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# Is regulation to blame for the decline in American entrepreneurship?

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## 1. INTRODUCTION

The movement of resources from low-productivity firms to high-productivity firms drives economic efficiency and growth. Startups contribute significantly to this reallocation process. Many startups fail within a few years, so startups contribute to both job creation and job destruction.<sup>1</sup> A small subset of startups, however, grow quickly, and contribute disproportionately to net job growth and to improvements in industry

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1 See Syverson (2004), Syverson (2011), and Bartelsman *et al.* (2013) for a review of the productivity literature and the linkage between reallocation and productivity.

## SUMMARY

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*Mounting evidence suggests that economic dynamism and entrepreneurial activity are declining in the United States. Over the past 30 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.*

*JEL codes: J23, K20, L26, M13*

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productivity. Workers also move among firms at tremendous rates which means that gross job creation and destruction are much larger than net job creation. As workers reallocate, productivity increases, knowledge diffuses, and the structure of production changes.

Although the US 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.<sup>2</sup> 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 (BDS). The decline in dynamism is associated with reductions in productivity, real wages, and employment. 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 US 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. This research uses a novel source of data on federal regulations to determine the extent to which federal regulations can explain the severity of the decline in dynamism at the industry level. We find no significant relationship between federal regulation and changing economic dynamism. The reason is essentially simple, the decline in dynamism is widespread and exists across highly regulated and less regulated sectors of the economy. 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.

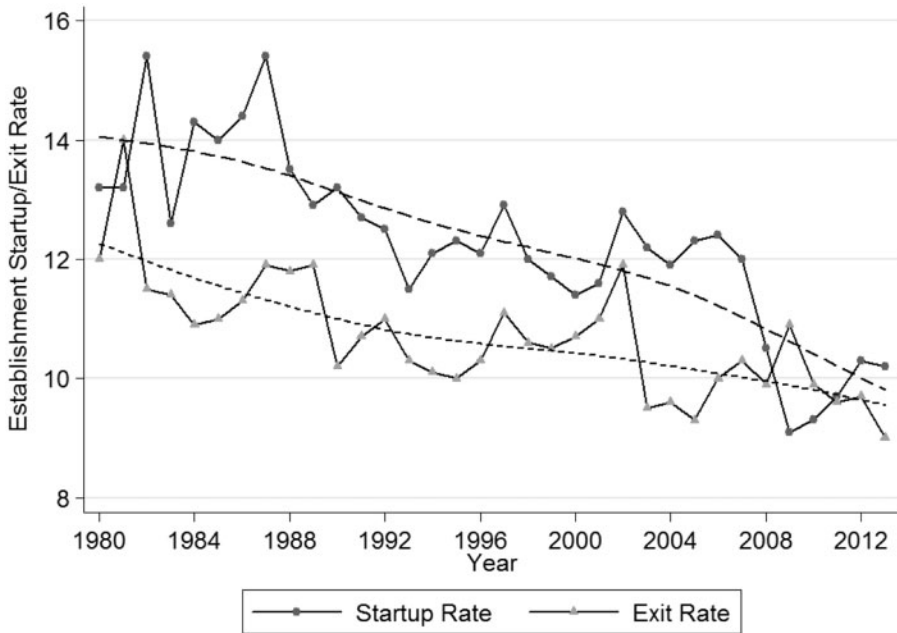
The remainder of the paper is organized as follows. Section 2 describes data on economic dynamism and federal regulation and illustrates important trends and stylized facts motivating the analyses. Section 3 presents a series of analyses that measure the relationship between federal regulation and economic 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 discuss the measures of dynamism used in the literature and some key facts about trends in economic dynamism in the United States since the 1980s. Using data from the Census Bureau's BDS, [Figure 1](#) shows the substantial decline in

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2 See [Decker \*et al.\* \(2014\)](#) and [Davis and Haltiwanger \(2014\)](#) for a review of the decline in US economic dynamism.



**Figure 1. US annual establishment startup and exit rates**

*Notes:* Startup and exit rates are calculated using establishment entry and exit. Following the [Davis et al. \(1998\)](#), establishment startup (exit) rates are calculated as  $100 * (\text{establishment entry (exit) at time } t \text{ divided by the average establishments at } t \text{ and } t-1)$ . Hodrick–Prescott filter shown with multiplier 400.

