



## Economic Policy 65th Panel Meeting

Hosted by the Central Bank of Malta  
Valletta, 21-22 April 2017

### Is Regulation to Blame for the Decline in American Entrepreneurship?

Nathan Goldschlag (George Mason University)  
Alexander Tabarrok (George Mason University)

The organisers would like to thank Central Bank of Malta for their support.  
The views expressed in this paper are those of the author(s) and not those of the supporting organization.

# Is Regulation to Blame for the Decline in American Entrepreneurship?

*Nathan Goldschlag<sup>1</sup>*  
*George Mason University*

*Alexander Tabarrok*  
*Department of Economics*  
*George Mason University*

## **Abstract**

Mounting evidence suggests that economic dynamism and entrepreneurial activity are declining in the United States. Over the past thirty years, the annual number of new business startups and the pace of job reallocation have declined significantly. We ask whether this decline in dynamism can be explained by federal regulation. We combine measures of dynamism with RegData, a novel dataset leveraging the text of the Code of Federal Regulations to create annual measures of the total quantity of regulation by industry. We find that rising federal regulation cannot explain secular trends in economic dynamism.

---

<sup>1</sup> Disclaimer: The research in this paper was undertaken while Goldschlag was at George Mason University. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. The research in this paper does not use any confidential Census Bureau information.

## 1. Introduction

The movement of resources from low-productivity firms to high-productivity firms is a key driver of economic efficiency and growth (Syverson, 2011; Hsieh and Klenow, 2009; Bartelsman et al., 2013). Startups contribute significantly to this reallocation process. Many startups fail within a few years, so startups contribute to both job creation and job destruction. A small subset of startups, however, grow quickly, and contribute disproportionately to net job growth and to improvements in industry productivity. Workers also move among firms at tremendous rates, which means that gross job creation and destruction is much larger than net job creation (Davis et al., 1998).

Although the United States economy exhibits a rapid pace of startups, job creation, and job destruction, these forces have been in decline for nearly three decades with a possible increase in the rate of decline in the past decade (Decker et al. 2014; Karahan et al., 2015; Molloy et al., 2016). The dynamism decline is robust, appearing in a variety of data including the Job Openings and Labor Turnover data, the Bureau of Labor Statistics' Business Employment Dynamics data, and business dynamics measures from the Census Bureau's Business Dynamics Statistics. The decline in dynamism is associated with reductions in productivity, real wages, and employment (Davis and Haltiwanger, 2014). The magnitude and pervasiveness of the decline, coupled with the theoretical importance of reallocation for efficiency and growth, underscores the importance of understanding and explaining the trend towards a less dynamic U.S. economy.

A variety of explanations for the decline have been suggested, including an increasing ability of firms to respond to idiosyncratic shocks, technology induced changes in the costs of hiring and training, increasing consolidation, slowing population growth, and increased regulation making reallocation slower and more costly (Decker et al., 2014; Hathaway and Litan, 2014). This

research uses a novel source of data on federal regulations to determine the extent to which the stringency of federal regulations affects the severity of the decline in dynamism at the industry level. We find no measurable relationship between federal regulation and changing economic dynamism. These results are robust to considering different subsets of firms, delayed impacts of regulation, different types of regulations and regulatory agencies, measuring the effects of regulation through supply chains, and controlling for measurement error.

The remainder of the paper is organized as follows. Section 2 describes data on economic dynamism and federal regulation and illustrates important trends and stylized facts motivating the analyses. Section 3 presents a series of analyses that measure the relationship between federal regulation and economic dynamism. Section 4 discusses a broader context for these findings and alternative explanations for trends in dynamism. Section 5 concludes.

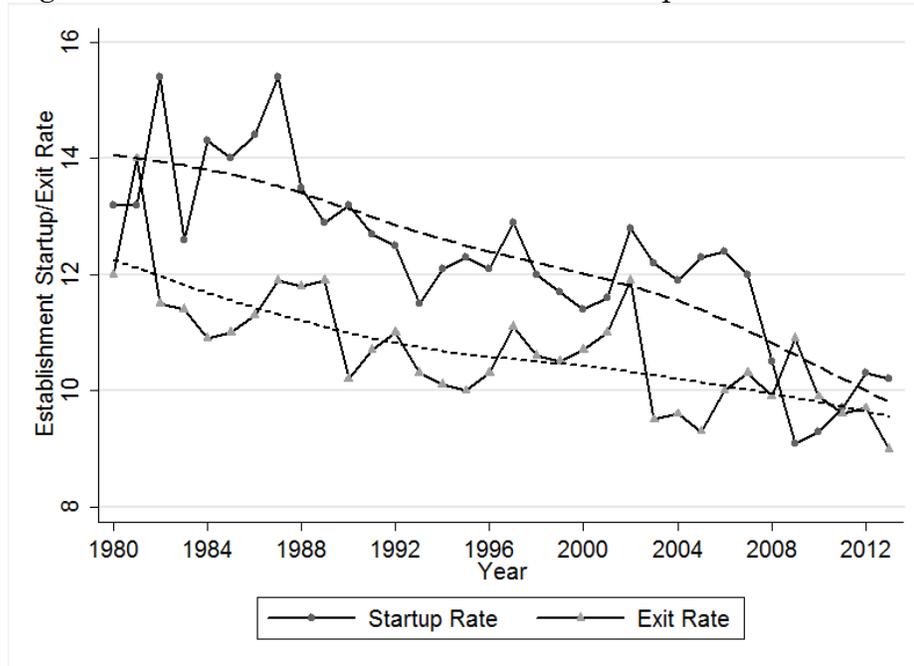
## 2. Economic Dynamism

In this section we briefly document some of the key measures of dynamism used in the literature and their decline in the United States since the 1980s. Using data from the Census Bureau's Business Dynamics Statistics, Figure 1 shows the substantial decline in startup and exit rates over the past several decades.<sup>2</sup> The startup rate fell from 13.7% in 1980 to 11.7% just before the Great Recession, with the exit rate falling from 12.1% in 1980 to 10.3% in 2007. Though startups are important for net job creation, it is not the case that all small or all young firms contribute to job creation. There is a significant population of stagnant firms that are small and experience no employment growth. Moreover, most startups fail—50% of jobs generated by an entering cohort of firms are lost after five years. However, conditional on survival some firms experience large employment growth, contributing disproportionately to net job creation.

---

<sup>2</sup> See Davis, Haltiwanger, Schuh (1998) for details.

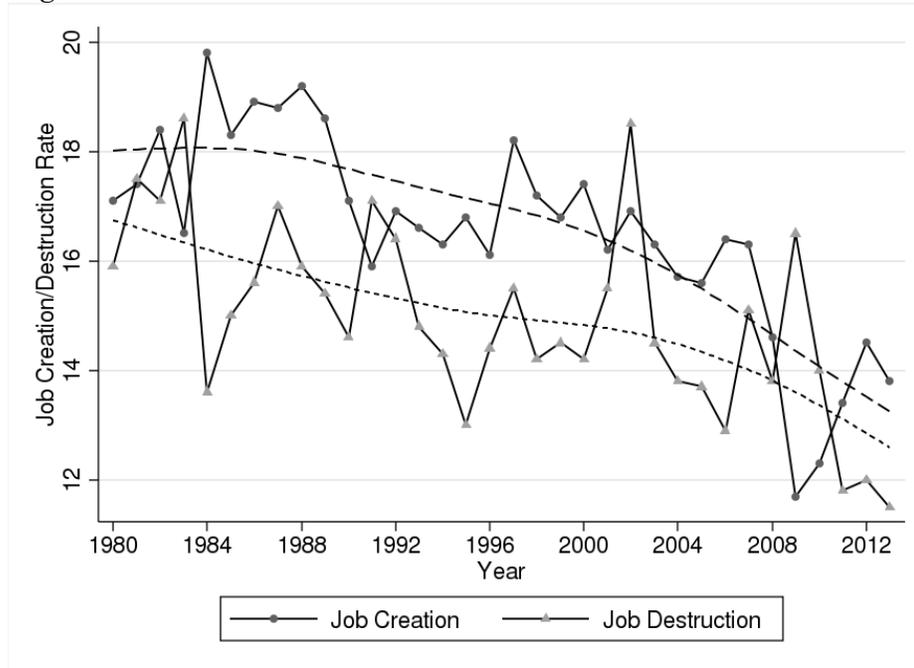
Figure 1: U.S. Annual Establishment Startup and Exit Rates



Source: Business Dynamics Statistics, U.S. Census Bureau, authors' calculations.  
 Notes: Startup and exit rates are calculated using establishment entry and exit. Following the Davis, Haltiwanger, Schuh (1998), establishment startup (exit) rates are calculated as  $100 \times (\text{establishment entry (exit) at time } t \text{ divided by the average establishments at } t \text{ and } t-1)$ . Hodrick-Prescott filter shown with multiplier 400.

Figure 2 shows the annual job creation and destruction rates for 1980 through 2013. The job creation rate fell from an average of 18.9% in the late 1980s to 15.8% prior to the Great Recession. Likewise, the job destruction rate fell from 16.1% in the late 1980s to just 13.4% in the same pre-Great Recession period. These declines are robust to different specifications of dynamism and exist at both the firm and establishment level in a variety of data sources. In addition to less job creation and destruction, Davis et al. (2010) use Bureau of Labor Statistics data to show that the pace of labour flows through the unemployment pool have declined since the 1980s. Similarly, Davis et al. (2012) show a decline in the pace of excess worker reallocation in the Job Openings and Labor Turnover data.

Figure 2: U.S. Annual Job Creation and Destruction Rates



Source: Business Dynamics Statistics, U.S. Census Bureau, authors' calculations.  
 Notes: Hodrick-Prescott filter shown with multiplier 400. Following the Davis, Haltiwanger, Schuh (1998), job creation (destruction) rates are calculated as  $100 \times (\text{job creation (destruction) at time } t \text{ divided by the sum of average establishment-level employment at } t \text{ and } t-1)$ .

The slowing entrepreneurial activity is also affecting firm-level distributions such as firm age. The Business Dynamics Statistics (BDS) data shows a declining startup rate and stagnant startup size (Haltiwanger et al., 2013). These trends are placing downward pressure on the share of economic activity attributed to young firms, leading to an aging firm population. In the late 1980s nearly half of all firms were young (aged less than five years) but only 39% of firms were young prior to the Great Recession. In contrast, the share of old firms (aged 16 or more) has increased substantially; rising by 50% from roughly 22% of all firms in 1992 to 34% of all firms by 2011 (Hathaway and Litan, 2014). Since young firms tend to contribute disproportionately to both job creation and destruction, the decreasing representation of young firms tends to decrease the overall rates of job creation and destruction (Decker et al., 2014). In addition, since 2000 there

have been fewer high-growth firms among the smaller stock of young firms (Decker et al., 2015).

Measures of economic dynamism are also intimately related to productivity. The literature on productivity has shown persistent differences in productivity across firms within industries. The extent of these differences is surprising—manufacturing firms at the 90th percentile of productivity produce twice as much as firms in the 10th percentile (Syverson, 2004). Perhaps less surprising, higher productivity firms are more likely to survive (Syverson, 2011). Reallocation in the form of entry, exit, expansions, and contractions have significant effects on productivity. Foster et al. (2006) show that, within the massive restructuring of the retail trade industry in the 1990s, nearly all of the labour productivity growth was driven by more productive establishments displacing less productive establishments.

Dynamism and entrepreneurship both have positive connotations but it is important to avoid letting those connotations cloud normative judgment because these are complex phenomena with multiple causes and consequences. Dynamism, for example, could be relabeled “churn” and reduced churn could be driven by better job matching and reduced uncertainty leading to a desirable consequence of longer job tenure. Entrepreneurship might also be relabeled self-employment and considered a negative consequence of a job-market that has failed to match workers to firms. We will return to these themes in the concluding discussion.

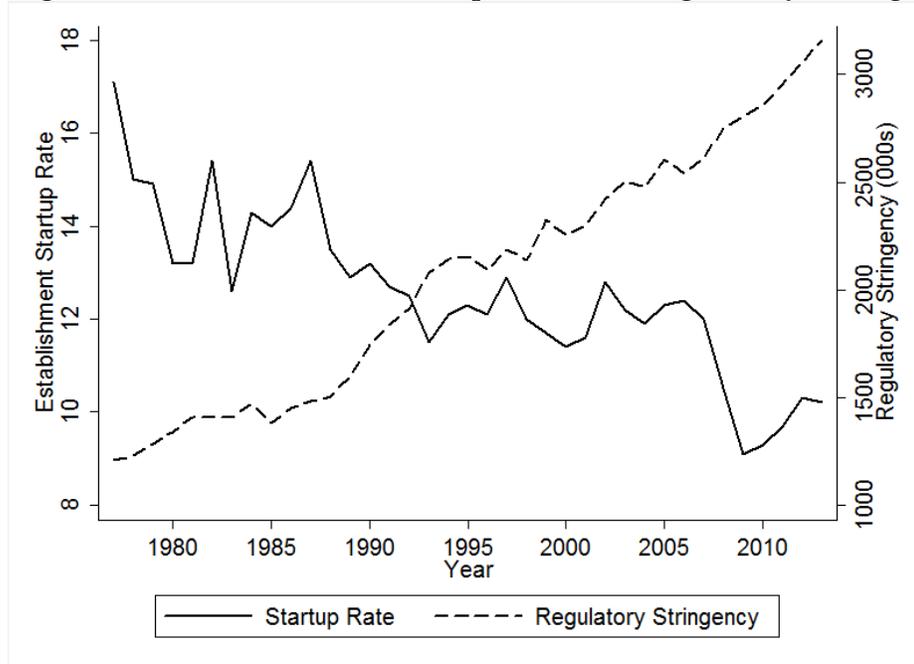
Improvements to firm-level data infrastructures have produced a flurry of empirical research describing the secular decline in dynamism. Despite the importance of the decline, relatively few papers have investigated its cause. In the following sections, we will investigate the extent to which federal regulations can account for the widespread, large and secular decline in economic dynamism.

## 2.1 Federal Regulation and Dynamism

Regulation can increase barriers to entry, tax job destruction, and slow the reallocation of capital. Hopenhayn and Rogerson's (1993) general equilibrium analysis shows that increasing adjustment costs through regulation reduces job destruction but also decreases job creation, startups, and productivity. The empirical literature using cross-country studies has shown that employment protection legislation and other labour market institutions tend to reduce job reallocation rates and could explain the differential performance between American and European labour markets (Haltiwanger et al., 2014). Other studies have shown that product and labour market regulations slow factor adjustment and cause allocative inefficiencies (Olley and Pakes, 1996; Eslava et al., 2010; Davis and Haltiwanger, 2014). Similarly, evidence suggests that entry deterrence regulations can slow employment growth (Bertrand and Kramarz, 2002) and discourage early stage entrepreneurship (Braunerhjelm and Eklund, 2014). Regulation may also reduce entrepreneurship indirectly by dampening the effects of skills, social networks, and attitudes towards risk (Ardagna and Lusardi, 2008). Finally, firms may capture regulators allowing them to consolidate and solidify monopoly power (Tullock, 1967; Stigler, 1971). Thus, regulation is a plausible candidate for explaining declining dynamism.

Figure 3 shows the aggregate level of federal regulation, as measured by RegData (explained in the following section), and the startup rate. The startup rate has decreased as federal regulation has increased. These opposing trends, combined with the theoretical mechanism by which regulation may reduce dynamism, provides motivation for measuring the extent to which federal regulation may explain the secular decline in business dynamism.

