weighted average of estimate of trend ψ	0.0061
Standard error	0.0051
t-statistic for hypothesis $\psi = 0$	1.20
p- value, one-tailed	0.11

Table 5: Evidence about the Statistical Reliability of the Finding of an Upward Trend in the Markup Ratio

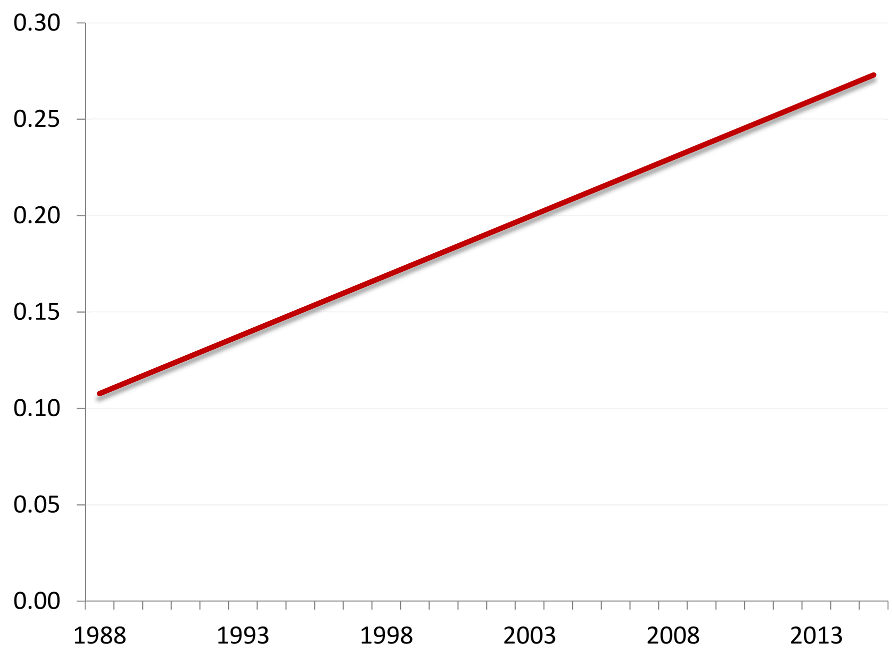

Figure 6: Implied Values of the Lerner index by Year

the increase, is 1.20. The p-value for the one-tailed test is 0.11, which is reasonably strong evidence against the null hypothesis.

Figure 6 plots the growth of the Lerner index at the weighted averages of the parameters ϕ_i and ψ_i. The index grew from 0.12 in 1988 to 0.27 in 2015. This finding indicates substantial growth in market power, though less than the economy-wise increase reported by De Loecker and Eeckhout (2017).

2.8 Conclusions about the approach to measuring market power

Direct measurement of market power using high-quality annual time-series productivity data for 60 industries yields good information of the heterogeneous incidence of positive market power in US industries. There is a good deal of noise in the calculations at the individual industry level. The noise is interpreted as the annual growth of Hicks-neutral technology. The paper tries to state the precision in its estimates using standard statistical tools. There is a good deal of cross-industry heterogeneity in the estimated parameters. All of the results are interpreted in a framework of heterogeneity.

The choice to use modern productivity data has advantages and disadvantages. The alternative is to use data from individual firms, such as Compustat for publicly traded firms or confidential survey or administrative data. The advantage of the productivity data is the care with which the BEA and BLS measure inputs and outputs. No data on individual firms comes close to the accuracy and detail of the productivity data. The advantage of the data on individual firms is much more variation in growth rates of inputs and outputs and thus lower sampling variation in the estimated coefficients.

3 Flows to Firms' Owners: Profit and Interest

One branch of the recent upsurge in the analysis of market power observes that, in recent decades, the owners of firms have received cash flows that are high relative to historical benchmarks. This section calculates flows accruing to owners in a framework that clarifies the set of firms under consideration, the identity of the owners, the flows that should be included in the calculation, and the denominator in the calculated ratios of profit and interest flows to asset stocks. The calculations generally support the hypothesis that recent flows to owners have exceeded earlier benchmarks. In particular, the value flowing to equity holders has been spectacular in recent years, because corporate borrowing has increased dramatically but the interest paid on the debt has remained moderate on account of very low interest rates.

The word "profit" is used frequently in discussions of corporate performance, but the term is seriously ambiguous. For example, some authors use profit to mean the entire flow accruing to equity holders, while others use it to mean the excess of the flow over the market cost of capital. I use the term profit in the sense used in the NIPAs—the flow of value to equity holders from business operations, with deductions for depreciation and amortization based on current replacement cost.

The owners of a firm comprise the debt holders and the equity holders. The former hold a prior claim on the value of the firm and the latter a residual claim. The flow of value accruing to the owners is reasonably well measured in national income accounting, as flows to the equity and debt holders. Debt holders receive their contractual claim, if available, and the equity holders receive the residual. Often the equity holders reinvest some of their flow as retained earnings. The residual flow is cash received by the firm from sales of its products less amounts paid to workers and suppliers. Purchases of capital inputs are smoothed over time through depreciation deductions.

Finance theory does not provide a usable concept of the *rate* of profit—that is, a ratio of the flow of profit to some stock, analogous to the rate of interest. The question, "Are US corporations earning a higher rate of profit today, relative to past decades?" is not well posed. One might think that a reasonable definition of the rate of profit would be the ratio of the flow of profit to the shareholders' stake, the stock of assets less the debt. But it is perfectly possible—indeed, found in the data for the chemical industry presented later in this section—that debt exceeds the measured stock of assets. In that case, the ratio would be negative, thanks to the negative denominator. Lenders happily lend to corporations with high profits, even if measured assets do not cover the amount of the debt. There is no natural benchmark for profit to serve as the denominator in a ratio called the rate of profit.

Assets do form a natural denominator for measuring the combined flow of profit and interest payments. In the case just noted, that ratio will be unusually large for a business that is unusually successful, rather than negative. Accordingly, a logical way to proceed is to combine the flows to equity and debt holders and use total business operating assets as the denominator. This approach is often taken in practical finance, where it is called "de-leveraging" the data. Discussions of corporate performance also often focus on the flow measure EBITDA, earnings before interest, taxes, depreciation, and amortization. Comparisons involving that measure need to consider differences in depreciation and amortization rates. This paper considers what would analogously be called EBIT, earnings before interest and taxes. Among economists, the ratio of earnings to assets is often called the *rate of return to capital*, but I avoid that term because it is easily confused with the rate of return earned by shareholders. I will use the term *earning rate on assets* or earning rate for short. As I will show in this section, in the current US economy, shareholders earn a rate of return about 0.4 times the earning rate on assets. The reason is simple—securities markets value the corporate sector at about 2.5 times the reproduction cost of its assets.

Within this framework, this section looks first at data for the aggregate of all US corporations, using data from the NIPAs. It finds that the adjusted earning rate for the equity and debt holders combined, stated as a ratio to business assets, rose from about 7 percent per year in 1987 through 2003 to about 9 percent since then. There is modest confirmation to the hypothesis that business owners—equity and debt holders—jointly enjoyed higher flow ratios in the past decade.

