ACCOUNTING FOR RISING CORPORATE PROFITS: INTANGIBLES OR REGULATORY RENTS?

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Abstract: Since 1980, US corporate valuations have risen relative to assets and operating margins have grown. The possibility of sustained economic rents has raised concerns about economic dynamism and inequality. But rising profits could represent growing returns to corporate investments in intangibles instead of returns to political rent seeking. Using new data on Federal regulation and data on lobbying, campaign spending, R&D, and organizational capital, this paper finds that both intangibles and political factors account for a substantial part of the increase in profits, but since 2000 much of the rise in profits is caused by growing political rent seeking.

Key words: Regulation, intangibles, economic rents

JEL: D72, L1, E22

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Summary of Empirical Findings

- Corporate valuations relative to the cost of assets (Tobin’s Q) have risen by about 20% since 1970 for firms publicly listed in the US. About half of this increase is accounted for by observed investments in intangibles, such as research and development spending (R&D), and in politically related rent seeking activity. Activity associated with increased Federal regulation is the most important explanatory factor, especially after 2000. Spending on R&D and other intangibles has fallen relative to conventional assets since 2000.

- Operating margins for these firms have also risen since 1990. Margins increased by over 2% in aggregate. Variables associated with Federal regulation and corporate campaign contributions account for about half of this increase.

- The impact of political rent seeking is large in absolute terms, corresponding to an increase in the value of non-financial public corporations of about $2 trillion. The markup on sales implied by increased operating margins amounts to an annual transfer from consumers to firms of about $200 billion.

- Most of this effect occurs in five heavily regulated industries: chemicals, including pharmaceuticals; petroleum refining; transportation equipment; electric, gas, and sanitary utilities; and communications.

- Several tests suggest that the link between industry regulation and corporate profits is causal, flowing from regulation to profits. This is consistent with Stigler’s (1971) account of regulatory capture. While regulation might be initiated with the goal of fixing market failures (Pigou 1920) or by government bureaucrats and politicians seeking to extract rents (McChesney 1987; Djankov et al. 2002), the net effect is to increase rents for publicly listed corporations.

- The rise in profits is not significantly associated with industry concentration measured by the share of sales going to the top four firms in 4-digit NAICS industries. The sources of firm rents might arise, instead, from concentration in local markets (e.g., utilities), in highly differentiated product markets (e.g., pharmaceuticals), or from rents on government-supplied inputs (e.g., wireless spectrum or oil leases).
Introduction

Corporate valuations in the US have seen a sustained rise relative to assets over the last three decades; corporate profits have seen a similar sustained rise relative to sales. Figure 1 shows the log of aggregate Tobin’s Q, the ratio of firm market value to firm assets, for the nonfinancial corporate sector. The black line (smoothed and dashed) shows the log ratio of aggregate firm value over firm assets from the US System of National Accounts.\(^1\) The gray line shows the aggregate estimate of log Tobin’s Q for a large sample of publicly listed firms described below.\(^2\) Both lines show a substantial rise in corporate valuations relative to tangible assets since 1980. Figure 2 shows measures of current profit flows. The black line, also drawn from the National Accounts, represents the ratio of the net operating surplus to gross value added for the corporate sector (nonfinancial and financial). The gray line is the ratio of aggregate operating income after depreciation to revenues for firms publicly listed in the US. Again, both series show a substantial rise, in this case beginning around 1990.

Does this rise signal that US firms are extracting greater economic rents and, if so, what does that imply for economic dynamism and inequality? The implications are potentially troubling. A large literature associates regulatory rents with diminished dynamism because of wasteful rent seeking (Tullock 1967, Posner 1975) that creates barriers to entry (Olson 1982) or diverts talent from productive endeavors (Murphy, Shleifer, and Vishny 1991). In addition, Stiglitz (2012) attributes much of the inequality in our economy to

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\(^1\) Aggregate firm value (total liabilities + inventories – current assets) over firm assets (nonfinancial assets excluding intellectual property products plus equity and investment fund shares) using data from the Bureau of Economic Analysis, see http://www.bea.gov/national/nipaweb/Na_FedBeaSna/Index.asp.

\(^2\) Estimates of Tobin’s Q derived from firm microdata are typically higher than estimates derived from national accounts because of accounting and other differences. See Piketty and Zucman (2014).
political rent seeking while Piketty (2014) sees rising corporate valuations leading to greater wealth inequality and the rise of a rentier society.\textsuperscript{3}

Yet not all rents arise from political rent seeking activity nor do all rents imply social waste. For example, firms can earn rents on innovations. These rents constitute an important incentive to encourage investment in innovation. Generally, firms capture returns on intangible investments as rents, that is, as supra-normal profits. This includes returns on R&D, on “brand capital,” and on organizational investments.

This paper explores the roles of intangible investments and regulatory rents in accounting for the recent rise of corporate valuations and profits. Finding an economically substantial association between regulation and profits, I further explore the causal nature of this link and I consider other factors such as changes in industry concentration.

Any attempt to understand the significance of economic rents must account for the source and nature of the rents for several reasons. First, if economic rents simply reflect returns to growing investments in new technology, they might signal greater economic dynamism, not less.\textsuperscript{4}

Similarly, to the extent that economic inequality arises from rents, the nature of those rents matters. The rise in the capital share of corporate income (Figure 2) corresponds to a fall in labor’s share of income, one indicator of inequality.\textsuperscript{5} Again, the rise in markups might not be too troubling if it simply represents returns to investments in technology.

\textsuperscript{3} See also Baker (2015).
\textsuperscript{4} In patent race models (Loury 1979; Dasgupta and Stiglitz 1980), R&D spending can, in some circumstances, exceed the socially optimal level. But while such wasteful spending might not be socially optimal, it nevertheless leads to increased dynamism, perhaps excessively so.
\textsuperscript{5} Piketty (2014) and Piketty and Zucman (2014) attribute the general rise in capital’s share to increased saving; Karabarbounis and Neiman (2014) attribute it to falling prices for investment goods; Rognlie (2015) shows evidence against both of these explanations, attributing most of the growth in the capital share of income
Also, much of the increase in wage dispersion has been attributed to differences between firms or between establishments (Davis and Haltiwanger 1991; Abowd, Kramarz, and Margolis 1999; Dunne et al. 2004; Song et al. 2015). Furman and Orszag (2015) propose that rising corporate rents are shared with workers at affected firms, leading to rising inter-firm wage differences. But if firm rents are rising primarily because of greater investments in new technology, then pay might rise at those firms because of greater demand for technology-specific skills. Indeed, Dunne et al. (2004) find that a significant fraction of the growth in the dispersion of wages between plants is accounted for by differences in plant investments in computer technology. The story clearly means something different if firm rents are rising primarily because of regulatory capture.

Regulation and rents

This paper looks at rent seeking activity as one possible source of the rise in profits. I focus mainly on political or regulatory rent seeking, that is, rent seeking activity that is directed at changing laws and regulations or that is enabled by such changes. Not all rent seeking is political. For example, when firms collude to form a cartel or when a monopolist engages in exclusionary conduct, the firms seek rents, but not political rents. I focus on political rent seeking for two reasons. First, there is a deep concern that the rise in profits may reflect a damaging corruption of the political system. Second, I find that measures of political rent seeking have particularly strong association with the rise in profits.

across all sectors to housing, but he also finds a significant contribution in the corporate sector from rising corporate valuations, which he attributes to increased markups.

See also Card et al. (2016).
Yet it is not clear a priori that regulation and political rent seeking necessarily increase profits. In theory, regulation can affect corporate rents in diverse ways. In one view, regulators develop new regulations in order to fix market failures (as in Pigou 1920), including monopoly rents. For example, in response to concerns that excessive cable television prices reflected monopoly rents, Congress passed the 1992 Cable Act “to provide increased consumer protection.” In this view, economic rents give rise to new regulation that reduces rents.

On the other hand, the “tollbooth” view of regulation (McChesney 1987; Djankov et al. 2002) sees regulation imposing costs on industry for the benefit of bureaucrats and politicians; that is, regulators extract rents earned by firms. In this account, regulation also decreases rents, but with different motivation. In either case, regulators did indeed expect the 1992 Cable Act to reduce industry rents; the Federal Communications Commission expected that cable prices would fall 10%, saving households over $1 billion (FCC 1993).