*Source:* Business Dynamics Statistics, US Census Bureau, Authors' Calculations.

startup and exit rates over the past several decades. The startup rate, which captures the share of age zero businesses in the economy, fell from 13.7% in 1980 to 11.7% just before the Great Recession. Similarly, the exit rate fell from 12.1% in 1980 to 10.3% in 2007.

Similar patterns can be seen in annual job creation and destruction rates. The job creation rate, which captures positive employment changes as a share of total employment in the period, 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.

The slowing of entrepreneurial activity is also affecting firm-level distributions such as firm age. The BDS data show 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 ageing firm population. In the

late 1980s, nearly half of all firms were young (aged less than 5 years) but only 39% of firms were young prior to the Great Recession. In contrast, the share of old firms (aged 16 years 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. In addition, since 2000 there have been fewer high-growth firms among the smaller stock of young firms (Decker *et al.*, 2016).

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 produces twice as much as firms in the 10th percentile. Perhaps less surprising, higher productivity firms are more likely to survive. Reallocation in the form of entry, exit, expansions, and contractions has 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 judgement because these are complex phenomena with multiple causes and consequences. Dynamism, for example, could be relabelled ‘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 relabelled 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.

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 has catalogued the relationship between economic outcomes and a number of different policies, institutions, and regulations.<sup>3</sup> Studies using cross-country variation have shown that employment protection

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3 For example, see Haltiwanger *et al.* (2014), Olley and Pakes (1996), Eslava *et al.* (2010), Davis and Haltiwanger (2014), Bertrand and Kramarz (2002), Braunerhjelm and Eklund (2014), and Ardagna and Lusardi (2008).

legislation and other labour market institutions tend to reduce job reallocation rates and could explain the differential performance between American and European labour markets. Other studies have shown that product and labour market regulations slow factor adjustment and cause allocative inefficiencies. Similarly, evidence suggests that entry deterrence regulations can slow employment growth and discourage early stage entrepreneurship. Regulation may also reduce entrepreneurship indirectly by dampening the effects of skills, social networks, and attitudes towards risk. 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.

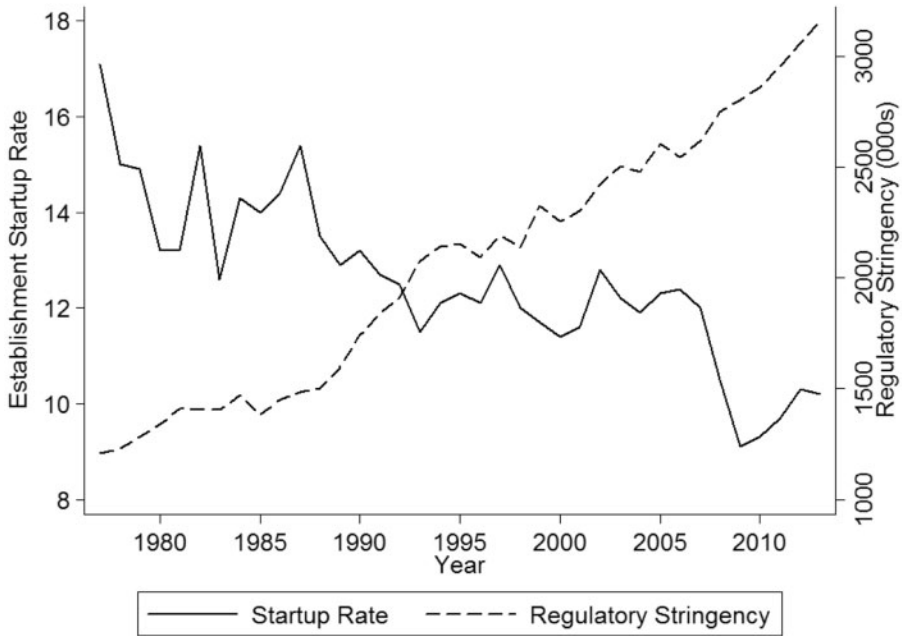
It is important to note, however, that regulation need not reduce dynamism. A tax, for example, might reduce the level of economic activity but in equilibrium it need not reduce the rate of firm entry or exit or impede the reallocation process that shifts resources from low productivity to high productivity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

It is also the case that 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, 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.