It is possible and useful to divide the earning rate into the part received by shareholders and the part received by debt holders. The two parts sum to the earning rate—the parts are not to be interpreted as rates of return themselves.

3.1 Modifications to the NIPA profit measure

This subsection discusses issues that arise in measuring profit in the corporate sector as a whole and in the industries studied earlier with the KLEMS data. The focus is on corporations, to avoid the unsolved problem of separating ownership income from labor income in proprietorships and partnerships. The starting point is the measure called "profit" in the National Income and Product Accounts. This measure is a residual that excludes interest payments. It incorporates careful adjustment of depreciation cost based on current replacement cost. It separates the accounting for the business operations—selling products and buying inputs—from firms' transactions in financial assets. For example, capital gains on securities held by a firm are not included in revenue. The NIPA approach to measuring profit corresponds to an approach to the firm's balance sheet in which the net value of financial claims appears on the left side and the value of business operating assets appears on the right side. For further discussion of this approach, see Hall (2001).

For the value accruing to all owners, I add data on net interest payments. The NIPAs do not break down corporate interest by industry, so I use data from the Internal Revenue Service for calculations at the industry level.

The NIPA data cover all corporations, including those taxed under subchapter S of the Internal Revenue Code—see Bureau of Economic Analysis, US Department of Commerce (2017), chapter 13. Until the 2017 tax reform, accounting profit of these corporations was taxed as ordinary income. Although owners of S-corporations were generally required to pay themselves salaries, these corporations also included significant amounts of labor income in the profits they reported for tax purposes. Smith, Yagan, Zidar and Zwick (2017) provide the best evidence about the magnitude of labor income included in S-corporation profits. They study the decline in profits that occurs when the major owner of an S-corporation dies prematurely. The decline is 61 percent. The inference is that only 39 percent of S-corporation reported profit is actually capital income. The tax reform of 2017 adopted a similar limit on the fraction of the income of S-corporations and other pass-through businesses that is allowed to be treated as capital income eligible for reduced taxation.

The NIPAs' treatment of S-corporations results in an overstatement of corporate profit, and, in view of the growth of S-corporations relative to C-corporations, results in an overstatement of the *growth* of corporate profits. To remove this bias, I proceed as follows. Let $\tilde{y}$ be the reported total profit of both types of corporations, and let $\tilde{y}_C$ and $\tilde{y}_S$ be the unreported breakdown between the two types. Let y, y_C, and y_S denote the inferred values of the same variables after correction for the overstatement of the S-corporation component.

The calculation proceeds on the assumption that the share of S-corporations in correctly measured profits is the same as the share in reported sales. I denote the share as s. Thus

$$\frac{y_S}{y_C + y_S} = s, \tag{36}$$

Further, it uses the estimate in Smith et al. (2017) about the relation between true and measured C-corporation profits:

$$z = \frac{y_s}{\tilde{y}_S} = 0.39. \tag{37}$$

The solution to the system of equations is

$$y_S = \frac{s}{s/z - s + 1}\tilde{y}. \tag{38}$$

$$y_C = \tilde{y} - \frac{y_S}{z}. \tag{39}$$

and

$$y = y_C + y_S. \tag{40}$$

3.2 Modifications to the NIPA's Fixed-Asset data

At the aggregate level, the Fixed-Asset data affiliated with the National Income and Product Accounts report data for corporations, but the data for industries report only for all businesses. To adjust the data by industry, I deduct IRS data for partnerships for business assets and deduct IRS data for sole proprietors for depreciation divided by 0.10, an estimate of the depreciation rate.

3.3 Results for corporations in general

The National Income and Product Accounts (including the Fixed-Asset Accounts), provide the basic data needed to calculate the earning rate for all US corporations—the ratio of profit and interest flows to the reproduction cost of reported operating assets at current prices. Both are nominal quantities, so the ratio is free from effects of changes in the overall price level. Aggregate profit for corporations is from NIPA Table 6.17, net interest is from NIPA Table 7.11, and fixed-asset value is from FA Table 4.1. To make the adjustment for excess attribution of S-corporation's capital income, I use business receipts for all corporations from Internal Revenue Service, Statistics of Income, Table 13. "Corporation Income Tax Returns: Balance Sheet, Income Statement, and Tax Items for Income Years, 1990-2013 Expanded" (irs.gov/statistics/soi-tax-stats-historical-table-13). Business receipts for S-corporations are from Statistics of Income, Table 14, "Returns of Active Corporations, Form 1120S, for 1998 through 2003, and Table 7, S-Corporation Returns: Balance Sheet and Income Statement Items, by Major Industry" for later years, both from irs.gov/statistics/soi-tax-stats-historical-data-tables. The data for S-corporations are limited to the years 1998 through 2013. For earlier years, I used the calculated ratio of S to total corporate receipts ratio for 1998 and for later years, I use the ratio for 2013. I also include the value of inventories in operating asset value, using Census data for the trade and manufacturing sectors and data from the Quarterly Financial Reports for other sectors.

Figure 7 plots the earning rate, the ratio of the adjusted flow of value accruing to owners—profit and interest—normalized by dividing by the value of corporate business operating assets. The ratio moves with the business cycle. It declined in each of the three recessions, 1990-91, 2001, and 2007-2009. Growth was mild during the prolonged expansion of the 1990s but was spectacular in the expansion from 2001 through 2007. After a brief contraction around the financial crisis in 2008 and 2009, the ratio remained around 10 percent through 2016.

The conceptual framework underlying Figure 7 and the numerical results are similar to those in Gomme, Ravikumar and Rupert (2011), though the calculations differ in some respects, including the treatment of taxes and S-corporations. On the other hand, Barkai and Benzell (2018) calculate a residual concept of profit by subtracting a measure of the cost of capital.

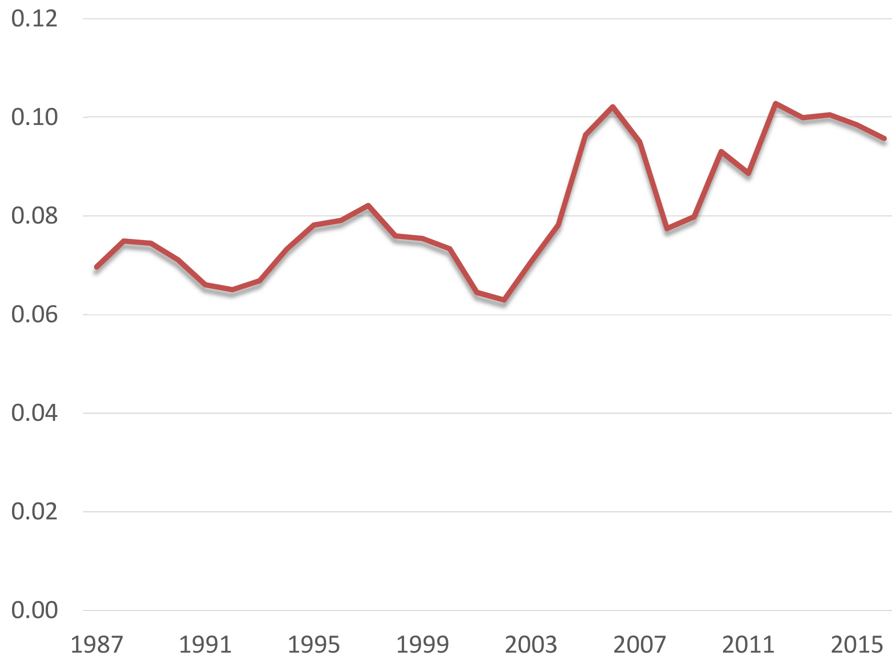

Figure 7: The Earning Rate for US Corporations—the Ratio of Profit and Interest to the Replacement Cost of Assets