Figure 3: Establishment Startup Rate and Regulatory Stringency



Source: RegData 2.1, Business Dynamics Statistics, U.S. Census Bureau, authors' calculations.  
 Notes: Total aggregate regulatory stringency calculated as the sum of restrictive terms weighted by the probability of association between each industry and CFR part aggregated economy wide. For details on RegData see section 2.2.

Prior studies of regulation have relied upon crude measures of U.S. regulation such as file sizes, page counts, and word counts of the Federal Register or Code of Federal Regulations (Mulligan and Shleifer, 2005; Coffey et al., 2012; Dawson and Seater, 2008). Mulligan and Shleifer (2005), for example, measure regulation in kilobytes.

Dawson and Seater (2008) estimate a dynamic model of growth on U.S. data and include the page count of the Code of Federal Regulations as a measure of regulation. They find that regulation has reduced output and productivity. Time-series evidence from one country, however, could be subject to considerable biases and can be interpreted as causal only with strong assumptions. In this paper, we will be focusing on the effect of federal regulation on dynamism, which has not been done previously, and we will use novel industry-level measures of regulation rather than national measures. It is important to note that regulation need not reduce dynamism. A tax, for

example, might reduce the level of economic activity but in equilibrium it need not reduce the rate of firm entry or exit or impede the reallocation process that shifts resources from low productivity to high productivity firms. Similarly, regulations might primarily affect the level of economic activity rather than economic dynamism.

A number of international studies have found a negative relationship between entry regulation and entrepreneurship. Djankov et al. (2002) summarizes the stylized facts that have emerged from this literature. First, starting a business is expensive and time consuming but those costs vary significantly across countries. Second, regulation of entry is positively correlated with corruption and the size of the unofficial economy, and negatively associated with political freedoms and restrictions on government power. Studies have also found a negative relationship between product market regulations and investment (Alesina et al., 2005), and a negative relationship between entry regulations and entry, technological change, and growth (Ciccone and Papaioannou, 2007; Bruhn, 2013; Klapper and Laeven 2006). It is important to note that the international variation in regulation is different in scope and scale than the variation seen across time in the United States. The international studies compare countries like the Dominican Republic, where it costs 4.6 times GDP per capita to start a simple firm, to the United States, where that costs is only 0.5 percent of GDP per capita (Djankov et al., 2002). Entry regulations in the Dominican Republic may reduce entry and entrepreneurship but this need not imply that federal regulation in the U.S. has led to the secular decline in U.S. entry and entrepreneurship.

An alternative source of information on regulations directly related to economic dynamism can be found in the World Bank's Doing Business measures. These data, specifically the starting a business measures, capture the procedural burden entrepreneurs face in launching and formally

operating new industrial and commercial businesses.<sup>3</sup> One of the primary advantages of these data is their ability to study the comparative impacts of regulation at the country-level as in Djankov et al. (2002). However, there has been relatively little change in the Doing Business measures for the U.S. between 2004 and 2016. Table 1 shows several of the Doing Business distance to frontier measures, which capture the gap between an economy's performance and a measure of best practice across all in-sample countries. The U.S. is relatively close to frontier best practices (a score of 100) across most measures. For the starting a business measure, there has been relatively little movement over time with the U.S. inching slightly closer to the frontier by 2016. Likewise, getting credit, paying taxes, and resolving insolvency have all improved in the U.S. over this period while enforcing contracts declines slightly. Since regulation has not changed dramatically by these measures, the Doing Business data do not point to regulation as a major cause of declining dynamism.

Table 1: World Bank Doing Business Measures

Year	Starting Business DTF	Getting Credit DTF	Paying Taxes DTF	Enforcing Contracts DTF	Resolving Insolvency DTF
2004	91.18	.	.	77.22	86.46
2008	91.17	93.75	72.49	76.76	81.72
2012	91.34	93.75	78.69	76.76	87.72
2016	91.22	95.00	83.89	72.61	89.2

Source: World Bank Doing Business Statistics, authors' calculations.

Notes: Distance to frontier measures capture the gap between the U.S. and the best practice frontier. See [www.doingbusiness.org](http://www.doingbusiness.org) for details.

In addition, some regulations could increase dynamism. Antitrust law, for example, has the explicit goal of increasing dynamism. As another example, it is possible that making health insurance more easily available on the individual market and making it more portable could reduce job lock and increase entrepreneurship (Gruber and Madrian, 2002; Heim and Lurie,

<sup>3</sup> See <http://www.doingbusiness.org/> (accessed 2/18/2017) for details.

2014). Health and safety regulations and certification and licensing could also increase competition. Health regulation in the restaurant marketplace, for example, could increase the willingness of customers to try new and smaller restaurants thus increasing the startup rate.

The thesis we seek to test is whether federal regulation can explain a large share of the reduction in dynamism in the U.S. economy. For this purpose, it is important to look at all federal regulations, large and small, and to consider the net effect of regulation. It is common, for example, to analyze the consequences of a particular piece of legislation that passed at a particular time. Such an analysis might discover that regulation X increased and regulation Y decreased dynamism. But we are interested in the net effect. If some regulations increase and others decrease dynamism in equal measure then regulation cannot explain the decline in U.S. dynamism over the past three decades.

It is also important to consider the net effect of regulation because when regulation accumulates it can have a different effect than when one regulation is considered at a time. Consider Mancur Olson's (1984) theory of regulation in *The Rise and Decline of Nations*. Lobbying for a regulation is a collective action problem. Every group with a common interest does not organize instantaneously or automatically; it takes time and effort to organize. In a stable society, interest groups slowly accumulate. As interest groups accumulate, regulations increase in number and complexity as different groups come to an understanding over how to divide the surplus. Dynamism declines because interest groups limit entry and regulate to avoid rent disruption. Bargaining among interest groups is slow so dynamism slows even when Pareto-optimal moves are possible.

Notice that in Olson's theory no single regulation or handful of regulations explains declining dynamism. Taken in isolation, each regulation might conceivably pass a cost-benefit test. Rather than any single regulation, it is the accumulation of regulations that reduces dynamism. Regulations in this

view are like pebbles tossed into a stream. Each pebble in isolation has a negligible effect on the flow but toss enough pebbles and the stream is dammed.

## 2.2 Federal Regulation and RegData

The Code of Federal Regulations (CFR) is the stock of all federal regulations in effect in a given year. RegData builds on prior studies of regulation that use page counts or other size measures from the Code of Federal Regulations or the Federal Register (e.g. Mulligan and Shleifer, 2005; Coffey et al., 2012; Dawson and Seater, 2008).<sup>4</sup> RegData improves upon earlier measures in two ways. First, not every page in the CFR is equally impactful so rather than a simple page count RegData counts the number of restrictive words or phrases such as “shall,” “must,” “may not,” “prohibited,” and “required” in each section of text. Restrictive word counts are likely to better measure the regulations that influence choice, binding regulations, than will simple page counts.

The second way that RegData improves upon previous measures is by disaggregating the measure of regulation to the industry level. The CFR is divided into sections, including titles, chapters, subchapters, parts, and subparts. Although the titles of the CFR often have suggestive names such as “Energy,” “Banks and Banking,” and “Agriculture,” a single regulation in any CFR section can affect many industries so there is no simple way to connect the number of regulatory restrictions by section to an industry. To solve this problem, Al-Ubaydli and McLaughlin (2015) draw on developments in machine learning and natural language processing techniques.

Algorithms have been produced that can classify images. Google’s image search, for example, is trained on a set of tagged images and it is then able to classify images out-of-sample based on the training set. Classification algorithms for text—a much simpler problem—work in a similar way. After being exposed to a set of already-classified training documents, the

---

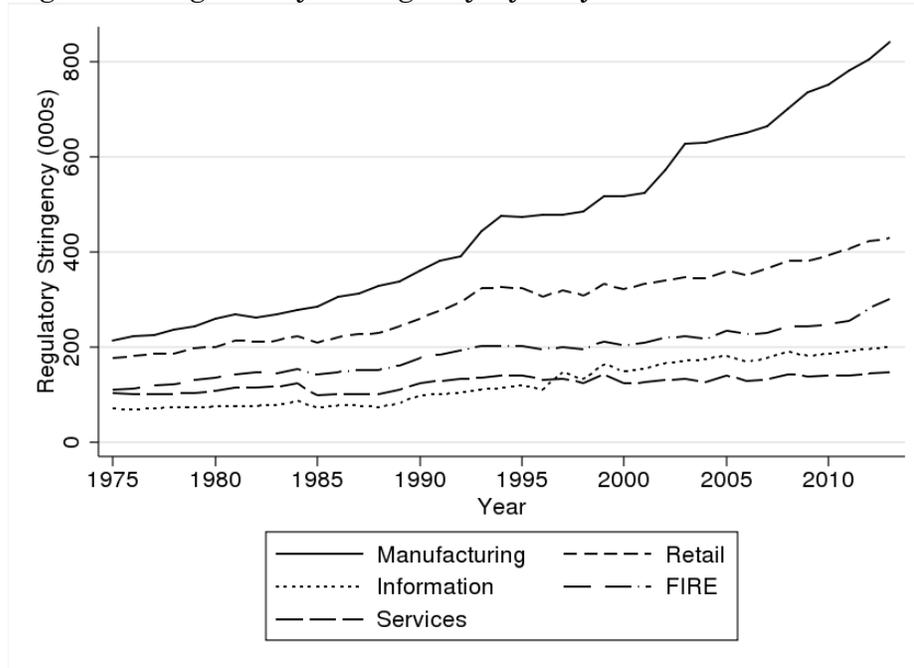
<sup>4</sup> For background and history of RegData see <http://regdata.org/about/> (accessed 2/18/2017)

algorithms recognize patterns in “wild” documents and classify them into categories according to probabilities. These kinds of techniques have become standard in the computer science and machine learning literature (Witten and Frank, 2005).

Al-Ubaydli and McLaughlin (2015) train their algorithm on long-form descriptions of each industry found in the North American Industry Classification System (NAICS) and on Federal Register (FR) entries that explicitly identify affected industries by NAICS code. (Whereas the CFR contains the stock of federal regulations, the FR captures the flow of new regulations and rules proposed by federal agencies.) The training set is then used to probabilistically match text in the CFR to each industry. Thus, each section in the CFR has a regulatory restrictiveness count and each section can be weighted by the probability that it is about or affects each industry. The restrictions and probability weights are then aggregated to produce an index of regulatory stringency by industry and year. An example of the regulatory text from the CFR, along with its restrictive term count, can be found in Appendix A.

Figure 4 shows the steady increase in regulatory stringency by major sector by year. The popular notion that regulation has been increasing over the past several decades can be seen in the text of the CFR. Especially notable are relatively large increases in regulatory stringency in manufacturing relative to other sectors.

Figure 4: Regulatory Stringency by Major Sector



Source: RegData 2.1, authors' calculations.

Notes: Total regulatory stringency by major sector is calculated as the sum of restrictive terms weighted by the probability of association between each industry and CFR part aggregated by major sectors. FIRE includes finance, insurance, and real estate.

There are no other measures of regulatory stringency by industry that we can compare to, but RegData varies in ways that are plausible. Industries, for example, differ widely in the amount of regulation that they face with industries like waste management (NAICS 562) having a regulatory stringency index (97,326) more than 10 times higher than that for courier and messengers (NAICS 492) (7,340). This means that more sections of the CFR text relate to waste management and that these sections contain many restrictive words such as “must” and “prohibited” as compared to sections of the text about couriers and messengers. The large variation in regulation by industry provides scope to identify the possible influence of regulation on dynamism. In particular, if the cause of declining dynamism is a slow accumulation of regulations and regulatory complexity then we ought to see differences in dynamism across industries associated with the regulatory stringency index.

Sections of the CFR can also be associated with the responsible agency. Therefore, we can measure the regulation produced by each agency. Table 2 below shows the top federal agencies by mean regulatory impact between 1999 and 2013 with the values for each agency indexed to the top regulatory agency. According to RegData, the Environmental Protection Agency is responsible for a greater portion of regulations than any other agency, a plausible finding. Other agencies with notable regulatory incidence are the Department of Homeland Security, Internal Revenue Service, and the Occupational Safety and Health Administration. The distribution of regulation across agencies is highly skewed, with the top agency accounting for more than 14 times as much regulation as the agency with the 10th highest regulatory incidence.

**Table 2: Regulatory Stringency by Agency (Average 1999-2013)**

Agency Name	Regulatory Stringency
Environmental Protection Agency	100.00
Internal Revenue Service	41.12
Occupational Safety and Health Administration	37.40
Department of Homeland Security	17.22
Office of the Secretary of Defense	10.54
Federal Acquisition Regulation	10.03
Department of Energy	9.30
Federal Aviation Administration	9.22
Federal Communications Commission	8.96
Food and Drug Administration	6.90

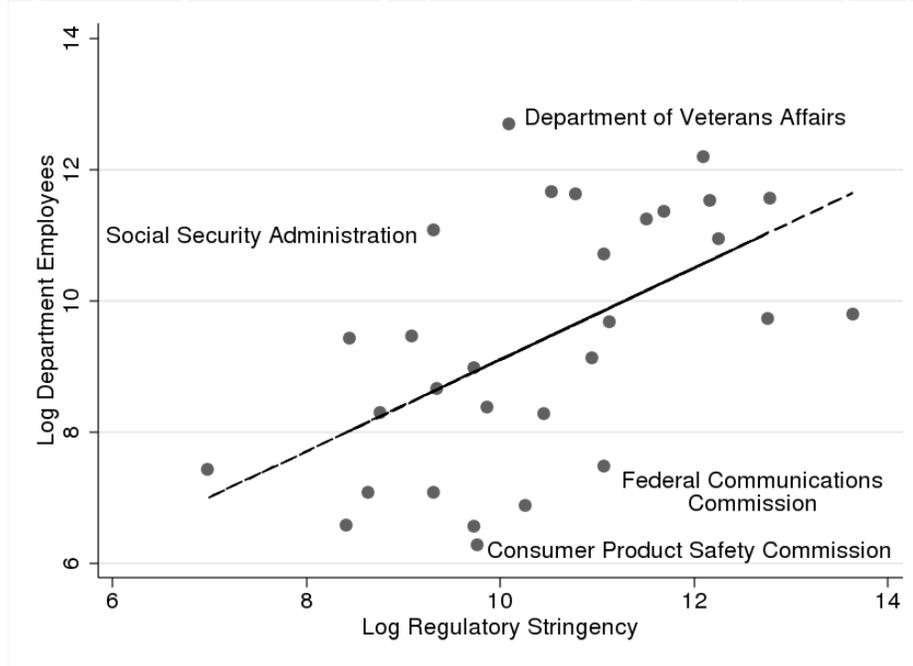
Source: RegData 2.1, authors' calculations.

Notes: Total regulatory stringency by agency calculated as the sum of restrictive terms weighted by the probability of association between each industry and CFR part aggregated by the agency responsible for each CFR part. All values indexed to the agency with the highest associated regulatory stringency.