Although the impact of regulation on dynamism is unclear in theory some crude evidence supports a negative impact. Figure 2 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, provide motivation for measuring the extent to which federal regulation may explain the secular decline in business dynamism.

Prior studies of regulation have relied upon crude measures of US regulation such as file sizes, page counts, and word counts of the Federal Register (FR) or Code of Federal Regulations (CFR). Mulligan and Shleifer (2005), for example, measure regulation in kilobytes.<sup>4</sup> Dawson and Seater (2013) estimate a dynamic model of growth on US data and include the page count of the CFR as a measure of regulation. They find that regulation has reduced output and productivity. Dawson and Seater (2013) do not examine the dynamism issues that are the focus of this paper. In addition, time-series evidence from one country could be subject to considerable biases and can be interpreted as causal only with strong assumptions.

4 Examples of empirical studies of regulation include Mulligan and Shleifer (2005), Coffey *et al.* (2012), and Dawson and Seater (2013).



**Figure 2. Establishment startup rate and regulatory stringency**

*Notes:* Total 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.

*Source:* RegData 2.1, Business Dynamics Statistics, US Census Bureau, Authors' Calculations.

A number of international studies have found a negative relationship between entry regulation and entrepreneurship. Djankov *et al.* (2002) summarize 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, and a negative relationship between entry regulations and entry, technological change, and growth.<sup>5</sup>

The international variation in regulation, however, 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 cost is only 0.5% of GDP per capita. Entry regulations in the Dominican Republic may reduce entry and entrepreneurship but this need not imply that federal regulation in the United States has led to the secular decline in US entry and entrepreneurship.

5 See Alesina *et al.* (2005), Ciccone and Papaioannou (2007), Bruhn (2013), and Klapper *et al.* (2006).

In fact, there has been relatively little change in the World Bank's Doing Business measures for the United States between 2004 and 2016. The United States is relatively close to frontier best practices across most measures. For the starting a business measure, for example, there has been relatively little movement over time with the United States inching slightly closer to the frontier by 2016. Likewise, getting credit, paying taxes, and resolving insolvency have all improved in the United States over this period while enforcing contracts declines slightly. Since regulation has not changed dramatically by these measures, the Doing Business data do not suggest a strong relationship between federal regulation and declining dynamism.

It is common to analyse 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 US 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

Our primary source of information on regulation is RegData, a database built upon the CFR.<sup>6</sup> The CFR captures 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 CFR or the FR. 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

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



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.

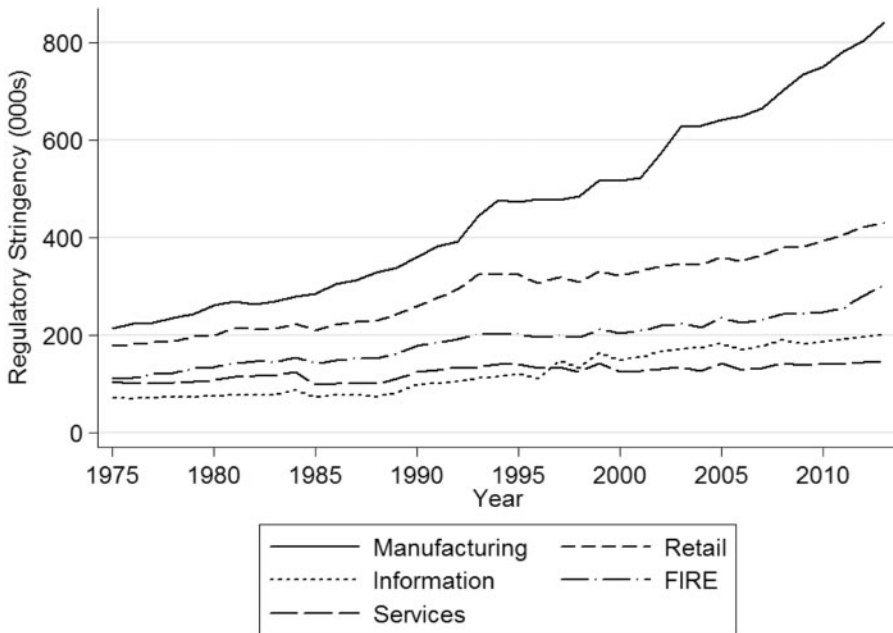
The second way that RegData improves upon previous measures is by disaggregating the measure of regulation to the industry level. The CFR is divided into sections, including titles, chapters, subchapters, parts, and subparts. Although the titles of the CFR often have suggestive names such as ‘Energy’, ‘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 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, 2011](#)).