Figure 8 describes the adjustment for excess attribution of S-corporation income to owners. The lower line gives the share of S-corporations in total corporate income, based on the available data on business receipts. Only the years from 1994 through 2013 are based on the annual data. The share rose fairly rapidly until the financial crisis, then only slightly through 2013. The resulting estimated value of the overstatement in the earning rate is quite cyclical, but its trend tracks the underlying share. Since 2005, the exaggeration of the ratio has been in the range of 2.5 to 4 percentage points.

Figure 9 separates the profit and interest components of the earning rate in Figure 7. The profit component fluctuated in a narrow range from 5 to 7 percent until 2003, when it began to increase to over 9 percent, was briefly interrupted by the financial crisis, and then regained 9 percent. The interest contribution began at two percent, fell to one percent, reached almost two percent again in 2000, fell to near zero in 2004, rose to about 1.3 percent, fell only slightly after the crisis, and leveled at one percent in 2016. The stability of the interest ratio was the essentially a tie between a large increase in the volume of debt, offset by falling rates paid on the debt.

Figure 10 confirms that the volume of corporate debt rose dramatically as a ratio to business operating assets during the period of low interest rates. To measure debt, I divide

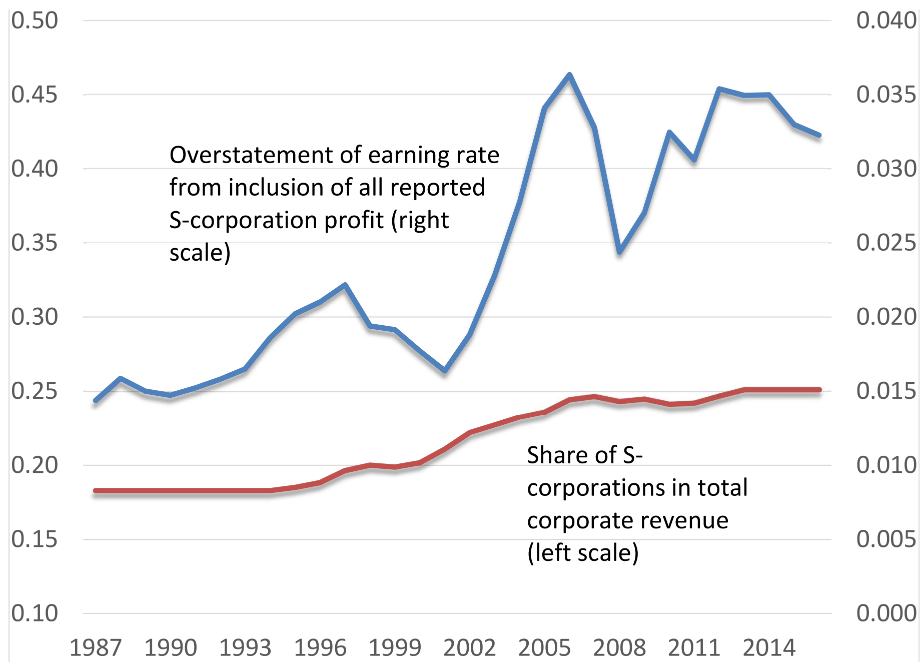

Figure 8: Overstatement of Level and Growth of Corporate Earning Rate on Account of the Inclusion of all of the Reported Profits of Sub-Chapter S Corporations

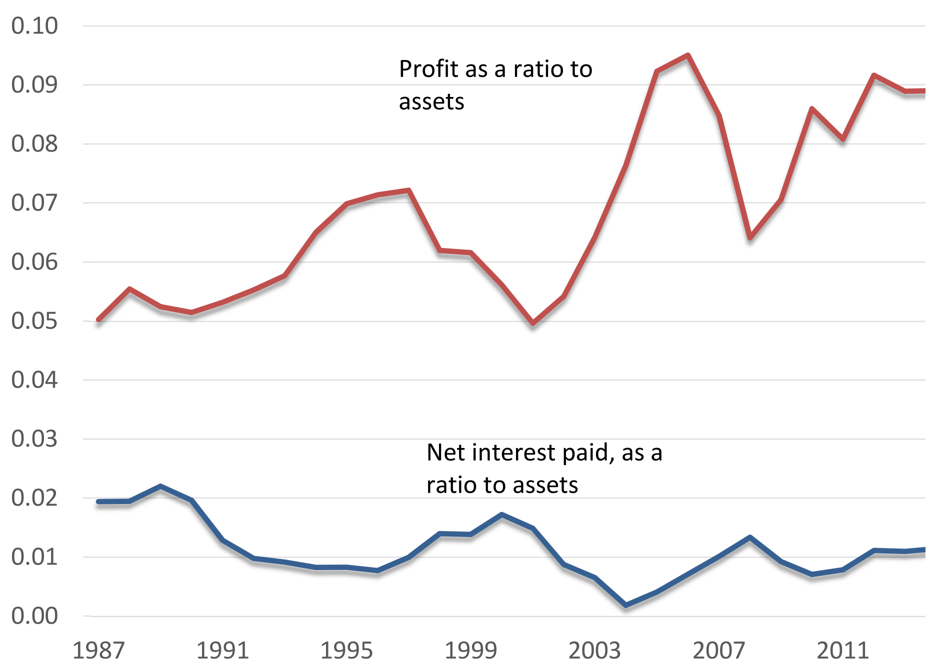

Figure 9: Corporate Profit as a Ratio to Business Assets, and Interest Paid to Debt Holders as a Ratio to Assets

