The Failure of Free Entry*

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Abstract

We study the entry and exit of firms across U.S. industries over the past 40 years. The elasticity of entry with respect to Tobin's Q was positive and significant until the late 1990s but declined to zero afterwards. Standard macroeconomic models suggest two potential explanations: rising entry costs or rising returns to scale. We find that neither returns to scale nor technological costs can explain the decline in the Q-elasticity of entry, but lobbying and regulations can. We reconcile conflicting results in the literature and show that regulations drive down the entry and growth of small firms relative to large ones, particularly in industries with high lobbying expenditures. We conclude that lobbying and regulations have caused free entry to fail.

The efficiency of a market economy requires free entry. Free entry plays a critical role for allocative efficiency and incentives. As industries adapt to various economic shocks, economic efficiency requires exit from less profitable industries and entry into more profitable ones. This naturally leads to a Q-theory of entry, similar to that for investment. Just as scaling up a high-Q firm generates economic value, reallocating firms from low- to high-Q industries also generates value. This paper studies the evolution of Free Entry in the US over the past 40 years.

Figure 1 provides the main motivation for our paper: it shows that free-entry rebalancing has diminished in the U.S. economy over the past 20 years. Figure 1 shows the elasticity of changes in the number of firms to the industry-median Q over the past 40 years. This elasticity used to be around 0.4: when the median value of Q in a particular industry increased by 0.1 (say from 1.1 to 1.2), the standardized change in the number of firms would be 4% higher over the following 2 years, relative to other industries. Firms used to enter more and exit less in industries with larger values of Tobin's Q, exactly as free entry would predict. In recent years, however, this elasticity has been close to zero. The decline – further documented in section 1 – is consistent across data sources and is stronger outside manufacturing, as we explain in greater detail below.[1] The contribution of our paper is to document and explain this fact.

Our first contribution is to shift the focus away from the *average* decline in entry and towards the *cross-sectional allocation* of entry, as illustrated in Figure 1. A series of important papers has documented declines

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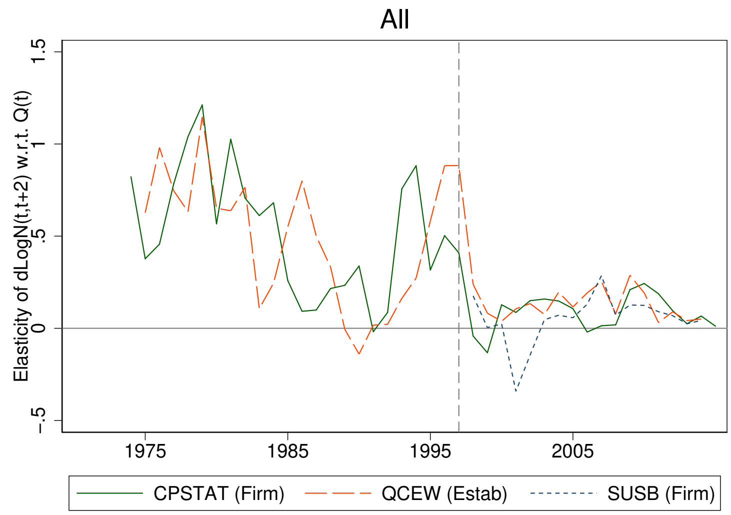
Figure 1: *Elasticity of Number of Firms to Q Across U.S. Industries*



Note: Figure plots the coefficient β_t of year-by-year regressions of changes in the log-number of firms/establishments on the industry-median Q (i.e., $\Delta \log (N)^j_{t,t+2} = \alpha_t + \beta_t \text{med } (Q)^j_t + \varepsilon^j_t$, where j is an industry index). Compustat and SUSB series based on the number of firms by NAICS-4 industry. QCEW series based on the number of establishments by SIC-3 industry up to 1997 and NAICS-4 industries afterwards. Changes in the number of firms standardized to have mean zero and variance of one to ensure comparability across data sources. Industry-median Q based on Compustat. See Section 1 and the Data Appendix for more details.

in entry, exit, and reallocation in the U.S. economy: Davis et al. (2006) find a secular decline in job flows, and Decker et al. (2015) show that the decline is widespread, including in the traditionally high-growth information technology sector.

Focusing on the *allocation* of entry helps us distinguish among competing explanations for the decline in dynamism. Moreover, an efficient *allocation* improves welfare irrespective of the *average* level of entry. Several papers, for example, argue that the decline in population (and labor force) growth might be responsible for the decline in business formation (Hathaway and Litan, 2014; Karahan et al., 2015; Hopenhayn et al., 2018). Such demographic trends can explain changes in the number of entrepreneurs. But they would struggle to explain the decreasing correlation with Q documented in Figure 1. Even if entrepreneurs are few, they should still enter first in high-Q industries. In fact, the smaller the aggregate pool of entrepreneurs, the more important it is to allocate them efficiently. An increase in the shadow price of entrepreneurship increases the incentives to allocate them to high Q industries. Demographic explanations, therefore, predict a *stable or increasing* elasticity of entry to Q, not a *decrease* as we find in the data.

The timing of the decrease in figure 1 is also informative. Unlike measures of average entry rates, which

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[1]We show later that panel regression of the elasticity of $\Delta \log N$ to Q turns negative after 1999 for services. Covarrubias et al. (2019) show that the turnover of industry leaders has decreased since the late 1990s; and that the rank correlation of firm has increased. All of these effects are stronger for service industries. In unreported tests, we also find that future growth of sales no longer predicts entry after 1999.

collapse after 2008, ours is not much affected by the great recession.[2] The drop happens earlier, in the early 2000s. This rules out a host of cyclical explanations. For instance, Davis and Haltiwanger (2019) argue that the collapse of the market for home-equity loans has made it harder for would-be entrepreneurs to get access to capital. That might explain the decline in the average entry rate after the Great Recession, but it cannot explain our main fact.

To study the forces underlying figure 1, we present a simple model of entry in section 2. The model is driven by three shocks: industry demand (or productivity) shocks as in the macroeconomic literature; entry cost shocks, as in the IO and political economy literatures; and shocks to production technologies affecting returns to scale. Holding production technologies constant, we show that the elasticity of entry to Q reveals the relative importance of demand and entry cost shocks. Demand shocks create a positive correlation between entry and Q, while entry cost shocks lead to a negative correlation: they decrease the number of entrants at the same time as they raise the market value of incumbents. A shift from an economy dominated by demand and productivity shocks, as in standard models, towards an economy where entry cost shocks play a more important role may, therefore, explain the trends in figure 1. But this is not the only explanation. Changes in production technology that increase returns to scale also increase the profits and Q of incumbents while decreasing the entry of smaller firms. So we have two potential explanations for figure 1: either the importance of entry costs relative to demand and productivity shocks increased; or there has been a shift towards increasing return technologies – perhaps due to the rise of intangibles (Crouzet and Eberly, 2018). The rest of the paper aims to differentiate between these explanations.

We begin with returns to scale. We estimate returns to scale at the industry-level by applying the methodology of Basu et al. (2006) to the BLS KLEMS accounts – while incorporating the instruments of Hall (2018). We find a small increase after 2000 – from 0.78 to 0.8, on average. These estimates follow well-established approaches but have limited power given the availability of a single time series per industry. To complement our results, we also estimate returns to scale at the firm-level following Syverson (2004) and De-Loecker et al. (2019). We do not find evidence of a broad increase in returns to scale over the past 20 years, which is consistent with Ho and Ruzic (2017) for manufacturing in the US, and Salas-Fumás et al. (2018); Diez et al. (2018) for all industries globally. Moreover, the estimated changes in returns to scale in our panel of industries are uncorrelated with the decline in the Q-elasticity of entry. We conclude that returns to scale cannot be the main explanation for the failure of free entry, which leaves us with entry costs.

Entry costs come in several varieties, from regulation to technology and financial frictions. We construct proxies for all these costs and we test whether they can explain the failure of free entry. We find strong support for regulation, and limited or no support for the remaining hypotheses. We therefore focus on regulations in the remainder of the paper.

Regulations are endogenous, and the regulation of entry is the subject of a long literature in political economy. Following Pigou (1932), the public interest theory emphasizes corrective regulations to deal with externalities and protect consumers. Public choice theorists are suspicious of this idea, however. Stigler (1971) argues that "as a rule, regulation is acquired by the industry and is designed and operated primarily for its benefit." In an influential paper, Djankov et al. (2002) document large differences in entry costs across

[2] If anything, the cross-sectional elasticity of of $d \log N$ to Q increases as firms in low-Q industries exit.

countries, and provide empirical support for the public choice theory. We present five tests to (i) document the role of regulation in the failure of free entry and (ii) distinguish between benign regulation à la Pigou (1932) and captured regulation à la Stigler (1971).

Our first test follows directly from the model. Proposition 2 says that the link between entry and Q depends on the difference between the volatility of industry output growth rates (σ_y^2) and the volatility of changes in entry costs (σ_κ^2). Consistent with the prediction of the model, we find that the variance of output growth rates has remained stable, while the variance of regulation shocks has increased. Our second test studies the elasticity of entry to Q directly, and shows that measures of regulation are correlated with the decline in the elasticity of entry to Q.

Our third test focuses on large versus small firms. Under the public choice theory, large firms are more likely to influence regulators. Consistent with this prediction, we find that regulations hurt small firms, and lead to declines in business dynamism (employment growth, establishment creation, establishment growth) in small relative to large firms. Regulations do not always harm large firms and this explains why there are conflicting results in the literature (e.g., Goldschlag and Tabarrok, 2018; Bailey and Thomas, 2015).

Next, we look at changes in the profitability of incumbents around large regulatory changes. Large changes are most likely to motivate lobbying efforts. Until 2000, we find that large regulatory changes were not correlated with changes in incumbents' profits. After 2000, however, we find that large regulatory changes are systematically followed by significant increases in incumbents' profits. Since regulatory complexity and lobbying expenditures increased after 2000, this suggests that large firms may be increasingly able to influence regulation to their benefit.

Our last test, therefore, considers lobbying. We know that lobbying is overwhelmingly done by large firms. Under the public choice theory, we would expect lobbying to hurt small firms relative to large ones, and indeed, this is what we find – both regressing lobbying directly and instrumenting lobbying with shocks to incumbents' free cash-flows. When we interact regulation and lobbying expenditures, we find that the confluence of lobbying and regulation are particularly harmful to small firms.

Overall, our analyses suggest that rising entry costs and a shift from benign regulation à la Pigou (1932) towards increasingly captured regulation à la Stigler (1971) explain the failure of free entry.

Related Literature Free entry is a central concept in economics, and the subject of a large theoretical literature. One useful way to classify the literature is as follows. A first class of papers considers dynamic competitive entry models. Jovanovic (1982) and Hopenhayn (1992) are the standard models of competitive entry with decreasing returns to scale. In Jovanovic (1982) fundamental productivity is constant but unknown and firms learn it over time as they produce. His theory of noisy selection can then explain why large firms survive while small firms exit, why inequality among firms tends to grow as a cohort ages, and why average industry profits and productivity increase over time. In Hopenhayn (1992) fundamental productivity is observable and follows a Markov chain. His model predicts that older firms are larger, more profitable and more likely to survive.

A second class of papers considers non-strategic models of imperfect competition. Spence (1976) and Dixit and Stiglitz (1977) study the welfare properties of entry and product selection under monopolistic competition. The basic issue is that product selection and entry decisions depend on expected revenues, but revenues differ from welfare in two ways. On the one hand, revenues do not include consumer surplus, therefore entry can be inefficiently low. On the other hand, revenues are partly diverted from one firm to another, therefore entry can be inefficiently high. We have known since Spence (1976) and Dixit and Stiglitz (1977) that the strength of these two effects depends on the curvature of the utility aggregator.[3] Dhingra and Morrow (2016) generalize the analysis to a setting where firms have different levels of productivity. A key assumption in the non-strategic literature is the free entry condition. It ensures that positive ex-post profits are just enough to cover sunk entry costs.

In strategic models, instead, the threat of mutually destructive actions plays a key role in entry decisions. Salop (1979) explains that "a more efficient entrant may be deterred by an established firm who has sunk sufficient costs to make his own exit uneconomical, and hence, entry mutually destructive." Wilson (1992) distinguishes three categories of strategic entry deterrence: (i) preemption, where early investments become a credible commitment to stay and fight would-be entrants; (ii) signaling with costly actions to send credible information about private costs; and (iii), predation, by fighting current entrants to build a reputation to deter future entrants. Entry, exit and reallocation play a key role for productivity growth in deregulated industry. Olley and Pakes (1996), for instance, find that the reallocation of output from less to more productive plants accounts for the entire increase in productivity of the telecommunications equipment industry after its deregulation.

The political economy literature has also studied entry costs. Arthur Pigou, building on Marshall, agues that governments can intervene to correct externalities that create a gap between the social net product and the private net product of an activity. For instance, Pigou argues that "The private net product of any unit of investment is unduly large relatively to the social net product in the businesses of producing and distributing alcoholic drinks. Consequently, in nearly all countries, special taxes are placed upon these businesses."(Pigou, 1932). Stigler (1971) and the social choice school emphasize the capture of regulators and politicians. The empirical evidence is that corruption is more prevalent in poor countries, and so are barriers to entry via regulation. De Soto (1990) discusses the failures of government-enforced regulations regarding property rights and how underground economies have became a dominating presence in Peru as a result. Djankov et al. (2002) measure entry cost in a large number of countries. They find that entry regulations are associated with higher levels of corruption and that countries with more open and accountable political systems regulate entry less.

Much of the literature following Djankov et al. (2002) used the U.S. as a benchmark for competitive markets and free entry. Alesina and Giavazzi (2006) captured well the common wisdom of the late 1990s and early 2000s when they wrote "*If Europe is to arrest its decline [..] it needs to adopt something closer to the American free-market model.*"[4] However, a growing literature documents a decline in dynamism

[3]Under constant elasticity of substitution, entry is efficient in partial equilibrium (i.e., with fixed factor supplies). The intuition is that a planner maximizes $\int u(c_i)$, while firm i maximizes $p_i c_i$. Consumer demand implies $p_i = u'(c_i)$, hence firm i maximizes $u'(c_i)\, c_i$. If we define $\rho = cu'/u$, we can equivalently say that firms maximize ρu. If ρ is constant – i.e., if preferences are CES – this is equivalent to maximizing u. The CES case is often used in application in macro and trade, as in Melitz (2003) for instance. If ρ is increasing, existing firms will expand beyond what the planner would choose and, given the resource constraint, firms will be at the same time too few and too large. Reciprocally, if ρ is decreasing, there is excess entry.

[4]Multilateral agencies such as the World Bank and the OECD provided similar advice around the world. In 1999, the OECD

and a rise in concentration, profits, and markups in the US. Haltiwanger et al. (2011) find that "job creation and destruction both exhibit a downward trend over the past few decades." Grullon et al. (2019) show that concentration and profit rates have increased across most U.S. industries (see also Barkai (2017) and De-Loecker et al. (2019)). Furman (2015) and CEA (2016) argue that the rise in concentration suggests "economic rents and barriers to competition." Covarrubias et al. (2019) argue that concentration in the US has shifted from mostly beneficial in the 1980s and 1990s to mostly harmful in the 2000s. Lee et al. (2016) – perhaps the closest paper to our work – documents that capital stopped flowing to high Q industries in the 2000s and Gutiérrez and Philippon (2017) link the decrease in corporate investment to the decline in competition. Gutiérrez and Philippon (2018) show that competition policy (i.e., antitrust and regulation) has weakened in the US relative to Europe. Kozeniauskas (2018) concludes that increasing fixed costs are the main explanation for the decline in entrepreneurship.[5] Jones et al. (2019) estimate a structural DSGE model with cross-sectional firm and industry data and find that the model-implied entry costs align well with independent measures of entry regulation and M&A.