Figure 5 also provides some suggestive evidence on the ability of the RegData algorithm to accurately measure regulation. Agency employment increases with regulatory stringency as identified by the algorithm. It is also notable that there is some intuition for the agencies off the regression line. The Department of Veterans Affairs, for example, has very high employment

but relatively low regulation since most of its employees are not involved in regulating private markets. The FCC, in contrast, is responsible for much more regulation with relatively few employees. RegData is also highly correlated with agency budgets.<sup>5</sup>

Figure 5: Department Employment and Regulatory Stringency

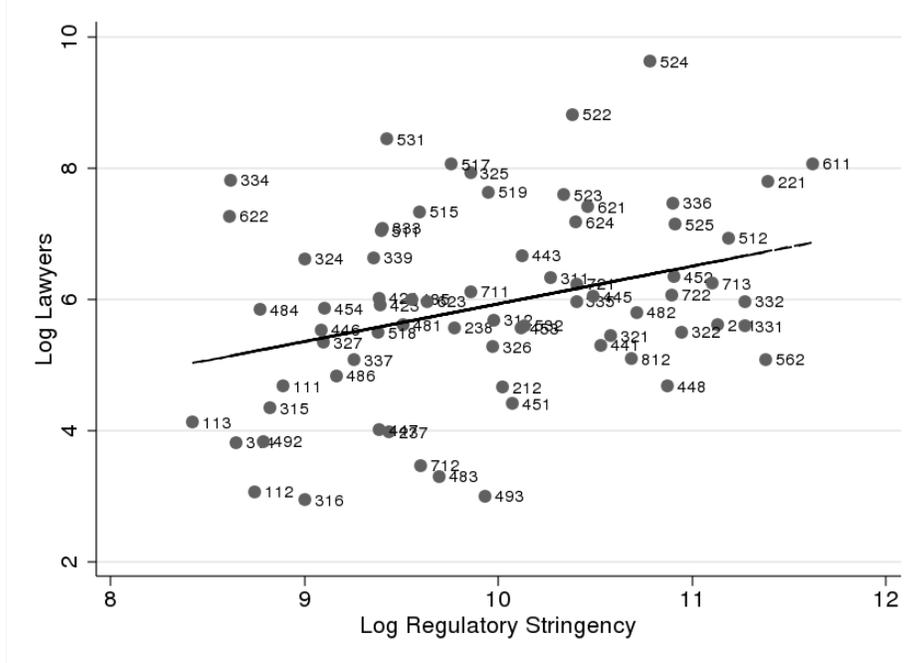


Source: RegData 2.1, OPM FedScope Employment Cube September 2012, authors' calculations. Notes: Log regulatory stringency by department calculated as the sum of restrictive terms weighted by the probability of association between each industry and CFR part aggregated by the department responsible for each CFR part. Total log count of lawyers by department calculated as the sum of persons covered in the OPM FedScope Employment Cube with occupations including General Attorney (0905) and Tax Law Specialist (0987) by department. The fitted line shows the predicted values of an OLS regression of the logged federal employees as a function of log regulatory stringency.

RegData at the industry level also correlates positively although at a low level with employment of lawyers by industry, a possible sign of regulatory complexity by industry. Figure 6 shows counts of lawyers employed by each industry and that industry's regulation index.

<sup>5</sup> See <http://regdata.org/the-high-correlation-between-agency-budgets-and-agency-regulations/> (access 2/18/2017) for additional details.

Figure 6: Industry Employment of Lawyers and Regulatory Stringency

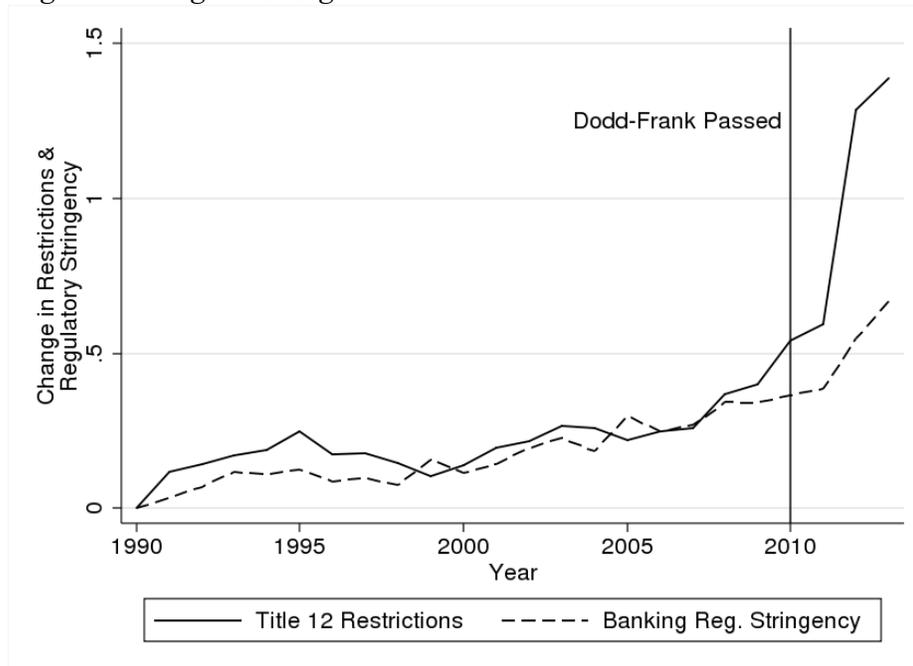


Source: RegData 2.1, IPUMS 2000 5% Census microdata, authors' calculations.  
 Notes: Log regulatory stringency by industry is calculated as the sum of restrictive terms weighted by the probability of association between each industry and CFR part aggregated by 3-digit 2007 NAICS industries. Log lawyers by industry derived from the IPUMS microdata as the weighted sum of persons classified with primary occupation of Lawyer (0210) by the type of establishment the person worked classified by 3-digit 1997 NAICS, which are translated to 3-digit 2007 NAICS. The figure excludes NAICS 541 Professional, Scientific, and Technical Services, which includes the industry code for establishments that exclusively provide legal services, 54111 Office of Lawyers. The fitted line shows the predicted values of an OLS regression of the logged count of lawyers as a function of log regulatory stringency.

Perhaps most importantly, RegData clearly signals when major pieces of legislation contribute to regulatory stringency. Figure 7, for example, shows changes in the count of restrictions in Title 12 of the CFR (Banks and Banking) and changes in the regulatory stringency index (the count of restrictions multiplied by the probability such restrictions are about banking). Regulation slowly accumulated in the 1990s and 2000s but the count of words like “shall” and “must” jumps shortly after the Dodd-Frank Act is passed (note that it takes time for legislation to be reflected in the

regulatory rulings of the CFR) as does the regulatory stringency index for banking.<sup>6</sup>

Figure 7: RegData Signals the Dodd-Frank Act



Source: RegData 2.1, authors' calculations.

Notes: Title 12 restrictions is calculated as the annual sum of restrictive terms, e.g. “shall” and “must,” within Title 12 Banks and Banking of the CFR. Total banking regulatory stringency is calculated as the sum of restrictive terms weighted by the probability of association between each industry and CFR part for 2007 NAICS 52 Finance and Insurance. Both time series are normalized to show percentage change relative to 1990.

Our conclusion is that the relative values of the regulatory stringency index capture well the differences in regulation over time, across industries, and across agencies. Consistent with this, a growing literature finds that regulation as measured by RegData has a significant influence on economic and political variables of interest. Bessen (2016), for example, finds that RegData helps to explain why Tobin’s Q (firm value relative to assets) has been rising. Pizzola (2015) takes advantage of the industry structure of RegData and finds that regulation can help to explain firm-level investment decisions. Other papers use RegData to look at productivity (Davies 2014)

<sup>6</sup> See <http://regdata.org/dodd-frank-federal-reserves-regulations/> (accessed 2/18/2017) for additional details.

and consumer prices (Chambers and Collins, 2016). Once again, the ability of RegData to measure regulation at the industry level is a key advantage over previous measures of regulation. See Al-Ubaydli and McLaughlin (2015) and references cited therein for further discussion.

### 2.3 Statistics of U.S. Businesses (SUSB)

Statistics of U.S. Businesses (SUSB) is a public use<sup>7</sup> annual dataset containing detailed information on establishments, employment, and payroll by geographic area, industry (NAICS 2, 3, and 4-digit), and firm size. SUSB is derived from the Business Register, which contains the Census Bureau's most complete, current, and consistent data for the universe of private nonfarm U.S. business establishments. In addition to tabulations for firms, establishments, employment, and payroll, SUSB also provides data on year-to-year employment changes by births, deaths, expansions, and contractions. These employment change tabulations are available for 1992 and 1997 through 2013. By combining SUSB and RegData, we can gain a better understanding of the relationship between federal regulation and economic dynamism.

One limitation of the SUSB data with respect to the analysis to follow is that establishment birth counts in SUSB show positive bias in Economic Census years as some births are incorrectly timed due to census processing activities.<sup>8</sup> As explained in the following section, any bias these year-specific effects might have will be controlled via year fixed effects. Another drawback of the SUSB data is the lack of firm age. The subsequent analysis will be unable to address the declining share of employment for young firms as evidence for the secular decline in dynamism and entrepreneurship.

---

<sup>7</sup> See <https://www.census.gov/econ/susb/> (accessed 2/18/2017) for additional details.

<sup>8</sup> Other sources of business dynamics such as Business Dynamic Statistics (BDS) exhibit smoother birth and death time series because it is derived from the Longitudinal Business Database (LBD), which is subjected to algorithms that re-time incorrect births and deaths (Haltiwanger et al., 2009). Nevertheless, the correlations between SUSB measures and BDS measures of dynamism over the same period are very high with correlations of .99, .97 and .91 for job creation, destruction, and startups respectively.

A possible advantage of the SUSB is that the measures of dynamism are at the establishment level rather than at the firm level. Thus, we can take into account the effects of regulation on any expansion regardless of the source (see Tabarrok and Goldshlag, 2015 on different measures of entrepreneurship). In practice, however, many of the economic conditions and regulations that raise or lower the costs of starting a firm will also raise or lower the cost of starting a new establishment (e.g. land use regulations). As a result, the establishment entry rate and the firm entry rate are highly correlated (see Appendix B).

The industry classification codes used in the employment change data vary over time, making it necessary to translate between NAICS vintages. The Census Bureau provides concordances between subsequent iterations of the NAICS classification system. In some cases, multiple concordances must be combined to arrive at a consistent classification scheme. To translate between different NAICS we use weights, assuming equal weighting for each match at the 6-digit NAICS level.

Table 3: Summary Statistics for RegData-SUSB Panel

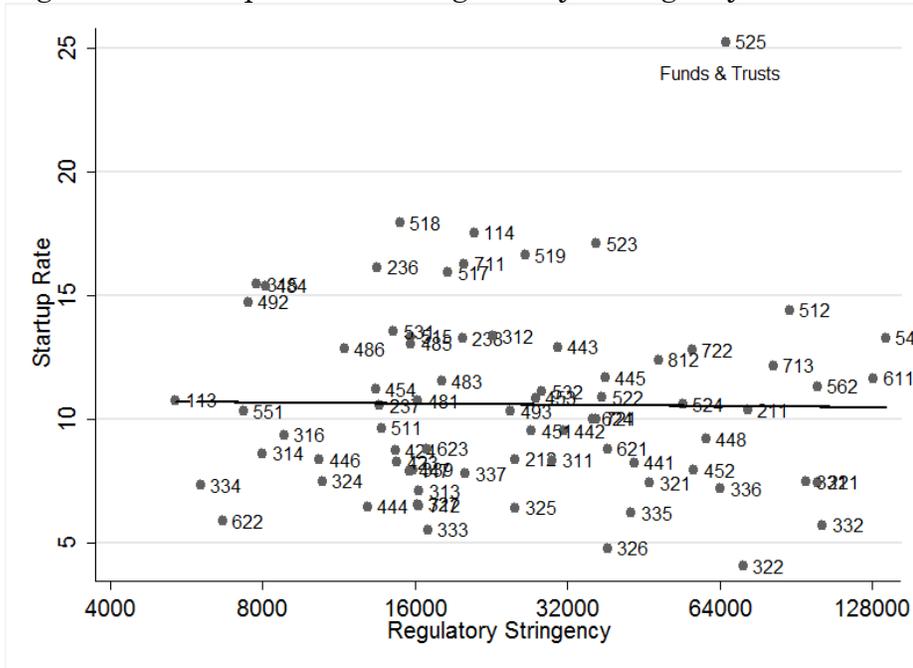
	Obs	Mean	Std Dev	Min	Max
Regulatory Index	1,125	34,339	30,040	4,463	147,890
Annual Pct Chg Regulatory Index	1,125	3.32	8.49	-51.06	116.94
Specific Regulatory Index	1,125	2,702	5,021	130	33,307
General Regulatory Index	1,125	12,099	13,117	365	77,324
Total Regulatory Index (Leontief)	840	374,429	93,471	67,375	727,848
Startup Rate	1,125	10.61	4.28	2.46	46.85
Job Creation Rate	1,106	14.15	5.46	3.17	59.74
Job Destruction Rate	1,105	14.49	5.08	3.13	48.66

Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.

Notes: Observations are industry-year combinations 1999 to 2013 for 75 3-digit NAICS industries. Specific and general regulatory index calculated using concentration of RegData probabilities within CFR parts as described in the following sections. Total regulatory index calculated using input-output tables, and therefore only include industries for which input-output data exist, as described in the following sections. Some industry-year observations are missing values for economic dynamism due to disclosure issues (see SUSB documentation <http://www.census.gov/econ/susb/definitions.html> accessed 2/18/2017). Startup rate is calculated as  $100 \times (\text{establishment entry at time } t \text{ divided by the average of estabs at } t \text{ and } t-1)$ . Job creation (destruction) rate is calculated as  $100 \times (\text{job creation (destruction) at time } t \text{ divided by the average of employment at } t \text{ and } t-1)$ .

The final SUSB-RegData panel contains observations between 1999 and 2013. Table 3 provides summary statistics for several measures of regulation and economic dynamism. The variables of interest, which will be used as measures of entrepreneurship and dynamism, are startups, job creation, and job destruction. Figure 8 shows average startup rate versus the average regulation index by industry. The regulatory index axis is plotted on a log scale due to the wide variation in the regulation across industries. The fitted line suggests no obvious relationship between regulation and startups. Figure 9 and Figure 10 show the relationship between job creation and destruction rates respectively and the average regulatory index by industry. Job creation appears just slightly positively correlated with regulation at the industry level and job destruction just slightly negatively correlated.

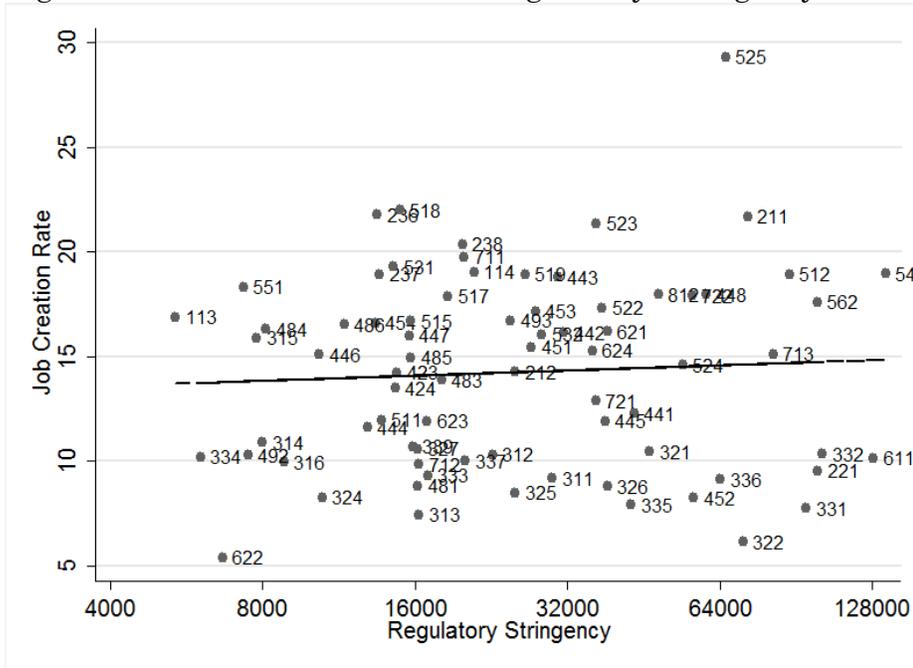
Figure 8: Startup Rates vs. Regulatory Stringency



Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.