In contrast, in Stigler’s (1971) theory of regulation, “as a rule, regulation is acquired by the industry and is designed and operated primarily for its benefit.” That is, regulation creates or increases industry rents. The example of the 1992 Cable Act suggests that industry rents can grow despite the intentions of the public and regulators. Figure 3 shows the aggregate log of Tobin’s Q for a balanced panel of publicly listed cable TV firms. Corporate valuations appear to have appreciated substantially following the passage of the bill in 1992 and the promulgation of major new regulations in 1993. How did this happen? Crawford (2000) shows that the regulations provided cable companies with substantial latitude to

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7 See Peltzman (1989) for an overview of the theory of regulation.
8 The calculation of these variables is described below. Seven firms in SIC 4841 were active from 1989 through 1997: Comcast, TCA Cable, TCI, Century Communications, Directv, Adelphia, and Cablevision. Note that the Act also affected satellite TV.
 evade the price decreases by changing programming mix and quality. In addition to influencing the details of this rather complex legislation and regulation, the cable companies engaged in substantial market-based rent seeking activity by changing their offerings.

While these different views are not necessarily mutually exclusive, they do imply that regulation and rents could be either positively or negatively correlated. Also, this example highlights the importance of viewing political rent seeking broadly, involving more than direct political contributions and lobbying.

Measuring rent seeking

Indices of industry concentration might provide a means of measure rent generating activity, both private and political. In the analysis below, I use standard measures of concentration such as the share of revenues going to the top four firms in 4-digit NAICS industries. However, I find that these indices of industry concentration have little explanatory power for corporate valuations or operating margins.

Measures of political rent seeking might have greater explanatory power. Two obvious choices are corporate lobbying expenditures and election campaign contributions. A substantial literature has explored the association between legislative voting and campaign contributions. Ansolabehere, de Figuieredo, and Snyder (2003) review this literature, finding little evidence that campaign contributions influence voting. They conclude that this spending might be viewed primarily as a consumption good. However, legislative votes are only one channel through which firms influence regulation; campaign spending and lobbying might also affect the drafting of legislation (firms may benefit from the particular wording of laws), agency rulemaking, rate setting, and other regulator actions.
Indeed, evidence shows numerous ways that rent seeking activities seem to pay. Case studies have found that corporate political activity is associated with favorable tax treatment (Richter, Samphantharak, and Timmons 2009; Alexander, Mazza, and Scholz 2009), regulatory rate setting (Bonardi et al., 2006), tariffs (Mayda et al., 2010), government contracts (Goldman et al., 2013), and bailouts (Duchin and Sosyura 2012). Moreover, recent research finds strong associations between corporate valuations and profits and measures of lobbying activity and corporate campaign contributions (Cooper, Gulen, and Ovtchinnikov 2010; Hill et al. 2013; Chen, Parsley, and Yang 2015), including possibly corrupt activity (Borisov, Goldman, and Gupta 2016).

This evidence suggests that campaign spending and lobbying expenditures are useful measures of rent seeking activity. They are likely incomplete, however, for several reasons. First, reporting requirements have changed over time as well as the restrictions on spending.9 Second, most firms do not spend in either category.10 This does not mean, however, that most firms do not engage in rent seeking. The full range of rent seeking activities is much broader than US campaign spending and the use of registered lobbyists: firms pursue favorable decisions from regulators on rate setting or leases on Federal property or tax treatments, they challenge regulatory rules and decisions in court, they make extensive investments in order to gain regulatory approval (e.g., clinical drug trials), they hire former regulators, and they may make major changes in business strategy in order to capture regulatory rents (Posner 1975) as appeared to be the case with the Cable Act. Moreover,

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9 The requirements on reporting of campaign spending and spending limits have been affected by a number of agency and legislative changes as well as Supreme Court decisions affecting campaign spending; data on lobbying was only reported following the Lobbying Disclosure Act of 1995.

10 In the Compustat sample of publicly listed firms in 2014, 18% spent on lobbying while 11% made PAC campaign contributions. In addition to being incomplete, this raises concerns about selection bias. For example, Yu and Yu (2011) found an association between lobbying and fraudulent activity, suggesting possibly severe agency problems.
firms pursue rents not only from the US Federal government, but also from state, local, and foreign jurisdictions.

Furthermore, firms may earn rents even when regulators are not “captured.” For example, the cost of compliance with EPA regulations appears to have served as an entry barrier in some manufacturing industries (Dean and Brown 1995); an entry barrier can generate rents for industry incumbents. Similarly, costly accounting regulations may have created an entry barrier benefiting large accounting firms (Nitzan, Procaccia, and Tzur 2013).

Because regulation might generate rents in many ways other than as a direct result of lobbying or campaign contributions, it would help to have a more general indicator of the rent seeking activity associated with regulation. One such gauge might be a measure of the complexity or extent of regulation. At least since Mancur Olson (1982, pp. 69-73), economists have noted that regulation tends to grow more complex over time and they have identified several reasons why growing complexity might reflect rent seeking: rent seekers might exact special provisions and exceptions to regulations; because the general public has limited interest, special interests may succeed with more complex regulation; regulation may become more complex as firms find loopholes or ways to evade prior regulation, requiring new regulation. In all these cases, significant potential rents would encourage firms to contest the regulations aggressively.

I propose that the extent of regulatory restrictions reflects the degree to which regulations are contested and that this reflects rent seeking activity. While firm behavior may

11 The evidence on whether regulation tends to reduce entry in general is mixed. See Goldschlag and Tabarrok (2016) but also Bailey and Thomas (2015).

12 See also Kearl 1983; Quandt 1983; Krueger and Duncan 1993.
not be the only factor influencing regulatory complexity, an industry with more extensive regulation will have more actively contested those regulations, all else equal. Thus the extent of regulatory restrictions might proxy for industry rent seeking. I use a new index of industry-specific regulatory constraints called Regdata, developed by Al-Ubaydli and McLaughlin (2015) described below.

Incorporating this index of regulation into the regression analysis along with measures of campaign spending and lobbying expenditures, I find that all are associated with Tobin’s Q and firm operating margins but the association with the regulation index is particularly significant. However, this association must be interpreted carefully because it is not clear which way causality flows. As above, regulators might develop new regulations in order to fix market failures, including monopoly rents. In this case, regulations would be developed in response to economic rents rather than creating rents. To distinguish between these two effects, I also conduct several causality tests below.

**Estimation strategy**

Accounting for the sources of rents

In order to account for the relative roles of intangibles and of regulatory rents, I use a well-established empirical framework for estimating the contribution of intangible investments to firm market value. Beginning with Griliches (1981), numerous studies have used regressions on Tobin’s Q (or firm market value) to estimate the economic value of intangibles including R&D (Cockburn and Griliches 1988; Hall 1993; Lev and Sougiannis 1996), advertising and marketing (Fullerton and Lyon 1988, Villalonga 2004), union rents (Salinger 1984), patents (Hall, Jaffe, and Trachtenberg 2005; Bessen 2009), and organization capital (Lev and Radhakrishnan 2005; Eisfeldt and Papanikolaou 2013). Using a large sample
of firms listed on US public exchanges from 1970 through 2014, I use this approach to estimate the association between firm market values and stocks of R&D, advertising and marketing expenditures, and organizational investments measured via sales, general, and administrative expense. I also use a regression analysis to test the relationship between firm operating margins and these intangibles.

This framework can be expanded to include measures of political rents. I add variables to capture firm political rent seeking and the industry-specific measure of regulation.

**Specification**

Viewing firm value as the present value of future profits, Hayashi (1982) provides a formal model relating firm value to the current value of capital stocks. Hayashi and Inoue (1991) and Hall (1993) extend this model to multiple capital stocks that might include both tangible capital and stocks of intangibles. I use a simplified variation of their models and include stocks of not only capitalized investments in productive intangibles, but also capitalized investments in rent seeking.

I assume that profits are a function of an aggregate capital stock for firm $j$ at time $t$

\[ K_{jt} = \sum_{i} \gamma_i k_{ijt}, \]  

(1)

where the $\gamma_i$ coefficients represent the relative profit-generating potential of different types of capital stocks, $k_{ijt}$ (Hall 1993). Let $i=0$ represent tangible capital and normalize $\gamma_0 = 1$. Assuming for simplicity that firms optimize variable inputs at each point in time, the production function has constant returns to scale, and there are adjustment costs to investment, then Tobin’s Q, defined as firm market value over the current value of tangible capital, is equal to (see Appendix),
Where $V$ is firm value and $p$ is the user cost of capital. Hayashi calls the variable $q_t$ “marginal $q$,” it is assumed to be approximately equal to 1 and, given competitive capital markets, it is equal across firms at any given time.