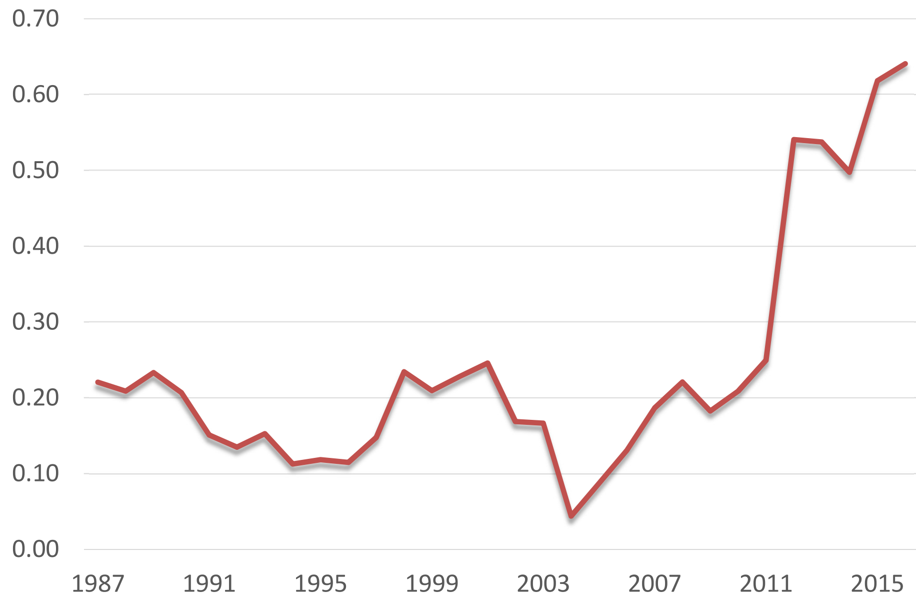

Figure 10: Ratio of Corporate Debt to Operating Assets

the net interest paid by the corporate sector by FRED variable HQMCB5YR, "5-Year High Quality Market Corporate Bond Spot Rate". The use of a series that contains only a small default premium is appropriate because the default premium is not a cost to the borrower—it is not actually paid in the event of default. Although gross debt outstanding is measured in the Financial Accounts of the US, determining net debt by deducting debt held on the asset side is a huge challenge.

It is useful to compare these results for flows of value to owners with the same situation in the stock market. The corresponding current value flow to shareholders is earnings. The earnings yield in the stock market has a similar economic character to the profit component shown in Figure 9. Figure 11 shows the earnings/price ratio for the S&P 500 stock market index, calculated from Robert Shiller's data (econ.yale.edu/ shiller/data/ie_data.xls). The ratio fell gradually from the late 1980s to a trough during the tech boom, then rose during the immediate pre-crisis years, experienced a downward spike when the stock market collapsed briefly in the crisis, and has been level at around 6 percent since then.

Figure 7 reports much higher values for the earning rate than shareholders receive from the stock market according to Figure 11. One way to illustrate the magnitude of the disagreement between the two rates is to ask what would be the multiple of reported business assets that would equate the two rates by lowering the calculated earning rate. This multiplier, q,

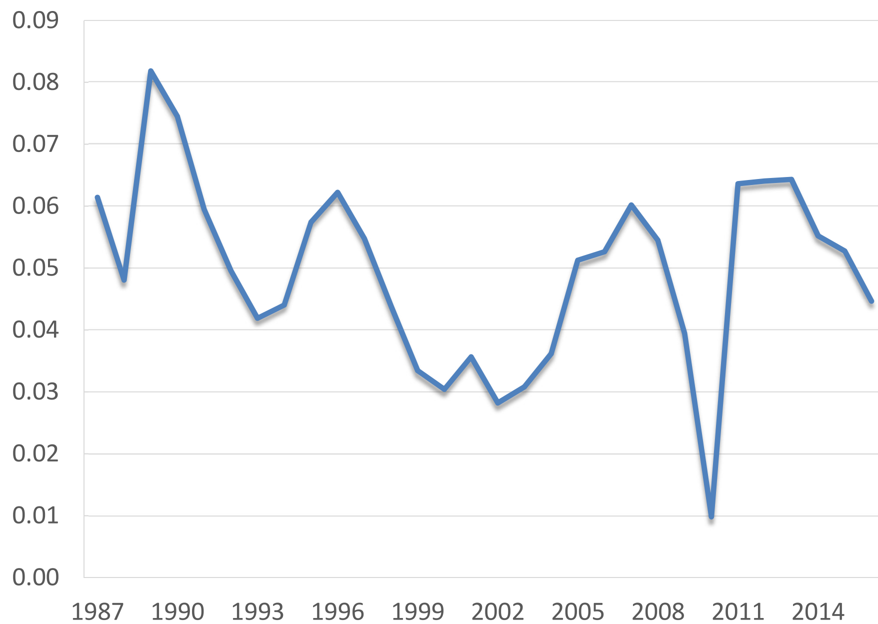

Figure 11: Earnings/Price Ratio for the S&P 500 Stock Portfolio

is defined by

$$\frac{\text{profit}}{q \times \text{ assets - debt}} = \text{earnings yield in stock market.} \tag{41}$$

That multiplier is an estimate of Tobin's q, as can be seen by solving for q:

$$q = \frac{\text{profit/yield + debt}}{\text{assets}}, \tag{42}$$

the standard definition of q as the ratio of the market enterprise value of corporations (sum of equity and debt values) to replacement cost of assets. Direct calculation of q is challenging because it requires matching equity values from publicly traded stocks to operating results of corporations in general. A further complication is deducting debt claims held by corporations as assets (take a look at Hanno Lustig's supporting materials for Hall (2001) to grasp how hard this is). The shortcut here amounts to inferring the enterprise value as the sum of the capitalized profit (using the capitalization factor from the S&P) and the debt. Note that I also calculate debt by dividing net interest paid by the market yield of debt, but this further step is not intrinsic to the idea.

Tobin's q has exceeded one by most measures since the early 1990s. Hall (2001) discussed the interpretation of this finding, in terms of adjustment costs and the presence of unmeasured intangibles among business operating assets. Crouzet and Eberly (2018) is a recent comprehensive discussion of these and related sources of elevated q. Recent commen-

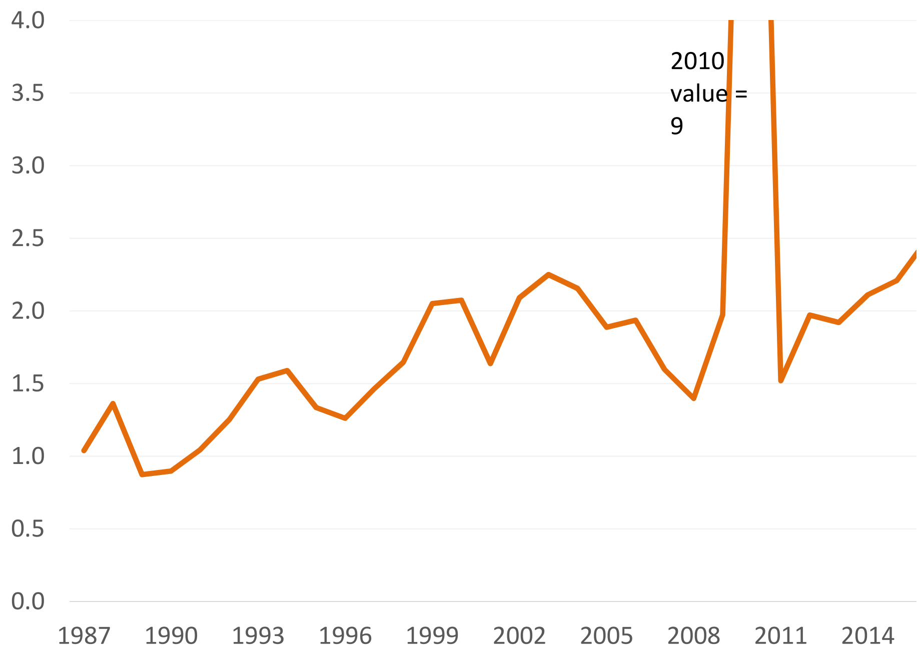

Figure 12: Ratio, q, of the Implied Total Asset Value to Observed Asset Value

tary has added rising market power to the list of influences raising q. Crouzet and Eberly emphasize the growing role of scalable factors of production, such as software, in the rise of market power. In addition, the growth in the share of products and services that enjoy network externalities limits entry of rivals and defends the profits of early entrants. A decline in antitrust enforcement in mergers and other forms of anti-competitive conduct has been identified as a source of higher profits.