[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 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 3](#) 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 industries relative to other sectors.

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 more than 10 times higher than that for courier and messengers (NAICS 492). 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’ when compared with sections of the text about couriers and messengers. The large variation in regulation by industry provides scope to identify



**Figure 3. Regulatory stringency by major sector**

*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.

*Source:* RegData 2.1, Authors' Calculations.

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 1 shows the top federal agencies by mean regulatory impact between 1999 and 2013 with the values for each agency relative to the agency responsible for the most regulation. 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 include 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.

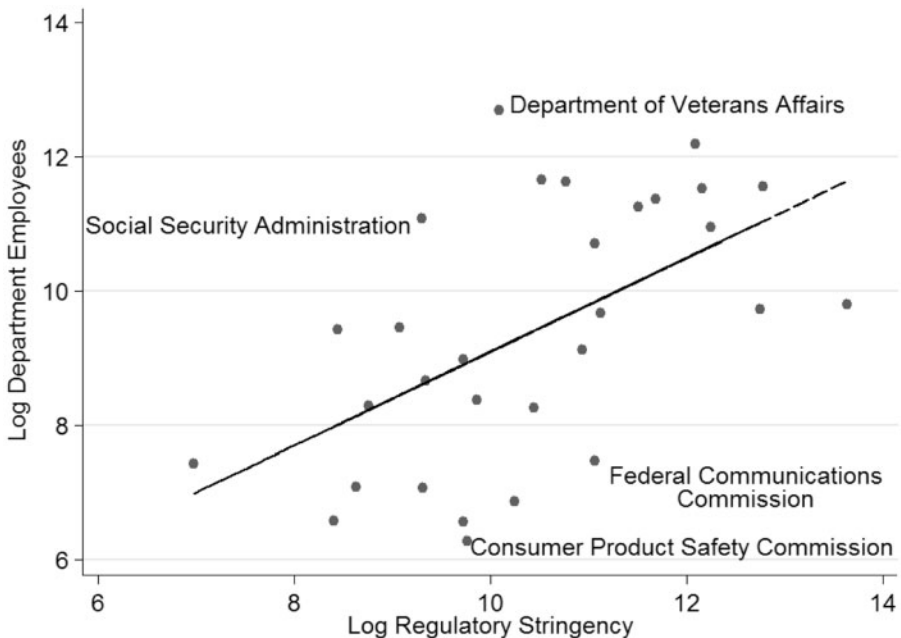
Figure 4 also provides some suggestive evidence on the ability of the RegData algorithm to accurately measure regulation. Agency employment increases with regulatory stringency as identified by the algorithm. It is also notable that there is some intuition for the agencies off the regression line. The Department of Veterans Affairs, for

**Table 1. Regulatory stringency by agency (average 1999–2013)**

| Agency name                                   | Regulatory stringency (EPA = 100) |
|---|-----------------------------------|
| 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 Defence            | 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                              |

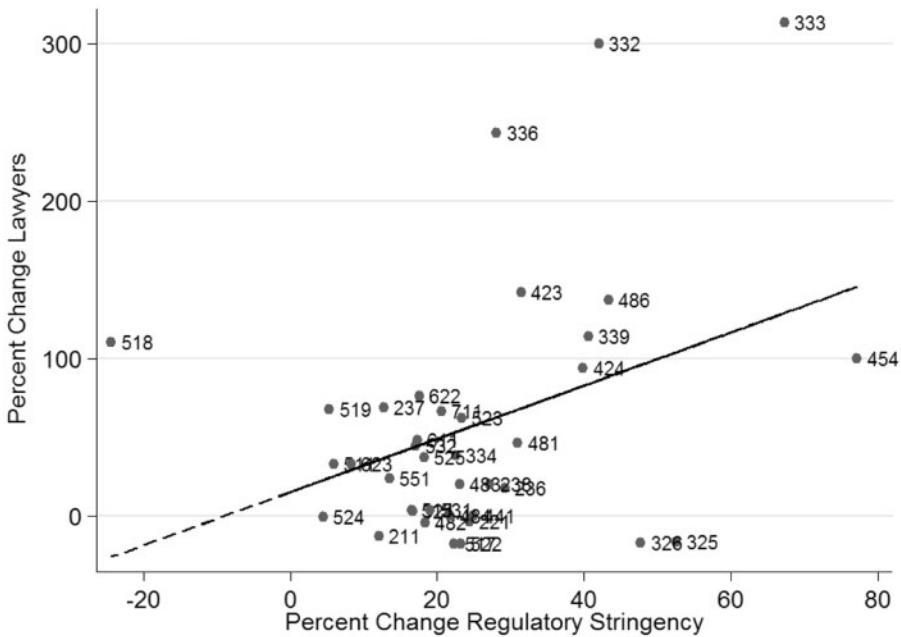
*Notes:* Total regulatory stringency by agency calculated as the sum of restrictive terms weighted by the probability of association between each industry and CFR part aggregated by the agency responsible for each CFR part. All values indexed to the agency with the highest associated regulatory stringency.