This simple equation captures two intuitions. One intuition is Tobin’s original insight that the market value of a firm is related to the replacement cost of its assets. In a competitive market, firms will add capacity (either new entrants or existing firms) at the replacement cost of capital, driving prices down until, in long run equilibrium, the discounted stream of expected future profits (market value) equals the cost of those assets. However, because of adjustment costs, the long run equilibrium is not reached immediately. Instead, marginal $q$ differs from unity, exceeding 1 when the capital stock is below the equilibrium level, less than 1 when there is excess capacity. Marginal $q$ captures variation in firm value associated with the business cycle and also with shocks such as globalization. The second intuition is that investments in intangibles or in rent seeking create supra-normal profits reflected in a market value that exceeds that of a competitive firm.

I assume that disturbances are multiplicative so that, taking logarithms,

$$\log Q_{jt} = \log \left( 1 + \gamma_1 \frac{k_{1jt}}{k_{0jt}} + \gamma_2 \frac{k_{2jt}}{k_{0jt}} + \cdots \right) + \sum T \delta_T \cdot I(t = T) + \varepsilon_{ijt},$$

where $I$ is an indicator function. I estimate this equation using nonlinear least squares. The coefficients $\gamma_i$ tell us about the relative importance of the different capital stocks for generating profits.

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13 See Hall (1993) and Bessen (2009) for discussion of other specifications. Note that the Taylor series approximation of $\log (1 + x) \approx x$ for $x \approx 0$ does not work well for the data here because the implied values of $x$ are too large.
However, other factors could contribute to a sustained rise in profits in some industries. Firms might have greater market power in more concentrated industries, generating sustained higher profits. Although regulation might create market power as noted above, other independent factors might also create market power that could raise Tobin’s Q such as changes in antitrust policy, financial innovations facilitating mergers, or new technologies that generate strong network effects. To test for these possibilities I include an industry concentration measure in some estimates. Also, investors might demand higher risk premiums for more volatile companies, rewarding them with lower stock prices. Declining volatility might also contribute to rising values of Tobin’s Q. I also estimate specifications including a measure of stock volatility below.

Data

Sample

The main sample consists of Compustat firms traded on US exchanges between 1970 and 2014. I exclude firms that are missing data on market value, sales, and assets. For the regression analyses shown in the paper, I also exclude the 1 percent tails of the dependent variable to counter measurement error at the extremes.

The calculation of Tobin’s Q requires estimating the replacement cost of the firm’s capital. For non-financial firms this estimate is based substantially on the firm’s investments in plant and equipment. Many financial firms do not report plant and equipment and the meaning of their capital assets is mainly financial in any case. I exclude these financial firms from the Tobin’s Q analysis, leaving a sample of 193,148 firm-year observations in an unbalanced panel.
Because regulation data is central to the analysis, I also restrict the sample to firms in industries that are assigned a regulation index. As described below, the sections of the Code of Federal Regulation are assigned to different industries using a computer algorithm. In some cases, sampling variance makes the industry match unreliable and the industry is not assigned a regulation index in Regdata.\textsuperscript{14} At the 3-digit industry level, 31\% of the firm-year observations lack a regulation index. In the analysis reported below, I exclude these observations, leaving a sample of 133,198. I repeated the regressions including them but coding the regulation index to zero. The results were quite similar except that the coefficient of the regulation variable was attenuated, as expected.

For the regressions on firm operating margins, I include the financial firms. However, for these analyses I thought it appropriate to exclude startups that are in a predominately research phase, prior to meaningful “regular” sales. I excluded firm where research and development costs exceeded half of net revenues, leaving a sample of 137,646 firm-year observations.

Variables

Key variables are defined as follows:

The \textit{market value} of the firm consists of the sum of all the claims on the firm, namely, the sum of the value of the common stock, the preferred stock (valued by dividing the preferred dividend by Moody’s Index of Medium Risk Preferred Stock Yields), long term debt adjusted for inflation, and short term debt net of current assets. While the market value of short-term debt is assumed to equal its book value, the market value of long-term debt

\textsuperscript{14} Specifically, the creators of Regdata use an algorithmic classifier including industries where the classifier has an ROC AUC score greater than or equal to 0.75 in 5-fold cross validation.
depends on the age structure of the debt and the change in interest rates over time. I use the method of and Brainard et al. (1980) to estimate the market value of long-term debt.

The value of assets is the sum of the net value of plant and equipment, inventories, accounting intangibles, and investments in unconsolidated subsidiaries adjusted for inflation. I calculate the replacement value of plant and equipment using the method of the method of Lewellen and Badrinath (1997) using the NIPA investment deflator. Note that financial firms often do not include plant and equipment on their balance sheets; these firms are excluded from the Tobin’s Q regression, but are included in the regressions on operating profits.

The various capital stocks are calculated using the perpetual inventory method with deflators to calculate current value stocks. Following the literature, I assign a depreciation rate and pre-sample growth rate to each series. Robustness checks show that the estimated marginal effects are not sensitive to the particular choice of these rates. The R&D stock is calculated assuming a 15% annual depreciation rate and an 8% pre-sample growth rate (Hall 1990); R&D expenditures are deflated using an R&D deflator. The advertising stock is based on advertising and marketing expenditures and assumes a 45% annual depreciation rate and 5% pre-sample growth rate (Villalonga 2004, p. 217). The “organizational capital” stock is calculated using sales, general, and administrative expenditure (SGA), assuming a 15% depreciation rate and a 6% pre-sample growth rate. Note that these expenditures include advertising and marketing spending. They also typically include spending on IT services and most inhouse software development. Both expenditures are deflated using the GDP deflator.

15 Thanks to Bronwyn Hall for providing Stata code to compute this. The code was developed by Bronwyn and Daehwan Kim.
Financial statements do not report R&D, advertising, or SGA when the quantities are not material to the financial results of the firm. In these cases, the quantities might still be positive, but small. In the regressions, I code missing data for these variables to zero but I include a dummy variable flagging the missing data.

The lobbying and campaign expenditure data come from the Center for Responsive Politics.\(^\text{16}\) For each data set, I matched the company name (the client parent entity in the lobbying data, the short name of the political action committee for business PACs in the expenditure data) to Compustat companies.\(^\text{17}\) The lobbying data begin in 1998; the campaign expenditure data are assigned to the election year beginning in 2000. I assumed a 25% depreciation rate and a 6% pre-sample growth rate for each and deflated both using the GDP deflator.

To measure *industry concentration*, I use data from the US Economic Census for the share of receipts going to the top four firms in each NAICS industry.\(^\text{18}\) I used the Census data for 2002 and 2012, interpolating and extrapolating linearly from 2000 through 2014. In order to measure concentration over the entire sample time frame, I also developed an alternative measure based on the share of 3-digit SIC industry revenues reported in Compustat going to the top three firms in Compustat.\(^\text{19}\)

To measure *stock volatility*, I measure the annual standard deviation in firm daily stock returns reported in the data of the Center for Research in Security Prices (CRSP).

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\(^{17}\) For the lobbying data, of the 19,359 entities (companies, unions, trade associations, other organizations), 11% were matched to Compustat firms; these firms accounted for 53% of all lobbying expenditures. Of the 3,720 PACs, 38% were matched to Compustat, accounting for 54% of all expenditures.

\(^{18}\) In Compustat, firms are assigned to NAICS at different levels of industry detail, from 2-digit to 6-digit. I matched to the concentration ratio for each level of detail. I also used an SIC to NAICS walkway for firms that listed SIC industries, but not NAICS.

\(^{19}\) Details and results available from author.
Regulation index

The final key variable is the index of industry-specific regulatory constraints developed by Al-Ubaydli and McLaughlin (2015). Prior researchers attempted to measure regulatory complexity using page counts, word counts, or file sizes of the text of the Federal Register or Code of Federal Regulations (Coglianese 2002; Mulligan & Shleifer 2005; Dawson & Seater 2013; Crews 2011; Coffey et al. 2012). This new index improves on these measures by providing a quality-adjusted measure of the restrictiveness of regulation. It does this by counting restrictive text strings within the sections of the Code of Federal Regulations.\(^\text{20}\) Additionally, Al-Ubaydli and McLaughlin use an algorithm to probabilistically assign each section of the Code to a specific NAICS industry. They do this assignment for sets of 2-digit, 3-digit, and 4-digit NAICS industries. The result is a time series of the extent of regulation for specific industries since 1970.

Figure 4 shows the time series of this measure for the electric power generation industry (NAICS 2211). In this industry, regulatory complexity has grown substantially over time, partly as the result of incremental additions but also with major changes following significant new legislation shown by the vertical dashed lines (the Public Utility Regulatory Policies Act of 1978 and the Energy Policy Acts of 1992 and 2005).