Finally, there is much disagreement in the empirical literature on the impact of regulation on business dynamism. Bailey and Thomas (2015) argue that dynamism declines in industries with rising regulation, but Goldschlag and Tabarrok (2018) – using similar dataset – argue that regulation is not to blame for declining business dynamism. A contribution of our paper is to clarify and reconcile this conflicting results by emphasizing the heterogenous impact of regulations on small and large firms.

1 Evidence on the Q-Elasticity of Entry

In this section we present more details about the allocation of entry. The Appendix summarizes the evolution of entry, profits and growth of young firms. These average trends are consistent with increasing entry costs, but may also be explained by other trends (e.g., demographics). As argued in the introduction, however, demographic trends cannot readily explain the decrease in the allocation of entry towards high Q industries, which is the focus of our paper.

The Decline in the Q-Elasticity of Entry is Economically and Statistically Significant Let us first present the empirical regression behind Figure 1. Our baseline statistical model relates the growth in the number of firms N_t^j in industry j between year t and $t+2$ to the median value of Tobin's Q in that industry

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noted that the *"United States has been a world leader in regulatory reform for a quarter century. Its reforms and their results helped launch a global reform movement that has brought benefits to many millions of people"*. The idea that free and competitive markets work best is supported by much empirical evidence, and the gospel of free market spread relatively successfully. For instance, Djankov et al. (2002) report that it took 15 procedures and 53 days to begin operating legally in France in 1999, versus 3 procedures and 3 days in New Zealand. In 2016, it took only 4 days to start a business in France and 1 day in New Zealand. Gutiérrez and Philippon (2018) provide a detailed and quantitative discussion of how EU markets became free(er). Over the same period, however, the entry delay in the US went up from 4 days to 6 days. This is not an isolated indicator. The OECD's Product Market Regulation indices (discussed in detail later) show clear decreases in entry regulation over the past 20 years in all countries except the US.

[5] He uses a model of occupational choice to study the contribution of four explanations to the decline in entrepreneurship: changes in wages driven by skill-biased technical change; changes in technology facilitating the expansion of large firms; changes in the fixed costs (which combine sunk entry costs and per-period operating costs); and changes in demographics.

Table 1: *Elasticity of* $\Delta\log(N)$ *to* Q

Table reports panel regression results of the 2Y log-change in the number of firms on median industry Q. Columns 1-3 include all industries, columns 4-6 manufacturing industries and columns 7-9 service industries. For each group, the first column focuses on the pre-1998 period, second on the post-1999 period; third includes the full period but interacts Q with a dummy variable equal to one after 1999. All regressions based on Compustat, following NAICS-4 industries. Standard errors in brackets clustered at industry-level. + p<0.10, * p<0.05, ** p<.01.

	All Sectors			Manufacturing			Services		
	(1) 74-98	(2) 99-16	(3) 74-16	(4) 74-98	(5) 99-16	(6) 74-16	(7) 74-98	(8) 99-16	(9) 74-16
$Med(Q_t)$	0.389**	0.056	0.389**	0.441**	0.270**	0.441**	0.339**	-0.080	0.339**
	(0.065)	(0.082)	(0.065)	(0.031)	(0.048)	(0.031)	(0.103)	(0.091)	(0.103)
$Med(Q_t) \times \geq 99$			-0.334**			-0.172**			-0.418**
			(0.109)			(0.064)			(0.139)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2	.17	.084	.2	.33	.28	.36	.15	.091	.21
Observations	7,039	4,298	11,337	2,108	1,388	3,496	4,131	2,472	6,603

$$\log N_{t+2}^{j} - \log N_{t}^{j} = \alpha_t + \beta_\tau \text{med}_{i\in j}\left\{Q_{i,t}\right\} + \varepsilon_t^j,$$

over the sample period τ. We include year dummies α_t to remove any common aggregate trend between the two series. Figure 1 plots the elasticity β_τ, estimated year by year. For simplicity, in Table 1 we estimate the model separately over two samples: $\tau = 1974 - 1998$ and $\tau = 1999 - 2016$. The overall elasticity has decreased from 0.39 to 0.056. It remains positive, albeit smaller, in manufacturing. Outside manufacturing, the point estimate in the recent sample is negative.[6]

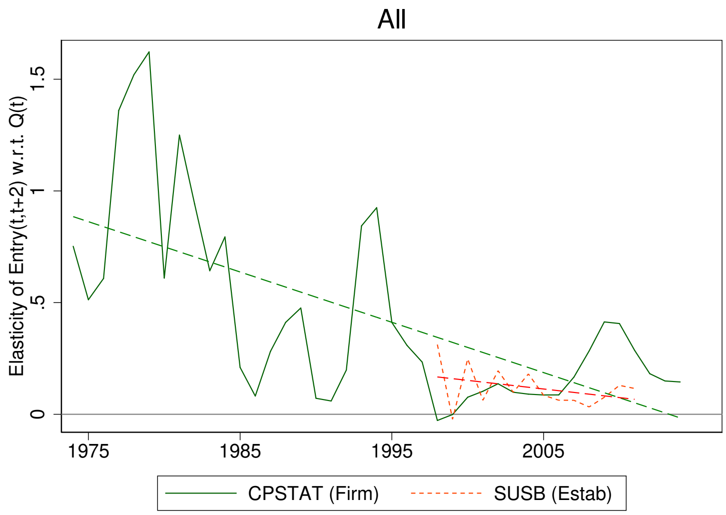
Entry, not Exit, Explains the Decline Let us then establish one more basic fact. Figure 1 shows that the elasticity of the number of firms to the industry-median Q. The growth in the number of firms depends on entry and exit. Exit rates have in fact been relatively stable (see appendix figure 11). Figure 2 shows that the decline in the elasticity of $\Delta\log(N)$ to Q is primarily due to a decline in entry sensitivity.

2 Model

Let us now introduce a simple model to help us understand Figures 1 and 2. The key features of the model are entry costs and returns to scale. Entry costs are taken as fixed technological parameters in most modern models. Clementi and Palazzo (2016), for instance, build a DSGE model with investment where firms' dynamics follow Hopenhayn (1992). In their model, a positive shock to productivity (or demand) makes entry more appealing – introducing a form of Q-theory of entry (Jovanovic and Rousseau, 2001). Figure 1 shows that this is no longer a good description of the economy. There are two leading explanations for the stylized facts that we have documented above: fixed costs and returns to scale. The model will help us sharpen the predictions of each explanation.

[6] Appendix figure 15 plots the time series of elasticities by sector.

Figure 2: *Elasticity of Entry Rate to Q Across U.S. Industries*



Note: Figure plots the coefficient β_t of year-by-year regressions of the 2Y firm/establishment entry rate on the median industry Q $\left(i.e., \text{Entry rate}^j_{t,t+2} = \beta \text{med } (Q)^j_t + \varepsilon^j_t\right)$. Both series based on NAICS-4 industries j. Compustat series based on entry of firms to the dataset. SUSB series based on the average establishment start-up rate. Entry rates standardized to have mean zero and variance of one to ensure comparability across data sources.

2.1 Setup and Steady State

Consider the following simplified model of an industry. Let N_t be the number of active firms in the industry in period t. There are three levels of analysis in this model. At the firm level, there is production $y_{i,t}$ and price $p_{i,t}$. At the industry level there is an aggregation of firm level outputs and a price index P_t. Finally, at the aggregate level there is a final good which is a composite of all the industry goods. We normalize the price index of the final composite good to 1. Let us start by describing the demand system. The industry good is defined by

$$Y_t^{\frac{\sigma-1}{\sigma}} = \int_0^{N_t} y_{i,t}^{\frac{\sigma-1}{\sigma}} di$$

where $\sigma > 1$ is the elasticity of substitution between different firms in the industry. This demand structure implies that there exists an industry price index $P_t^{1-\sigma} \equiv \int_0^{N_t} p_{i,t}^{1-\sigma} di$ such that the demand for variety i is

$$y_{i,t} = Y_t \left(\frac{p_{i,t}}{P_t}\right)^{-\sigma}$$

At the aggregate level, the demand for the industry good is $Y_t = (P_t)^{-\bar{\sigma}} D_t$ with $D_t = \tilde{d}_t \bar{Y}_t$, where $\bar{Y}_t$ is real GDP and $\tilde{d}_t$ is an industry demand shifter. To keep the model simple, we assume Cobb-Douglas aggregation across industries so $\bar{\sigma} = 1$ and therefore nominal industry output $P_t Y_t = D_t$ is exogenous to industry specific supply shocks.

Let us now describe the production side. Firms use the final good as an input in production. Let a_i be the productivity of firm i. We assume for simplicity that a_i is fixed at the firm level but it is straightforward to extend our results when a changes over time. The profits of firm i are then given by

$$\pi_{i,t} = p_{i,t} y_{i,t} - \frac{y_{i,t}}{a_i} - \phi_i$$

where ϕ_i is a fixed operating cost. Firm i sets a markup μ over marginal cost

$$p_{i,t} = \frac{1+\mu}{a_i}$$

so that its profits are $\pi_i = \frac{\mu}{(1+\mu)^\sigma} a_i^{\sigma-1} P^\sigma Y - \phi_i$. If we assume monopolistic competition, the optimal mark-up $\mu^m = \frac{1}{\sigma-1}$ maximizes $\frac{\mu}{(1+\mu)^\sigma}$. But we do not need to consider only this case. We could assume limit pricing at some mark-up $\mu < \frac{1}{\sigma-1}$, strategic interactions among firms, and so on. The industry price index is

$$P_t = \frac{1+\mu}{A_t N_t^{\frac{1}{\sigma-1}}}$$

where $A_t \equiv \left(\int a^{\sigma-1} dF_t(a)\right)^{\frac{1}{\sigma-1}}$ is the average productivity and F_t is the distribution of a across active firms. We can finally write the flow profit function as

$$\pi(a, \phi; A_t, D_t, N_t) = \frac{\mu}{1+\mu} \left(\frac{a}{A_t}\right)^{\sigma-1} \frac{D_t}{N_t} - \phi. \tag{1}$$

Our model is highly stylized, but it captures the key elements that are important in the data. In particular, profits depend on markups, fixed costs, relative productivity, nominal industry demand, and the number of firms.

Let us now turn to the dynamics of entry and exit. Active firms disappear with probability δ and it takes one period to enter. Let n_t be the number of new firms. The number of firms evolves according to

$$N_{t+1} = (1-\delta) N_t + n_t. \tag{2}$$

Let V_t be the value of an existing firm. It solves

$$V_t = \pi_t + \frac{1-\delta}{1+r_t} \mathbb{E}_t [V_{t+1}] \tag{3}$$

where the expectations are taken under the risk neutral measure. Entry requires an entry cost κ_t. Free entry requires

$$\frac{\mathbb{E}_t [V_{t+1}(a, \phi)]}{1+r_t} \leq \kappa_t. \tag{4}$$

Equation (4) should be evaluated using the parameters (a, ϕ) of potential entrants and must hold with equality when $n_t > 0$.

Consider a symmetric steady state with $a = A$ where V and N are constant. From (1) and (3), we obtain

$V = \frac{1+r}{r+\delta}\left(\frac{\mu D}{(1+\mu)N} - \phi\right)$. Entry is such that $V = (1+r)\,\kappa$, therefore

$$N = \frac{\mu}{1+\mu}\frac{D}{(r+\delta)\,\kappa + \phi} \tag{5}$$

The solution is unique and from (2), we know that $n = \delta N$. As expected, entry increases with demand and profit margins, and decreases with entry costs, discount rates and fixed costs.

Proposition 1. *In steady state, an increase in entry cost κ leads to a proportional increase in firm value V and a decrease in the number of firms N. An increase in fixed operating costs ϕ or a decrease in demand D lead to a decrease in N.*

2.2 Entry Costs and the Q-elasticity of Entry

Let us consider a symmetric equilibrium with fixed technology ($a = A$) and random entry costs κ_t. The Bellman equation of an active firm is

$$V_t = \frac{\mu}{1+\mu}\frac{D_t}{N_t} - \phi + \frac{1-\delta}{1+r_t}\mathbb{E}_t\left[V_{t+1}\right]$$

The endogenous state variable of the model is N, the number of firms. As usual, we index the value function by t to capture its dependence on the exogenous stochastic processes κ_t and D_t. Let us consider an equilibrium path with strictly positive entry at all times. In that case we must have, for all t:

$$\mathbb{E}_t\left[V_{t+1}\right] = (1+r_t)\,\kappa_t$$

From the Bellman equation we get

$$V_t = \frac{\mu}{1+\mu}\frac{D_t}{N_t} - \phi + (1-\delta)\,\kappa_t.$$

The Bellman equation is truncated by free entry. Combining the two, we get $(1+r_t)\,\kappa_t = \frac{\mu}{1+\mu}\frac{\mathbb{E}_t[H_{t+1}]}{N_{t+1}} - \phi + (1-\delta)\,\mathbb{E}_t\left[\kappa_{t+1}\right]$. We can therefore solve the equilibrium in closed form:

$$N_{t+1} = \frac{\frac{\mu}{1+\mu}\mathbb{E}_t\left[H_{t+1}\right]}{(1+r_t)\,\kappa_t + \phi - (1-\delta)\,\mathbb{E}_t\left[\kappa_{t+1}\right]}.$$

All that is left to do is to specify the stochastic processes for the shocks. We assume that demand and entry costs are random walks, so $\mathbb{E}_t\left[H_{t+1}\right] = D_t$ and $\mathbb{E}_t\left[\kappa_{t+1}\right] = \kappa_t$. In that case we have simply $N_{t+1} = \frac{\frac{\mu}{1+\mu}D_t}{\phi+(r_t+\delta)\kappa_t}$ and thus

$$\frac{N_{t+1}}{N_t} = \frac{\phi + (r_{t-1}+\delta)\,\kappa_{t-1}}{\phi + (r_t+\delta)\,\kappa_t}\frac{D_t}{D_{t-1}}.$$

This equation is intuitive: the growth rate of the number of firms rises with demand growth, and decreases with entry costs and discount rates. In this paper, we focus on micro evidence from the cross-section of firms and industries where changes in discount rates are not important. Jones et al. (2019) discuss in details the role of discount rates and risk premia. We assume that the parameters are such that gross entry is positive: $\frac{N_{t+1}}{N_t} > 1 - \delta$.

Lemma 1. *Current market values are increasing in concentration, demand shocks, and entry cost shocks. Entry is increasing in demand shocks, and decreasing in entry cost.*

To be consistent with the empirical discussion, we need to relate entry to the Tobin's Q of incumbents. In the model, entry is the only investment decision, so κ is the book value of assets. For simplicity, we assume that κ is constant until time t, so all incumbents have the same book value $\psi \kappa_{t-1}$. Incumbents' Q can therefore be defined as

$$\begin{aligned} Q_t &\equiv \frac{V_t}{\kappa_{t-1}} \\ &= \frac{\mu}{1+\mu} \frac{D_t}{\kappa_{t-1} N_t} - \frac{\phi}{\kappa_{t-1}} + (1-\delta) \frac{\kappa_t}{\kappa_{t-1}} \\ &= \left(r + \delta + \frac{\phi}{\kappa_{t-1}} \right) \frac{D_t}{D_{t-1}} - \frac{\phi}{\kappa_{t-1}} + (1-\delta) \frac{\kappa_t}{\kappa_{t-1}} \end{aligned}$$

Let us define $\sigma_y^2 \equiv \mathbb{VAR}\left(\frac{D_t}{D_{t-1}}\right)$ as the variance of demand growth, and $\sigma_\kappa^2 \equiv -\mathbb{COV}\left(\frac{\kappa_{t-1}}{\kappa_t}; \frac{\kappa_t}{\kappa_{t-1}}\right)$, which, to a first order, is simply the variance of the growth of entry costs. We can then state our main result

Proposition 2. *The covariance $\mathbb{COV}\left(\frac{N_{t+1}}{N_t}; Q_t\right)$ between entry rates and Q increases with the variance of demand shocks and decreases with the variance of entry cost shocks:*

When ϕ is small,[7] we have the simple formula

$$\mathbb{COV}\left(\frac{N_{t+1}}{N_t}; Q_t\right) \approx (r+\delta)\,\sigma_y^2 - (1-\delta)\,\sigma_\kappa^2.$$

Proposition 2 offers an interpretation of Figure 1. The decreasing correlation between entry rates and Q reveals that entry cost shocks have become relatively more prevalent than demand shocks (or TFP shocks) in recent years.