Figure 12 shows the resulting value of q for all US corporations. In 1987, q was about one. During the 1990s, the multiple rose smoothly to just over two, then fell to 1.5 at the time of the crisis. Since 2011, q rose to nearly 2.5. These results make it clear that US corporations own huge and growing amounts of some kinds of assets or privilege or market power that the stock market recognizes but is not recorded in the data on corporate operating assets.

3.4 Metrics for individual industries

The US statistical agencies do not publish all the data needed to carry out calculations at the detailed industry level comparable to those just discussed at the aggregation level of the all corporate corporations. The main limitation is the lack of data on corporate assets. The fixed-asset accounts include partnerships, proprietorships, and non-profit organizations along with corporations. The IRS publishes data on partnership assets, but the figures include large volumes of partnership data that are not the non-financial business operating assets recognized in the NIPAs. For 2007, the fixed-assets tables report that the total non-corporate holdings were \$151 billion, but the IRS reports that partnerships held \$598 billion in assets. Plainly these must have included non-operating financial assets.

Total holdings of operating assets in manufacturing for 2007 were \$2.8 trillion, so it is clear that neglecting non-corporate assets is acceptable in manufacturing. In addition to all the manufacturing industries in KLEMS, I have included others that presumably involve large organizations that are entirely corporate, such as utilities, movies, air-rail-water transport, and pipelines. I report results for 31 of the 60 distinct KLEMS industries.

Here is an example set of calculations, for the chemical industry in 2007: S-corporations accounted for 4.3 percent of corporate receipts in the industry that year. Profit reported in the NIPAs was \$72 billion. Profit after the adjustment for over-attribution of S-corporation profit was \$68 billion. Total earnings were \$84 billion. The industry held \$626 billion in business fixed assets. For the reason noted above, I took all of this to be corporate, despite the IRS's report that the industry had \$147 billion in partnership assets. Corporations in the industry held \$70 billion in inventories. Total business operating assets of corporations in the industry were thus \$696 billion. S-corporations made \$0.4 billion in net interest payments and \$C-corporations \$15.5 billion. The interest rate in 2007 was 5.4 percent, so I divided this figure into the interest payment to get an estimate of \$291 billion for the industry's net debt. The earning ratio was \$84 billion/ \$696 billion = 12.0 percent per year. The calculation of q is

$$\frac{68/0.060 + 291}{696} = 2.0. \tag{43}$$

Table 6 shows the calculated earning rates for about half of the KLEMS industries, together with the earlier findings on the Lerner indexes of the same industries.

3.5 Conclusion from the evidence on earning rates

The evidence of positive earnings growth is much stronger than the evidence of growth in the Lerner index. The logical conclusion is that corporations own valuable things that are not counted as business assets in the NIPAs, including, possibly, the sources of rising market power.

Industry	*Earning rate*	*Earning growth*	*Average q*	*Lerner level*	*Lerner growth*
Oil and coal	25.4	16.5	6.08	1.02	-0.002
Insurance	16.0	9.3	4.34	-0.33	0.063
Food-beverage	13.4	0.2	3.75	-0.09	-0.017
Apparel	11.8	0.8	3.02	-0.49	0.048
Miscellaneous products	11.3	2.0	3.25	0.16	-0.032
Chemicals	9.4	1.6	2.57	0.12	0.010
Furniture	9.3	-1.5	2.40	0.32	0.000
Administration	8.9	1.9	2.39	0.08	0.007
Office medicine	8.7	2.2	2.45	-0.05	0.025
Fabricated metal	8.3	0.7	2.19	0.34	0.005
Printing	7.7	-0.9	2.06	0.24	0.020
Machinery	7.6	4.2	1.92	0.17	0.010
Mineral products	7.0	-2.5	1.66	0.35	-0.001
Wood products	6.7	-1.9	1.69	0.06	-0.013
Plastic and rubber	6.7	1.7	1.76	0.04	-0.016
Paper	6.4	2.9	1.68	0.07	-0.015
Waste	5.3	1.8	1.46	0.02	-0.004
Primary metals	4.9	5.1	1.17	-0.03	-0.004
Movies and records	4.6	3.1	1.33	-0.26	0.033
Electronics	4.3	6.5	1.26	0.70	0.004
Vehicles	3.6	0.0	0.93	0.32	0.009
Utilities	3.5	-0.5	0.90	0.53	0.036
Recreation	3.0	0.2	0.74	0.37	0.009
Accomodation	2.8	-0.3	0.65	0.43	0.027
Passenger transport	2.6	0.2	0.70	-0.02	-0.040
Textiles	2.5	0.6	0.61	0.18	-0.005
Hospitals and nursing home	1.4	0.4	0.37	-0.03	0.004
Air-Rail-Water transport	1.1	1.5	0.30	0.43	0.007
Rental	1.0	0.7	0.26	-0.10	0.002
Pipelines	1.0	-0.3	0.25	0.71	-0.016
Electrical products	0.4	2.7	0.47	-0.14	0.021
Mean	6.7	1.9	1.8	0.17	0.006
Standard deviation	5.2	3.6	1.3	0.32	0.022
Percent positive	100	74	100	68	61
Minimum	0.4	-2.5	0.3	-0.49	-0.04
Maximum	25.4	16.5	6.1	1.02	0.06
t- statistic for zero growth		5.5			0.2

Table 6: Earning Rates for 31 of the KLEMS Industries, with Levels and Rates of Growth of Lerner Indexes

The correlation across industries in the earning rate for the KLEMS industries with earning data and the estimates of the Lerner index is 0.08. The correlation of the rates of change is 0.15.

4 Concentration and Market Power

Some theories of oligopoly imply a structural relation between the distribution of market shares across sellers in an industry—higher inequality among shares implies a higher Lerner index. A common summary of share inequality is the fraction of sales among the four firms with the highest shares—the four-firm concentration ratio. This section studies data from the Economic Census for 2002 and 2012 on that ratio for manufacturing firms.