I propose using the Regdata index of industry regulatory restrictions as a proxy for industry rent seeking. Presumably, industry regulations affect all firms in the industry. To the extent that these regulations create market power, we should expect that the absolute measure of rents would be proportional to firm revenues, all else equal. That is, an oligopoly markup of prices over cost would benefit all firms in proportion to their revenues. I thus measure the rent-generating potential of regulation for a firm as the number of restrictions

\[\text{Specifically, they count the occurrences of “shall,” “must,” “may not,” “prohibited,” and “required.”}\]
for a given year times firm revenues. This rent-generating potential can thought of as reflecting an accumulated stock of rent seeking activity, roughly comparable to the stocks of other investments. I use 3-digit NAICS industry restrictions from Regdata version 2.2 and I normalize the index of restrictions so that the mean number of restrictions is 1.0 in 1970. The 3-digit data provide coverage for most of the Compustat sample (69%).

**Summary statistics**

Sample means, weighted by net capital in order to represent aggregate ratios, are shown in Table 1 at three different dates. Tobin’s Q increased sharply from 1970 to 2000 and declined modestly since then. A similar pattern is seen in the R&D and advertising stocks. The SGA stock shows a secular decline while the regulation stock shows a large secular increase. Since 2000, industry concentration and lobbying stocks have increased; campaign spending has increased dramatically. However, both lobbying and election spending quantities are quite small compared to the other stocks measured.

The two most important independent variables in the regressions below are R&D and regulation. Figure 5 shows the time trends of two key variables, the R&D stock/capital ratio and the regulation index, both weighted by firm capital for the sample used in the Tobin’s Q regressions. While regulation has been rising steadily, R&D rose initially but has declined relative to net capital since about 2000.

It is also significant that both of these variables are highly concentrated in a few industries. Table 2 shows the shares of the top five 2-digit SIC industries for each in 2014.

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21 I also ran regressions using the unscaled variable (not shown); the R-squareds and standard errors were significantly worse.

22 The non-normalized mean is 5,389.
These sets of five industries account for most of the stocks. Chemicals (including pharmaceuticals) and transportation equipment are among the top five in both groups.

**Accounting for firm profits**

**Accounting for Tobin’s Q**

Table 3 shows estimates of equation (3). I estimate the equation using Non-linear Least Squares with robust standard errors clustered by major industry group. All regressions include year dummies, as per equation (3) that are not reported. For observations missing data in the R&D, advertising, and SGA variables, I coded the variable to zero and included a dummy variable to flag the missing data.

The first column uses only the stocks of intangible assets. These all have highly significant coefficients. The coefficients for R&D and advertising are not significantly different from 1, which is what we would expect if investments in these assets are roughly as productive as investments in plant and equipment. The coefficient for SGA is significantly less than one, likely indicating that not all sales, general, and administrative expenditures necessarily contribute to organizational capital.

The bottom panel of the table shows the extent to which the coefficients can account for the change in log Q. I take the difference between the sample mean of the independent variable between the end and beginning of the sample period. These means are weighted by net capital in order to capture the impact on aggregate log Q. I multiply the difference in means by 100 times the coefficient to present the impact in percentages. As can

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23 Using firm SIC codes, I classified firms into major industry groups according to the 9 major divisions of the SIC hierarchy with two additional groups for chemicals and pharma (SIC 28) and for tech (SIC 357, 367, and 737).
be seen, growth in intangibles “explain” about one sixth of the rise in Tobin’s Q from 1970 to 2014. R&D and advertising had a positive impact, but SGA had a negative impact.

Column 2 adds the regulation variable. The coefficient is significant and the implied impact on log Q is substantial. Combined, the regression variables account for nearly half of the rise in Tobin’s Q.

Column 3 adds the volatility of the firm’s common stock and the measure of industry concentration derived from Compustat data. Volatility tends to reduce firm value while industry concentration increases it. But neither effect is large and the industry concentration coefficient is not statistically significant. This suggests that the substantial association between regulation and firm value is not explained by these measures of industry concentration. It could be that this concentration measure does not pick up the relevant effect of market power, for example, the relevant market might be much narrower than the 3-digit industry classification.

The regulation variable is an industry specific measure; most of the variation in industry restrictions is cross-sectional rather than time based. It is possible that the coefficient on the regulation variable might reflect some other industry specific variable that is omitted from the regression. To control for omitted industry specific effects, column 4 adds dummy variables for major industry group. Compared with column 2, the dummy variables improve the R-squared modestly and decrease the coefficient on regulation modestly, leaving it statistically significant only at the 10% level (P = .071). But the overall impression is that the regulation coefficient does not seem to be mainly reflecting some omitted industry specific variable. I will test this further below with a difference-in-differences specification.
Finally, column 5 adds the industry concentration ratio from the Economic Census and also stocks for lobbying and campaign expenditures. Because these data are only available for more recent years, this regression only covers from year 2000 through 2014. As in column 3, the industry concentration measure is positive but neither economically nor statistically significant. It might be the case that neither measure captures the relevant source of market power; this might be the case if products are highly differentiated or markets are highly localized.

The lobbying coefficient is highly significant while the campaign-spending coefficient is statistically significant at the 5% level. The coefficients on both are much larger than one, suggesting that these investments appear to generate much larger returns than investments in plant and equipment. The high level of returns has been noted in the literature (Alexander, Mazza, and Scholz 2009; Cooper, Gulen, and Ovtchinnikov 2010; Hill et al. 2013; Chen, Parsley, and Yang 2015). Hill et al. (2013, p. 955) propose that various frictions might constrain the extent to which firms lobby so that they cannot increase spending until the marginal benefit equals the marginal cost. Another explanation is that lobbying and campaign spending comprise only a small part of firms’ investments in rent seeking. These variables serve as proxies for much more extensive investments and, so, their coefficients are inflated. This interpretation is supported by the large role played by the regulation variable, which reflects other rent seeking investments. The impact of regulation is larger than the impact of the other political variables combined.

24 A case study by Alexander, Mazza, and Scholz (2009) found that one dollar in lobbying expense returned $220 in tax savings. Cooper, Gulen, and Ovtchinnikov (2010) report that “in our sample, firms invest an average total contribution amount per year of $23,471 and earn an average increase in shareholder wealth of $163.8M per year.”
Overall, the relative contributions of the different variables to the change in Tobin’s Q changed after 2000. The variables representing intangible investments tended to decline while the political variables increased.

Accounting for operation margins

As a check, I also ran comparable regressions on firm operating margins. Because corporate valuations reflect investors’ expectations of future profits, current profits should exhibit similar associations with investments in intangibles and political rent seeking, albeit possibly with higher standard errors. Assuming a linear homogeneous profit function (see Appendix), current profits can be written as the sum of returns on the various capital stocks,

\[ \pi_{jt} = \frac{\partial \pi}{\partial k} \sum_i Y_i k_{ijt}, \]

recognizing that the rate of return on the aggregate stock will change over time. Using time dummies and adding an error term, operating margins can then be written as

\[ \frac{\pi_{jt}}{S_{jt}} = \sum_i \beta_i \frac{k_{ijt}}{S_{jt}} + \sum_r \delta_r \cdot I(t = T) + \epsilon_{ijt}. \]

Table 4 shows three such regressions on operating margins (operating income after depreciation before interest and taxes divided by net revenues) corresponding to columns 2, 4, and 5 of Table 3. These are estimated using weighted least squares where the weights are deflated sales so that the results reflect aggregate profit margins. Here the independent variables are beginning-of-year stocks (that is, lagged stocks) divided by sales. As before, missing data on intangibles are coded to zero.\(^{25}\) The right hand variables include R&D, advertising, SGA, lobbying, and election campaigns. I also include the regulation index and

\(^{25}\) Because operating profit is calculated by subtracting expenditures from revenues, I use lagged variables because any measurement error will spuriously cause a negative correlation. In addition some time lag naturally arises before many of these investments pay off.
the net capital stock divided by sales, in order to capture returns on tangible capital as well. The bottom panel of shows the effect on the change in operating margins for each independent variable calculated at the sample means as in Table 3.

The first column covers the entire period (less the first year, dropped for lagged variables). Both intangibles and regulation have statistically significant and economically substantial effects on operating margins, especially regulation. The second column adds industry group dummy variables. As before industry dummies reduce the coefficient on regulation but it remains statistically significant. The third column includes the political variables. Because campaign spending is assigned to election years, this regression covers only odd years from 2001 through 2013. Campaign spending has a large and statistically significant impact. During this period, however, the contribution of intangibles was negative because spending declined in these categories. In contrast, spending increased on political activities and the regulation index also grew.