Notes: Average regulatory stringency by industry is calculated as the average of the sum of the annual regulatory stringency index between 1999 and 2013 by 3-digit 2007 NAICS industries. Startup rate is calculated as  $100 \times (\text{establishment entry at time } t \text{ divided by the average of estabs at } t \text{ and } t-1)$ . Births are establishments that have zero employment in the first quarter of the initial year and positive employment in the first quarter of the subsequent year. The fitted line shows the predicted values of an OLS regression of the startup rate as a function of regulatory stringency.

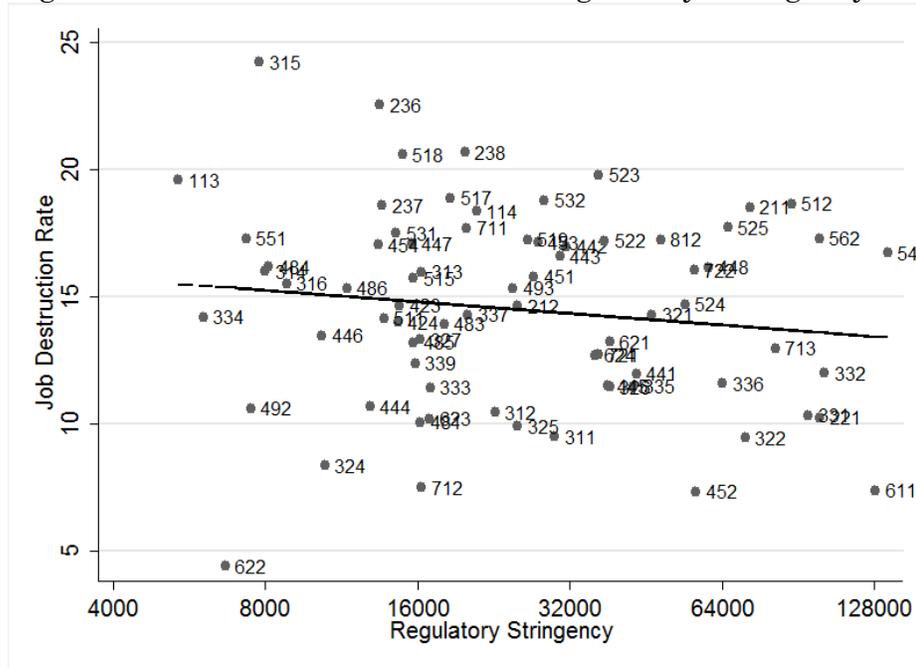
Figure 9: Job Creation Rates vs. Regulatory Stringency



Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.

Notes: Average regulatory stringency by industry is calculated as the average of the sum of the annual regulatory stringency index between 1999 and 2013 by 3-digit 2007 NAICS industries. Job creation rate is calculated as  $100 \times (\text{job creation at time } t \text{ divided by the average of employment at } t \text{ and } t-1)$ . The fitted line shows the predicted values of an OLS regression of the job creation rate as a function of regulatory stringency.

Figure 10: Job Destruction Rate vs. Regulatory Stringency



Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.  
 Notes: Average regulatory stringency by industry is calculated as the average of the sum of the annual regulatory stringency index between 1999 and 2013 by 3-digit 2007 NAICS industries. Job destruction rate is calculated as  $100 \times (\text{job destruction at time } t \text{ divided by the average of employment at } t \text{ and } t-1)$ . The fitted line shows the predicted values of an OLS regression of the job destruction rate as a function of regulatory stringency.

Simple cross-sectional averages may be distorted by endogeneity. High dynamism industries, for example, may be more likely to attract scrutiny and regulation. The analysis in the next section will control for year and industry effects to reveal the relationship between regulation and economic dynamism within an industry over time.

### 3. Methods and Results

#### 3.1 Relationship Between Federal Regulation and Dynamism

To investigate the potential role of federal regulation in the decline in economic dynamism we estimate the effect of our regulatory stringency index by year and NAICS on several key measures of dynamism and entrepreneurship. Year and industry fixed effects are included to focus estimation on changes in dynamism that are explained by changes in

industry regulatory stringency over time. We estimate the following fixed effects regression model,

$$Y_{t,n} = \beta_0 + \beta_1 \ln Reg_{t,n} + \lambda_t + \gamma_n + \varepsilon_{t,n} \quad [1]$$

Where  $Y_{t,n}$  is our measure of dynamism at time  $t$ , for 3-digit NAICS  $n$ . Measures of dynamism include: startup rate, job creation rate, and job destruction rate. Startup rate is calculated as 100 times the number of establishments created at time  $t$  divided by the Davis-Haltiwanger-Schuh (DHS) denominator, which is the mean number of establishments for times  $t$  and  $t-1$ . The DHS denominator is symmetric and prevents a bias in net growth statistics due to transitory shocks (Davis et al., 1998). Job creation (destruction) rate is calculated as 100 times the number of jobs created (destroyed) divided by the mean aggregate employment for times  $t$  and  $t-1$ .  $Reg_{t,n}$  is the regulatory stringency index at time  $t$ , in 3-digit NAICS  $n$ . Finally,  $\lambda_t$  and  $\gamma_n$  are fixed effects for time and industry category respectively. Year fixed effects will control for economy-wide variation in economic dynamism and any upward bias in the SUSB data due to incorrectly timed births and deaths stemming from economic census activities. Industry fixed effects will control for differences in dynamism across industries that do not vary with time.

Estimation results are shown in Table 4. After controlling for year and industry fixed effects, our regulatory stringency index shows no statistically significant effect on startups, job creation, or job destruction. In short, no evidence for a negative effect of regulation on dynamism. Recall from the introduction that declining dynamism is associated with a decline in job destruction rates not an increase so regulation here has the opposite to the hypothesized sign in most specifications for all measures of dynamism. Moreover, adding in the regulatory index adds less than a percentage point to the variation explained above that of the time and industry fixed effects.

It could be the case that the negative effects of regulation take years to materialize. To examine whether this is the case we add the regulation index  $t-1$  and  $t-2$ . The regulatory stringency index once lagged is positive and statistically significant in the job creation regression but the effect is small. Overall, the results suggest that lagged regulation indices are no better able to account for the decline than regulation at time  $t$ .<sup>9</sup>

Table 4: Dynamism and Regulatory Stringency

	Startups	Job Creation	Job Destruction	Startups	Job Creation	Job Destruction
Log Regulatory Stringency	0.661 (1.043)	1.474 (0.957)	1.459 (1.193)	-1.061 (0.984)	-1.002 (1.348)	0.700 (1.335)
Log Reg Stringency (-1)				2.581 (1.709)	1.804 (0.999)	-0.408 (1.361)
Log Reg Stringency (-2)				-0.155 (0.823)	1.542 (1.147)	1.365 (1.126)
Constant	4.289 (10.30)	0.986 (9.484)	-0.472 (11.92)	-2.503 (14.59)	-7.419 (11.20)	-2.390 (13.81)
Observations	1,125	1,106	1,105	1,125	1,106	1,105
R-squared	0.193	0.279	0.330	0.199	0.283	0.331
Number of Industries	75	75	75	75	75	75
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.

Notes: Robust standard errors in parentheses, \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ . Observations are industry-year combinations. Some industry-year combinations were suppressed in the source SUSB data due to disclosure issues. All dependent variables are rates, except when otherwise denoted. Unless otherwise noted, the  $R^2$  reported in regressions that include fixed effects are calculated after demeaning the data.

Table 5 breaks establishments into three classes by firm size, small (1-9 employees), medium (10-499) and large (>500) and looks at job creation and destruction rates within these classes. As before, we find a few statistically

<sup>9</sup> For robustness, reported in Appendix C we show that this remains true using  $t-1$  or  $t-2$  in place of regulation at time  $t$ , including time trends along with year fixed effects (omitting one year), and with the inclusion of industry trends. We also estimate specifications that directly address non-linearities between regulation and dynamism, replacing Log Regulatory Stringency with Regulatory Stringency and Regulatory Stringency squared. These specifications also produce similar results. Finally, we estimate regressions using a CFR word count index rather than focusing exclusively on restrictive terms. This CFR word count index is more directly comparable to Mulligan and Shleifer (2005).

significant results especially for large firms but the signs suggest regulatory stringency is associated with small increases not decreases in dynamism as measured by job creation and job destruction rates.

Table 5: Regulatory Stringency and Dynamism by Firm Size

	Small <10		Medium 10-499		Large >499	
	Job Creation	Job Destruction	Job Creation	Job Destruction	Job Creation	Job Destruction
Log Regulatory Stringency	-0.430 (3.244)	1.647 (1.858)	1.349 (1.238)	1.685 (1.817)	2.467** (1.012)	2.698 (1.491)
Constant	32.90 (32.46)	1.416 (18.60)	1.122 (12.22)	-3.029 (18.33)	-10.63 (10.01)	-14.03 (14.93)
Observations	1,061	1,050	1,088	1,092	1,018	1,014
R-squared	0.060	0.169	0.196	0.131	0.306	0.263
Number of Industries	75	75	75	75	74	74
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.

Notes: Robust standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05. Observations are industry-year combinations. Some industry-year combinations were suppressed in the source SUSB data due to disclosure issues. Firm (enterprise) size is a categorical variable determined by the summed employment of all associated establishments under common ownership.

The primary negative impacts of regulation could be in the extent to which they change over time, causing firms to incur adjustment costs. Table 6 indicates that shifting focus to the year over year percent change in the regulation index does not suggest that regulation is a major factor contributing to the decline in dynamism.

Table 6: Dynamism and Regulatory Change

	Startups	Job Creation	Job Destruction
Annual Change in Reg Stringency	-0.0120 (0.00693)	-0.00798 (0.00841)	-0.00144 (0.00863)
Constant	11.01*** (0.219)	15.78*** (0.302)	14.10*** (0.318)
Observations	1,125	1,106	1,105
R-squared	0.194	0.278	0.328
Number of Industries	75	75	75
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.

Notes: Robust standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05. Observations are industry-year combinations. Some industry-year combinations were suppressed in the source SUSB data due to disclosure issues.

The above analysis shows that regulation, lagged regulation, or changing regulation does not account for the decline in economic dynamism. It may be the case that only certain types of regulations are important for economic dynamism, and our focus on all regulations weakens that relationship. If two types of regulation have offsetting effects, that isn't a problem for our analysis since we are interested in the net effect of all regulation. If only one type of regulation has a negative effect, however, then combining it with other types having a zero effect could attenuate our results. Thus, we next distinguish general from specific regulation and ask whether either of these types of regulation alone is responsible for declines in dynamism.

Some types of regulation concern only a single industry, such as those relating to specific techniques of mining. Other types of regulation, such as labour regulation, cut across many different industries. As mentioned in the previous section, our index is the aggregation of the probability a block of text is related to an industry multiplied by the number of restrictions in that block of text. A probability of association is calculated between each CFR part and all 3-digit NAICS industries. A CFR part which deals only with the mining industry will have a vector of probabilities that is highly concentrated

on the mining industry. A CFR part that is more general, however, will exhibit a less concentrated vector of probabilities. In order to separate out these types of regulation we create for each part in the CFR an HHI index of concentration. To give one example, we find that the Title 29 subchapter which covers topics such as the minimum wage and employer record-keeping is considerably more general, i.e. less concentrated, than Title 30 subchapter K, which discusses the use of explosives and waste disposal in mineral mines.

Using our HHI concentration measure, we create a specific and general regulatory index. The specific regulation index only includes CFR parts where the HHI index on the probabilities is greater than the 80<sup>th</sup> percentile of concentration indices across all parts. Conversely, the general regulation index uses only text with a concentration value less than the 20<sup>th</sup> percentile. The regression results using these new indices are reported in Table 7. Neither the specific nor general regulatory indices are related to dynamism in a statistically significant manner in the hypothesized direction.

Another advantage of the specific and general regulatory index is that to the extent that reverse causation from dynamism to regulation is an issue, it is an issue that affects regulation about a specific rather than general regulations, which affects many industries. As Olson (1977, 1984) pointed out, industries face a collective action problem when lobbying for favorable regulation. As a result, specific regulation is much more likely to be industry driven than general regulation. We find, however, that neither type of regulation drives dynamism so reverse causation does not appear to be a significant problem. We address issues of endogeneity and measurement error at greater length in Section 3.4.

Table 7: Dynamism and Industry Regulation, Specific and General Regulations

	Startups	Job Creation	Job Destruction
Log Specific Regulation Index	0.000149 (0.000130)	-0.000120 (0.000234)	5.89e-05 (0.000146)
Log General Regulation Index	1.02e-05 (2.63e-05)	7.80e-05*** (2.52e-05)	5.81e-06 (2.55e-05)
Constant	10.41*** (0.408)	15.17*** (0.689)	13.88*** (0.539)
Observations	1,125	1,106	1,105
R-squared	0.194	0.288	0.328
Number of Industries	75	75	75
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.

Notes: Robust standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05. Observations are industry-year combinations. Some industry-year combinations were suppressed in the source SUSB data due to disclosure issues. Specific and general regulation indices are calculated using the concentration of probabilities across industries within CFR parts, which is calculated as the sum of squared probabilities of association between the text and each industry by CFR part. Specific regulation index includes only CFR parts where the concentration is greater than the 80<sup>th</sup> percentile of concentrations across all parts and years. General regulation index includes only CFR parts where the concentration is less than the 20<sup>th</sup> percentile of concentration.

Alternatively, it could be the case that only the most active regulatory agencies write binding and impactful regulations. Thus, we focus on the top ten agencies responsible for the most regulation as measured by our stringency index. Table 8, however, again shows that none of our measures of dynamism are associated with regulatory stringency, even for the most active regulatory agencies.<sup>10</sup>

<sup>10</sup> It could also be the case that it is primarily the complexity of tax regulation that inhibits the creation of new firms and hiring and separation decisions (Djankov et al., 2010). In Appendix C we report regressions that include only regulations associated with the Internal Revenue Service, which show similar patterns of insignificance for all of our measures of dynamism.

Table 8: Dynamism and Regulation: Top Ten Regulatory Agencies

	Startups	Job Creation	Job Destruction
Log Regulatory Stringency	0.00329 (0.00357)	-0.000940 (0.00357)	-0.000183 (0.00299)
Constant	10.86*** (0.200)	15.70*** (0.288)	14.08*** (0.272)
Observations	10,950	10,768	10,758
R-squared	0.194	0.278	0.324
Number of Industries	75	75	75
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.

Notes: Robust standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05. Observations are agency-industry-year combinations. Sample includes only the top ten agencies by regulatory incidence, calculated as the sum of the regulatory stringency index between 1999 and 2013. The observation count is less than the number of agencies (10) times the number of years (13) and the number of industries (75) because not all of the top agencies are observed in all years.