2.3 Increasing Returns and the Q-elasticity of Entry

The other main hypothesis put forward in the literature to explain the changing dynamics of industries is that of increasing returns to scale. Suppose that firms can choose between two technologies after entry: low fixed cost & low productivity (A_L, ϕ_L) or high fixed cost & high productivity (A_H, ϕ_H). Profits are then

$$\pi_t(a, \phi) = \frac{\mu}{1+\mu} \left(\frac{a}{A_t}\right)^{\sigma-1} \frac{D_t}{N_t} - \phi$$

[7] Note that $\frac{\phi}{\kappa_{t-1}}$ is of the order of $r+\delta$, and as long as $\frac{D_t}{D_{t-1}} - 1$ is small – as it is in the data, a few percents – then $\frac{\phi}{\kappa_{t-1}}\left(\frac{D_t}{D_{t-1}} - 1\right)$ is second order small and we have $Q_t \approx (r+\delta)\frac{D_t}{D_{t-1}} + (1-\delta)\frac{\kappa_t}{\kappa_{t-1}}$.

The choice clearly depends on the size of the market, the elasticity of demand and the fixed-cost productivity bundles. Assume that technology L was optimal until time t. Profits were $\pi_{L,t} = \frac{\mu}{1+\mu}\frac{D_t}{N_t} - \phi_L$. Free entry required $V_{L,t} = (1+r)\,\kappa_t$. In steady state we have $\pi_L = (r+\delta)\,\kappa$ and therefore

$$N_L = \frac{\mu}{1+\mu}\frac{D}{(r+\delta)\,\kappa + \phi_L}.$$

Now imagine a one time shock that makes technology H more appealing and leads firms to switch. In the new steady state we have

$$N_H = \frac{\mu}{1+\mu}\frac{D}{(r+\delta)\,\kappa + \phi_H}.$$

The switch happens if H dominates L at the old steady state, so $\phi_H - \phi_L$ needs to be small enough.[8] The following proposition characterizes the change in the economy.

Proposition 3. *A switch to increasing return technology leads to more concentration and higher productivity. With idiosyncratic risk, we would also observe higher profits and higher Q.*

Our simple model has ignored idiosyncratic risk for simplicity. If we take into account idiosyncratic risk – so that firms draw their productivity from a distribution with mean A – then we have the standard selection effect that low productivity firms drop out, as in Hopenhayn (1992). It is straightforward to show that this selection effect is stronger with technology H (see Covarrubias et al. (2019) for a discussion and further references). We therefore have a second potential explanation for the failure of the Q-entry condition. If industry dynamics are dominated by shocks that increase the degree of returns to scale, then we could observe the decline in Figure 1.

In the rest of the paper, we test the two explanations: entry costs, and returns to scale.

3 The Stability of Returns to Scale

Proposition 3 says that the appearance of technologies with stronger returns to scale can generate a decline in the entry-Q relationship. In this section, we test this explanation directly by estimating returns to scale over time. We perform the test at the industry level following Basu et al. (2006) and then at the firm level following Syverson (2004) and De-Loecker et al. (2019).

[8] We need profitable entry at the old equilibrium, so $\pi_H(N_L) = \frac{\mu}{1+\mu}\left(\frac{A_H}{A_L}\right)^{\sigma-1}\frac{D}{N_L} - \phi_H > \pi_L(N_L) = \frac{\mu}{1+\mu}\frac{D}{N_L} - \phi_L$, or $\phi_H - \phi_L < \frac{\mu}{1+\mu}\frac{D}{N_L}\left(\left(\frac{A_H}{A_L}\right)^{\sigma-1} - 1\right)$. Using the old free entry condition we can write the profitability requirement simply as

$$\frac{\phi_H - \phi_L}{\phi_L + (r+\delta)\,\kappa} < \left(\frac{A_H}{A_L}\right)^{\sigma-1} - 1.$$

The simplest way to think about the experiment is that this condition was violated until time t, and that it became satisfied at time t thanks to an improvement in the high returns to scale technology. Note that the switch can also happen when σ increases, as in the "winner-take-most" argument.

3.1 Industry-level

Let us begin with industry-level estimates of return to scale. We apply the methodology of Basu et al. (2006) to the BLS KLEMS tables, which cover 1987 to 2016. Assume that all firms in a given industry have the same production function and seek to minimize their costs given quasi-fixed capital stock and number of employees. As shown in Basu et al. (2006), we can recover returns to scale estimates γ_i for industry i by estimating

$$d\log y_{i,t} = c_i + \gamma_i d\log x_{i,t} + \beta_j dh_{i,t} + \epsilon_{i,t} \tag{6}$$

where y denotes output, x denotes total inputs (capital, labor, and materials), h denotes detrended hours worked. The residual captures log differences in total factor productivity. We restrict β to be the same for three broad sectors, indexed by j: manufacturing, services and other industries. We instrument the change in inputs with the lagged price of oil, four government defense spending items, real GDP, real non-durable consumption and real non-residential investment in fixed assets.[9] Appendix figure 16 plots the long-run return to scale estimates.

To evaluate whether returns to scale increase after 2000, we estimate:

$$d\log y_{it} = c_i + \gamma_{i0} d\log x_{it} + \gamma_{1j} d\log x_{it} 1_{year\geq 2000} + \beta_j dh_{it} + \epsilon_{it}$$

where γ_{1j} captures the increase in returns to scale after 2000 for manufacturing, services and other industries. We obtain low and insignificant estimates $\hat{\gamma}_1$ of 0.02 for manufacturing, 0.005 for services and 0.037 for the remaining industries. Taking the weighted average by output, this implies a small increase in returns to scale from 0.78 to 0.8. Alternatively, if we estimate a different γ_{1i} for each industry, we observe a large heterogeneity in results, with no clear pattern among industries and no correlation with changes in entry rates. The results γ_{1i} are available upon request.

3.2 Firm-level

Industry-level estimates follow well-established approaches. However, the limited data availability implies that we can only estimate long-run average changes – such as an increase from before to after 2000. To obtain more robust time-varying estimates, we follow De-Loecker et al. (2019) – who in turn follow Syverson (2004) – and we estimate returns to scale using firm-level data from Compustat. We estimate the average return to scale γ across all firms from

$$\Delta \log q_{it} = \gamma \left[\alpha_V \Delta \log v + \alpha_K \Delta \log k + \alpha_X \Delta \log x\right] + \omega, \tag{7}$$

[9] See appendix C for the complete details and results. Like Basu et al. (2006), we exclude farm and mining and use the Christiano and Fitzgerald band pass filter. We also exclude 'petroleum and coal products' and 'pipeline transportation' due to large variation in prices due to oil. Basu et al. (2006) use the categories durable manufacturing, non-durable manufacturing and the rest while we use manufacturing, services and the rest. The results are barely affected, and our categorization facilitates the exposition of changes after 2000. The choice of the price of oil and government defense spending as instruments (Equipment, Ships, Software and Research and Development) is common in the literature and our particular implementation follows Hall (2018). We add aggregate business cycle indicators under the assumption that they are uncorrelated with industry-specific technological improvements (such as during the Great Recession, for instance). The results are robust to estimating industry-specific β's instead of using industry groups, as shown in appendix C.

where v, k and x denote, respectively, costs of goods sold (COGS), capital costs and overhead costs (SG&A). The fraction $\alpha_V = \frac{P^V V}{P^V V + rK + P^X X}$ denotes the cost-share of COGS, and likewise for $\alpha_K$and α_X. As in De-Loecker et al. (2019), we deflate COGS and SG&A with the GDP deflator, capital costs with the relative price of investment goods. Capital costs are set equal to 12% times the deflated value of gross property, plan and equipment (Compustat PPEGT). We weight observations by deflated sales.[10]

We use a specification in log-differences because the De-Loecker et al. (2019) model relies on OLS and we cannot control for firm-level prices. If we estimated (7) in levels, an increase in the mark-ups of large relative to small firms would appear as an increase in quantities, and result in an over-estimation of the change in returns to scale. Growing mis-measurement of intangible capital would have a similar effect. Another way to mitigate these issues is to add firm fixed effects to the levels regression. This yields similar conclusions as the specification based on changes. Figure 3 reports the results. The left plot reports returns to scale estimates based on a pooled regression across all firms, while the right one reports the sales-weighted average of separate estimates across NAICS-2 industries. Our estimates of returns to scale have remained relatively stable since 1980 – in line with our industry-level estimates and with much of the literature.[11]

We do not find a significant, secular increase in returns to scale – in line with Ho and Ruzic (2017) for manufacturing in the US; Salas-Fumás et al. (2018) for all EU industries and Diez et al. (2018) globally. We conclude that the broad decline in the Q-elasticity of entry cannot be explained by returns to scale and we turn next to entry costs. Of course we do not rule out that returns to scale might matter for some industries in some time periods (see Covarrubias et al. (2019) for details on industry specific changes), and we control for estimated returns to scale in our tests below.

4 Entry Costs

Entry costs may have increased for a variety of reasons, most prominently changes in technology or regulation. Appendix D builds several proxies for each of these explanations, including measures of intangible intensity, IT intensity and patenting for the former; and regulation and lobbying for the latter.[12] We use these proxies to test whether these explanations are consistent with the decline in the level and elasticity of entry to Q. Measures of technological change are correlated with the decline in the *level* of entry, but cannot explain the decline in the *elasticity* of entry to Q.[13] By contrast, we find that lobbying and regulation exhibit

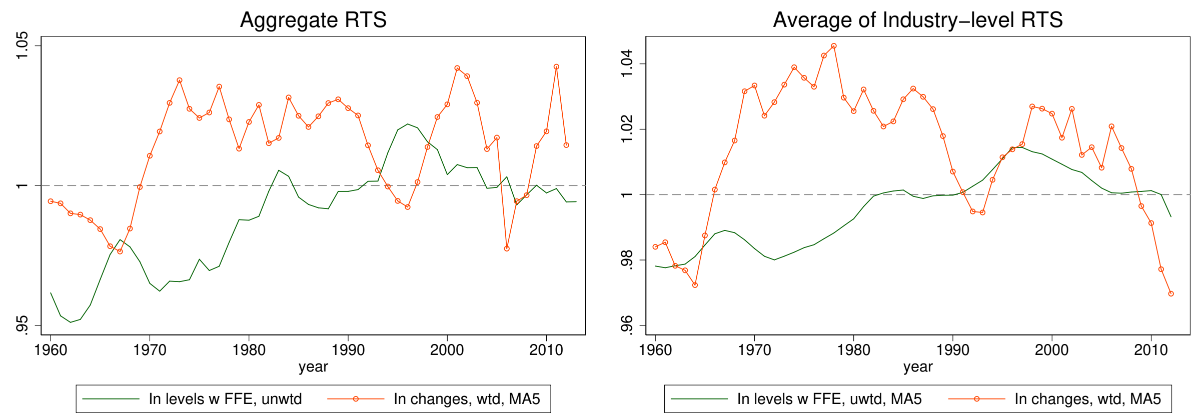
[10] Using changes implies that new firms are excluded in the first observations. In unreported tests, we confirm that adding an observation with near zero sales and near zero inputs at the year prior to a firm entering Compustat does not affect our conclusions.

[11] De-Loecker et al. (2019) – using a specification in levels – estimate increases from 0.97 to 1.08 overall and from 0.99 to 1.04 and when aggregating industry estimates, respectively. Using the methodology of De Loecker and Warzynski (2012), De-Loecker et al. (2019) estimate a similar increase from 1.03 to 1.08 but again the lack of firm-level prices may affect the results. The level of return to scale estimates differ widely when using industry vs. firm-level data. This can reflect sample selection as public firms likely use more advanced technologies than small and medium enterprises. It is also consistent with different adjustment costs at the firm and industry levels. A firm can expand by hiring already trained workers from its competitors, while an expansion at industry might require more training.

[12] In unreported tests, we also consider globalization (rising foreign competition and foreign profits) and financial frictions (including measures of external finance and bank dependence). Neither of these explanations appear to explain the decline in the Q-elasticity of entry so we omit them for brevity.

[13] These results align with the common wisdom that, as far as technology is concerned, it has never been easier to start a business. Recent advances in technology have lowered search costs (online marketing, etc.) and drastically reduced fixed IT costs (cloud-based computing and data storage).

Figure 3: *Firm-level Returns to Scale Estimates*



Notes: Firm-level return to scale estimates based on Compustat. Left plot based on a pooled regression across all firms in Compustat. Right plot based on the sales-weighted average of separate estimates across NAICS-2 industries. Green series based on log-level specification with firm fixed effects. Red dotted series based on log-differences. See text for details.

significant correlations with both levels and elasticities – consistent with a political economy interpretation of entry costs. We therefore focus on regulation and lobbying in the remainder of the paper.

4.1 The Rise of Regulation

Let us start by describing the data on regulations. Figure 4 shows the rise in Federal regulations in the US along with the decline in the firm entry rate. As emphasized by Davis (2017), the 2017 vintage of the Code of Federal Regulations (CFR) spans nearly 180,000 pages following an eight-fold expansion over the past 56 years.

The number of restrictions is based on RegData, which serves as our main proxy of regulation. Bailey and Thomas (2015) and Goldschlag and Tabarrok (2018) also use RegData to study the effects of regulation on business dynamism. RegData is a relatively new database – introduced in Al-Ubaydli and McLaughlin (2015) – that aims to measure regulatory stringency at the industry-level. It relies on machine learning and natural language processing techniques to count the number of restrictive words or phrases such as 'shall', 'must' and 'may not' in each section of the Code of Federal Regulations and assign them to industries.[14] Federal laws are written by congress but more than 60 executive agencies can issue subordinate regulations. Executive agencies issue thousands of new regulations each year. Federal Regulations are compiled in The Code of Federal Regulations (CFR).[15]

[14] This represents a vast improvement over simple measures of 'page counts', but it is still far from a perfect measure. Goldschlag and Tabarrok (2018) provide a detailed discussion of the database and its limitations, including several validation analyses that, for example, compare RegData's measure of regulatory stringency to the size of relevant regulatory agencies and the employment share of lawyers in each industry. Goldschlag and Tabarrok (2018) conclude that "the relative values of the regulatory stringency index capture well the differences in regulation over time, across industries, and across agencies."

[15] One limitation is that the main RegData database covers only federal regulation. State and Local governments also have regulatory responsibilities – which further add to the regulatory burden. It is hard to summarize the scale or growth of State and Local regulation, but the increase has also been significant. Occupational Licensing is an area that has received substantial attention. CEA (2016), for example, show that the share of workers required to obtain a license increased from under 5 percent in the 1950s to over 25 percent in 2008 – in large part because greater prevalence of licensing requirements at the State-level.

Figure 4: *Regulation Index and Firm Entry Rate*

Source: Firm entry rates from Census' Business Dynamics Statistics. Regulatory restrictions from RegData. See text for details.