In summary, the growth of intangibles and the growth of regulation and political rent seeking activities are substantially associated with the rise in corporate valuations and operating profits. However, since 2000, investments in intangibles have declined relative to tangible capital while regulation and election spending have continued to increase. Thus political rent seeking “explains” much of the rise in profits and corporate valuations since 2000.

**Causality Tests**

However, this is only an accounting exercise. While greater regulation is associated with higher profits and valuations, this exercise does not necessarily imply that greater regulatory rent seeking *caused* the rise in profits and valuations. In fact, there might be good
reasons why the causality could flow from higher profits to greater regulation. In the
Pigovian view, regulation aims to correct market failures. Sustained corporate market power
might be an indication of a market failure, providing a target for regulators. Historically, for
example, large profits by monopolists encouraged “trust-busting” by Progressive reformers.

Also, both profits and regulation might grow in response to some third factor. For
example, major new technologies could bring profits and they might also bring about new
regulations as they affect existing industries. In this case it would be a mistake to assume that
the regulatory rent seeking caused the profits.

This section performs several tests of the causal link between regulation and
corporate valuations and profits.

Granger causality

Granger causality (1969) provides a baseline test. This procedure tests whether
lagged values of an independent variable have explanatory power beyond the lagged values
of the dependent variable. Table 5 shows these regressions for dependent variables log Q
(top panel) and operating margins (bottom panel) and the regulation index (both). I omit the
first lag of the regulation variable in the top panel because regulations typically require a year
or longer to take effect and investors may respond to pending regulation during this time.
New regulations typically go through a period for public comment and review; often they
result from new legislation. Because information about pending regulation is public,
investors’ knowledge will affect firm valuations prior to the final implementation of the
regulation. I omit the first lag of regulation to avoid a misleading result.
The table shows that regulation Granger-causes Tobin’s Q and operating margins, but Tobin’s Q and operating margins do not Granger-cause regulation. Information about profits and corporate valuations does not explain subsequent regulation.

This finding is sufficient to reject the simple reverse causality story; if high profits caused regulators to act, then regulation would reflect lagged profits. However, Granger causality does not mean that regulation causes increased profits or valuations in the normal sense of causation. For instance, both profits and regulation might be caused by some third factor, yet regulation might respond more rapidly than profits, so that regulation would have explanatory power before profits.

Such an explanation is possible, but the slow nature of regulatory change makes this sort of explanation seem unlikely. As noted, the regulatory approval process has built-in delays and it is largely public. In contrast, investors are typically seen as responding rapidly to new information that affects future expected earnings, including information about new pending regulations. If some third factor is driving both new regulations and corporate profits, it seems hard to see how typically slow regulators would be able to respond several years before investors do.

Major regulatory changes

This Granger analysis considers all regulatory changes affecting the sample industries over three decades. Most regulatory changes are relatively small. It is possible, however, that firms and political actors behave differently when major regulatory changes are at stake.

This might be the case, for instance, if public advocacy faces a collective action problem (Olson 1965). Those industries most affected by regulations will have the greatest incentive to invest in rent seeking, tending to dominate the ordinary process of regulation, all
else equal. Other interests that are less directly affected have greater difficulty organizing collective action because the individual rewards are lower. Occasionally, however, broad coalitions of opposing interests may be motivated to act, they may overcome their collective action problem, and when they do, one might expect major regulatory changes to follow. This seems to have been the case with the 1992 Cable Act.

If this view is correct, then major regulatory changes might be relatively more affected by public interests that act in response to corporate market power. It might be the case that major regulatory changes are influenced by prior corporate profits even if that is not the case in general as suggested by the Granger analysis above.

To consider this possibility, I identified those cases where the regulatory index increased by 1,000 words for a 4-digit NAICS industry in a given year. As seen in Figure 4, major legislative changes were sometimes followed by such large changes in regulatory restrictions. There were 36 such regulatory changes corresponding to 1,096 firm-year observations in the Compustat dataset used for the Tobin’s Q analysis; this is out of a total sample of 193,148 observations.

Table 6 shows probit regressions on the occurrence of a major regulatory change. The first regression includes the log of real sales, in order to control for firm size, and the lag of log Tobin’s Q. I use a lagged value to control for the possibility that pending regulation might influence corporate valuations. This column finds both independent variables are significant, but the sign on the Tobin’s Q coefficient is negative, contrary to what one would expect if high profits induced major regulatory change. The second column adds

---

26 I wanted the most specific industry classification to tie the regulator change as close as possible to industry firms. Note that I excluded cases where another major change occurred within three years. In the industry data, these major changes comprised 1.3% of the industry-year observations. The mean change was 60.5 words and the median was 3.9 words.
capital/sales and industry dummies for 2-digit SIC industries. The industry dummies add substantial explanatory power; the capital intensity measure does not. The third column adds additional lags of log Tobin’s Q. None of these is individually significant and an F-test finds that the sum of these lagged coefficients is not significantly different from zero (P = .182). I also tested the explanatory power of the intangible capital stocks (regressions not shown), but found no significant relationships.

In summary, these tests reject the hypothesis that high Tobin’s Q is responsible for subsequent major increases in regulation.

Difference-in-differences

In order to consider other possible causal interactions, I used these events of major increases in regulation to conduct a difference-in-differences analysis. The firms affected by major changes in industry regulation comprised the treatment group. I constructed a control group by selecting firms in industries that did not experience major regulatory change during the year of the treatment event or during the preceding four years or the following four years. I included 4-digit industries in the control group if the count of regulatory restrictions changed by fewer than 500 words in either direction. For both the treatment and control groups, I collected firm data for the event year, for the four preceding years and the four subsequent years. I then pooled these unbalanced panels.

I used two dependent variables: the log of Tobin’s Q and the Lerner index, calculated as the operating margin less .05 x net capital/sales (capital valued at current prices). The Lerner index incorporates the cost of capital, assuming a 5% cost of capital,

27 I experimented with lower thresholds for defining the treatment group however at a threshold of 500 words for defining a major event there were substantial problems with overlapping events.
rather than using net capital as an independent variable as above.\footnote{I experimented with other values for the cost of capital, but the results did not change substantively.} With both dependent variables, I excluded the 10% tails to eliminate outliers.

Under the assumption that the control and treatment groups share a common underlying trend aside from the treatment, a difference-in-difference analysis compares the difference between the treatment and control groups before and after the event. A simple way to estimate these differences is with a regression of the form

\[
(5) \quad y_i = \alpha \cdot I(\text{treatment group}) + \beta \cdot I(\text{post event}) + \gamma \cdot I(\text{treatment & post}) + \varepsilon_i,
\]

where \(y_i\) is the dependent variable and \(I\) is an indicator function designating a dummy variable. The coefficient \(\gamma\) is the measure of the average treatment effect on the treated.

The critical assumption is that the treatment and control groups follow the same trend between the pre- and post-periods so that in the counterfactual case without treatment, the difference in differences would be zero. While this assumption cannot be directly tested, it can be thrown into doubt if the treatment and control groups exhibit different trends before the event. Panel A of Table 7 shows the differences between the dependent variables during the year before the regulatory change and four years before the regulatory change. The hypothesis of common trend during the pre-treatment period cannot be rejected.

Panel B shows the estimation of (5) for the two dependent variables. Because of concerns about serial correlation (Bertrand, Duflo, and Mullainathan 2004), the standard errors are block bootstrapped by firm using 200 repetitions. Both regressions show a positive treatment effect. For log Q the effect is significant at the 5% level of significance (\(P = .017\)); for the Lerner index it is only significant at the 10% level (\(P = .078\)).
These regressions do not control for other firm characteristics that might differ between the treatment and control groups and that might also influence the time trend of the dependent variables. The analysis of Table 6 identified two variables that differ between the treatment and control groups: firm size and industry. To control for possible time effects from these variables, I stratify the sample into cells based on four size quartiles and 55 2-digit SIC industries. For each firm, I average all of the pre-treatment observations and, separately, all of the post-treatment observations in order to avoid problems of serial correlation (Bertrand, Duflo, and Mullainathan 2004).

I then use the matching estimator of Angrist (1998) to weight the differences for each cell:

\[
\tilde{D}_t = \sum_j w_j (\bar{y}_{j1t} - \bar{y}_{j0t}), \quad w_j = \frac{n_{j1}}{\sum_t n_{i1}},
\]

where \(\bar{y}_{jgt}\) is the mean value of the dependent variable over observations in cell \(j\), group \(g\) (control = 0, treatment = 1), and period \(t\) (pre-event = 0, post-event = 1) and \(n_{j1}\) is the number of observations in the treatment group within cell \(j\). The difference-in-differences estimate is then just \(\tilde{D}_1 - \tilde{D}_0\).