Market shares take their meaning from a market definition. A group of sellers constitutes a market if their products are reasonably close substitutes within the group but not close substitutes for the products of sellers in other markets. I proceed on the assumption that products within an industry defined by a 6-digit NAICS product code satisfy the criterion for market definition. The industries in the KLEMS data used in this paper each contain dozens of 6-digit NAICS industries. I consider the average across those detailed industries, for the industries that have identical names in both years, thus omitting the ones that were consolidated or divided between the two years.

The first two columns of Table 7 shows the four-firm concentration ratios in 2002 and 2012 for the KLEMS manufacturing industries, sorted in declining order of concentration in 2002. The third column shows the change in the ratios between the two years, in percentage points. Thefourth and fifth columns show the level and change coefficients for the Lerner index for the manufacturing industries from the earlier estimates.

A distinct majority of the concentration ratios grew over the 10 years, and the mean across the 18 changes was 2.2 percentage points, with a standard deviation of 3.6 percentage points and a t-statistic of 8.0 for the hypothesis of zero average change. The statistical evidence in favor of growth of concentration is strong.

The bottom line in Table 7 gives the correlations between the levels of the concentration ratios in 2002 and 2012, and the level coefficient, ϕ, in the equation for the Lerner index. They are both somewhat negative. On the other hand, the correlation of the change coefficient, ψ, and the change in the concentration ratio is positive. The lack of a tight connection between the estimated Lerner index and the concentration ratio reflects the sampling error in the

Manufacturing industry	*Average four-firm concentration ratio, percent*		*Percentage points of growth*	*Lerner level*	*Lerner growth*
	2002	2012			
Food and Beverage and Tobacco Products	49.8	51.2	1.3	-0.09	-0.02
Textile Mills and Textile Product Mills	34.1	34.4	0.3	0.18	0.00
Apparel and Leather and Applied Products	56.5	65.1	8.6	-0.49	0.05
Paper Products	45.8	50.0	4.1	0.07	-0.01
Printing and Related Support Activities	22.9	30.5	7.7	0.24	0.02
Petroleum and Coal Products	42.4	49.1	6.7	1.02	0.00
Chemical Products	49.1	47.2	-1.9	0.12	0.01
Plastics and Rubber Products	35.6	34.6	-1.0	0.04	-0.02
Wood Products	29.0	30.2	1.2	0.06	-0.01
Nonmetallic Mineral Products	42.7	44.2	1.5	0.35	0.00
Primary Metals	37.8	41.0	3.2	-0.03	0.00
Fabricated Metal Products	26.9	29.3	2.4	0.34	0.00
Machinery	38.1	38.7	0.6	0.17	0.01
Computer and Electronic Products	42.5	38.0	-4.5	0.70	0.00
Electrical Equipment, Appliances, and Components	49.2	54.8	5.6	-0.14	0.02
Transportation Equipment	61.5	57.5	-4.0	0.32	0.01
Furniture and Related Products	34.0	37.8	3.8	0.32	0.00
Miscellaneous Manufacturing	30.9	35.1	4.2	0.16	-0.03
Average	40.5	42.7	2.2	0.2	0.0
Standard deviation	10.0	10.0	3.6	0.3	0.0
t-statistic for no growth			8.0		
Correlation with Lerner index and change in Lerner index	-0.22	-0.31	0.31		

Table 7: Four-Firm Concentration Ratios for the KLEMS Manufacturing Industries

estimates of ϕ and ψ, and the fairly loose connection in oligopoly theory between market power and concentration.

Table 8 provides some sense of the economic significance of the measured concentration ratios. The first step is to translate the concentration ratios—the only published information about concentration given Census rules about data disclosure—to the measure favored by the Department of Justice using confidential data. This is the Herfindahl index, the sum of the squared percent market shares of all sellers in a market. I approximate the Herfindahl from the 4-firm concentration ratio as the average of the highest possible Herfindahl given the concentration ratio and the lowest possible Herfindahl. The first attributes the entire four-firm ratio to one firm and the second spreads the ratio equally among the top 4 firms. The average is 5/8 of the squared concentration ratio. I then apply the Department's criteria for screening proposed mergers, based on classifying markets as not concentrated if the Herfindahl post-merger is under 1000, as moderately concentrated if it is between 1000, and highly concentrated if it is above 1800. Mergers that result in a market that remains unconcentrated are screened as not anti-competitive, mergers that raise the Herfindahl by more than 100 and leave the market moderately or highly concentrated are screened as anti-competitive, and mergers that raise the Herfindahl by more than 50 and involve a market that is highly concentrated are also screened as anti-competitive (this case does not occur in the table).

Among the 18 industries in Table 8, half are scored as not concentrated in 2012, after the general rise in concentration ratios over the decade since 2002. Recall that each of the industries contains numerous 6-digit markets, so this conclusion holds on the average and does not imply that all of the markets were unconcentrated. Among the 6 industries that were moderately concentrated in 2012, three—apparel, paper, and electrical equipment—had concentration growth above the cutoff of 100 points which would cause the Department to screen a merger as anti-competitive and launch a fuller investigation. And among the remaining 3 industries that had become highly concentrated, two had Herfindahl increases since 2002 well into the territory deemed likely to results in a conclusion adverse to a proposed merger in the typical market. These are apparel, a shrinking industry with an increase of 653 points, and electrical equipment with an increase of 365 points. The third highly concentrated industry, transportation equipment, had a decline of 298 points.

Manufacturing industry	2002		*2012*		*Points of Herfin-dahl growth*
	Approximate Herfindahl	*Extent of concentration*	*Approximate Herfindahl*	*Extent of concentration*	
Food and Beverage and Tobacco Products	1551	moderate	1636	moderate	85
Textile Mills and Textile Product Mills	727	not	740	not	14
Apparel and Leather and Applied Products	1992	high	2645	high	653
Paper Products	1312	moderate	1559	moderate	248
Printing and Related Support Activities	326	not	581	not	255
Petroleum and Coal Products	1126	moderate	1508	moderate	382
Chemical Products	1506	moderate	1394	moderate	-112
Plastics and Rubber Products	794	not	748	not	-45
Wood Products	526	not	571	not	45
Nonmetallic Mineral Products	1137	moderate	1221	moderate	83
Primary Metals	893	not	1052	moderate	159
Fabricated Metal Products	452	not	537	not	85
Machinery	906	not	936	not	31
Computer and Electronic Products	1131	moderate	903	not	-228
Electrical Equipment, Appliances, and Components	1510	moderate	1875	high	365
Transportation Equipment	2363	high	2065	high	-298
Furniture and Related Products	724	not	894	not	170
Miscellaneous Manufacturing	599	not	772	not	173
Average	1087		1202		115
Standard deviation	528		569		218
t-statistic for no growth					32.9
Correlation with Lerner index and change in Lerner index	-0.24		-0.35		0.39

Table 8: Levels and Changes in Approximate Herfindahl Indexes, and Level and Change in Lerner Infex, for the KLEMS Manufacturing Industries

As the Department criteria suggest, rising concentration is mainly an issue of concern among markets that reach a worrisome *level* of concentration. Market power is a quadratic function of the concentration ratio in models where concentration maps directly into the oligopoly price. The results in Table 8 suggest that a substantial fraction of 6-digit product markets in manufacturing are fairly unconcentrated, so any increase in the concentration ratios in those markets has resulted in only small increases in the Lerner indexes of those markets. But worrisome increases in concentration that were probably associated with meaningful increases in market power did occur in some markets. Sunset markets, such as apparel, are particularly vulnerable to declining competition, because entry is unprofitable and exit is occurring among less efficient producers. Note that the manufacturing industry most closely with high-tech products—computers and electronic products—had a substantial decline in concentration of 228 points. The results in the table give little support to the hypothesis that dominant big firms are taking over in the US manufacturing sector.