Figure 4 is consistent with the hypothesis that regulation hurts entry, but the trends could also be explained by some common factor, perhaps linked to changing demographics. More importantly, we know from Proposition 1 that the long-run number of firms is proportional to the average entry cost. If entry costs rise steadily, average firm size increases and the number of firms declines. The elasticity of the entry rate to Q, however, would remain stable. To understand the allocation of entry, we need to look at shocks.

4.1.1 Dispersion of Output and Regulations

Proposition 2 says that the link between entry and Q depends on the volatility of output σ_y^2 and that of entry costs σ_κ^2. Figure 5 shows the standard deviation of industry output. It does not show a trend.

Figure 6, on the other hand, shows increasing dispersion in regulatory changes. The timing is also consistent with our hypothesis since we observe a significant increase in the late 1990s, roughly at the same time as we observe the decline in the Q-elasticity of entry. Entry cost shocks driven by regulation are thus a plausible explanation for the decrease in the Q-Elasticity of Entry.

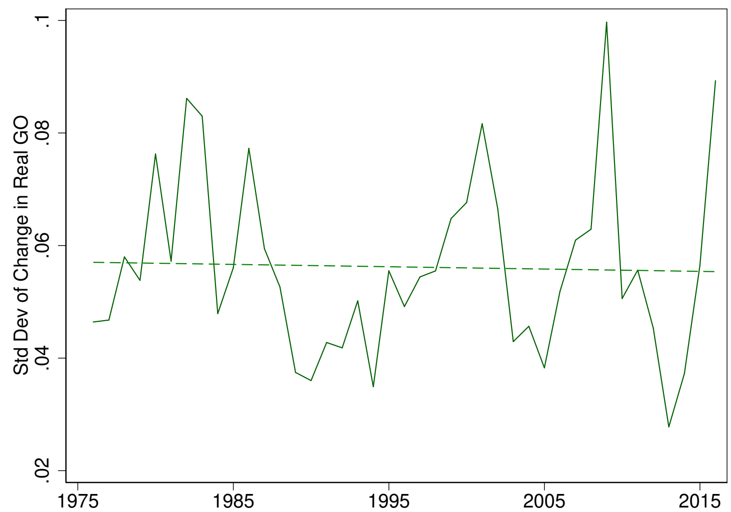
4.1.2 Regulation and the Q-Elasticity of Entry

We can test this directly by estimating

$$\Delta \log (N)^j_{t,t+2} = \beta_1 \log(Reg^j_t) + \beta_2 \log(Reg^j_t) \times \text{med } (Q)^j_t + \beta X^j_t + \alpha_t + \varepsilon^j_t,$$

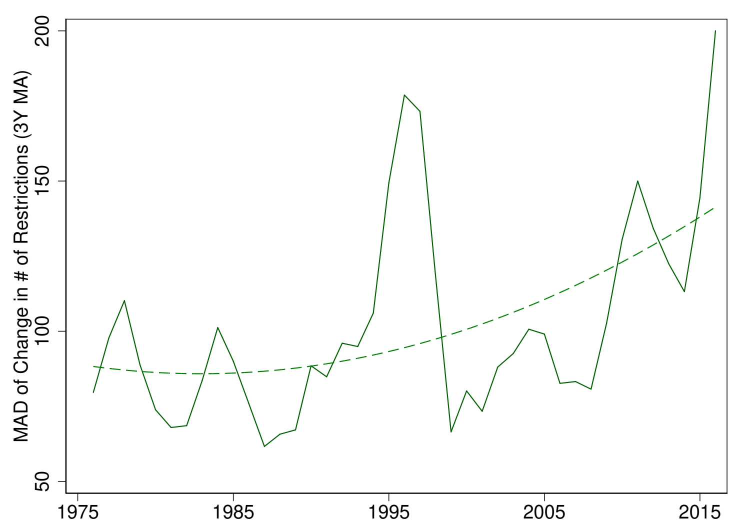
where β_2 measures the impact of regulation on the Q-elasticity of entry and X^j_t denotes return to scale controls. We include only year fixed effects α_t because we want to compare elasticities across industries. As shown in Table 2, increases in regulation appear to explain the decline in the elasticity of entry to Q across all datasets.

Figure 5: *Standard Deviation of Industry Output*



Note: Standard Deviation of changes in log real gross output across U.S. industries. Based on the most granular industries in the BEA's GDP By Industry Accounts (file GDPbyInd_GO_1947-2017), which roughly follow NAICS-3 .

Figure 6: *Median Absolute Change in Regulations*



Note: Median Absolute Change in the number of Regulatory Restrictions among NAICS-4 industries, as measured by RegData.

Table 2: *Explaining the Elasticity of Entry relative to Q*

Table reports panel regression results of changes in the number of firms, entry rate and number of establishments on Q and measures of regulation. Number of firms and entry rates based on Compustat; number of establishments from QCEW. Regressions based on NAICS-4 industries. Standard errors in brackets clustered at industry-level. + p<0.10, * p<0.05, ** p<.01.

	(1) $\Delta log(\#of Firms)_{j,t,t+2}$	(2) $EntryRate_{j,t,t+2}$	(3) $\Delta log(\#of Estabs)_{j,t,t+2}$
$\log(RegIndex_{j,t})$	0.017**	0.015*	0.010*
	(0.007)	(0.006)	(0.004)
$MedianQ_{j,t}$	0.104**	0.115**	0.067**
	(0.031)	(0.037)	(0.022)
$MedianQ_{j,t} \times \log(RegIndex_{j,t})$	-0.010*	-0.010*	-0.007**
	(0.004)	(0.004)	(0.003)
$RTS_{j,t}$	0.017	-0.024	-0.018
	(0.032)	(0.026)	(0.019)
$MedianQ_{j,t} \times RTS_{j,t}$	-0.001	-0.001	0.002
	(0.007)	(0.008)	(0.004)
Year FE	Y	Y	Y
R2	.14	.15	.13
Observations	4,780	4,779	2,783

4.2 The Effect of Regulation on Small and Large Firms

A rise in entry costs due to regulation yields several predictions in addition to a decline in the elasticity of entry to Q. Proposition 1, in particular, shows that a rise in entry costs leads to a decline in the number of firms and an increase in the profits of incumbents. The decline would be particularly pronounced among smaller, less productive firms. We test these predictions next.

4.2.1 Impact of Regulation on Firm Creation and Growth

The impact of regulation on business dynamism is controversial. Bailey and Thomas (2015) use RegData to argue that business dynamism declined in industries with rising regulation. Yet Goldschlag and Tabarrok (2018) use essentially the same datasets to argue the opposite: that regulation is not to blame for declining business dynamism.[16] In this section, we reconcile these apparently contradictory results, and propose an

[16] Bailey and Thomas (2015) use RegData 2.0 and consider NAICS-4 industries over the 1998 to 2011 period, focusing on establishment entry, establishment exit, and new hires. They estimate regressions for all firms, as well as small and large firms separately. They find a negative and significant relationship between regulation and business dynamism for all firms and for small firms. For large establishments the point estimate is negative but often insignificant. By contrast, Goldschlag and Tabarrok (2018) use RegData 2.1 and consider NAICS-3 industries from 1999 to 2013. They focus on 'flow' measures of dynamism (start-up, job creation and job destruction rates) and find a positive but insignificant relationship – either in the aggregate or separating small and large firms. They conclude that, if anything, regulation has a positive effect on business dynamism and point to other explanations for declining dynamism such as globalization. Measures of business dynamism in both Bailey and Thomas (2015) and Goldschlag and Tabarrok (2018) are based on the Census' SUSB. The new version of RegData (3.0) covers fewer NAICS-3 and NAICS-4 industries. We cannot replicate previous results exactly because RegData versions prior to 2.2 are no longer available. That said, we are able to obtain similar conclusions. A substantial source of discrepancy appears to be granularity: following the same specification as Goldschlag and Tabarrok (2018) but using NAICS-4 industries, our results are closer to those of Bailey and Thomas (2015) – albeit still insignificant. See Appendix Section E.1 for a more detailed discussion of our reconciliation efforts.

alternate empirical specification that better controls for firm heterogeneity and industry-specific trends.

Our main idea is to compare the impact of regulation on large versus small firms *within* each industry. This comparison controls for time-varying industry trends, such as technological change affecting both industry dynamism and the need for regulation. Prior studies included only industry fixed effects, which address unobservable variation that is fixed over time but not time-varying variation. If, for example, regulators focus their attention on growing (aging) industries, we would recover a spurious positive (negative) relationship. We run the following set of regressions

$$\Upsilon_{jt} = \beta_0 + \beta_1 \ln(Reg\,Index_{jt}) + \beta_2 \ln(Reg\,Index_{jt}) \times \mathbb{I}\{Small\} \\ + \beta_3 \mathbb{I}\{Small\} + \beta_4 RTS_{jst} \times \mathbb{I}\{Small\} + \alpha_j + \eta_t + \varepsilon_{jt}$$

where j indexes industry-by-size groupings, and Υ_{jt} denotes a given outcome.[17] To control for the role of returns to scale, we include the estimates based on levels regressions with firm fixed effects at the NAICS-2 industry-level (return to scale estimates based on changes are even less correlated to firm dynamics). We report the coefficients on returns to scale in some but not all columns for readability but the interaction with size is included throughout.

Table 3 considers the growth in the number of firms (columns 1-3) and the growth in total employment (columns 4-6) and payroll (columns 7-9). When we pool all firms together, we find that regulation has a negative but insignificant impact, consistent with the controversy in the literature. This noisy 'average' effect, however, hides an important degree of heterogeneity. Regulations have strong negative impact on small firms *relative* to large firms – even after controlling for returns to scale. As shown in column 2, a doubling of the regulation index, leads to a 2.5% lower annual growth rate in the number of small firms relative to large ones – a sizable effect considering that measures of regulation doubled since 1995. The effect on small firm employment is similar. Columns 3, 6 and 9 disaggregate the small firm buckets to show that the effect is monotonic in firm size.[18] Appendix E shows similar results for establishment dynamism.

4.2.2 Impact of Regulation on Incumbent Profit Rates

Let us now consider the impact of large changes in regulations on incumbent profit rates. We focus on large changes because they are the most likely to involve significant lobbying efforts by industry insiders. We define large changes in two ways. We first look at the industry with the largest increase in the number of restrictions in any given year. Figure 7 shows the average change in profitability among incumbents in Compustat, in industries that experience these large changes in regulations. By definition we have one

[17] The comparison between small and large firms is also natural. As Davis (2017) explains, "the burdens of regulation and regulatory complexity tend to fall more heavily on younger and smaller businesses for three reasons. First, there are fixed costs of regulatory compliance... Second, there are one-time costs of learning the relevant regulations, developing compliance systems and establishing relationships with regulators... Third, compared to smaller, newer and would-be competitors, larger and incumbent firms have greater capacity and incentive to lobby for legislative exemptions, administrative waivers, and favorable regulatory treatment."

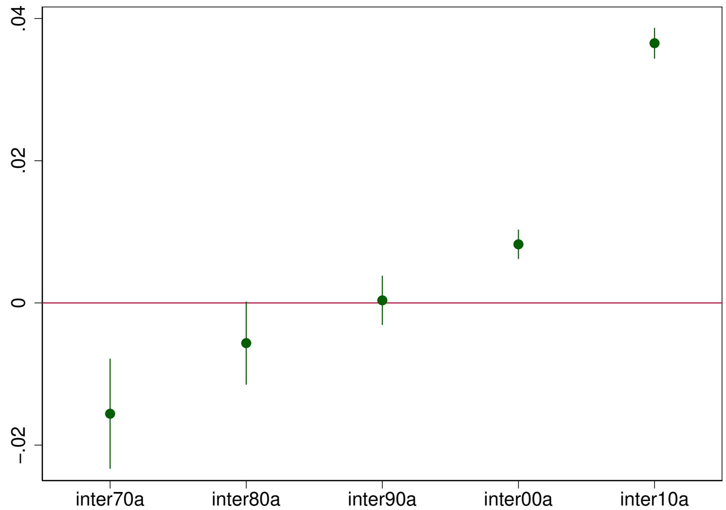
[18] We focus on firms larger than 10 employees to ensure economic significance. Coefficients are similar, but sometimes noisier, for firms with less than 10 employees.

Table 3: *Impact of Regulation on Firms, Employment and Payroll Growth*

Table reports panel regression results of the growth in the number of firms (columns 1-3) and growth in total employment (columns 4-6) and payroll (columns 7-9) on the log-number of regulatory restrictions. Index j measures NAICS-4 industry-by-size groupings, where size is measured by the number of employees. All regressions include return to scale controls, as well as industry-by-size and year fixed effects. Observations weighted by total payroll. Number of firms and employees from the Census' SUSB. Regulation indexes from RegData. Standard errors in brackets clustered at industry-level. + p<0.10, * p<0.05, ** p<.01.

	$\Delta log(N)_{j,t,t+2}$			$\Delta log(Emp)_{j,t,t+2}$			$\Delta log(Pay)_{j,t,t+2}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RTS_{jt-1}	8.74	-3.46	-4.63	-5.18	-1.92	-2.56	4.98	12.23	12.10
	(14.87)	(10.62)	(11.78)	(14.52)	(21.67)	(21.87)	(11.18)	(12.23)	(12.32)
$RTS_{jt-1} \times < 500$		-6.01			-8.03			-22.23	
		(14.87)			(29.36)			(20.68)	
$\log(Reg)_{jt}$	-0.34	1.91	1.00	-3.15	-0.27	-0.70	0.83	3.43	3.33
	(2.57)	(1.92)	(1.98)	(3.82)	(3.84)	(3.96)	(6.45)	(6.92)	(7.01)
$\log(Reg)_{jt} \times < 500$		-5.10^{**}			-5.63^{*}			-6.24	
		(1.65)			(2.77)			(3.81)	
$\log(Reg)_{jt} \times 10-19$			-6.48^{**}			-8.82^{**}			-10.68^{*}
			(2.35)			(2.93)			(4.08)
$\log(Reg)_{jt} \times 20-99$			-4.52^{+}			-6.47^{*}			-9.81^{*}
			(2.29)			(2.84)			(4.13)
$\log(Reg)_{jt} \times 100-499$			-1.96			-2.56			-1.43
			(2.37)			(2.98)			(3.89)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Ind x Size FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
RTS Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2	.28	.28	.3	.36	.34	.34	.37	.37	.36
Observations	1,878	3,680	7,305	1,759	3,419	6,778	1,759	3,432	6,795

Figure 7: *Impact of Large Changes in Regulation on Profits*



Note: Figure plots the coefficients β^d of firm-level regressions of operating profit margin (Compustat OIADP/SALE) on regulatory increases

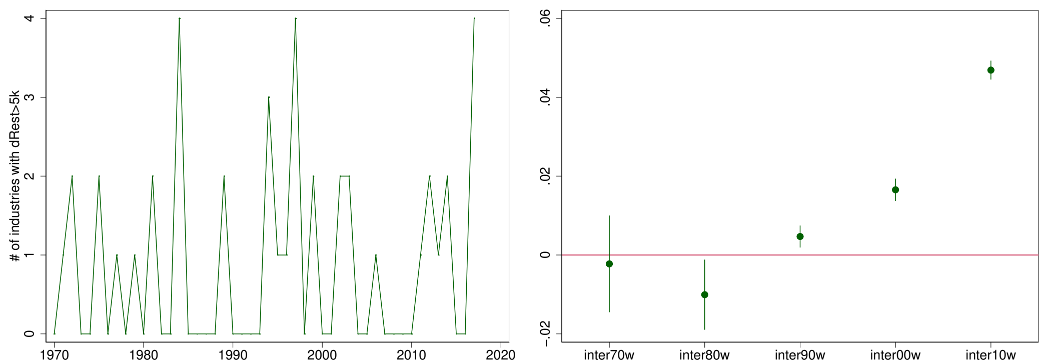
$$\frac{OIADP_{it}}{SALE_{it}} = \sum_d \beta^d \times post \times d + \alpha_i + \eta_t + \varepsilon_{jt},$$

where j, d and t are industry, event-decade and year indexes. $post$ is an indicator equal to one for the two years following an event, where an event is defined as the firm's NAICS-3 industry j having the largest absolute increase in the number of restrictions in that year. Note that d measures event-years (not calendar years), hence remains constant for the three years following the event. We include all US-headquartered firms in Compustat, and control for firm and year fixed effects. See text for more details.

industry per year so we group the data by decades. We measure profitability as operating income after depreciation over sales, and we compute sales-weighted averages at the industry level. The coefficient, therefore, measures changes in profitability relative to other industries. In the 1970's, 80's and 90's we do not observe economically significant changes in profits after large bursts of regulation. The effect is negative but small in the 1970s, and rather precisely zero during the 1980s and 1990s. In recent years, however, large increases in regulations are followed by large increases in relative profit margins. The impact is statistically and economically significant. The sales-weighted average OIAD/Sales in our sample is around 13% and the increase in the recent decade is about 4 percentage points.