### 3.2 A Leontief Measure of Regulation

The RegData methodology probabilistically assigns regulatory text to industries, which may only capture partial or "first-round" regulatory incidence. For example, while regulations directed at the production of basic chemicals may affect chemical manufacturers, presumably those restrictions also impact industries that rely on those chemicals as an intermediate good. Similarly, regulations on petroleum and coal product manufacturers, which rely heavily on chemical manufacturing, may also impact the dynamism of the chemical manufacturing industry. To address this concern, we use the 2007 detailed industry level Input-Output tables published by the Bureau of Economic Analysis to construct more complete or holistic measures of regulation.<sup>11</sup> The Input-Output data show how each industry relies on inputs from all other industries. We use these relationships to calculate new measures of up-stream and down-stream regulatory incidence, which capture

<sup>11</sup> See [http://www.bea.gov/industry/io\\_annual.htm](http://www.bea.gov/industry/io_annual.htm) for details (accessed 2/18/2017).

the extent to which each industry is exposed to regulation via its purchases from and sales to other industries.

Our up and down-stream measures simply multiply the use share from the input-output table for industry  $i$  from industry  $j$  by the regulatory stringency of the input industries (excluding purchases from the same industry) summed as shown below:

$$RegUP_i = \sum_{j=1}^n inShare_{ij} Reg_j \quad [2]$$

$$RegDN_i = \sum_{j=1}^n outShare_{ij} Reg_j \quad [3]$$

Where  $inShare_{ij}$  is the share of inputs used by industry  $i$  sourced from industry  $j$  and  $outShare_{ij}$  is the share of outputs produced by industry  $i$  being consumed by industry  $j$ .<sup>12</sup> Thus  $RegUP$  increases in size when an industry buys a significant share of inputs from industries that are themselves highly regulated and  $RegDN$  increases when an industry sells a significant share of its output to highly regulated industries.

Our third measure of full regulatory incidence is inspired by the Leontief input-output model.<sup>13</sup> In that model there is some consumer or final demand for outputs such as gasoline and steel but the gasoline industry also uses gasoline and steel to produce gasoline as does the steel industry. The question is to find the gross production of gasoline and steel such that both the intermediate and final demands can be satisfied. Note that in solving the model one solves for all the ripple effects—that is, to produce an extra final gallon of gasoline requires additional gasoline and steel but to produce the additional gasoline and steel requires additional gasoline and steel and so forth.

---

<sup>12</sup> In the BEA's Input-Output use table  $inShare_{ij}$  corresponds to the column percent for each industry and  $outShare_{ij}$  corresponds to the row percent for each industry.

<sup>13</sup> See Simon and Blume (1994) for an elementary treatment.

In an analogous way we treat the regulation imposed by law as the final level of regulation and the regulation that ripples from industry to industry through the input-output matrix as the intermediate level. We then look for gross levels of regulation such that the final and intermediate levels of regulation are satisfied.<sup>14</sup> We label the result the Leontief Regulatory Stringency Index.

Table 9 shows our measures of dynamism against our “partial” regulatory index (as used previously) and our up-stream and down-stream measures as well as the Leontief regulatory measure. Results are consistent with previous estimates. In particular, we find no effect of either measure of regulatory incidence on startup or job destruction rates. The regulatory stringency index is negative and small in the regression for job creation when including the Leontief regulatory index, which is positive and significant in that regression.<sup>15</sup> The up-stream and down-stream measures of regulatory stringency might also be used to address concerns of endogeneity, which we explore in section 3.4.

---

<sup>14</sup> More formally, we can write  $A$  as the  $n$  by  $n$  matrix of input-output shares,  $B$  as a  $n$  by 1 vector of final regulatory stringency, and  $X$  as the full regulatory incidence faced by each industry.

$$X = AX + B$$

Solving for  $X$  we have full regulatory incidence for each industry as the Leontief inverse multiplied by the vector of industry specific regulatory stringency.

$$X = (I_n - A)^{-1}B$$

<sup>15</sup> We also considered that our full incidence measures of regulation could be proxying for the number of connections to other industries which might be associated with dynamism. Thus, in regressions not shown here we also included a Herfindahl-Hirschman input index over the shares of inputs from other industries (thus an industry that purchased 25% of its inputs from one industry would receive a higher HHI index than one that purchased 5% of its inputs from five industries.). Results were similar to those in the text.

Table 9: Dynamism and Regulation: Full Regulatory Incidence

	Startups	Job Creation	Job Destruction	Startups	Job Creation	Job Destruction
Log Regulatory Stringency	0.431 (1.111)	-2.317 (1.279)	2.239 (1.513)	1.970 (1.572)	-3.554** (1.581)	3.059 (2.244)
Log Up-Stream Regulatory Stringency	6.959*** (2.588)	24.52*** (9.015)	1.926 (3.551)			
Log Down-Stream Regulatory Stringency	-5.708 (3.249)	12.20*** (4.337)	-0.589 (6.508)			
Log Leontief Regulatory Stringency				-12.71 (9.182)	46.31*** (12.59)	-6.298 (14.07)
Constant	-7.263 (41.63)	-340.9*** (103.3)	-22.53 (64.07)	152.8 (106.3)	-536.8*** (149.6)	63.16 (159.8)
Observations	840	821	820	840	821	820
R-squared	0.167	0.290	0.339	0.159	0.241	0.339
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Source: RegData 2.1, Statistics of U.S. Businesses, BEA Input-Output Accounts data, authors' calculations.

Notes: Robust standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05. Observations are industry-year combinations. Sample includes only industries for which both RegData and input-output data exists. Up-stream (down-stream) regulatory incidence is calculated as the sum of the percent of inputs (outputs) purchased from each industry multiplied by the regulatory stringency of that industry, exclusive of purchases from own industry. Input-output shares are the 2007 detailed industry use tables. Leontief regulatory stringency calculated as the total regulatory stringency the solves the input-output equations of the form  $X = (I_n - A)^{-1}B$ , where X is total regulatory stringency, A is the input-output shares, and B is the regulatory stringency by industry.

Overall, we continue to find little to no evidence that regulatory stringency, whether measured at a partial equilibrium level or using full incidence, is correlated with reduced economic dynamism.

### 3.3 Digging Deeper - The Case of Manufacturing

To better understand the relationship between changes in regulation and changes in measures of dynamism, we now focus on manufacturing industries. With RegData, we are able to identify manufacturing industries that experienced the largest increases and decreases in regulatory stringency between 1999 and 2013. Research has shown that regulation can have a significant effect on firm productivity and the ability to compete internationally. Most analyses of regulation in the manufacturing sector

focus on the impacts of environmental regulations. Using plant level micro data, Gray and Shadbegain (1993), show that more heavily regulated plants have significantly lower productivity levels and slower productivity growth. Manufacturing regulation can also have significant impacts on the dynamics of the industry. Becker and Henderson (2000) find that differential regulatory incidence by attainment status decreases startups and alters the timing of investments.

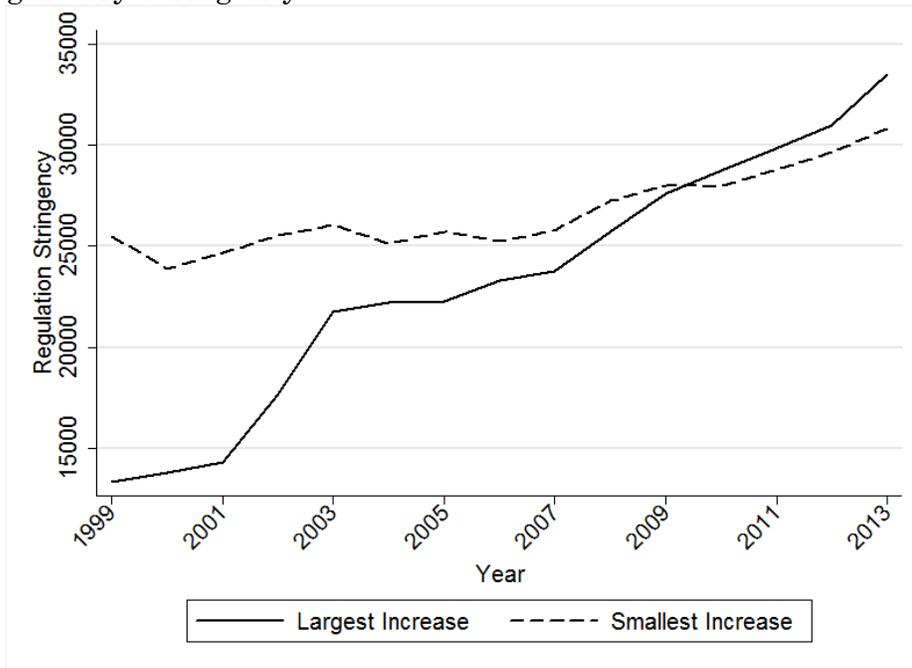
Table 10 shows the five manufacturing industries that experienced the largest and smallest percent change in our regulatory index from 1999 to 2013. Mineral products, furniture, and plastics experience the largest increase in regulatory stringency, while beverages, food, and leather products experienced a loosening in regulatory stringency. Figure 11 shows the regulatory index for these two groups. The average regulation index for the largest increase group more than doubles, where the smallest increase remains flat from 1999 through 2013.

Table 10: Manufacturing - Change in Regulation Index 1999 to 2013

Largest Increase in Regulation Stringency		Smallest Increase in Regulation Stringency	
Name (NAICS Code)	Percent Change	Name (NAICS Code)	Percent Change
Nonmetallic Mineral Products	264.77	Beverage and Tobacco Product	-11.15
Furniture and Related Product	153.70	Food	4.97
Plastics and Rubber Products	149.86	Leather and Allied Product	25.27
Textile Mills	116.67	Apparel	31.83
Chemicals	113.14	Transportation Equipment	44.40

Source: RegData 2.1, authors' calculations.

Figure 11: Manufacturing Industries with Highest and Lowest Increase in Regulatory Stringency

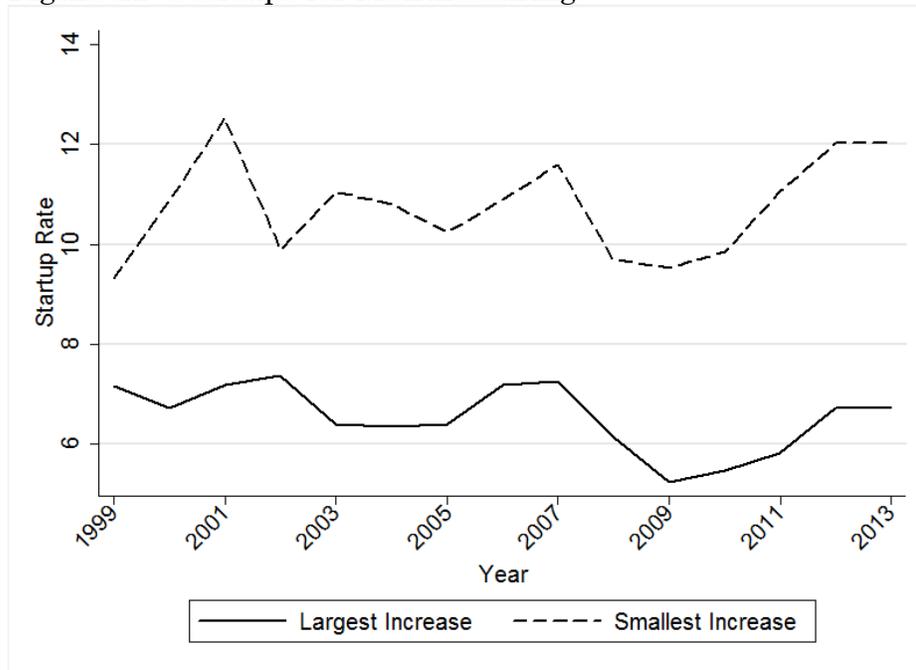


Source: RegData 2.1, authors' calculations.

Notes: Regulatory stringency for the largest increase sample includes the sum of regulatory stringency for the five manufacturing industries experiencing the largest increase in regulatory stringency between 1999 and 2013, shown in Table 10. Similarly, the smallest increase sample includes the five industries shown in Table 10 that experience the smallest increase in regulatory stringency.

Figure 12 shows the startup rates for those industries that saw the largest and smallest increase in regulatory stringency. The industries that saw big increases in regulation had lower startup rates throughout the period, showing little difference in trend compared to industries that saw the smallest increase in regulation. Despite experiencing dramatic increases in regulation, the increasingly regulated industries did not see increasingly lower startup rates.

Figure 12: Startups for Manufacturing

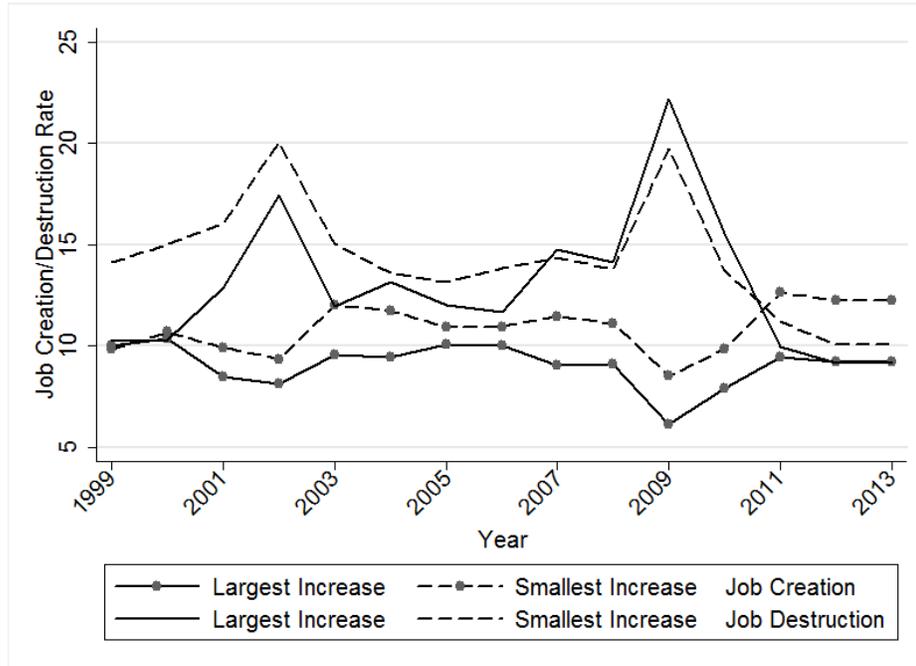


Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.

Notes: Startup rate is calculated as  $100 \times (\text{establishment entry at time } t \text{ divided by the average of estabs at } t \text{ and } t-1)$ .

A similar story appears in the job creation and destruction rates for these two groups. Figure 13 shows that job creation and destruction rates follow similar trajectories, experiencing the same peaks and troughs, despite the fact that these groups of industries saw very different trends in regulatory stringency. The fact that trends in startups, job creation, and job destruction follow a similar path for manufacturing industries with large and small increases in regulatory stringency suggests that causes other than regulation are driving changes in dynamism.

Figure 13: Job Creation and Destruction in Manufacturing



Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.

Notes: Job creation rate is calculated as  $100 \times (\text{job creation at time } t \text{ divided by the average of employment at } t \text{ and } t-1)$ . Job destruction rate is calculated as  $100 \times (\text{job destruction at time } t \text{ divided by the average of employment at } t \text{ and } t-1)$ .

### 3.4 Measurement Error, Endogeneity, and Attenuation Bias

Measurement error and endogeneity bias are alternative explanations for our failure to find large impacts of regulation on dynamism. We test for the presence of measurement error by exploring the effects of increasing length of differencing in both dependent and independent variables. These methods involve assumptions about the structure of the measurement error. We relax these assumptions in a complementary approach investigating the effects of increasing aggregation along our industry dimension. Finally, we leverage the up and down-stream measures of regulation as a way to reduce endogeneity of the regulation measure.