4.1 Conclusions from the data on concentration

Average concentration in US manufacturing rose from 2002 to 2012. The overall rise was statistically unambiguous. The rise was economically important in half of the KLEMS industries, judged by the screening criteria in federal law enforcement. Some of these industries shrank dramatically over the decade, so the increase in concentration was a byproduct of the forces causing the shrinkage. The computer industry, probably the most important technology user and generator, had declining concentration, along with transportation equipment and chemicals, both technology users. In general the pattern of rising concentration does not suggest that the growth of superstar firms was an important source. The main generalization is essentially the reverse—the survivors in shrinking markets tend to be the stars and to gain share.

Within the manufacturing industries, the correlation of the levels of concentration and the levels of the estimated Lerner indexes is -0.31 and the correlation of the changes in concentration and the trends in the Lerner Indexes is 0.31.

5 Mega-Firms and Market Power

Autor, Dorn, Katz, Patterson and Van Reenen (2017) describe superstar firms that grow to account for large fractions of sales in their output and input markets and presumably

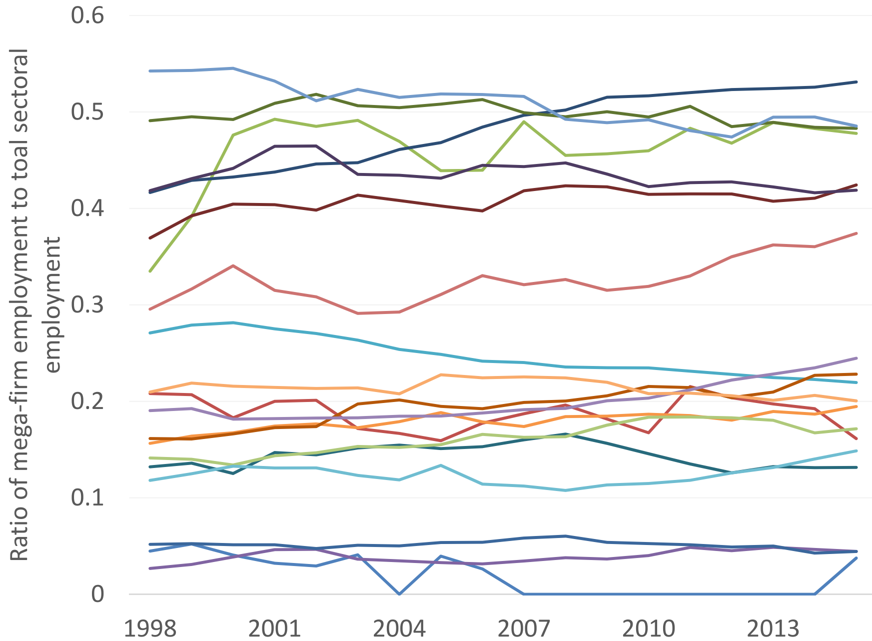

Figure 13: Ratio of Employment in Mega-Firms to Total Sectoral Employment, 1998 through 2015

acquire growing market power. The rise of these firms is thought to account for the decline in the labor share in the US and many other countries in recent decades. Here I investigate the relation between the employment share of high-employment mega-firms and the Lerner indexes found in this paper. I study the level and growth of the shares of mega-firms using the data described earlier. Table 9 shows the employment shares of firms with 10,000 or more workers in the 19 NAICS sectors in the first year the data are available, 1998, and the most recent year, 2015.

Growth in the shares of mega-firms has been anything but uniform across sectors. In four of the 19 sectors, very high-employment firms declined in importance over the 17-year span of the data. These sectors include all of manufacturing, which is the third-largest sector. The largest positive growth was in utilities, where mega-firms rose from 33.5 percent of employment in 1998 to 46.0 percent in 2015. Retail trade was another sector with a large increase in concentration by this metric. The weighted-average increase across all sectors was only 1.8 percentage points, from 25.3 percent to 27.1 percent. Thus it seems unlikely that rising concentration played much of a role in the general increase in market power that probably occurred over the 17 years. Figure 13 shows the movements of the high-firm-employment share by sector in the intervening years.

NAICS	*Description*	*Employment, 2015, millions*	*Mega-firm ratio in 1998*	*Mega-firm ratio in 2015*	*Change*
11	Agriculture, Forestry, Fishing and Hunting	0.2	0.045	0.038	-0.007
21	Mining, Quarrying, and Oil and Gas Extraction	0.7	0.208	0.161	-0.047
22	Utilities	0.6	0.335	0.478	0.143
23	Construction	6.0	0.027	0.044	0.018
31-33	Manufacturing	11.6	0.271	0.220	-0.051
42	Wholesale Trade	6.1	0.156	0.195	0.038
44-45	Retail Trade	15.7	0.416	0.531	0.115
48-49	Transportation and Warehousing	4.6	0.369	0.424	0.055
51	Information	3.4	0.491	0.483	-0.008
52	Finance and Insurance	6.1	0.418	0.419	0.001
53	Real Estate and Rental and Leasing	2.1	0.132	0.132	-0.001
54	Professional, Scientific, and Technical Services	8.8	0.161	0.228	0.067
55	Management of Companies and Enterprises	3.3	0.542	0.485	-0.057
56	Administrative and Support and Waste Management and Remediation Services	11.1	0.296	0.374	0.079
61	Educational Services	3.6	0.141	0.172	0.030
62	Health Care and Social Assistance	19.2	0.190	0.245	0.054
71	Arts, Entertainment, and Recreation	2.2	0.118	0.149	0.031
72	Accommodation and Food Services	13.2	0.210	0.200	-0.009
81	Other Services (except Public Administration)	5.4	0.052	0.044	-0.007
	Weighted average		0.253	0.286	0.034

Table 9: Ratio of Employment in Mega-Firms to Total Sectoral Employment, 1998 and 2015