Alternatively, we can define large changes in absolute terms. We say that an industry experiences a large increase in regulation when the number of regulatory restrictions increases by more than 5,000. Figure 8 shows that this captures on average between 1 and 2 industries each year. Importantly, there is no trend in that number, which means that our measure is comparable over time. This new definition only reinforces our previous conclusion. In recent years, industries that experienced large increase in regulation also experienced large increases in profit margins over the following three years, relative to other industries.

Figure 8: *Impact of Large Changes in Regulation on Profits*



Note: Left plot shows the number of NAICS-3 industries where the number of regulatory restrictions increased by more than 5,000 in a given year. Right plot shows the coefficients β^d of firm-level regressions of operating profit margin on regulatory increases

$$\frac{OIADP_{it}}{SALE_{it}} = \sum_d \beta^d \times post \times d + \alpha_i + \eta_t + \varepsilon_{jt},$$

where j, d and t are industry, event-decade and year indexes. $post$ is an indicator equal to one for the two years following an event, where an event is defined as the number of regulatory restrictions in firm's NAICS-3 industry increasing by more than 5,000.

4.3 The Effect of Lobbying on Small and Large Firms

Our results so far show that regulations have negatively affected small firms relative to large ones. The divergence appears to have exacerbated after 2000, precisely when lobbying and regulatory complexity increased. We now study whether these two trends are related – namely, whether the confluence of lobbying and regulation are negatively affecting small firms.

4.3.1 Impact of Lobbying on Firm Creation and Growth

We begin by studying lobbying individually. Lobbying is skewed towards large firms, so we again study the effects on small relative to large firms. Table 4 presents the results, which replicate Table 3 above, but replacing the regulation index with total lobbying expenditures at the industry-level as measured by the Center for Responsible Politics. Like Regulation, lobbying appears to negatively affect firm, employment and payroll growth of small firms.

4.3.2 Interaction of Lobbying and Regulation

Lobbying is primarily used to influence regulators, so that lobbying and regulations are likely to interact with each other. Table 5 replicates the above results but interacting regulation with lobbying. Because lobbying is highly skewed, we further disaggregate firms and compare those with more than 1,000 employees to smaller ones. As shown, the confluence of lobbying and regulation has a negative effect on small firms.

Table 4: *Impact of Lobbying on Firms, Employment and Payroll Growth*

Table reports panel regression results of the growth in the number of firms (columns 1-3) and growth in total employment (columns 4-6) and payroll (columns 7-9) on industry lobbying expenditures. Index j measures NAICS-4 industry-by-size groupings, where size is measured by the number of employees. All regressions include return to scale controls, as well as industry-by-size and year fixed effects. Observations weighted by total payroll. Number of firms and employees from the Census' SUSB. Lobbying expenditures from OpenSecrets.com. Standard errors in brackets clustered at industry-level. + p<0.10, * p<0.05, ** p<.01.

	$\Delta log(N)_{j,t,t+2}$			$\Delta log(Emp)_{j,t,t+2}$			$\Delta log(Pay)_{j,t,t+2}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RTS_{jt-1}	2.00	-5.28	-5.95	-14.04	-4.06	-4.64	-7.88	2.22	1.92
	(10.00)	(8.06)	(8.75)	(10.84)	(12.07)	(12.30)	(10.47)	(10.76)	(10.79)
$RTS_{jt-1} \times < 500$		-7.00			-18.14			-19.81	
		(10.53)			(15.78)			(13.92)	
$\log(Lobby)_{jt}$	-0.75	1.49	1.53	-1.05	0.63	0.66	-1.85	-0.71	-0.64
	(1.24)	(1.08)	(1.15)	(1.53)	(1.70)	(1.78)	(1.86)	(1.91)	(1.99)
$\log(Lobby)_{jt} \times < 500$		-2.95**			-3.09**			-2.16+	
		(0.86)			(1.16)			(1.18)	
$\log(Lobby)_{jt} \times 10-19$			-3.61**			-3.46**			-3.03**
			(0.90)			(1.15)			(1.16)
$\log(Lobby)_{jt} \times 20-99$			-3.12**			-3.11*			-2.19+
			(0.97)			(1.23)			(1.27)
$\log(Lobby)_{jt} \times 100-499$			-3.34**			-3.10*			-1.77
			(0.87)			(1.26)			(1.24)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Ind x Size FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
RTS Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2	.28	.28	.29	.36	.35	.34	.38	.37	.36
Observations	4,416	8,648	17,282	4,138	7,982	15,992	4,140	8,050	16,082

Table 5: *Interaction of Lobbying and Regulation*

Table reports panel regression results of the growth in the number of firms (columns 1-3) and growth in total employment (columns 4-6) and payroll (columns 7-9) on measures of regulation and lobbying. Index j measures NAICS-4 industry-by-size groupings, where size is measured by the number of employees. All regressions include return to scale controls, as well as industry-by-size and year fixed effects. Observations weighted by total payroll. Interactions of regulation x size and lobbying x size are omitted for presentation purposes. Number of firms and employees from the Census' SUSB. Regulation indexes from RegData. Lobbying expenditures from OpenSecrets.com. Standard errors in brackets clustered at industry-level. + p<0.10, * p<0.05, ** p<.01.

	$\Delta log(N)_{j,t,t+2}$			$\Delta log(Emp)_{j,t,t+2}$			$\Delta log(Payroll)_{j,t,t+2}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(Reg)_{jt-1}$	0.730	-9.949^{+}	-10.989*	-1.073	-12.294	-13.227	-1.233	-15.820^{+}	-16.181^{+}
	(4.636)	(5.602)	(5.355)	(6.770)	(8.653)	(8.668)	(8.512)	(8.358)	(8.396)
$\log(Lobby)_{jt-3}$	-0.205	-14.664*	-13.181^{+}	2.505	-16.694	-16.327	0.881	-36.941**	-36.744**
	(4.513)	(6.779)	(6.958)	(4.871)	(10.540)	(10.281)	(5.805)	(12.292)	(12.375)
$\log(Reg)_{jt-1} \times \log(Lobby)_{jt-3}$	-0.508	1.900*	1.778*	-0.775	1.777	1.669	-0.523	3.944**	3.899**
	(0.552)	(0.762)	(0.827)	(0.542)	(1.241)	(1.211)	(0.603)	(1.164)	(1.154)
$\log(Reg)_{jt-1} \times \log(Lobby)_{jt-3} \times < 500$		-2.077^{+}			-2.523^{+}			-4.642**	
		(1.095)			(1.487)			(1.648)	
$\log(Reg)_{jt-1} \times \log(Lobby)_{jt-3} \times 500-999$		-1.772			-3.159^{+}			-4.514*	
		(1.236)			(1.702)			(2.068)	
$\log(Reg)_{jt-1} \times \log(Lobby)_{jt-3} \times 10-19$			-1.916			-1.981			-4.185**
			(1.199)			(1.497)			(1.596)
$\log(Reg)_{jt-1} \times \log(Lobby)_{jt-3} \times 20-99$			-2.500*			-2.495^{+}			-4.713**
			(1.129)			(1.437)			(1.584)
$\log(Reg)_{jt-1} \times \log(Lobby)_{jt-3} \times 100-499$			-3.009*			-3.313*			-5.512**
			(1.298)			(1.626)			(1.875)
$\log(Reg)_{jt-1} \times \log(Lobby)_{jt-3} \times 500-999$			-1.816			-3.186^{+}			-4.529*
			(1.223)			(1.695)			(2.066)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Ind x Size FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
RTS Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2	.33	.35	.37	.4	.42	.42	.42	.43	.43
Observations	1,586	2,912	5,967	1,471	2,505	5,305	1,471	2,593	5,397

4.3.3 Instrumenting Lobbying with Incumbent Cash Flows

Our results so far show that regulations and lobbying are bad for small firms relative to large ones. They are consistent with lobbying being used strategically by large firms to protect their rents à la Stigler (1971). But they could also be consistent with a more benign or even positive view of lobbying. For instance, rising regulation (and regulatory complexity) may provide little benefits yet hurt all firms. Anticipating a rise in regulation, large firms may lobby to protect themselves. Lobbying could then be beneficial as it could prevent the negative impact of inefficient regulations on some large firms. To test this idea we need a "lobbying shock" that is not driven by overly zealous regulators. We use changes in incumbent free cash flows as an instrument. Free cash flows are not exogenous, so they cannot rule out all explanations. In particular, they would not be a valid instrument to test the returns to scale explanation. They can, however, help us test the regulatory zeal hypothesis, to the the extent that free cash flow shocks mostly reflect shocks to demand and production costs, which is the standard assumption in the corporate finance literature.

We therefore estimate the following regressions (first and second stages):

$$\log\left(Lobby\right)_{jt} = \theta_0^1 + \theta_1^1 \log\left(CF\right)_{jt-1}^{MA2} + \gamma^1 X_{jt} + \eta_t^1 + \varepsilon_{jt}^1, \tag{8}$$

$$\Upsilon_{jt} = \beta_0 + \beta_2 \log\widehat{\left(Lobby\right)}_{jt} + \gamma X_{jt} + \eta_t + \varepsilon_{jt} \tag{9}$$

where X_{jt} denotes industry controls (log-total employment as a measure of industry size and the industry mean Q), and η_t denotes year fixed effects. We use NAICS-3 as opposed to NAICS-4 industries in the above results because cash-flow shocks and lobbying are noisy.

Tables 6 report the results for growth in the number of firms. Column 1 shows the first stage result corresponding to column 2. Columns 2-4 regress the growth in the number of firms for all firms combined, firms above 500 employees and firms with 100-499 employees, respectively. Columns 5 interacts (instrumented) lobbying with firm size.[19] As shown, lobbying has a negative effect, on average, which is concentrated on small firms.[20]

Table 6 presents the results for payroll. Again, instrumented lobbying has a negative effect on payroll across all firms, with the effect being more severe at the smallest ones.

5 Conclusion

In standard models, the elasticity of entry with respect to Tobin's Q is an important determinant of allocative efficiency. We show that it has declined towards zero in the US over the past 20 years. We find that returns to scale cannot explain this phenomenon. Returns to scale have not increased significantly, and they are not correlated with the decline in the entry elasticity across firms and industries.

[19] We add the interaction of cash-flows and size as the second instrument

[20] In unreported tests we add industry fixed effects. These fixed effects absorb a substantial amount of variation, which reduces the weak identification F-statistic below 10 and increases the standard error on the coefficients. Nonetheless, the coefficients point to the same conclusion and are sometimes significant.

Table 6: *Impact of Instrumented Lobbying on Growth in the Number of Firms*

Table reports panel regression results following Equations 8 and 9. Columns (1) reports first stage results. Columns 2 to 4 present second stage results for individual size-groupings. Columns 5 and 6 interact (instrumented) lobbying with firm size. Higher cash flows lead to higher lobbying, which in turn leads to lower firm and employment growth – particularly at smaller firms. All regressions based on NAICS-3 industries. Business dynamism data from the Census' SUSB. Regulation data from RegData. Lobbying expenditures from OpenSecrets.com. Industry cash flows based on all US-headquartered firms in Compustat. Standard errors in brackets clustered at industry-level. + p<0.10, * p<0.05, ** p<.01. See text for details.

	$\log(Lobby)_{jt}$	$\Delta log(N)_{j,t,t+2}$			
	(1) 1st Stage	(2) Total	(3) 500+	(4) <500	(5) Small vs. Large
$MeanQ_{jt}$	0.026	1.228*	3.354**	1.233*	2.940**
	(0.029)	(0.519)	(0.817)	(0.519)	(0.693)
$\log(CF^{MA2})_{jt-1}$	0.113**				
	(0.036)				
$\log(Emp)_{jt}$	0.069	-10.376**	-12.813**	-10.234**	-12.635**
	(0.051)	(1.182)	(1.663)	(1.167)	(1.694)
$\log(Lobby)_{jt}$		-2.584*	-1.396	-2.853*	-2.949*
		(1.283)	(1.482)	(1.327)	(1.295)
$\log(Lobby)_{jt} \times 10-19$					-0.323^{+}
					(0.178)
$\log(Lobby)_{jt} \times 20-99$					-0.468**
					(0.136)
$\log(Lobby)_{jt} \times 100-499$					-0.112
					(0.116)
Year FE	Y	Y	Y	Y	Y
Ind FE	N	N	N	N	N
RTS controls	Y	Y	Y	Y	Y
R^2	.98	.16	.14	.15	.13
Observations	1,076	1,076	1,076	1,076	3,974
Weak id F-stat		54	54	54	13

Table 7: *Impact of Instrumented Lobbying on Payroll Growth*

Table reports panel regression results following Equations 8 and 9. Columns (1) reports first stage results. Columns 2 to 4 present second stage results for individual size-groupings. Columns 5 and 6 interact (instrumented) lobbying with firm size. Higher cash flows lead to higher lobbying, which in turn leads to lower firm and employment growth – particularly at smaller firms. All regressions based on NAICS-3 industries. Business dynamism data from the Census' SUSB. Regulation data from RegData. Lobbying expenditures from OpenSecrets.com. Industry cash flows based on all US-headquartered firms in Compustat. Standard errors in brackets clustered at industry-level. + p<0.10, * p<0.05, ** p<.01. See text for details.

	$\log(Lobby)_{jt}$	$\Delta log(Payroll)^{s}_{j,t,t+2}$			
	(1)	(2)	(3)	(4)	(5)
	1st	Total	500+	<500	Small vs. Large
$MeanQ_{jt}$	0.026	5.119**	6.182**	3.802**	4.556**
	(0.029)	(0.903)	(1.065)	(0.875)	(0.892)
$\log(CF^{MA2})_{jt-1}$	0.113**				
	(0.036)				
$\log(Emp)_{jt}$	0.069	-18.633**	-19.290**	-16.354**	-16.735**
	(0.051)	(3.300)	(3.531)	(3.244)	(2.678)
$\log(Lobby)_{jt}$		-5.973**	-6.560**	-6.797**	-6.033**
		(2.066)	(2.326)	(2.075)	(1.818)
$\log(Lobby)_{jt} \times 10-19$					-0.851**
					(0.286)
$\log(Lobby)_{jt} \times 20-99$					-0.880**
					(0.260)
$\log(Lobby)_{jt} \times 100-499$					-0.456*
					(0.223)
Year FE	Y	Y	Y	Y	Y
Ind FE	N	N	N	N	N
RTS Controls	Y	Y	Y	Y	Y
R^2	.98	.2	.17	.15	.12
Observations	1,076	1,000	978	984	3,981
Weak id F-stat		53	52	52	13

By contrast, we find that regulations and lobbying explain rather well the decline in the allocation of entry. In doing so we reconcile conflicting results in the literature and show that regulations have a negative impact on small firms, especially in industries with high lobbying expenditures. Our results also show that regulations have a first order impact on incumbent profits and suggest that the regulatory capture may have increased in recent years.