Griliches and Hausman (1986) develop a method to directly measure the impact of measurement error in panel data. If we assume that the measurement error is not serially correlated, and that the error generation

process is common across industries, then differencing the data will reduce attenuation bias. We estimate the following differenced regression model,

$$\Delta_s Y_{t,n} = b_1 \Delta_s Reg_{t,n} + \Delta_s \varepsilon_{t,n} \quad [4]$$

Where  $\Delta_s Y_{t,n}$  is difference in each measure of dynamism of length  $s$  at time  $t$ , for 3-digit NAICS  $n$ , and  $\Delta_s Reg_{t,n}$  is the difference in regulatory stringency of length  $s$  at time  $t$ . The relationship between the coefficient  $b_1$  and the "true" coefficient will be a function of the variance of the measurement error and the variance of the differenced regulation measure.<sup>16</sup> The bias in  $b_1$  changes in  $s$  according to,

$$b_1 = \beta_1 \left[ 1 - \frac{2\sigma_v^2}{Var(\Delta_s Reg_{t,n})} \right] \quad [5]$$

Where  $\beta$  is the "true" coefficient estimate and  $\sigma_v^2$  is the variance of the measurement error. As the difference length  $s$  increases the variance of our differenced regulation measure  $\Delta_s Reg_{t,n}$  rises and  $b_1$  approaches  $\beta_1$ . Table 11 shows the results of estimating equation [4] for lag differences ranging from 1 to 5 years and 14 years, with the 14 year difference being the full length of the time series. Each row captures a different dynamism measure and the columns show the estimated coefficient on the differenced regulatory stringency of varying lengths. If measurement error attenuates the estimated relationship between regulation and dynamism we would expect the absolute value of the estimated coefficient to increase with longer differences. In fact, we find no clear direction of change in the estimates. Most estimates, even with longer differences, remain insignificant as the difference length

---

<sup>16</sup> See Griliches and Hausman (1986) for detailed discussion.

increases. The coefficients on job creation, though significant in longer differences, are of the wrong sign.<sup>17</sup>

Table 11: RegData, Dynamism, and Measurement Error

	$\Delta_s Reg_{t,n}$ $s = 1$	$\Delta_s Reg_{t,n}$ $s = 2$	$\Delta_s Reg_{t,n}$ $s = 3$	$\Delta_s Reg_{t,n}$ $s = 4$	$\Delta_s Reg_{t,n}$ $s = 5$	$\Delta_s Reg_{t,n}$ $s = 14$
$\Delta_s$ Startups	-6.11e-05 (3.63e-05)	-4.15e-05 (2.59e-05)	-1.92e-05 (2.68e-05)	-2.55e-05 (2.33e-05)	-4.05e-06 (2.09e-05)	-3.49e-05 (2.88e-05)
$\Delta_s$ Job Creation	3.78e-05 (4.52e-05)	8.27e-05 (5.43e-05)	0.000104** (5.08e-05)	7.66e-05** (3.44e-05)	5.90e-05** (2.84e-05)	6.88e-05 (4.04e-05)
$\Delta_s$ Job Destruction	2.13e-05 (4.45e-05)	5.67e-06 (4.59e-05)	-6.57e-05 (5.14e-05)	-1.74e-05 (3.88e-05)	-2.80e-05 (3.37e-05)	-3.67e-05 (3.19e-05)

Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.

Notes: Robust standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05. Observations are industry-year combinations. Some industry-year combinations were suppressed in the source SUSB data due to disclosure issues. All dependent variables are rates, except when otherwise denoted. Columns show coefficients of OLS regressions using regulatory stringency index with varying difference lengths. Rows show the dependent variable used, with the difference length equal to the corresponding column.

Differencing the data to detect and account for measurement error requires the assumption that the measurement error is not serially correlated. In our case, however, there may be serial correlation since the CFR changes only slowly over time and therefore word counts and industry associations will change slowly over time. Griliches and Hausman's (1986) insights suggests a second test. Measurement error is likely to be uncorrelated across industries because the relevant words that the machine learning algorithms use for linking will be quite different for different industries. Thus, measurement error should diminish when we aggregate along the industry dimension. Errors at lower levels of aggregation will tend to cancel out as we aggregate to NAICS sectors and super-sectors. Table 12 shows the results of estimating equation [1] using 2 and 1-digit NAICS industries respectively. Again, we find little evidence of attenuation bias in the estimated relationship between federal regulation and dynamism.

<sup>17</sup> For robustness we also estimate instrumental variables regressions using lagged values as instruments for differences as suggested in Griliches and Hausman (1986). The results, reported in Appendix C, are consistent with Table 11, suggesting a relatively limited role of measurement error in explaining our previous results.

Table 12: Measurement Error and Aggregated Industries

	Startups	Job Creation	Job Destruction
<i>2-Digit Industries</i>			
Log Regulatory	0.840	-2.651	-4.889
Stringency	(1.650)	(4.251)	(3.659)
Observations	345	345	345
R-squared	0.385	0.405	0.389
Number of Industries	23	23	23
<i>1-Digit Industries</i>			
Log Regulatory	-0.287	1.942	-9.195
Stringency	(2.030)	(5.262)	(4.483)
Observations	120	120	120
R-squared	0.642	0.652	0.619
Number of Industries	8	8	8

Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.

Notes: Robust standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05. Observations are industry-year combinations. Some industry-year combinations were suppressed in the source SUSB data due to disclosure issues. All dependent variables are rates, except when otherwise denoted. Columns show coefficients of regressing a given dynamism measure using regulatory stringency index with varying level of industry aggregation.

In addition to measurement error, our estimates could be biased by the presence of endogeneity. More dynamic industries may attract regulation, which could attenuate coefficient estimates. We have already covered one test of reverse causation—neither general nor industry-specific regulation appears to explain dynamism. We now perform a second test using the two measures of regulation, up-stream and down-stream regulatory incidence that we developed in Section 3.2. An industry's upstream suppliers and downstream buyers do not necessarily share the same dynamics or political economy as the industry itself. An industry may buy or sell to more or less dynamic or concentrated or politically active industries, for example. Thus, regulations imposed on an industry as a consequence of its up and down-stream connections is less likely to be the result of strategic behavior based on industry dynamism. We can thus use this source of variation in regulation to estimate the influence of regulation on dynamism in a way that is less subject to endogeneity concerns. Table 13 shows estimation results of regressing dynamism measures on up and down-stream regulation. These

regression include only indirect measures rather than simultaneously including the industry specific regulation as in Table 9. Again we find little evidence of attenuation bias in our estimates. Up-stream regulation is actually positively associated with the startup rate and job creation rate, which suggests that industries relying on more heavily regulated inputs tend to be more dynamic not less.

**Table 13: Endogeneity, Regulation, and Supply Chains**

	Startups	Job Creation	Job Destruction
Log Up-Stream Regulatory Stringency	7.312** (2.781)	22.60** (8.580)	3.783 (3.685)
Log Down-Stream Regulatory Stringency	-5.380 (3.225)	10.44** (4.526)	1.106 (6.038)
Constant	-9.936 (43.68)	-326.4*** (101.5)	-36.53 (62.39)
Observations	840	821	820
R-squared	0.167	0.286	0.336
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Source: RegData 2.1, Statistics of U.S. Businesses, BEA Input-Output Accounts data, authors' calculations.

Notes: Robust standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05. Observations are industry-year combinations. Sample includes only industries for which both RegData and input-output data exists. Up-stream (down-stream) regulatory incidence is calculated as the sum of the percent of inputs (outputs) purchased from each industry multiplied by the regulatory stringency of that industry, exclusive of purchases from own industry. Input-output shares are the 2007 detailed industry use tables.

Finally, we consider the plausibility of measurement error driving our results based on the observed variation in our regulation measure. As shown in Figure 8, Figure 9, and Figure 10 there is substantial variation in both our measures of dynamism and regulation. Table 14 quantifies this variability across industries and over time. The 90th percentile industry by regulatory incidence is subject to more than 10 times as much regulation as the 10th percentile industry. The 90-10 gap in measures of dynamism range from 8.9 to 10.8 points. These gaps are quite large, ranging from 61 to 89 percent of

the mean value. Long differences exhibit similarly skewness. The 90th percentile industry by the change in regulatory stringency from 1999 to 2013 saw a 17.5 times greater increase in regulatory stringency relative to the 10th percentile industry. Similarly, the 90-10 gap for our measures of dynamism ranges from 6.1 to 9.4 points.

Table 14: Variation in Regulation and Dynamism

	Industry Mean			1999-2013 Difference	
	Mean	10th	90th	10th	90th
Regulatory Stringency	34,339	8,129	81,567	1,632	28,623
Startup	10.61	6.48	15.94	-3.48	2.64
Job Creation	14.15	8.50	19.26	-6.31	3.10
Job Destruction	14.49	9.89	18.79	-5.29	1.25

Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.

Notes: First column shows the mean across all industries and years. Second and third columns show the 10th and 90th percentiles respectively of the industry means of each measure. The fourth and fifth columns show the 10th and 90th percentile respectively of the difference by industry from 1999 to 2013. Measures of dynamism are rates except when otherwise denoted.

Not only is there significant variation in our regulation measure, but as shown in section 2.2, it varies in plausible ways across industries, agencies, and time. Our measure also aligns well with measures of the overall size of the CFR, such as page counts and file sizes, that have been used in the literature (Mulligan and Shleifer, 2005; Coffey et al., 2012; Dawson and Seater, 2008).<sup>18</sup> All of this suggests that in order for measurement error to explain our negative results, the error variance would have to be quite substantial. Under the classical error-in-variables model the true coefficient is attenuated by the signal-to-total variance ratio, which is equal to the variance of the true measure divided by the variance of the true measure plus the variance in the measurement error. Given the large and reasonable variation in our regulation measure, any attenuation bias due to

<sup>18</sup> The correlation between restrictions by CFR part and the total word count, which is plausibly a more accurate measure of the overall size of regulatory text relative to page counts and file sizes, is almost 0.92.

measurement error would likely be swamped by variation in the true regulation term.

Regulation does not appear to be a major explanation for the decline of dynamism seen in the United States and neither measurement error nor endogeneity bias appear to be large enough to reverse this conclusion.

### 3.5 Industry Size, Import Penetration, and Reallocation

In this section, we offer two additional tests of the regulation hypothesis that do not rely on RegData or measuring regulation. The tests are simple but suggestive.

Our first alternative test of the regulation theory compares changes in industry reallocation rates with changes in industry employment. As described in the previous sections, the Hopenhayn and Rogerson (1993) model shows that regulation when modeled as a tax on labour destruction can reduce hiring, firing, and productivity growth.<sup>19</sup> Regulation reduces the size of the industry *and* it reduces reallocation flows within the industry since the tax dampens both the firm's size and adjustments. Other models will tend to have similar results—industries that are heavily regulated will tend to be smaller and also less dynamic, all else equal. Put differently, if regulation is the primary cause of declining dynamism then we ought to see a positive correlation between declining dynamism and declining industry size.

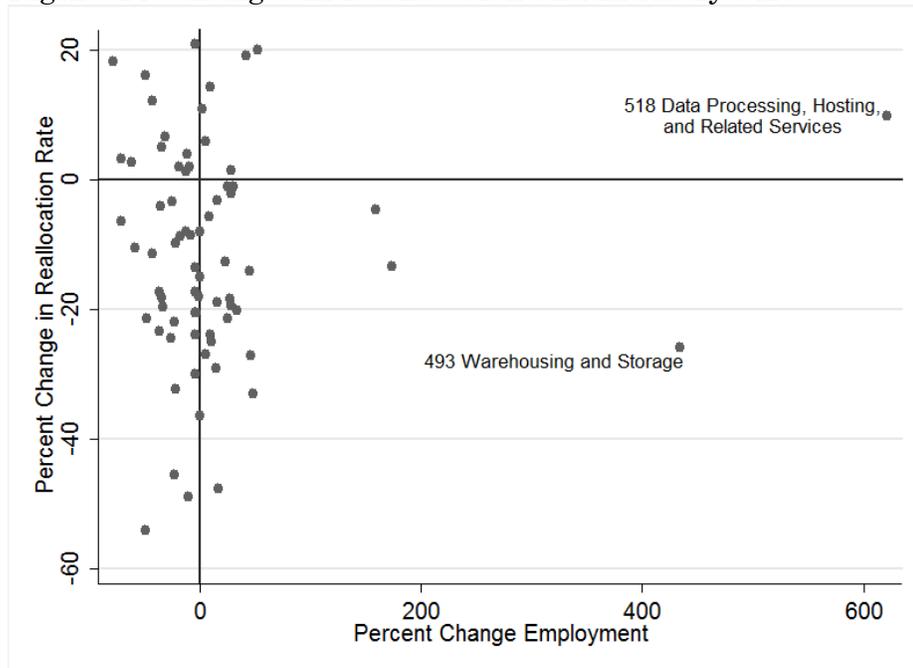
Figure 14 shows the percent change in the reallocation rate against the percent change in employment within industries between 1999 and 2013. We use excess reallocation rates—reallocation above that due to net changes in employment so that changes in employment are not mechanically linked to changes in reallocation rates (Davis et al., 1998). As expected, most industries (~73 %) saw a decline in the industry reallocation rate. Most industries (~57%) also saw employment declines during this period. However,

---

<sup>19</sup> It's also not clear that the kind of regulation modelled by Hopenhayn and Rogerson (1993), a tax on labour destruction, has increased in the United States—while some hiring and firing costs have increased the most obvious cause of such a tax, unionization, has decreased.

there is no clear relationship between declines in reallocation and declines in industry growth because growing industries also exhibited declining reallocation rates.<sup>20</sup> In other words, dynamism is falling throughout the economy. Since regulation and changes in regulation vary greatly across industries but dynamism is falling everywhere—this suggests that regulation is not the primary cause of declining dynamism.

Figure 14: Changes in Reallocation and Industry Size



Source: Statistics of U.S. Businesses, authors' calculations.

Notes: Reallocation rate is defined as the excess reallocation rate developed in Davis et al. (1998), which is calculated as the sum of job creation and destruction rates less the absolute value of net change. Vertical and horizontal lines at zero.