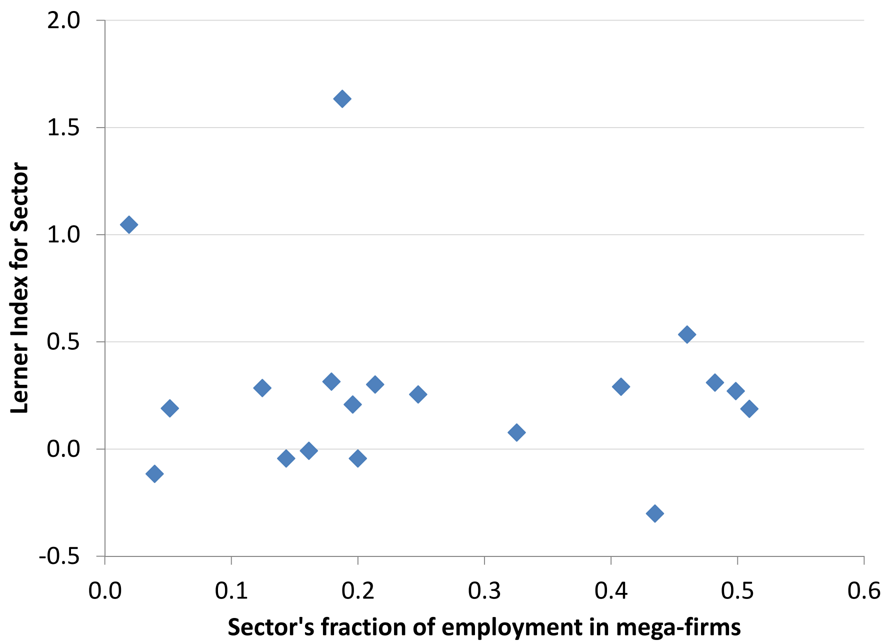

Figure 14: Relation between Employment in Mega-Firms and the Lerner index

Figure 14 shows that there is essentially no systematic relation between the mega-firm employment ratio, on the horizontal axis, and the Lerner index found earlier in the paper, measured as the parameter ϕ. Over the wide range of variation in the employment ratio, sectors with low market power and with high market power are found, with essentially the same average values. There is no cross-sectional support for the hypothesis of higher markup ratios in sectors with more very large firms and thus more concentration in the product markets contained in those sectors. In Section 2.2, I observed that monopsony power in the labor market results in a downward bias in the estimated markup ratio. Thus the finding of no relation between labor-market concentration and the markup ratio could reflect the canceling of the offsetting upward effect on true markups and the downward bias from monopsony power.

The upper row of Table 10 describes the relation between the level of the mega-firm employment ratio and the estimated markup ratio. It confirms the lack of a relationship. But the standard error of the coefficient is high enough that the results do not refute the hypothesis of a meaningful positive relationship.

Figure 15 shows the relation between the change in the mega-firm employment ratio, on the horizontal axis, and the trend coefficient ψ in the price/marginal cost ratio. The plot suggests some upward-sloping relation. The point at the lower left, for mining, quarrying,

Left-hand variable	*Right-hand variable*	*Slope, standard error, and 1-tail p value*
Estimated Lerner index	Level of mega-firm ratio	0.12
		(0.15)
		0.21
Estimated Lerner index trend coefficient, ψ	Change in mega-firm ratio	0.045
		(0.049)
		0.18

Table 10: Slope Coefficients for the Relation between Employment in Mega-Firms and the Trend Coefficient for the Lerner Index

and oil and gas extraction, is both influential and suspicious. Extraction industries present a challenge to the measurement of productivity and its cousin, the markup ratio measured in this paper. The other influential observation supporting an upward slope, for utilities, is at the upper right. The lower row in Table 10 confirms that there is moderate evidence in favor of an upward slope. Thus the hypothesis that a movement toward higher labor-market concentration has a role in rising market power receives some support here.

5.1 Conclusions about mega-firms and market power

There is no evidence that concentration, measured by the fraction of workers in a sector employed at firms with 10,000 or more workers, is related to market power, but some evidence that growth of superstar mega-firms is associated with rising market power. The correlation of the level of the mega-firm ratio with the level coefficient for the Lerner index is -0.14 and the correlation of the changes is 0.19.

6 Concluding Remarks

All of the measures in this appear support the hypothesis that the sellers in many industries in the US economy have substantial market power. The distribution of the Lerner index across industries includes many with Lerner indexes above 1.3. Many industries have earning ratios above the benchmark from the stock market, as reflected in values of q that are greater than one. Some of this earning premium may arise from market power that is not offset by fixed costs. Many markets have concentration ratios sufficiently high to create concern under the

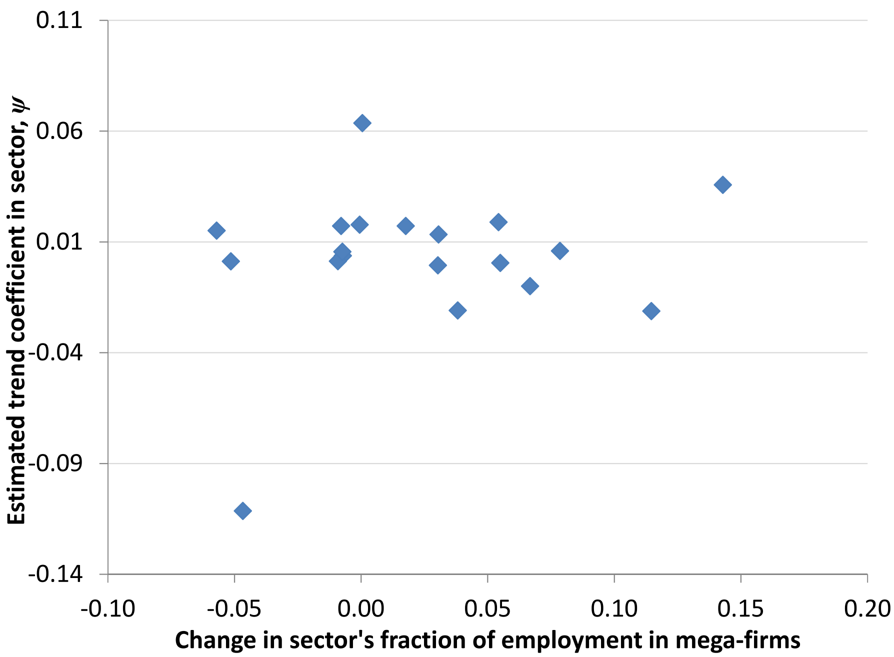

Figure 15: Relation between the Change in Employment in Mega-Firms and the Trend Coefficient for the Lerner Index, ψ

Justice Department's screening criteria for mergers that would raise market power. And many industries contain mega-firms accounting for substantial shares of employment.

An important caveat to this finding is the negative correlation of the estimated Lerner index and the two measures of concentration—the four-firm concentration ratio and the mega-firm employment ratio—together with the low correlation of the estimated Lerner index and the earning ratio. Sampling error in the estimates of the Lerner index is fairly high, which could explain low positive correlations, but not the negative correlations. There appears to be much more to the story of high concentration and high earning ratios than just market power.

With respect to growth of market power in recent decades, the evidence is more mixed. The coefficient capturing growth of the average level of the Lerner index is not statistically unambiguously positive. Growth of the earning ratio and concentration is statistically completely unambiguous, but its relation to market power is economically ambiguous.

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