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Appendices

A Data Appendix

The following section describes our main data sources. Some ancillary datasets are used for aggregate analyses and/or robustness. The details for those data-sources are provided in the relevant figures and/or in the following section.

A.1 BLS KLEMS

We use the BLS multifactor tables (2018 edition) for the estimation of returns to scale. This includes data on real output, input and hours worked from 1987 to 2016, at (roughly) the 3-digits NAICS industry level. We complement these data with several instruments:

- WTI crude oil price
- B.E.A. accounts for government defense spending items Equipment, Ships, Software and Research and Development
- Real GDP
- Real non-durable consumption and
- Real non-residential investment in fixed assets.

A.2 Compustat

Our firm-level data source is the CRSP-Compustat merged database, available through WRDS. We download tables Funda and Company from Compustat, and table msf from CRSP. We also download the CRSP-Compustat linking table (ccmxpf_linktable) to match the datasets. We apply standard screens to the Compustat dataset (consol = "C", indfmt = "INDL", datafmt = "STD", popsrc = "D" and curcd = "USD") and merge the CRSP and Compustat files using the linking table. We keep firm-year observations located in the USA (loc = "USA"), with non-missing year and gvkey. We apply additional screens as necessary for individual analyses.

We use the industry codes in the Compustat Company table. NAICS codes are populated for all firms that existed after 1985, but are sometimes missing for firms that exited beforehand. We map those firms to the most common NAICS-4 industry among those firms with the same SIC code and non-missing NAICS. We also map all retired/new NAICS codes from the 1997, 2002 and 2012 versions to NAICS 2007 using the concordances in link.

Industry Q. We estimate firm-level Q as the ratio of market value to total assets (AT). We compute market value as the market value of equity plus total liabilities (LT) and preferred stock (PSTK), where the market value of equity is defined as the total number of common shares outstanding (item CSHO) times the closing stock price at the end of the fiscal year (item PRCC_F). When either CSHO or PRCC_F are missing in Compustat, we fill-in the value using CRSP. We cap Q at 10 and winsorize it at the 2% level, by year to mitigate the impact of outliers. Last, we aggregate firm-level Q to the industry level by taking the mean, median and asset-weighted average across all firms in a given industry-year.

Number of Firms. Similarly, we define the number of firms in Compustat as the total number of firms that satisfy the above restrictions and belong to a given industry in a given year.

A.3 SUSB

We gather the number of firms, employment and payroll from the Statistics of US Businesses (SUSB), available at the industry x firm size-level. SUSB is derived from the Business Register, which contains the Census Bureau's most complete, current, and consistent data for the universe of private non-farm US business establishments. Data are available following NAICS 2 to 6 industries from 1998 to 2017. Additional tables provide year-to-year employment changes at the establishment level, split by births, deaths, expansions, and contractions. These more detailed data are used in Appendix E.[21] SUSB uses multiple NAICS vintages. We use the Concordances provided by the Census to map across NAICS hierarchies. In particular, we assume equal weighting for each match at the 3- or 4-digit NAICS level, depending on the analysis.

A.4 QCEW

The main drawback of SUSB is that it covers only the most recent 20 years. To complement it, we also gather the number of establishments in a given industry x year from the Quarterly Census of Employment and Wages. We use the code available in Gabriel Chodorow-Reich's website to download the data at the US-wide level. Data following SIC 2 to 4 industries are available from 1975 to 2000. Data following NAICS 2 to 6 industries are available from 1991 to 2016.We use only privately owned firms as of the fourth quarter of every year. We apply the same process to map between SIC and NAICS vintages as described above. Unfortunately, concordances for SIC are only available for Manufacturing industries, at link.

A.5 Regulation Index

We gather industry-level regulation indices from RegData 3.1, available at link and introduced in Al-Ubaydli and McLaughlin (2015). RegData aims to measure regulatory stringency at the industry-level. It relies on machine learning and natural language processing techniques to count the number of restrictive words or phrases such as 'shall', 'must' and 'may not' in each section of the Code of Federal Regulations and assign them to industries.[22] Note that most, but not all industries are covered by the index.

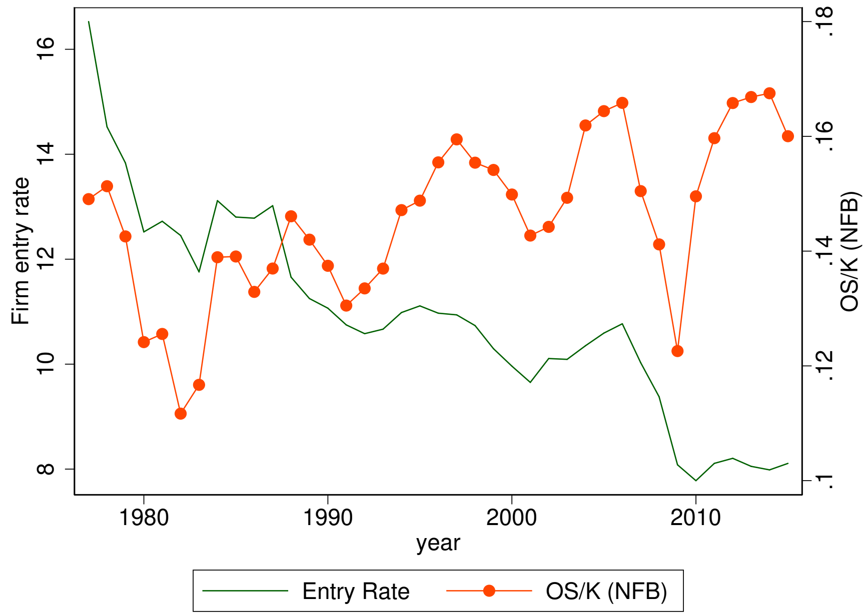
[21] One limitation of SUSB data is that the number of firms shows a positive bias in Economic Census years due to census processing activities. To control for this, all our analyses include year-specific fixed effects.

[22] This represents a vast improvement over simple measures of 'page counts', but it is still far from a perfect measure. Goldschlag and Tabarrok (2018) provide a detailed discussion of the database and its limitations, including several validation analyses that, for example, compare RegData's measure of regulatory stringency to the size of relevant regulatory agencies and the employment share of lawyers in each industry. Goldschlag and Tabarrok (2018) conclude that "the relative values of the regulatory stringency index capture well the differences in regulation over time, across industries, and across agencies."

A.6 Lobbying Expenditures

Data for Lobbying Expenditures if gathered from the Center for Responsive Politics (CRP), at link. We use the 'lob_indus' table, which provides total lobbying expenditures by CRP Industry code. CRP industry codes roughly follow the SIC 1987 hierarchy. In fact, CRP provides a one-to-many mapping between CRP codes and SIC industries. We assign lobbying expenditures to SIC codes using the relative shares of wages across SIC codes, as measured by QCEW. We then map SIC-1987 codes to NAICS-07 industries, using the SIC 1987 to NAICS-02 and NAICS-02 to NAICS-07 concordance. We assume equal weighting from SIC-4 to NAICS-4 industries.

Figure 9: *Firm Entry Rate vs Non-Financial Business OS/K*



Note: Annual data. Entry rate from Census' Business Dynamics Statistics (BDS). OS/K for Non-Financial Business sector based on the Financial Accounts of the US (via FRED).

B Additional Facts about Entry

B.1 Evolution of Average Entry Rates

Entry is Low relative to Profits and Q. We begin with a well-known fact: aggregate entry has decreased while profits have increased. Figure9 show the entry rate from the Census' Business Dynamics Statistics (BDS) against the profit rate, defined as operating surplus over the replacement cost of the capital stock from the Financial Accounts. The decline in aggregate entry is not explained by changes in industry composition (see Appendix).

Consider the following regression, estimated in a panel of industries:

$$\Delta \log{(N)}_{j,t,t+1} = \beta_1 Q_{j,t} + \beta_1 GOS/VA_{j,t} + \gamma_j + \alpha_t + \varepsilon_{jt}, \tag{10}$$

where j indicates an industry, t a year, N is the number of firms, Q the average (or median) ratio of market to book value, and GOS/VA is gross operating surplus over value added. Figure 10 plots the year fixed effects α_t. Somewhere in the late 1990s or early 2000s, the entry rate dropped and remained low.

Figure 11 repeats the exercise of Figure 10, but separating entry and exit. As shown, average exit rates controlling for Q and profits have been stable (except for a jump during the great recession. By contrast, average entry rates declined, which explains the decline in average $\Delta \log(N)$.

Entrants are Growing more Slowly. In the model of Section 2, entry happens in one step. In reality, young firms start small and grow over time, so when we talk about entry, we should combine the raw entry

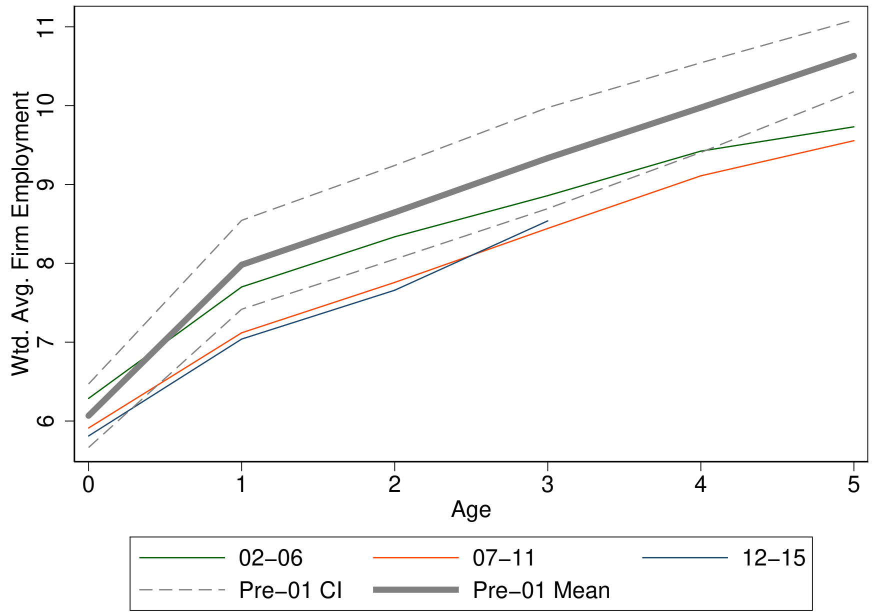
Figure 10: *Year Fixed Effects of $\Delta log(N)$, controlling for Q and Profits*

Notes: Figure shows the year fixed effects of a regression of $\Delta log\,(N)_{j,t,t+1}$ following equation (10), normalized to match the weighted average change in number of firms on 1978. Number of firms across 9 SIC sectors from the Census' BDS. GOS/VA from the BEA Industry Accounts (following SIC sectors up to 1997, and mapped from NAICS to SIC afterwards). Q from Compustat.

Figure 11: *Year Fixed Effects of Firm Entry and Exit Rates, controlling for Q and Profits*

Notes: Figure shows the year fixed effects of separate regressions for the entry and exit rates following equation (10). Fixed effects are normalized to match the weighted average entry and exit rates as of 1978. Entry and exit rates across 9 SIC sectors from the Census' BDS. GOS/VA from the BEA Industry Accounts (following SIC sectors up to 1997, and mapped from NAICS to SIC afterwards). Q from Compustat.

Figure 12: *Firm Size by Vintage and Age*



Notes: Annual data from Census BDS. See text for details.

rate and with the evolution of the size of young firms. Figure 12 shows that, in addition to the decline in the raw entry rate, there has been a decline in size of young firms: entrants are fewer, they start smaller and grow more slowly. The figure plots the average firm size by vintage of creation and age. We track the average firm size for each vintage as firms go from age zero to age five. The solid and dotted gray lines plot the mean and confidence interval of firm sizes across vintage groups before 2001. The colored lines show mean firm sizes for vintages 2002-2006, 2007-2011 and 2012-2015 periods. For example, the solid gray line at year five shows that, on average, vintages before 2001 had 10.5 employees. Recent vintages have started smaller and grown more slowly than older ones.

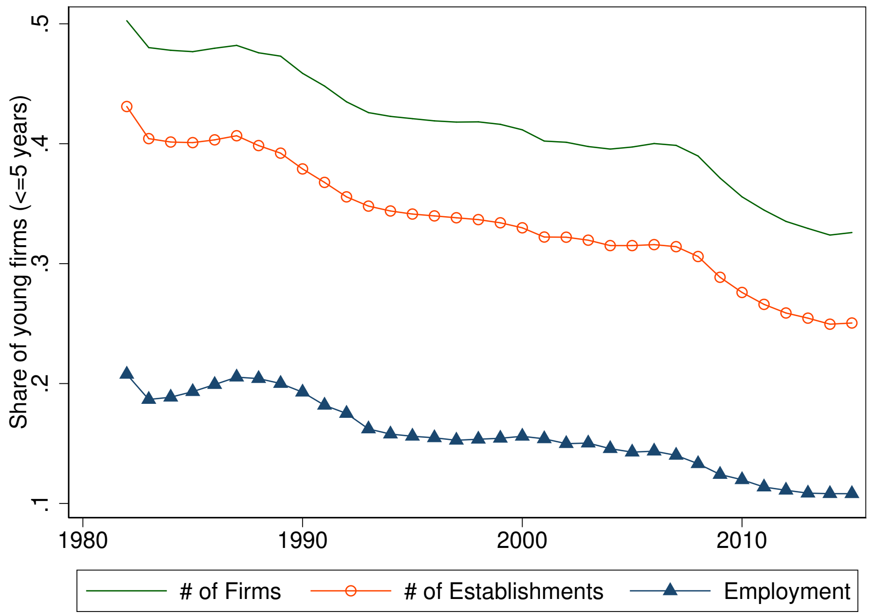
Young firms account for a smaller share of the economy. Combined, the decline in entry and slower growth has translated into a decreasing share of the economy captured by young firms, as shown in Figure 13. This is a well-known fact, emphasized in Decker et al. (2015).

Moreover, if we think more broadly about business dynamism, Figure 14 shows that the decline in entry of new firms explains most of the decline in job and establishment creation rates. Job and Establishment creation rates among existing firms have remained broadly stable.

B.2 Sectoral Evolution of Entry Elasticities

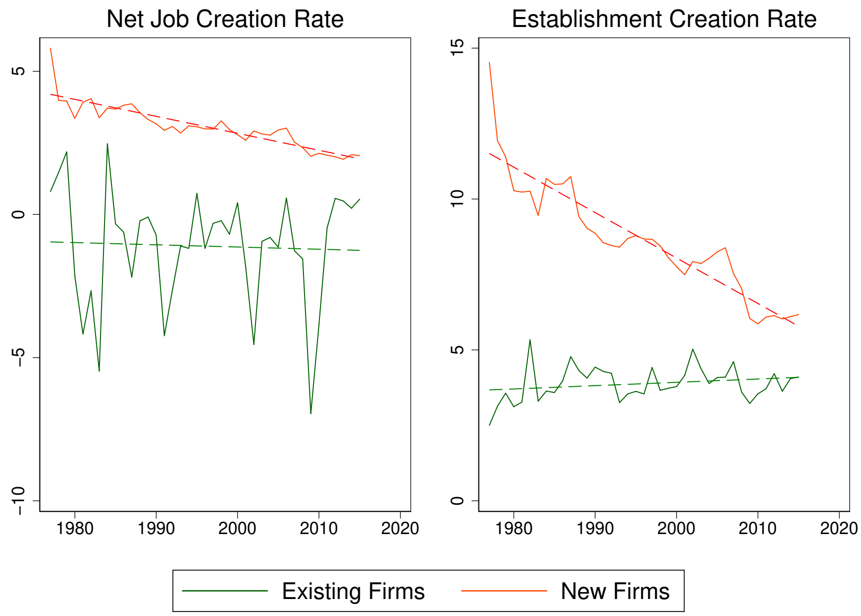
Figure 15 shows the elasticity of the growth in the number of firms to Q, separately for manufacturing and services. The Compustat and QCEW series exhibit similar trends of declining elasticities. The decline is more pronounced in services. SUSB starts too late to shed light on trends but confirms that the elasticity of number of firms to Q has been close to zero since 2000. It exhibits similar trends as QCEW.