Panel C summarizes these difference estimates. The first two columns show the difference estimates implied by the regressions in Panel B. Columns 3 and 4 shows the difference estimates using the matching estimator. With matching, the log Q difference-in-differences is larger and significant at the 1% level; the Lerner index estimator is about the same size, but not statistically significant.

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29 In order to ensure common support for the control group, I combine a small number of cells. For the log Q analysis, I add the first size quartile of SIC 29 to the second size quartile; for the Lerner index analysis, I add size 3 to size 4 for SIC 61 and size 3 to size 1 for SIC 60.

30 Comparing (5) and (6), \(\tilde{D}_0 = \alpha, \quad \tilde{D}_1 = \alpha + \gamma\).
In summary, these estimates provide support for the hypothesis that major changes in regulation cause increases in Tobin’s Q. There is some support for the hypothesis that increases in regulation also increase profits, but the estimates do not have high statistical significance. It may be that the profits associated with new regulations do not materialize immediately. This might be the case, for instance, if firms had to engage in costly rent seeking activity in order to adapt to new regulations. Then immediate profits might suffer relative to future expected profits.

**Conclusion**

Much of the growth in corporate valuations and profits since 1980 can be accounted for by growing investments in intangibles, especially investment in R&D. But it appears that an even larger share of the rise in valuations and profits can be accounted for by factors associated with growing regulation and political activity, especially after 2000.

I argue that the complexity of regulation is a proxy for a wide range of rent seeking activities—those regulations that are most contested tend to become the most complex. Using the index of regulatory restrictions, the evidence rejects the view that industries with the greatest rents attract the greatest regulation. Instead, causality flows from regulation to higher corporate valuations. Nor does regulation tend to reduce profits by burdening firms with compliance costs. While self-interested regulators and politicians may well impose costs on firms (the “tollbooth” view), firms benefit from regulations overall, in line with Stigler’s view (1971).

And these benefits appear to be large. Regulation corresponds to an increase in corporate valuations of about $2 trillion in the sample (Table 3, Column 2). Regulation and campaign spending are responsible for an increase in markups on the order of 1 percent
(Table 4). That corresponds to about a $200 billion increase in transfers from consumers to firms each year.

Some observers have highlighted the possible role of increasing industry concentration in generating economic rents (Grullon, Larkin, and Michaely 2015, CEA 2016). Using two different measures of concentration, I find only a weak relationship with profits that is neither statistically nor economically significant. However, that finding might simply mean that such broad industry measures do not capture the main sources of rents, which might occur in local or regional markets or in differentiated product niches or might be based on scarce government-supplied inputs.

Several qualifications affect the interpretation of these findings. First, regulatory rents are not substantial in most industries; they are highly concentrated in a small number of industries (see Table 2). This has implications for the dispersion of firm profits that might be related to rising inter-firm wage inequality.

Second, this study only looks at publicly listed firms. The effect of regulation might be quite different on private firms, especially small firms. Indeed, if rents are created via barriers to entry, one might expect large firms to benefit and small firms to be harmed.

This raises an additional limitation. While this study finds a large, causal effect from regulation and political activity, it does not identify the actual mechanism at work. Do rents rise because of barriers to entry or because of a diversion of resources to rent seeking or something else? This is important for understanding the implications of the rise in regulatory rents and their normative significance. Not all rent seeking activity is socially wasteful; clinical trials for drugs and pollution compliance costs may well benefit society. But even in these cases, rising economic rents may dampen economic dynamism, creating social costs not considered in typical cost/benefit calculations of new regulations. The rising significance
of election spending and lobbying in the regression analysis makes these concerns particularly worrisome. In the long run, if regulatory rent seeking decreases economic dynamism and increases economic inequality, the harm might be much greater than current static losses of consumer welfare.

References


Tables and Figures

Table 1. Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Year</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1970</td>
<td>2000</td>
<td>2014</td>
</tr>
<tr>
<td>Log Tobin’s Q</td>
<td>0.140</td>
<td>0.460</td>
<td>0.344</td>
<td></td>
</tr>
<tr>
<td>R&amp;D stock / net capital</td>
<td>0.060</td>
<td>0.116</td>
<td>0.108</td>
<td></td>
</tr>
<tr>
<td>Advertising stock / net capital</td>
<td>0.004</td>
<td>0.018</td>
<td>0.014</td>
<td></td>
</tr>
<tr>
<td>SGA stock / net capital</td>
<td>0.742</td>
<td>0.628</td>
<td>0.615</td>
<td></td>
</tr>
<tr>
<td>Regulation x revenues / net capital</td>
<td>1.094</td>
<td>3.174</td>
<td>3.568</td>
<td></td>
</tr>
<tr>
<td>Standard deviation, daily stock market returns</td>
<td>0.021</td>
<td>0.031</td>
<td>0.014</td>
<td></td>
</tr>
<tr>
<td>Four-firm share of receipts</td>
<td></td>
<td>0.429</td>
<td>0.438</td>
<td></td>
</tr>
<tr>
<td>Lobbying stock x 1000 / net capital</td>
<td></td>
<td>0.168</td>
<td>0.204</td>
<td></td>
</tr>
<tr>
<td>Election spending stock x 1000 / net capital</td>
<td></td>
<td>0.001</td>
<td>0.017</td>
<td></td>
</tr>
<tr>
<td>Number of firms</td>
<td>1445</td>
<td>3776</td>
<td>2456</td>
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</table>

Note: sample means weighted by net capital.
<table>
<thead>
<tr>
<th>R&amp;D Stock</th>
<th>SIC</th>
<th>Industry Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chemical, including pharmaceuticals</td>
<td>28</td>
<td>28%</td>
</tr>
<tr>
<td>Transportation equipment</td>
<td>37</td>
<td>18%</td>
</tr>
<tr>
<td>Electronic and electrical equipment, exc.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Computers</td>
<td>36</td>
<td>16%</td>
</tr>
<tr>
<td>Business services, including software</td>
<td>73</td>
<td>10%</td>
</tr>
<tr>
<td>Machinery, including computers</td>
<td>35</td>
<td>9%</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td></td>
<td><strong>81%</strong></td>
</tr>
</tbody>
</table>

<p>| Regulation x Revenues                            |     |                |
| Chemical, including pharmaceuticals             | 28  | 24%            |
| Petroleum Refining And Related Industries        | 29  | 21%            |
| Transportation Equipment                        | 37  | 16%            |
| Electric, Gas, And Sanitary Utilities           | 49  | 11%            |
| Communications                                   | 48  | 4%             |
| <strong>TOTAL</strong>                                        |     | <strong>76%</strong>        |</p>
<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>R&amp;D stock / net capital</td>
<td>0.738 (.129)**</td>
<td>0.771 (.134)**</td>
<td>0.886 (.147)**</td>
<td>0.734 (.121)**</td>
<td>0.564 (.104)**</td>
</tr>
<tr>
<td>Advertising stock / net capital</td>
<td>0.600 (.171)**</td>
<td>0.516 (.127)**</td>
<td>0.489 (.110)**</td>
<td>0.471 (.148)**</td>
<td>0.793 (.237)**</td>
</tr>
<tr>
<td>SGA stock / net capital</td>
<td>0.085 (.015)**</td>
<td>0.063 (.015)**</td>
<td>0.033 (.018)</td>
<td>0.066 (.015)**</td>
<td>0.082 (.022)**</td>
</tr>
<tr>
<td>Regulation stock / net capital</td>
<td>0.024 (.007)**</td>
<td>0.027 (.008)**</td>
<td>0.018 (.009)</td>
<td>0.024 (.008)**</td>
<td>0.024 (.008)*</td>
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<tr>
<td>Compustat 3 firm concentration ratio</td>
<td></td>
<td></td>
<td></td>
<td>0.222 (.163)</td>
<td></td>
</tr>
<tr>
<td>Standard deviation, daily stock returns</td>
<td>-2.519 (.632)**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Four-firm share of industry receipts</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.003 (.113)</td>
</tr>
<tr>
<td>Lobbying stock / net capital</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>25.27 (5.14)**</td>
</tr>
<tr>
<td>Election spending stock / net capital</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>462.65 (204.83)*</td>
</tr>
<tr>
<td>Dummies for missing R&amp;D, advert., &amp; SGA</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Industry group dummies</td>
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<td></td>
<td>✓</td>
</tr>
<tr>
<td>Year dummies</td>
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<td>No. observations</td>
<td>133,198</td>
<td>133,198</td>
<td>103,958</td>
<td>133,198</td>
<td>46,069</td>
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<td>Adjusted R-squared</td>
<td>0.545</td>
<td>0.557</td>
<td>0.553</td>
<td>0.567</td>
<td>0.653</td>
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<tr>
<td>Percent contribution</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>R&amp;D stock / net capital</td>
<td>3.50</td>
<td>3.65</td>
<td>3.14</td>
<td>3.48</td>
<td>-0.47</td>
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<tr>
<td>Advertising stock / net capital</td>
<td>0.60</td>
<td>0.52</td>
<td>0.58</td>
<td>0.47</td>
<td>-0.30</td>
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<tr>
<td>SGA stock / net capital</td>
<td>-1.08</td>
<td>-0.80</td>
<td>-0.71</td>
<td>-0.84</td>
<td>-0.11</td>
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<tr>
<td>Regulation stock / net capital</td>
<td>5.87</td>
<td>6.30</td>
<td>4.55</td>
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<tr>
<td>Compustat 3 firm concentration ratio</td>
<td></td>
<td></td>
<td></td>
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<td>0.55</td>
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<tr>
<td>Standard deviation, daily stock returns</td>
<td>-0.14</td>
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<tr>
<td>Four-firm share of industry receipts</td>
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<td>0.00</td>
</tr>
<tr>
<td>Lobbying stock / net capital</td>
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<td></td>
<td></td>
<td>0.09</td>
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<tr>
<td>Election spending stock / net capital</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.71</td>
</tr>
<tr>
<td>Change in log Q (percent)</td>
<td>20.39</td>
<td>20.39</td>
<td>16.59</td>
<td>20.39</td>
<td>-11.53</td>
</tr>
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</table>