Our second test follows a similar logic. If regulation is raising the cost of doing business in the United States relative to (some of) the rest of the world and if regulation is also reducing dynamism then we ought to see a negative correlation between dynamism and imports—i.e. declining dynamism and greater imports. The effect will be especially strong if regulation is reducing

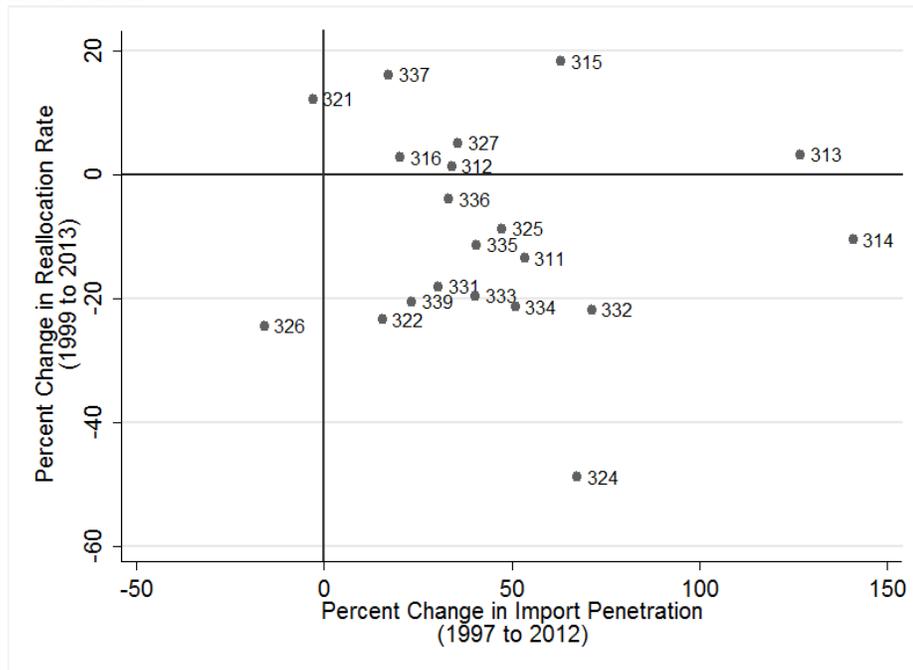
<sup>20</sup> This is also true when using longer time horizons at the broad sector level using Business Dynamics Statistics ([http://www.census.gov/ces/dataproducts/bds/data\\_firm.html](http://www.census.gov/ces/dataproducts/bds/data_firm.html) accessed 2/18/2017).

the kind of dynamism that increases productivity because in this case firms located abroad will be advantaged by lower costs and greater productivity gains.

As a measure of imports we use the share of domestic demand met by imports, the import penetration rate, for a set of 3-digit manufacturing industries.<sup>21</sup> As a measure of dynamism we use the reallocation rate as discussed earlier. The relationship is shown in Figure 15.

Figure 15 indicates that most manufacturing industries have seen greater import penetration over the period 1997 to 2012 but the relationship is not strongly correlated with changes in the reallocation rate.<sup>22</sup> Industries with increasing and decreasing reallocation rates have both seen increases in import penetration.

Figure 15: Changes in Reallocation Rates and Changes in Import Penetration



<sup>21</sup> Import penetration rate is calculated as  $PEN_{it} = \left( \frac{M_{it}}{M_{it} + Q_{it} - X_{it}} \right)$ , for industry  $i$  and time  $t$  where  $M_{it}$  represents the total value of imports,  $Q_{it}$  represents the total value of domestic production, and  $X_{it}$  represents the total value of exports. See Kamal and Lovely (2016) for additional details.

<sup>22</sup> The raw correlation between changes in the reallocation rate and changes in import penetration for these manufacturing industries is less than 0.21.

Source: Statistics of U.S. Businesses, authors' calculations.

Notes: Reallocation rate is defined as the excess reallocation rate developed in Davis et al. (1998), which is calculated as the sum of job creation and destruction rates less the absolute value of net change. Vertical and horizontal lines at zero. Import penetration measures are sourced from Foreign Trade Statistics and Census of Manufacturing data, see Kamal and Lovely (2016) for details.

Our direct test found that regulation was not a primary cause of declining dynamism/churn. Our two indirect tests find that declining reallocation rates are not associated with smaller industry sizes or greater import penetration—two correlations which we would expect if regulation were a primary driver of declining dynamism.

#### 4. Other Causes of Declining Dynamism

Both the authors expected to find a large role for Federal regulation in reducing dynamism. After working with the data, however, our view is that if the effect of Federal regulation on dynamism were strong then it would show up more consistently and clearly. As noted earlier, the question we examine is not whether regulation influences dynamism, it surely does in both positive and negative directions. The question is whether regulation on net has been an important cause of the large, secular, and widespread decline in dynamism in the United States. While other measures of industry-level regulation and other techniques are to be encouraged we suspect that the main message of our paper—we should be looking elsewhere than Federal regulation for the cause of declining dynamism—is robust. Thus, it is appropriate to briefly consider other possible causes of declining dynamism.

Federal law is the most extensive and widely-discussed source of regulation but other sources, such as state-based legislation or common-law judicial interpretation, may also be important for understanding trends in dynamism.<sup>23</sup> Davis and Haltiwanger (2014), for example, find that job

---

<sup>23</sup> The extent of federal regulation is likely to be greater than state regulation. Mulligan and Shleifer (2005), looking at state-level regulations, find that one page of law was equivalent to roughly one-kilobyte of data. On average, each state had about 48,000 kilobytes of law. The Code of Federal Regulations in 2013 had over 175,000 pages

reallocation rates are lower in states whose common-law courts weakened the employment at-will doctrine and they suggest that state-based minimum wages may also have decreased dynamism. The employment at-will doctrine and minimum wages affect some industries more than others, however, so it would be useful to investigate whether these factors can be used to understand trends in dynamism by industry.

Molloy et al. (2016) look at an important type of regulation at the state-level, land use regulation. They find, however, that declines in labour market fluidity are not more pronounced in states with greater land use regulation. Similarly, Jayaratne and Strahan (1996) focus on state-level banking deregulation. They find that state economies performed better following branch deregulation, primarily due to improvements in the quality of lending. Overall, although some differences exist, what is most remarkable about the decline in dynamism in the United States is that it is widespread both across industries and geography.

A variety of other reasons also suggest that regulation in general may play only a small role in the decline in dynamism in the United States. If we look around the world, for example, the most common type of regulations that impede dynamism are those that prevent firms from growing larger. The U.S. economy, however, hosts the largest firms in the world, which are growing even larger. Furthermore, larger firms are more productive on average and the positive relationship between size and productivity is strongest in the United States (Haltiwanger, 2012). If regulation were preventing small firms from growing large then we would expect startup size to be increasing. Instead, we observe no trend towards increased startup size (Haltiwanger et al., 2013).

Declining dynamism may have more fundamental causes than regulation. Gordon (2016) and Cowen (2011), for example, argue that the rate of

---

(<https://www.federalregister.gov/uploads/2014/04/CFR-Actual-Pages-published1-2013.pdf> accessed 02/18/2017).

technological growth has fallen. Declines in technology growth could explain declining rates of dynamism across developed economies. One reason to start a new firm, for example, is to implement a new idea. If progress on the technological frontier is slowing, then entrepreneurs would see fewer new ideas to be profitably implemented and would therefore be less likely to start a new firm (Tabarrok and Goldschlag, 2015).

An important fact is that the decline of dynamism is not limited to the United States (Criscuolo et al., 2014). Increasing regulation everywhere could be responsible for declining dynamism but countries are more likely to experience similar trends in technology than similar trends in regulation.

Hathaway and Litan (2014) and Karahan et al. (2015) argue that much of the decline in the rate of new firm growth can be accounted for in the United States by broad trends in the growth rate of the labour force. Explanations based on the labour force have the virtue of explaining declining trends across all U.S. industries and regions.

It should also be kept in mind that many measures of declining dynamism are associated with greater GDP per capita. For example, on average there are fewer entrepreneurs and more large firms in more developed economies both cross-sectionally and over-time (Bento and Restuccia, 2014; Lucas, 1978; Poschke, 2014). Improvements in information technology may be increasing the ability of large firms to adapt to shocks. Creative destruction brings benefits but at the price of bankruptcies, unemployment, and worker reallocation. If information technology can allow creative destruction to be internalized to the firm rather than the industry this may increase welfare. Declining dynamism and increasing stability are but two ways of naming the same thing.

Better measures of dynamism may be needed to sort out different types of declining dynamism. Some types of declining dynamism may be beneficial (reduced churn). Other types may be harmful but may have a variety of causes ranging from slowdown in technology growth to slowdown in labour

force supply and increases in regulation. It may be that better measures of dynamism are required before we are able to pinpoint the causes of the different types.

We also may be mis-measuring dynamism. As already noted, a great deal of internalized creative destruction or the remaking and restructuring of large firms is not captured by business dynamics statistics. Nor is globalized dynamism. The great majority of Apple's approximately 750 suppliers, for example, are located in Asia. The Apple eco-system, however, is not static. With each iPhone iteration, Apple drops some suppliers and adds others but as this dynamism occurs abroad it is not measured in U.S. statistics.<sup>24</sup> The U.S. may be outsourcing churn.

## 5. Conclusions

The decline in economic dynamism appears unsettling because theory suggests that reallocation plays an important role in economic efficiency. There are solid theoretical reasons to suspect that regulation may deter entry and slow the reallocation of labour. To investigate the extent to which the decline in entrepreneurship can be attributed to increasing regulation, we utilize a novel data source, RegData, which uses text analysis to measure the extent of regulation by industry. We find no evidence to suggest a strong link between federal regulation and the secular decline in U.S. economic dynamism. These results are robust to considering different subsets of firms, delayed impacts of regulation, different types of regulations and regulatory agencies, measuring the effects of regulation through supply chains, and controlling for measurement error.<sup>25</sup>

---

<sup>24</sup> We discuss these issues at greater length in Goldschlag and Tabarrok (2015).

<sup>25</sup> In some cases we found a positive relationship between measures of federal regulation and dynamism. For example, between the regulatory index and job creation among large firms (Table 5), between the general regulatory index and job creation (Table 7), between the upstream regulatory index and startups and job creation (Table 9 and Table 13). Assuming these estimates are robust, which is far from clear, future investigation would be required to detail the underlying mechanisms at work.

To the extent that federal regulation is not the cause of declining dynamism, attention should flow to other sources of regulation such as state and judicial regulation through the common law. Greater attention should also be given to deeper forces that may reduce dynamism such as a slowdown in the technological frontier that reduces the flow of new ideas ready to be profitably implemented. Technology, especially information technology, may also be changing the nature of dynamism in ways that are difficult to measure. The restructuring and rearranging of large firms, for example, can greatly improve the allocation of resources but is not currently well measured. The integration of business dynamic statistics globally would also give us a greater grasp on global dynamism, which may be increasing even as measured national dynamism decreases.

## Appendix A - RegData Example

As an example, the text below is highly associated with the Mining (except oil and Gas) industry.

-----

2010 Title 30 - Mineral Resources

SUBCHAPTER K—PERMANENT PROGRAM PERFORMANCE  
STANDARDS

PART 819—SPECIAL PERMANENT PROGRAM PERFORMANCE  
STANDARDS-AUGER MINING

§ 819.1 Scope.

This part sets environmental protection performance standards for surface coal mining and reclamation operations involving auger mining.

§ 819.11 Auger mining: General.

(a) Auger mining operations **shall** be conducted in accordance with the requirements of part 816 of this chapter, except as provided in this part.

(b) The regulatory authority may prohibit auger mining, if necessary to—

(1) Maximize the utilization, recoverability, or conservation of the solid-fuel resource, or

(2) Protect against adverse water-quality impacts.

§ 819.13 Auger mining: Coal recovery.

(a) Auger mining **shall** be conducted so as to maximize the utilization and conservation of the coal in accordance with § 816.59 of this chapter.

(b) Auger mining **shall** be planned and conducted to maximize recoverability of mineral reserves remaining after the operation and reclamation are complete.

(c) Each person who conducts auger mining operations **shall** leave areas of undisturbed coal, as approved by the regulatory authority, to provide access for future underground mining activities to coal reserves remaining after augering is completed, unless it is established that the coal reserves have

been depleted or are so limited in thickness or extent that it will not be practicable to recover the remaining coal. This determination **shall** be made by the regulatory authority upon presentation of appropriate technical evidence by the operator.

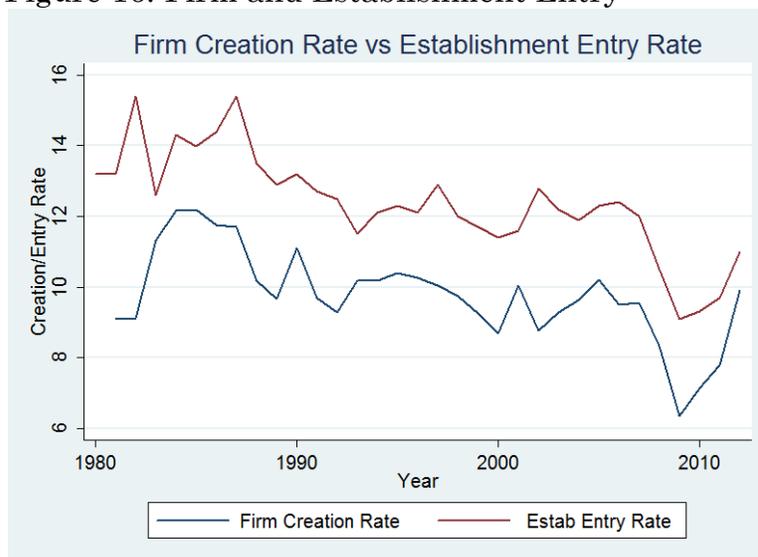
## Appendix B: Firm versus Establishment Startup Rate

In our view Steve Jobs was an entrepreneur when he co-founded Apple computer in 1976 (firm creation) but also when he returned to Apple in 1997 restoring Apple to productivity and greatly expanding the number of products and Apple stores (establishment entry) (Goldschlag and Tabarrok, 2015).

Thus it is appropriate to measure dynamism at the establishment level. Note also that most regulations will affect new establishments in a similar way to new firms. Regulation of labour, land use, safety and environmental regulations, for example, will affect new firms and new establishments thus it is better to use the larger measure.

In Figure 16 we show the national firm creation rate as defined by Hathaway and Litan (2014) and the national establishment entry rate from the BDS data. The establishment rate, which includes new firms, is above the firm creation rate but the two trend together both secularly and over shorter periods of time. The two correlate at .75.

Figure 16. Firm and Establishment Entry



Source: Business Dynamics Statistics, U.S. Census Bureau, authors' calculations.

## Appendix C: Robustness Exercises

Table 15 reports regression results including lagged regulatory stringency in place of regulation at time  $t$ . Table 16 reports regression results including time trends along with year fixed effects (omitting one year), and with the inclusion of industry trends. Table 17 presents regressions that directly address non-linearities between regulation and dynamism, replacing Log Regulatory Stringency with Regulatory Stringency and Regulatory Stringency squared. Table 18 reports regression results using regulatory stringency index that only includes regulations associated with the IRS. Table 19 presents regression results using CFR word counts associated with each industry rather than restrictive terms. Table 20 reports the results of estimating instrumental variables specifications, as suggested by Griliches and Hausman (1986), with varying difference length and instrument sets, estimated using both two-staged least squares (2SLS) and generalized method of moments (GMM) estimators. The results are consistent with Table 11, suggesting a relatively limited role of measurement error in explaining our previous results.

Table 15: Robustness, Including Only Lagged Regulatory Stringency

	Startups	Job Creation	Job Destruction
Log Reg Stringency (-1)	2.144 (1.770)	1.393 (0.804)	-0.121 (1.376)
Log Reg Stringency (-2)	-0.567 (0.799)	1.150 (0.955)	1.638* (0.981)
Constant	-4.698 (14.11)	-9.475 (11.35)	-0.956 (13.33)
Observations	1,125	1,106	1,105
R-squared	0.198	0.282	0.330
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.  
 Notes: Robust standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05.  
 Observations are industry-year combinations. Some industry-year combinations were suppressed in the source SUSB data due to disclosure issues. All dependent variables are rates, except when otherwise denoted.