Figure 13: *Percent of Firms, Establishments and Employment in Young Firms*



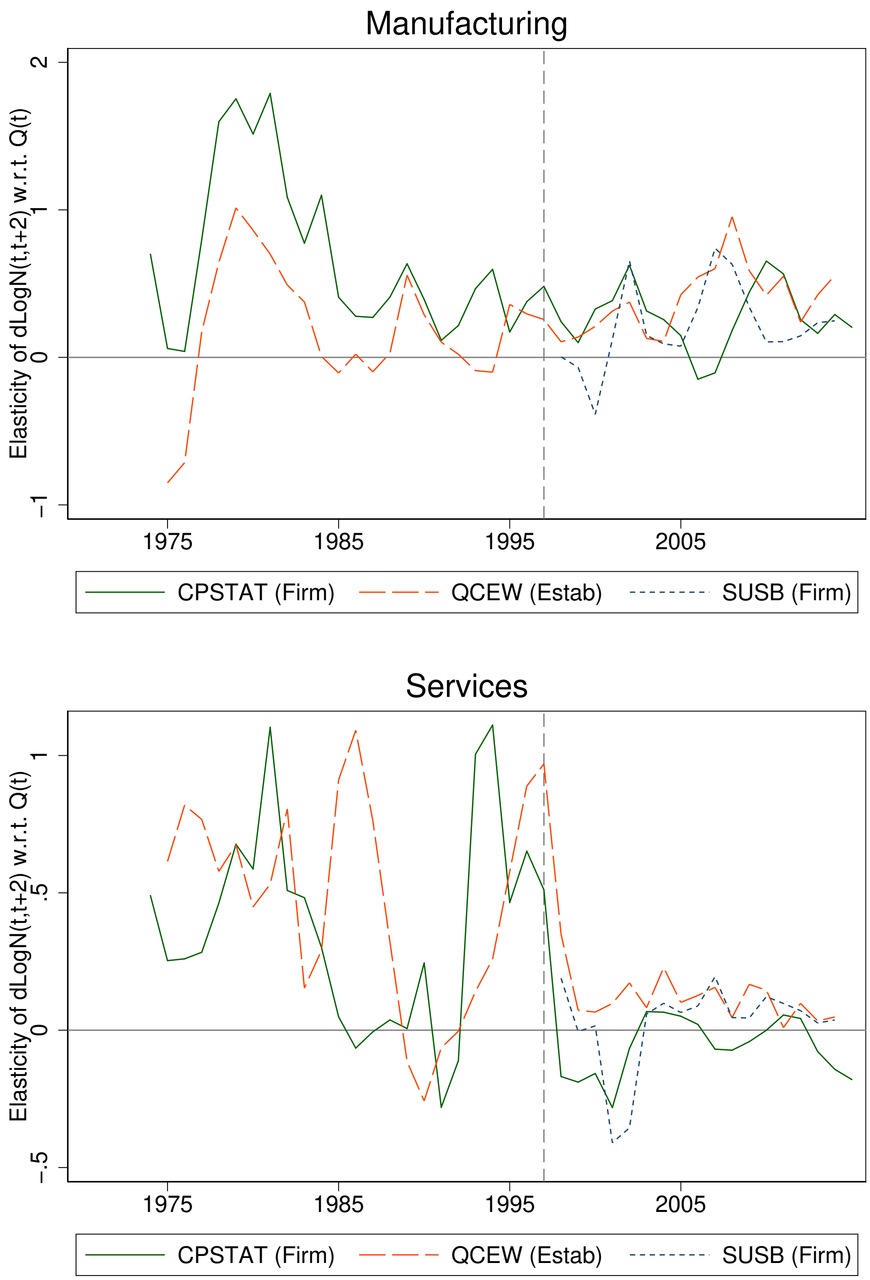
Notes: Annual data from Census BDS.

Figure 14: *Net Job and Establishment Creation: New vs. Existing Firms*



Notes: Annual data from Census' BDS. Establishment and Job Creation rates of new firms defined as the ratio of establishment and net job creation among establishments of age 0 over the total stock of initial establishments and the Davis-Haltiwanger-Schu (DHS) denominator, respectively.

Figure 15: *Elasticity of* $\Delta \log(N)$ *to* Q*, by sector*

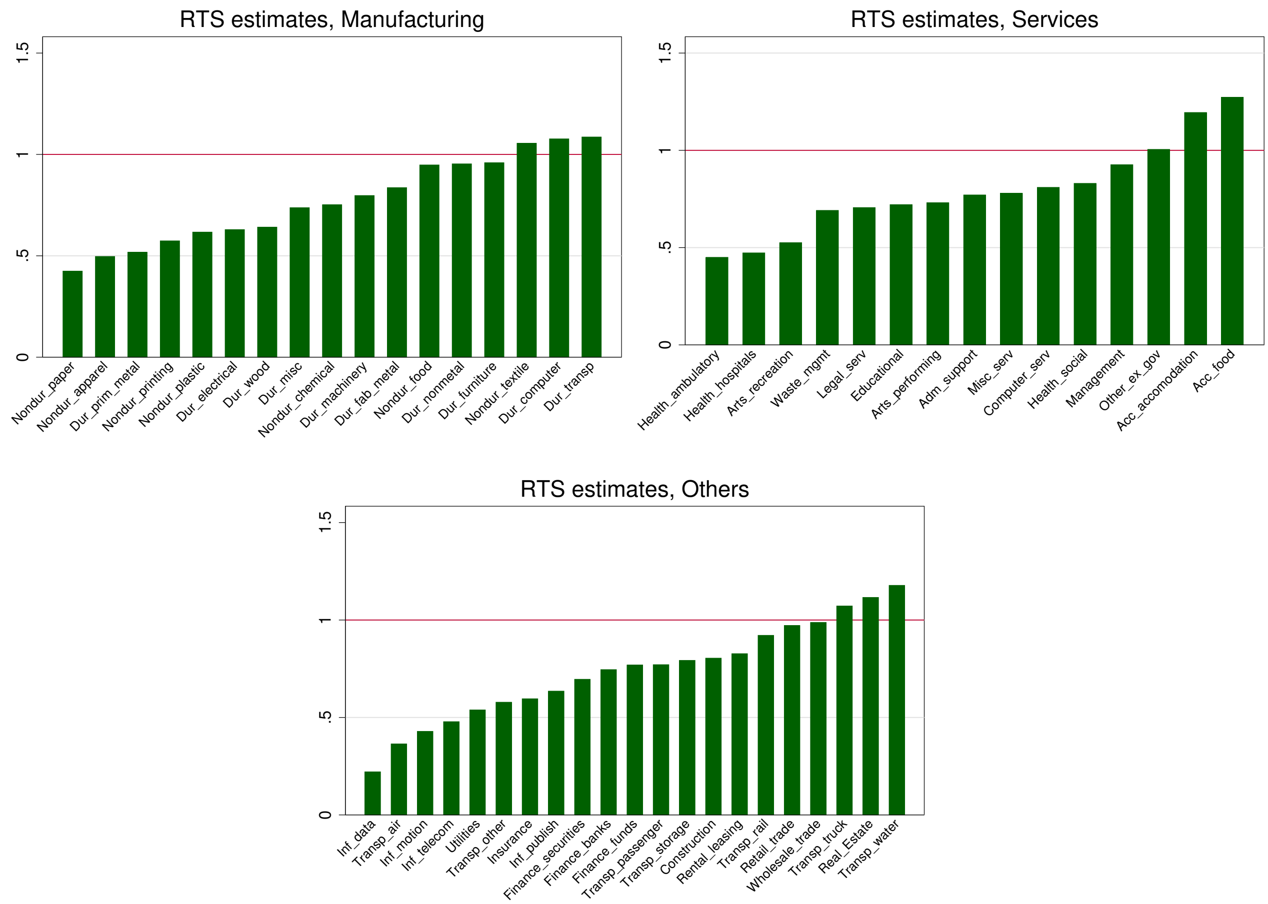


Note: Figure plots the coefficient β_t of year-by-year regressions of changes in the log-number of firms/establishments on the industry-median Q (i.e., $\Delta \log (N)^j_{t,t+3} = \alpha_t + \beta_t \text{med } (Q)^j_t + \varepsilon^j_t$, where j is an industry index). Compustat and SUSB series based on the number of firms by NAICS-4 industry. QCEW series based on the number of establishments by SIC-3 industry up to 1997 and NAICS-4 industries afterwards. Changes in the number of firms standardized to have mean zero and variance of one to ensure comparability across data sources. Industry-median Q based on Compustat. See Section 1 for more details.

C Additional Results on Returns to scale

Figure 16 shows the level estimates of returns to scale for each industry for the whole sample (1987-2017).

Figure 16: *Return to Scale Estimates by Industry*



Notes: Primarily based on the 2018 BLS multi-factor tables, which include output, input and hours worked. Instruments based on BEA accounts (government expenditures and aggregate business cycle variables) and FRED (WTI crude oil price).

D Explaining the Rise in Entry Costs: A Horse-Race

Several explanations for the rise in entry costs and the decline in the level of entry have been put forth in the literature. This section explores these explanations using empirical proxies for them. The explanations we consider are summarized in Table 8. For each proxy, we estimate two separate regressions: the first one aims to explain the decline in the *level* of entry:

$$\Delta \log{(N)}^j_{t,t+3} = +\beta_1 X^j_{t-1} + \beta_2 \text{med } (Q)^j_{t-1} + \beta_3 \text{med } \log{(age)}^j_{t-1} + \alpha_t + \gamma_j + \varepsilon^j_t,$$

Table 8: *Summary of data fields by potential explanation*

Potential explanation		Relevant data field(s)
Technological Change	1. **RTS**	Based on change specification
	2. Intangibles	Balance sheet Intangibles/Assets
		Peters & Taylor Intangibles/Assets (Peters and Taylor, 2016)
	3. IT intensity	% of employees in IT
	4. Patents	Patent concentration (Herfindahl / share of Patent MV owned by top X firms)
		Patent intensity (total value of patents in industry)
	5. Productivity divergence	Log-labor productivity difference between top-20% and rest of firms
		Log-TFP difference between top-20% and rest of firms
Regulation	**6. Regulation**	Mercatus industry-level regulation index (restriction count)
Globalization	**7. Globalization**	Share of foreign profits/sales, as proxy for foreign activities (Compustat)
		Chinese import competition (Mfg only)

where X_t^j denotes a given empirical proxy. We include year as well as industry fixed effects (α_t and γ_j , respectively) because want to compare changes within industries, controlling for common trends over time.

The second set of regressions aim to explain the decline in the *elasticity* of entry to Q. It follows

$$\Delta \log (N)_{t,t+3}^j = \beta_1 X_{t-1}^j + \beta_2 X_{t-1}^j \times \text{med } (Q)_t^j + \beta_3 \text{med } (Q)_{t-1}^j + \beta_4 \text{med } \log (age)_t^j + \alpha_t + \varepsilon_t^j,$$

where we add an interaction between the given proxy X_t^j and the median industry Q. We include only year fixed effects α_t because we want to compare elasticities across industries.

The significance for explaining the decline in the level and elasticity of entry are summarized in Table 9. Tables 10 and 2 present the underlying results for the leading explanations – after including simultaneously including the explanations that are significant in single-variable regressions, and dropping those with the lowest significance one by one. The single-variable regression results underlying Table 9 are available upon request. As shown, Patents and Frontier differences emerge as the leading explanations for the decline in the level of entry. This is consistent with a rise in fixed costs. Regulation emerges as the leading explanation for the decline in the elasticity of entry with respect to Q.

Table 9: *Summary of Industry and Firm-level results*

Explanation		Empirical Proxy	Level of Entry			Elasticity to Q		
			$\Delta \log N$	Entry Rate	$\Delta \log$ $Estab$	$\Delta \log N$	Entry Rate	$\Delta \log$ $Estab$
Technological Change	**1. RTS**	Syverson (2004)	✗	✗	✗	✗	✗	✗
	2. Intangibles	BS Intan/AT	✗	✗	✗	✓	✓	✗
		PT Intan/Assets	✗	✗	✗	✗	✗	✗
	3. IT intensity	% IT employment	✓	✗	✗	✗	✗	✗
	4. Patents	Patent concentration	✓	✓	✓ -	✗	✗	✗
		Patent intensity	✓	✓	✓ -	✗	✗	✗
	5. Productivity divergence	Log-LP difference	✓	✗	✗	✗	✓	✓
		Log-TFP difference	✓	✓	✗	✓ -	✗	✗
Regulation	**6. Regulation**	Regulation index	✗	✗	✗	✓	✓	✓
Globalization	**7. Foreign Competition**	Import Penetration	✓	✓ -	✗	✗	✗	✗
		Share of foreign profits	✗	✗	✓	✗	✗	✗

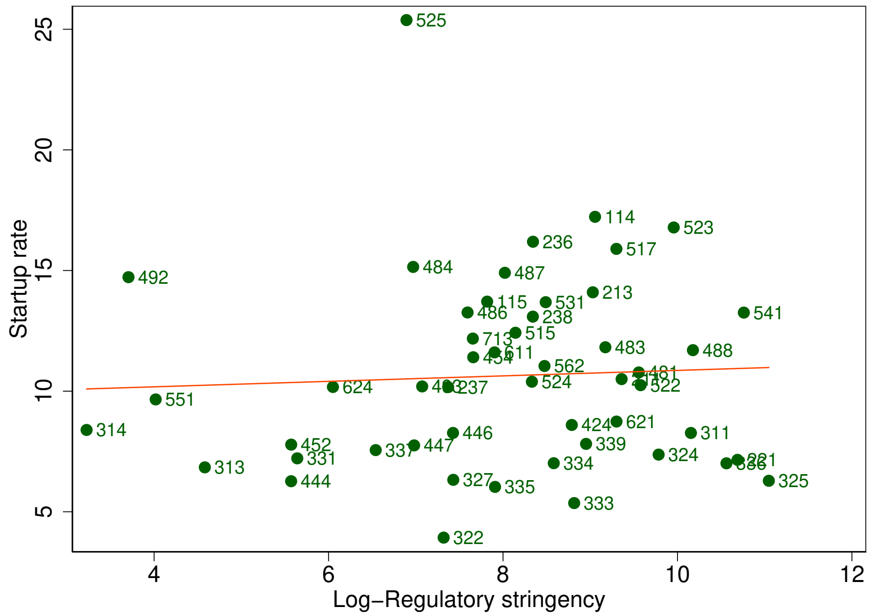
Notes: Table summarizes industry- and firm-level errors-in-variables regression results across all potential explanations. Tick-marks (✓) identify those variables that are significant and exhibit the 'right' coefficient. Crosses (✗) identify variables that are not significant or exhibit the 'wrong' coefficient. Only the regulation index is robust to inclusion of additional variables. See Appendix for detailed regression results and the text for caveats and discussions of the limitations of our results (e.g., in the case of bank dependence).