Note: NLLS estimations of equation (3) including dummies for missing data. Robust standard errors clustered by industry group. **= significant at 1% level; *= significant at 5% level. Sample is all US Compustat firms excluding 1% tails of log Q and financial firms. Percent contribution for variable $x$ is $100 \cdot \beta_x \cdot (\bar{x}_1 - \bar{x}_0)$ where the means are calculated for the beginning (0) and end years (1) weighted by net capital.
Table 4. Operating Profits / Sales

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>R&amp;D stock/sales, lagged</td>
<td>0.045 (.006)**</td>
<td>0.023 (.005)**</td>
<td>0.030 (.009)**</td>
</tr>
<tr>
<td>Advertising stock/sales, lagged</td>
<td>0.012 (.009)</td>
<td>0.007 (.006)</td>
<td>0.112 (.031)**</td>
</tr>
<tr>
<td>SGA stock/sales, lagged</td>
<td>0.001 (.001)</td>
<td>0.001 (.000)</td>
<td>0.000 (.000)</td>
</tr>
<tr>
<td>Regulation index</td>
<td>0.004 (.000)**</td>
<td>0.002 (.000)**</td>
<td>0.004 (.000)**</td>
</tr>
<tr>
<td>Lobbying stock/sales, lagged</td>
<td></td>
<td></td>
<td>1.292 (2.956)</td>
</tr>
<tr>
<td>PAC spending stock/sales, lagged</td>
<td></td>
<td></td>
<td>284.647 (42.857)**</td>
</tr>
<tr>
<td>Capital/sales</td>
<td>0.008 (.001)**</td>
<td>0.005 (.001)**</td>
<td>0.009 (.001)**</td>
</tr>
<tr>
<td>Industry group dummies</td>
<td>✓</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. of observations</td>
<td>135,968</td>
<td>135,968</td>
<td>29,798</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.186</td>
<td>0.233</td>
<td>0.244</td>
</tr>
</tbody>
</table>

Percent contribution

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>R&amp;D stock/sales, lagged</td>
<td>0.24</td>
<td>0.13</td>
<td>0.01</td>
</tr>
<tr>
<td>Advertising stock/sales, lagged</td>
<td>0.02</td>
<td>0.01</td>
<td>-0.02</td>
</tr>
<tr>
<td>SGA stock/sales, lagged</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Regulation index</td>
<td>1.18</td>
<td>0.58</td>
<td>0.33</td>
</tr>
<tr>
<td>Lobbying stock/sales, lagged</td>
<td></td>
<td></td>
<td>0.01</td>
</tr>
<tr>
<td>PAC spending stock/sales, lagged</td>
<td></td>
<td></td>
<td>0.45</td>
</tr>
<tr>
<td>Change in operating margin</td>
<td>2.51</td>
<td>2.51</td>
<td>2.26</td>
</tr>
</tbody>
</table>

Note: WLS estimations of equation (4), weighted by real revenues and including dummies for missing data and year dummies. Robust standard errors in parentheses. **= significant at 1% level; *= significant at 5% level. Sample is all US Compustat firms excluding 1% tails of operating margin and firms where R&D > .5*sales. Percent contribution for variable x is 100 \cdot \beta_x \cdot (\bar{x}_1 - \bar{x}_0) where the means are calculated for the beginning (0) and end years (1) weighted by real sales.
Table 5. Granger Causality Tests

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Log Q</th>
<th>Regulation index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Independent variable</td>
<td>/ Lags</td>
<td></td>
</tr>
<tr>
<td>Log Q</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>0.694 (.003)**</td>
<td></td>
</tr>
<tr>
<td>L2.</td>
<td>0.031 (.003)**</td>
<td>0.002 (.002)</td>
</tr>
<tr>
<td>L3.</td>
<td>0.035 (.003)**</td>
<td>0.000 (.002)</td>
</tr>
<tr>
<td>L4.</td>
<td>0.063 (.003)**</td>
<td>-0.002 (.002)</td>
</tr>
<tr>
<td>Regulation index</td>
<td>-0.023 (.006)**</td>
<td>1.098 (.003)**</td>
</tr>
<tr>
<td>L1.</td>
<td>0.046 (.009)**</td>
<td>-0.008 (.005)</td>
</tr>
<tr>
<td>L2.</td>
<td>-0.047 (.009)**</td>
<td>-0.071 (.005)**</td>
</tr>
<tr>
<td>L3.</td>
<td>0.037 (.006)**</td>
<td>-0.007 (.004)</td>
</tr>
<tr>
<td>L4.</td>
<td>0.024 (.005)**</td>
<td>1.094 (.003)**</td>
</tr>
<tr>
<td>No. observations</td>
<td>84,058</td>
<td>84,058</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.744</td>
<td>0.993</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Operating margin</th>
<th>Regulation index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Independent variable</td>
<td>/ Lags</td>
<td></td>
</tr>
<tr>
<td>Operating margin</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>0.106 (.001)**</td>
<td>0.001 (.001)</td>
</tr>
<tr>
<td>L2.</td>
<td>0.000 (.000)</td>
<td>0.000 (.000)</td>
</tr>
<tr>
<td>L3.</td>
<td>0.000 (.000)**</td>
<td>0.000 (.000)</td>
</tr>
<tr>
<td>L4.</td>
<td>0.001 (.000)**</td>
<td>0.000 (.000)</td>
</tr>
<tr>
<td>Regulation index</td>
<td>0.024 (.005)**</td>
<td>1.094 (.003)**</td>
</tr>
<tr>
<td>L1.</td>
<td>-0.002 (.008)</td>
<td>0.027 (.005)**</td>
</tr>
<tr>
<td>L2.</td>
<td>-0.017 (.008)*</td>
<td>-0.114 (.005)**</td>
</tr>
<tr>
<td>L3.</td>
<td>-0.011 (.006)</td>
<td>0.006 (.003)</td>
</tr>
<tr>
<td>L4.</td>
<td>0.020 (.006)</td>
<td>0.027 (.005)**</td>
</tr>
<tr>
<td>No. observations</td>
<td>96,200</td>
<td>96,285</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.106</td>
<td>0.991</td>
</tr>
</tbody>
</table>

Note: OLS estimation. Standard errors in parentheses. **=significant at 1% level; *=significant at 5% level. Sample for the top panel is the same as in the Tobin’s Q regression less observations dropped because of lags; bottom panel is the same as in the operating margin regressions less lagged observations.
Table 6. Probit of Major Regulatory Increases

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Q / lags</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>-0.097 (.013)**</td>
<td>-0.035 (.017)*</td>
<td>-0.062 (.038)</td>
</tr>
<tr>
<td>L2.</td>
<td>0.032 (.044)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L3.</td>
<td></td>
<td>-0.003 (.045)</td>
<td></td>
</tr>
<tr>
<td>L4.</td>
<td></td>
<td>0.001 (.034)</td>
<td></td>
</tr>
<tr>
<td>Capital / sales</td>
<td></td>
<td>0.000 (.000)</td>
<td></td>
</tr>
<tr>
<td>Log real sales</td>
<td>0.041 (.005)**</td>
<td>0.021 (.006)**</td>
<td>0.025 (.007)**</td>
</tr>
<tr>
<td>Industry dummies</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>No. of observations</td>
<td>172,663</td>
<td>172,663</td>
<td>118,634</td>
</tr>
<tr>
<td>Pseudo R-squared</td>
<td>0.014</td>
<td>0.270</td>
<td>0.271</td>
</tr>
</tbody>
</table>

Note: probit of the occurrence of major increase in the regulatory index during a given firm-year in the Tobin’s Q sample. Of a sample of 193,148 firm year observations, 1096 (0.6%) experienced major increases in regulation. Standard errors in parentheses. **=significant at 1% level; *=significant at 5% level. Industry dummies are for 2-digit SIC industries.
Table 7. Difference-in-differences on Major Increases in Regulation, with and without matching.