Table 16: Robustness, Time and Industry-Time Trends

	Startups	Job Creation	Job Destruction	Startups	Job Creation	Job Destruction
Log Regulatory Stringency	0.661 (0.620)	1.474** (0.708)	1.459 (0.978)	0.670 (0.617)	1.462** (0.707)	1.428 (0.974)
Constant	69.57 (52.39)	321.2*** (71.64)	392.4*** (73.69)	68.79 (51.67)	315.7*** (71.38)	383.8*** (72.60)
Observations	1,125	1,106	1,105	1,125	1,106	1,105
R-squared	0.791	0.759	0.704	0.791	0.759	0.704
Industry FE	Yes	Yes	Yes	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	No	No	No
Ind-Time Trend	No	No	No	Yes	Yes	Yes

Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.  
 Notes: Robust standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05. Observations are industry-year combinations. Some industry-year combinations were suppressed in the source SUSB data due to disclosure issues. All dependent variables are rates, except when otherwise denoted. One year fixed effect omitted when time trend included.

Table 17: Robustness, Non-Linearities

	Startups	Job Creation	Job Destruction
Regulatory Stringency	1.54e-05 (3.08e-05)	7.08e-05 (3.73e-05)	8.49e-05 (4.69e-05)
Regulatory Stringency^2	0 (1.36e-10)	8.84e-11 (1.77e-10)	-4.08e-10 (2.35e-10)
Constant	66.22 (54.81)	384.4*** (66.60)	393.9*** (72.60)
Observations	1,125	1,106	1,105
R-squared	0.791	0.762	0.704
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.

Notes: Robust standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05. Observations are industry-year combinations. Some industry-year combinations were suppressed in the source SUSB data due to disclosure issues. All dependent variables are rates, except when otherwise denoted.

Table 18: Robustness, Only IRS Regulations

	Startups	Job Creation	Job Destruction
Log Regulatory Stringency (IRS Only)	-0.909 (1.022)	-2.371 (1.674)	1.199 (1.336)
Constant	16.93** (6.825)	31.46*** (11.19)	6.112 (8.837)
Observations	1,125	1,106	1,105
R-squared	0.193	0.280	0.329
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.

Notes: Robust standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05.

Observations are industry-year combinations. Some industry-year combinations were suppressed in the source SUSB data due to disclosure issues. All dependent variables are rates, except when otherwise denoted. Sample includes only regulations associated with the Internal Revenue Service.

Table 19: Robustness, Industry Word Count (Rather than Restrictions)

	Startups	Job Creation	Job Destruction
Log Industry CFR Word Count	0.939 (1.104)	1.565 (1.049)	1.433 (1.196)
Constant	-2.660 (15.81)	-6.883 (15.09)	-6.594 (17.26)
Observations	1,125	1,106	1,105
R-squared	0.193	0.279	0.330
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.

Notes: Robust standard errors in parentheses, \*\*\* p<0.01, \*\* p<0.05.

Observations are industry-year combinations. Some industry-year combinations were suppressed in the source SUSB data due to disclosure issues. All dependent variables are rates, except when otherwise denoted. Industry CFR word count is generated using the count of all words in each CFR part rather than just restrictive terms as in our Regulatory Stringency Index.

Table 20: Measurement Error and Lagged Instruments

	$\Delta_s$ Startups	$\Delta_s$ Job Creation	$\Delta_s$ Job Destruction
<i>s</i> =1			
$\Delta_s Reg_{t,n}$ (2SLS)	1.84e-05 (0.000129)	0.000185 (0.000132)	-0.000142 (0.000158)
$\Delta_s Reg_{t,n}$ (GMM)	-1.36e-05 (0.000116)	0.000176 (0.000122)	-0.000208 (0.000154)
Lagged Instruments	t-2 to t-5	t-2 to t-5	t-2 to t-5
<i>s</i> =3			
$\Delta_s Reg_{t,n}$ (2SLS)	2.52e-06 (3.65e-05)	0.000134** (5.22e-05)	-0.000230*** (7.20e-05)
$\Delta_s Reg_{t,n}$ (GMM)	1.15e-06 (3.58e-05)	0.000156*** (5.01e-05)	-0.000238*** (7.20e-05)
Lagged Instruments	t-1 to t-2, t-4 to t-5	t-1 to t-2, t-4 to t-5	t-1 to t-2, t-4 to t-5
<i>s</i> =5			
$\Delta_s Reg_{t,n}$ (2SLS)	1.83e-05 (2.55e-05)	3.68e-05 (3.60e-05)	5.30e-05 (3.97e-05)
$\Delta_s Reg_{t,n}$ (GMM)	2.33e-05 (2.54e-05)	4.11e-05 (3.49e-05)	7.25e-05 (3.92e-05)
Lagged Instruments	t-1 to t-4	t-1 to t-4	t-1 to t-4

Source: RegData 2.1, Statistics of U.S. Businesses, authors' calculations.

Notes: Robust standard errors in parentheses, \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ . Observations are industry-year combinations. Some industry-year combinations were suppressed in the source USB data due to disclosure issues. All dependent variables are rates, except when otherwise denoted. Columns show coefficients of regressing the difference of a given dynamism measure on the same difference in the regulatory stringency index. Rows show the estimated coefficient of the difference regulatory index using either 2SLS or GMM for different length differences and combinations of lagged levels of the regulatory stringency index as instruments.

## References

- Alesina, A., Ardagna, S., Nicoletti, G., & Schiantarelli, F. (2005). Regulation and investment. *Journal of the European Economic Association*, 3(4), 791-825.
- Al-Ubaydli, O. and P. McLaughlin (2015). 'RegData: a numerical database on industry-specific regulations for all U.S. industries and federal regulations, 1997-2012.' *Regulation and Governance*, in press.
- Ardagna, S., & Lusardi, A. (2008). *Explaining international differences in entrepreneurship: The role of individual characteristics and regulatory constraints* (No. w14012). National Bureau of Economic Research.
- Bartelsman, E., Haltiwanger, J., & Scarpetta, S. 2013. Cross-Country Differences in Productivity: The Role of Allocation and Selection. *American Economic Review*, 103(1): 305–34.
- Becker, R., & Henderson, V. (2000). Effects of air quality regulations on polluting industries. *Journal of Political Economy*, 108(2), 379–421.
- Bento, P., & Restuccia, D. (2014). *Misallocation, Establishment Size, and Productivity*. Working Paper no. tecipa-517. University of Toronto, Department of Economics. Retrieved from <https://ideas.repec.org/p/tor/tecipa/tecipa-517.html>
- Bertrand, M. and Kramarz, F. (2002), 'Does Entry Regulation Hinder Job Creation? Evidence from the French Retail Industry', *The Quarterly Journal of Economics*, 117(4): 1369–1413.
- Bessen, J. (2016). Accounting for Rising Corporate Profits: Intangibles or Regulatory Rents? Boston Univ. School of Law, Law and Economics Research Paper No. 16–18.
- Braunerhjelm, P., & Eklund, J. E. (2014). Taxes, tax administrative burdens and new firm formation. *Kyklos*, 67(1), 1–11.
- Bruhn, M. (2013). A tale of two species: Revisiting the effect of registration reform on informal business owners in Mexico. *Journal of Development Economics*, 103, 275-283.

- Chambers, D. and C.A. Collins (2016). “How Do Federal Regulations Affect Consumer Prices? An Analysis of the Regressive Effects of Regulation.” Mercatus Working Paper. Arlington, VA: Mercatus Center at George Mason University.
- Ciccone, A., & Papaioannou, E. (2007). Red tape and delayed entry. *Journal of the European Economic Association*, 5(2-3), 444-458.
- Coffey, B., McLaughlin, P. A., & Tollison, R. D. (2012). Regulators and Redskins. *Public Choice*, 153, 191–204.
- Cowen, T. 2011. *The Great Stagnation: How America Ate All the Low-Hanging Fruit of Modern History, Got Sick, and Will (Eventually) Feel Better*. New York: Dutton Adult.
- Criscuolo, C., Gal, P. N., & Menon, C. (2014). *The Dynamics of Employment Growth*. OECD Science, Technology and Industry Policy Papers. Paris: Organisation for Economic Co-operation and Development. Retrieved from <http://www.oecd-ilibrary.org/content/workingpaper/5jz417hj6hgg6-en>
- Davies, Antony. (2014). “Regulation and Productivity.” Mercatus Research. Arlington, VA: Mercatus Center at George Mason University.
- Davis, S. J., Haltiwanger, J. C., & Schuh, S. (1998). Job creation and destruction. MIT Press Books, 1.
- Davis, S. J., Faberman, R. J., & Haltiwanger, J. (2012). Labor market flows in the cross section and over time. *Journal of Monetary Economics*, 59(1), 1–18.
- Davis, S. J., Faberman, R. J., Haltiwanger, J., Jarmin, R. and Miranda, J. (2010), ‘Business Volatility, Job Destruction, and Unemployment’, *American Economic Journal: Macroeconomics*, 2(2): 259–87.
- Davis, S. J., & Haltiwanger, J. (2014). *Labor Market Fluidity and Economic Performance*. Working Paper no. 20479. National Bureau of Economic Research. Retrieved from <http://www.nber.org/papers/w20479>
- Davis, S. J., Haltiwanger, J. C. and Schuh, S. (1998), *Job Creation and Destruction*. Cambridge, Mass.: The MIT Press.

- Dawson, J., & Seater, J. (2008). Federal Regulation and Aggregate Economic Growth. Working Paper.
- Decker, R., Haltiwanger, J., Jarmin, R., & Miranda, J. (2014). The role of entrepreneurship in US job creation and economic dynamism. *The Journal of Economic Perspectives*, 28(3), 3–24.
- Decker, R. A., Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2015). *Where Has All The Skewness Gone? The Decline In High-Growth (Young) Firms In The U.S.* Working Paper no. 21776. National Bureau of Economic Research. Retrieved from <http://www.nber.org/papers/w21776>
- Djankov, S., Ganser, T., McLiesh, C., Ramalho, R., & Shleifer, A. (2010). The effect of corporate taxes on investment and entrepreneurship. *American Economic Journal: Macroeconomics*, 2(3), 31-64.
- Djankov, S., La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2002). The regulation of entry. *The quarterly Journal of economics*, 117(1), 1-37.
- Eslava, M., Haltiwanger, J., Kugler, A., & Kugler, M. (2010). Factor adjustments after deregulation: panel evidence from Colombian plants. *The Review of Economics and Statistics*, 92(2), 378–391.
- Foster, L., Haltiwanger, J. and Krizan, C. J. (2006), 'Market Selection, Reallocation, and Restructuring in the U.S. Retail Trade Sector in the 1990s', *The Review of Economics and Statistics*, 88(4): 748–758.
- Gordon, R. J. 2016. *The Rise and Fall of American Growth: The U.S. Standard of Living since the Civil War*. Princeton: Princeton University Press.
- Gray, W. B., & Shadbegian, R. J. (1993). *Environmental regulation and manufacturing productivity at the plant level* (No. w4321). National Bureau of Economic Research.
- Gruber, J., & Madrian, B. C. (2002). *Health Insurance, Labor Supply, and Job Mobility: A Critical Review of the Literature*. Working Paper no. 8817. National Bureau of Economic Research. Retrieved from <http://www.nber.org/papers/w8817>

- Haltiwanger, J. (2012). Job creation and firm dynamics in the United States. In *Innovation Policy and the Economy, Volume 12* (pp. 17–38). University of Chicago Press.
- Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2013). Who creates jobs? Small versus large versus young. *Review of Economics and Statistics*, 95(2), 347–361.
- Haltiwanger, J., Jarmin, R., & Miranda, J. (2009). “Business Dynamics Statistics: An Overview.” Kauffman Foundation: Other Research. Available at SSRN: <http://ssrn.com/abstract=1456465>.
- Haltiwanger, J. & Scarpetta, S. & Schweiger, H. (2014). "Cross country differences in job reallocation: The role of industry, firm size and regulations," *Labour Economics*, Elsevier, vol. 26(C), pages 11–25.
- Hathaway, Ian, & Litan, Robert. (2014). *What's Driving the Decline in the Firm Formation Rate? A Partial Explanation*. The Brookings Institution.
- Heim, B. T., & Lurie, I. Z. (2014). Did reform of the non-group health insurance market affect the decision to be self-employed? Evidence from the State Reforms in the 1990s. *Health Economics*, 23(7): 841–860.
- Hopenhayn, H., & Rogerson, R. (1993). Job turnover and policy evaluation: A general equilibrium analysis. *Journal of Political Economy*, 101(5), 915–938.
- Hsieh, C.-T., & Klenow, P. J. (2009). Misallocation and Manufacturing TFP in China and India. *The Quarterly Journal of Economics*, 124(4): 1403–1448.
- Jayaratne, J., & Strahan, P. E. (1996). The finance-growth nexus: Evidence from bank branch deregulation. *The Quarterly Journal of Economics*, 111(3), 639-670.
- Kamal, F. and Lovely, M., *forthcoming*. "Import Competition from and Offshoring to Low-Income Countries: Implications for Employment and Wages at U.S. Domestic Manufacturers," *Journal of Asian Economics*.
- Karahan, F., Pugsley, B., & Sahin, A. (2015). *Understanding the 30 year Decline in Business Dynamism: a General Equilibrium Approach*. 2015

- Meeting Paper no. 1333. Society for Economic Dynamics. Retrieved from <http://econpapers.repec.org/paper/redsed015/1333.htm>
- Klapper, L., Laeven, L., & Rajan, R. (2006). Entry regulation as a barrier to entrepreneurship. *Journal of financial economics*, 82(3), 591-629.
- Lucas, R. E., Jr. 1978. On the Size Distribution of Business Firms. *The Bell Journal of Economics*, 9(2): 508–523.
- Molloy, R., Smith, C. F., Trezzi, R., & Wozniak, A. (2016). Understanding declining fluidity in the U.S. labor market. Brookings Papers on Economic Activity, Conference Draft.
- Mulligan, C., & Shleifer, A. (2005). The Extent of the Market and the Supply of Regulation. *Quarterly Journal of Economics*, 120: 1445–1473.
- Olley, G. S., & Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica: Journal of the Econometric Society*, 64(6): 1263–1297.
- Olson, Mancur. (1977). *The logic of collective action: public goods and the theory of groups*. Cambridge, Mass: Harvard University Press.
- Olson, M. (1984). *The Rise and Decline of Nations: Economic Growth, Stagflation, and Social Rigidities*. New Haven: Yale University Press.
- Pizzola, B. (2015). The impact of business regulation on business investment: Evidence from the recent experience of the United States. Working paper.
- Poschke, M. (2014). *The Firm Size Distribution Across Countries and Skill-Biased Change in Entrepreneurial Technology*. SSRN Scholarly Paper no. ID 2403128. Rochester, NY: Social Science Research Network. Retrieved from <http://papers.ssrn.com/abstract=2403128>
- Simon, C. P., & Blume, L. E. (1994). *Mathematics for Economists*. New York, NY: W. W. Norton & Company.
- Stigler, G. (1971). The Theory of Economic Regulation. *Bell Journal of Economics and Management Science* 2, 3–21.
- Syverson, C. (2004). Market Structure and Productivity: A Concrete Example. *Journal of Political Economy*, 112(6): 1181–1222.

- Syverson, C. (2011). What determines productivity? *Journal of Economic Literature*, 49(2): 326–365.
- Tabarrok, A., & N. Goldschlag. (2015). Is Entrepreneurship in Decline? In *Understanding the Growth Slowdown* (ed. Brink Lindsey) pp. 169–187. Wash. DC: Cato Institute Press.
- Tullock, G. (1967). The welfare costs of tariffs, monopolies, and theft. *Economic Inquiry*, 5(3), 224–232.
- Witten, I. H., & Frank, E. (2005). *Data Mining: Practical Machine Learning Tools and Techniques*. Morgan Kaufmann.
- Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.