Table 10: *Explaining the Level of Entry relative to Q*

Table reports panel regression results of changes in the number of firms, entry rate and number of establishments on Q and the leading explanations. All regressions based on Compustat following NAICS-4 industries. Standard errors in brackets clustered at industry-level. + p<0.10, * p<0.05, ** p<.01.

	(1) $\Delta log(\#ofFirms)_{j,t,t+3}$	(2) $EntryRate_{j,t,t+3}$	(3) $\Delta log(\#ofEstabs)_{j,t,t+3}$
$MedianQ_{j,t}$	0.030^{+}	0.035^{+}	0.016**
	(0.017)	(0.019)	(0.005)
$\log(MV\ of\ Pat_{j,t})$	-0.008*	-0.012*	-0.003
	(0.004)	(0.005)	(0.002)
TFP Diff: Lead vs. Lag (t-2)	-0.072**	-0.071**	
	(0.023)	(0.024)	
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
R2	.34	.41	.51
Observations	3,604	3,597	2,744

Figure 17: *Establishment Start-up Rate vs. Regulatory Stringency*



Notes: Average regulatory stringency by industry is the average log-regulation index between 1999 and 2013, by three-digit 2007 NAICS industries. Startup rate is calculated as 100 * (establishment entry at time t divided by the average of establishments at t and t1). .

E Additional Evidence on Regulation and Entry

E.1 Reconciliation of Prior Results

This section provides a reconciliation of the results of Goldschlag and Tabarrok (2018) (GT) and Bailey and Thomas (2015) (BT). We cannot replicate their results exactly because the versions of RegData used in these papers are no longer available.[23] Nonetheless, we can recover similar results, and use more recent RegData vintages to emphasize the evolution.

Figure 17 begins by replicating Figure 7 of Goldschlag and Tabarrok (2018), using RegData 2.2 – the oldest RegData vintage still available. Three items are worth highlighting. First, note that RegData 2.2 (and 3.1) cover much fewer industries than RegData 2.1. This substantially reduces the sample in our reconciliation effort. Second, the average start-up rates in our sample match those of GT, suggesting that differences in results are due to changes in Regulation Indices. Last, the measures of regulatory stringency differ substantially between RegData 2.2 and RegData 2.1. This is consistent with RegData 2.2 incorporating "significant refinements in the machine-learning algorithm used to classify regulations by industry."

Table 11 replicates the main results of GT and BT. The first three columns mirror columns 4 to 6 of GT Table 3. The next three columns mirror column 1 of BT Tables 2, 3 and 4. As shown, GT study establishment start-up and job creation/destruction rates while BT study log-births, log-deaths and log-hires. Our results roughly match those of the original papers – despite the differences in Regulatory Indices. We find insignificant and incorrectly signed coefficients when following GT, and (often) significant results

[23] Recall that BT and GT used RegData versions 2.0 and 2.1, respectively.

Table 11: *Elasticity of* $\log(N)$ *to* Q

Table reports panel regression results of establishment dynamism on the regulation index. See text for details. Robust standard errors in brackets. + p<0.10, * p<0.05, ** p<.01.

	GT (NAICS-3, RegData 2.2)			BT (NAICS-4, RegData 2.2)		
	(1) Startup	(2) Job Creation	(3) Job Destruction	(4) Log(births)	(5) Log(deaths)	(6) Log(Dest)
$\log(RegIndex)_{jt}$	0.097	-0.209	0.532^{+}	-0.157^{+}	-0.104	-0.121*
	(0.563)	(0.415)	(0.293)	(0.080)	(0.068)	(0.053)
Year FE	Y	Y	Y	Y	Y	Y
Ind FE	Y	Y	Y	Y	Y	Y
R^2	.19	.29	.43	.14	.11	.18
Observations	850	816	809	1,628	1,628	1,512

Table 12: *Elasticity of* $\log(N)$ *to* Q

Table reports panel regression results of establishment dynamism on the regulation index. See text for details. Robust standard errors in brackets. + p<0.10, * p<0.05, ** p<.01.

	GT (NAICS-4, RegData 2.2)			GT (NAICS-4, RegData 3.1)		
	(1) Startup	(2) Job Creation	(3) Job Destruction	(4) Startup	(5) Job Creation	(6) Job Destruction
$\log(RegIndex)_{jt}$	-0.188	-0.019	0.379	0.684	0.866	-0.069
	(0.332)	(0.375)	(0.381)	(0.483)	(0.605)	(0.503)
Year FE	Y	Y	Y	Y	Y	Y
Ind FE	Y	Y	Y	Y	Y	Y
R^2	.13	.22	.34	.11	.18	.33
Observations	1,628	1,512	1,493	2,022	1,870	1,858

when following BT. Table 12 walks through a reconciliation effort for GT. Columns 1-3 move from NAICS-3 to NAICS-4, while columns 4 to 6 use RegData 3.1. Again, we do not find any significant relationships. However, as shown in the following section, we find robust relationships when separating the large and small firms.

E.2 Evidence from Establishments

Tables 13 to 15 replicate results from the main body but considering establishment dynamism. We again find robust relationships – especially when interacting Regulation with Lobbying. Nonetheless, we note that firm entry and growth – not establishment entry and growth – are our main objects of interest. Large firms may benefit and grow as a result of regulation, but this still deters entry and reduces competitive threats from smaller firms.

Table 13: *Impact of Regulation on Establishments*

Table reports panel regression results of measures of establishment dynamism on regulatory restriction. Index j measures NAICS-4 industry groupings. All regressions include industry and year fixed effects. Measures of dynamism from the Census' SUSB. Regulation indexes from RegData. Standard errors in brackets clustered at industry-level. + p<0.10, * p<0.05, ** p<.01.

	Employment:			Establishments:	
	(1) Creation	(2) Destruction	(3) dPct	(4) Contraction	(5) Expansion
$\log(Reg)_t$	1.170^{+}	0.040	2.352**	-1.950	2.471*
	(0.666)	(0.618)	(0.670)	(1.262)	(1.233)
$\log(RegIndex)_t \times < 500$	-0.466	0.109	-2.038**	0.897	-3.336**
	(0.644)	(0.559)	(0.675)	(0.998)	(0.860)
Year FE	Y	Y	Y	Y	Y
Ind x Size FE	Y	Y	Y	Y	Y
RTS Controls	Y	Y	Y	Y	Y
R^2	.72	.63	.33	.64	.61
Observations	3,034	3,080	3,882	3,984	3,984

Table 14: *Impact of Lobbying on Establishments*

Table reports panel regression results of measures of establishment dynamism on industry lobbying expenditures. Index j measures NAICS-4 industry groupings. All regressions include industry and year fixed effects. Measures of dynamism from the Census' SUSB. Lobbying expenditures from OpenSecrets.com. Standard errors in brackets clustered at industry-level. + p<0.10, * p<0.05, ** p<.01.

	Employment:			Establishments:	
	(1) Creation	(2) Destruction	(3) dPct	(4) Contraction	(5) Expansion
$\log(Lobby)_{t-1}$	-0.316	-0.455	0.385	0.155	0.993*
	(0.287)	(0.305)	(0.397)	(0.439)	(0.402)
$\log(Lobby)_{t-1} \times < 500$	0.236	0.946**	-0.891**	0.197	-1.953**
	(0.221)	(0.220)	(0.270)	(0.316)	(0.316)
Year FE	Y	Y	Y	Y	Y
Ind x Size FE	Y	Y	Y	Y	Y
RTS Controls	Y	Y	Y	Y	Y
R^2	.72	.63	.36	.64	.56
Observations	6,493	6,570	8,485	8,802	8,802

Table 15: *Impact of the Interaction of Regulation and Lobbying on Establishments*

Table reports panel regression results of measures of establishment dynamism on regulatory restrictions and lobbying expenditures. Index j measures NAICS-4 industry groupings. All regressions include industry and year fixed effects. Measures of dynamism from the Census' SUSB. Regulation indexes from RegData. Lobbying expenditures from OpenSecrets.com. Standard errors in brackets clustered at industry-level. + p<0.10, * p<0.05, ** p<.01.

	Employment:			Establishments:	
	(1) Creation	(2) Destruction	(3) dPct	(4) Contraction	(5) Expansion
$\log(Reg)_{t-1}$	0.497	0.532	0.140	-1.246	0.646
	(0.941)	(0.720)	(1.140)	(0.885)	(0.934)
$\log(Lobby)_{t-2}$	2.258^{+}	-1.430	3.451^{**}	-4.737^{**}	3.714^{*}
	(1.247)	(1.007)	(1.276)	(1.189)	(1.567)
$\log(Reg)_{t-1} \times \log(Lobby)_{t-2}$	-0.279^{+}	0.259^{*}	-0.569^{**}	0.610^{**}	-0.575^{**}
	(0.150)	(0.126)	(0.162)	(0.158)	(0.192)
Year FE	Y	Y	Y	Y	Y
Ind x Size FE	Y	Y	Y	Y	Y
RTS Controls					
R^2	.72	.67	.34	.77	.75
Observations	1,563	1,552	1,687	1,702	1,702

F US Regulatory Processes

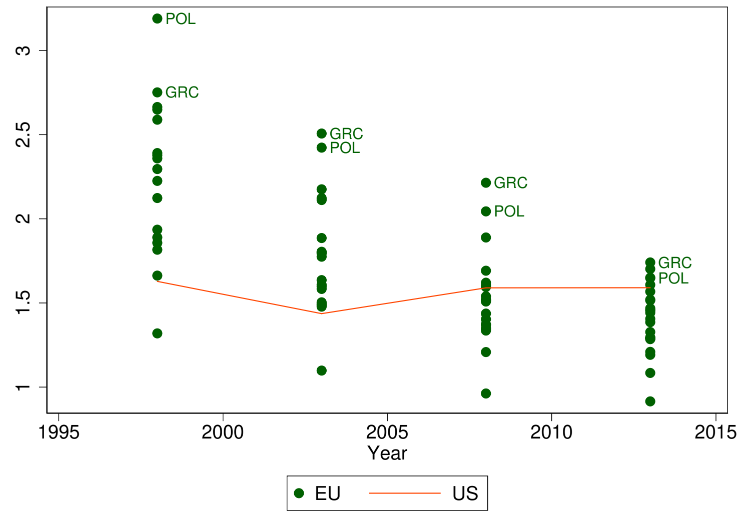
F.1 History

Regulation in the U.S. is enacted at the Federal, State and Local level. At the federal level, new laws are written only by congress but more than 60 executive agencies are authorized to issue subordinate regulations. Such executive agencies issue thousands of new regulations each year. Federal Regulations are compiled in The Code of Federal Regulations (CFR), which is the basis for the Mercatus' Regulation indices used in this paper. As of 2017, the CFR spans nearly 180,000 pages following an eight-fold expansion over the past 56 years (Davis, 2017).

State and Local government regulation further add to the regulatory burden. It is harder to summarize the scale or growth of such regulation, but the increase has also been significant. Occupational Licensing is an area that has received substantial attention. CEA (2016), for example, show that the share of workers required to obtain a license increased from under 5 percent in the 1950s to over 25 percent in 2008 – in large part because greater prevalence of licensing requirements at the State-level.

US regulatory processes have long followed political cycles. The last deregulation cycle started in the 1970s and, over the next three decades, covered the Air (1978), Road (1980) and Rail (1981) transportation industries, Electric Power (1978+), Natural Gas (1978), Banking (1980) and Telecommunications (1996) (OECD, 1999). The process of deregulation was deemed a success, with estimates of price reductions ranging from 30-75% across sectors, in addition to improved product quality and choice (OECD, 1999). Importantly, economic deregulation did not coincide with a reduction of total regulation. Environmental, health, and safety regulations increased substantially over the same period.

Figure 18: *Product Market Regulations, US vs EU*



Note: OECD PMR

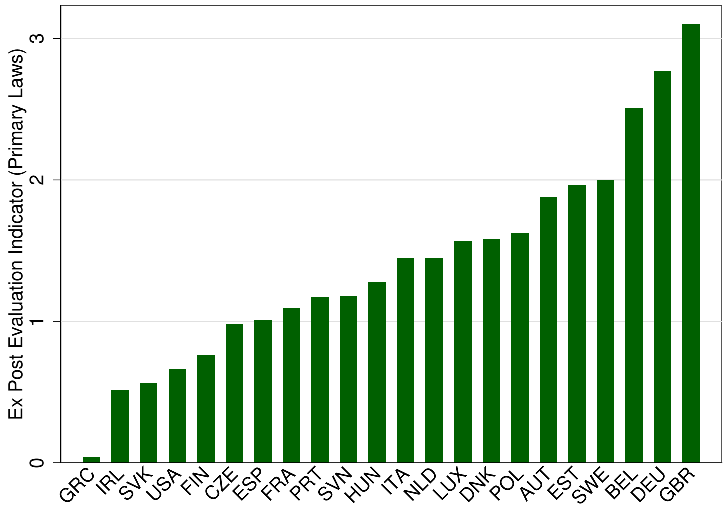
F.2 Comparison with Europe

The U.S. was viewed as a leader in regulation during the late 1990's. In 1999, for example, the OECD noted that the *"United States has been a world leader in regulatory reform for a quarter century. Its reforms and their results helped launch a global reform movement that has brought benefits to many millions of people"*. Since then, however, most countries have substantially improved their regulatory environment. Figure 18 shows the evolution of the OECD's Product Market Regulation indices for the US (line) and European countries (dots).[24] The US was clear leader in PMR in the late 1990s, following the extensive deregulation of the 1980s and 1990s. It obtained the second highest score across all countries, behind only Great Britain. Since then, however, the trends have reversed. PMR decreased drastically for all EU economies, yet remained stable in the US – consistent with the heavy focus on product market reforms of the Lisbon Strategy. As of 2013, only Greece and Poland scored worse than the US – and by a small margin. Not only that, some authors argue that the OECD's PMR indicators are excessively punitive for European economies because they (i) neglect areas where EU regulation is particularly strong (e.g., Safety, Health, Environment and Consumer Protection) and (ii) focus on individual countries, without accounting for the benefits of a single market for regulation and competition (Pelkmans, 2010). Indeed, as shown above, the EU scores higher than most countries in terms of Competition Policy and the Regulatory Process.

In addition, European countries have substantially improved their regulatory process while the US has not. The 'catch up' of Europe is evident across the OECD's regulatory process scores, in line with Figure 18 (OECD, 2009). There is one area, however, where the US appears to lag well-behind most European

[24] The World Bank and the World Economic Forum also publish measures of Regulatory Barriers to competition. Appendix **??** shows that World Bank measures yield similar conclusions. WEF measures suggest different story, but they are likely less reliable since they are based on a survey of business executives. Nonetheless, we focus on the OECD's measures because they are more widely accepted, detailed and specific. For instance, they "are a key tool for the OECD/IMF joint assessment the growth strategies submitted by G20 countries." See Pelkmans (2010) for a discussion of the alternate measures of regulatory barriers.

Figure 19: *OECD 2014 Score on Ex post Evaluation Primary Laws*



Note: OECD's 2015 Regulatory Indicator Survey results.

countries: processes for *ex post* evaluation of existing regulation. As shown in Figure 19 The US obtained the fifth worst score among OECD countries for *ex post* evaluation of primary laws – well below most EU countries. This is an ongoing limitation of the US regulatory framework, raised by the OECD as early as 1999 when it stated that "the current system is very weak with respect to systematic review of the vast body of existing laws and other regulations." (OECD, 1999). Results for subordinate laws are similar. This suggests that, once implemented, US regulation remains largely unchanged.