A. Pre-event trends. Difference between T-1 and T-4

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Log Q</th>
<th>Lerner Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control group</td>
<td>-0.086 (0.003)</td>
<td>-0.002 (0.008)</td>
</tr>
<tr>
<td>Treatment group</td>
<td>-0.100 (0.014)</td>
<td>-0.008 (0.003)</td>
</tr>
<tr>
<td>Difference</td>
<td>-0.014 (0.015)</td>
<td>-0.006 (0.008)</td>
</tr>
</tbody>
</table>

B. Difference-in-differences regression, without matching

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Log Q</th>
<th>Lerner index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment group</td>
<td>-0.303 (.021)**</td>
<td>0.073 (.005)**</td>
</tr>
<tr>
<td>Post-event</td>
<td>0.008 (.004)*</td>
<td>-0.003 (.001)**</td>
</tr>
<tr>
<td>Post x Treatment</td>
<td>0.039 (.017)*</td>
<td>0.005 (.003)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Unmatched control group</th>
<th>Control group matched by industry, firm size</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of observations</td>
<td>159,089</td>
<td>197,773</td>
</tr>
<tr>
<td>No. in treatment group</td>
<td>6,075</td>
<td>5,957</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.007</td>
<td>0.005</td>
</tr>
</tbody>
</table>

C. Difference-in-differences summary

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Unmatched control group</th>
<th>Control group matched by industry, firm size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Difference pre-event (treatment – control)</td>
<td>-0.303 (.021)**</td>
<td>0.073 (.005)**</td>
</tr>
<tr>
<td>Difference post-event (treatment – control)</td>
<td>-0.263 (.027)**</td>
<td>0.078 (.005)**</td>
</tr>
<tr>
<td>Difference in differences</td>
<td>0.039 (.017)*</td>
<td>0.005 (.003)</td>
</tr>
</tbody>
</table>

Note: Standard errors in parentheses. **=significant at 1% level; *=significant at 5% level. Panel A shows the mean of the difference in the dependent variable between the year before the major regulatory change and four years before. For log Q, the control group sample is 16,231 and the treatment group sample is 627; for the Lerner index, sample sizes are 19,993 and 699 respectively.
Panel B shows difference-in-differences regression on equation (5). The standard errors are block bootstrapped on firms using 200 iterations.
The first two columns of Panel C summarize the difference between treatment and control groups before and after the regulatory change and the difference between these differences as implied by the regression coefficients in Panel B. The last two columns matches the control group by stratifying the sample according to firm size quartiles and 2-digit SIC industries. The table shows weighted means where the weights are determined as per equation (6).
Figure 1. Log Tobin's Q

Note: Solid lines are kernel smoothed. Black line is aggregate firm value (total liabilities + inventories – current assets) over firm assets (nonfinancial assets excluding intellectual property products plus equity and investment fund shares) for the nonfinancial corporate sector, using data from the System of National Accounts, Bureau of Economic Analysis, [http://www.bea.gov/national/nipaweb/Ni_FedBeaSna/Index.asp](http://www.bea.gov/national/nipaweb/Ni_FedBeaSna/Index.asp). Gray line is from Compustat data for non-financial firms, sample and variables described in the text.
Figure 2. Operating Margins

Note: Solid lines are kernel smoothed. Black line is from the System of National Accounts, Bureau of Economic Analysis. It shows the ratio of the net operating surplus to gross value added for the corporate sector (nonfinancial and financial). The gray line is the ratio of aggregate operating income after depreciation before taxes to revenues for firms publicly listed in the US.
Figure 3. Log Tobin’s Q For Publicly Listed Cable TV Firms

Note: Aggregate corporate market value divided by aggregate net assets for a balanced panel of publicly listed cable TV firms, Comcast, TCA Cable, TCI, Century Communications, Directv, Adelphia, and Cablevision.
Figure 4. Regulatory Restrictions for the Electric Power Generation Industry, NAICS 2211

Figure 5. Trends in Two Independent Variables
Appendix. Tobin’s Q equation

I adapt a simplified version of Hayashi (1982) to incorporate multiple capital stocks where the aggregate capital stock, $K$, is a linear combination of different types of capital stocks, $k_i$,

\[(A1) \quad K(t) = \sum_i y_i k_i(t).\]

The $y_i$ coefficients represent the relative profit-generating potential of different types of capital (Hall 1993). Let $i=0$ represent tangible capital and normalize $y_0 = 1$. Assuming for simplicity that firms optimize variable inputs at each point in time and the production function has constant returns to scale, operating profits can be written as a linear function of aggregate capital, $\pi(K(t)) = \alpha K$.

Investments in each type of capital, $x_i$, do not translate directly into increases in the capital stock because of adjustment costs. Adapting Hayashi,

\[(A2) \quad \dot{K} = G(x_0, x_1, x_2, ..., K; t) - \delta K,\]

where $\delta$ is the depreciation rate and $G$ is linear homogeneous. The dynamic optimization problem is to maximize firm value, assumed to be the present value of future net profits,

\[(A3) \quad V = \int_0^\infty (\pi(K; t) - \sum_i p_i x_i) e^{-rt} dt,\]

subject to constraint (A2), where $p_i$ is the price of investment good $i$ and $r$ is the discount rate. The present value Hamiltonian is

\[(A4) \quad H(x_0, x_1, x_2, ..., K; t) = \pi(K; t) - \sum_i p_i x_i + \lambda (G(x_0, x_1, x_2, ..., K; t) - \delta K)\]

and the necessary conditions for a maximum are:

\[
\begin{align*}
\frac{\partial H}{\partial x_i} &= -p_i + \lambda \frac{\partial G}{\partial x_i} = 0, \\
\frac{\partial H}{\partial K} &= \frac{\partial \pi}{\partial K} + \lambda \frac{\partial G}{\partial K} - \lambda \delta = -\dot{\lambda} + r\lambda, \text{ and}
\end{align*}
\]
\[ \lim_{t \to \infty} \lambda(t)K(t)e^{-rt} = 0 \] (transversality condition).

Note that because \( G \) is homogenous of degree 1,

\[(A6) \quad G = \frac{\partial G}{\partial K} K + \sum_i \frac{\partial G}{\partial x_i} x_i.\]

Using the above, with some manipulation,

\[(A7) \quad \frac{d}{dt} (\lambda K e^{-rt}) = (\dot{\lambda} K + \lambda \ddot{K} - \lambda Kr) e^{-rt} = (-\pi + \sum_i p_i x_i) e^{-rt}.\]

Taking the integral of (A7) with respect to \( t \) from 0 to infinity and using the transversality condition gives

\[(A8) \quad -\lambda(0)K(0) = \int_0^\infty (-\pi + \sum_i p_i x_i) e^{-rt} \, dt.\]

Following Hayashi, marginal \( q \equiv \lambda/p_0 \), so that

\[(A9) \quad V(t) = \lambda(t)K(t) = q(t)p_0(t) \sum_i \gamma_i k_i(t),\]

or Tobin’s average \( Q \) is (using \( t \) as a subscript as in the text)

\[(A10) \quad Q_t = \frac{v_t}{p_{0t} k_{0t}} = q_t \left( 1 + \gamma_1 \frac{k_{1t}}{k_{0t}} + \gamma_2 \frac{k_{2t}}{k_{0t}} + \cdots \right).\]