*Source:* RegData 2.1, Authors' Calculations.

**Figure 4. Department employment and regulatory stringency**

*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.

*Source:* RegData 2.1, OPM FedScope Employment Cube September 2012, Authors' Calculations.



**Figure 5. Industry employment of lawyers and regulatory stringency, 2002–11**

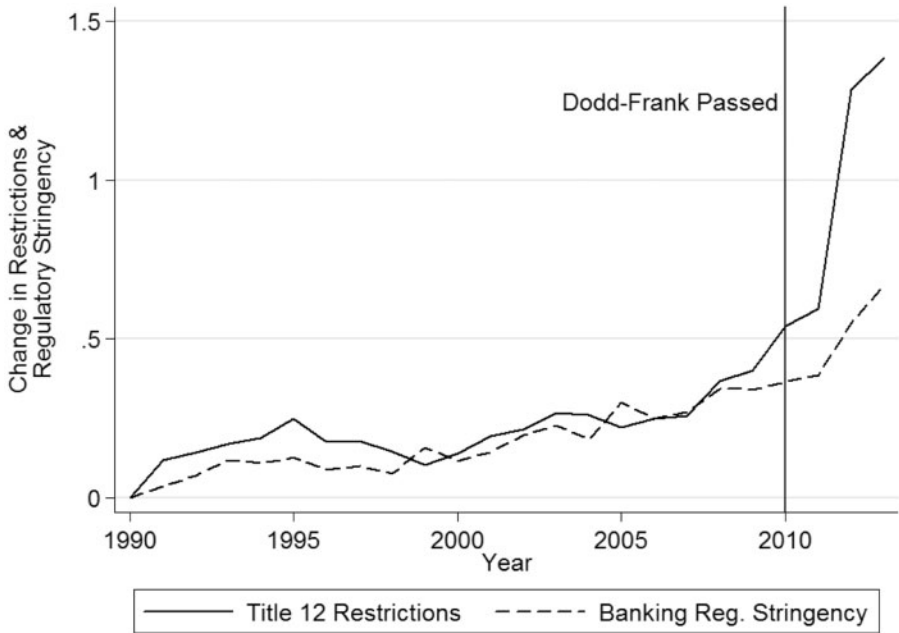
*Notes:* Figure shows percent change in values from 2002 to 2011. Percent change in regulatory stringency by industry is calculated as the percent change in the sum of restrictive terms weighted by the probability of association between each industry and CFR part aggregated by three-digit 2007 NAICS industries. Percent change in lawyers derived from BLS Occupation Employment Statistics Data using total employment in the standard occupation code for Lawyer (23-1011) by industry. Industry codes for 2002 conformed using equal weighting to 2007 NAICS codes. 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 and NAICS 624 Social Assistance, which shows an anomalous 10-fold increase in the OES data. The fitted line shows the predicted values of an OLS regression of the percent change in lawyer employment as a function of the percent change in regulatory stringency.

*Source:* RegData 2.1, BLS Occupational Employment Statistics, Authors' Calculations.

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>7</sup>

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. The intuition being that industries that are exposed to more regulations will tend to employ a relatively greater number of lawyers to manage the impact of those regulations. Changes in regulation also correlate with changes in the employment of lawyers.

<sup>7</sup> See <http://regdata.org/the-high-correlation-between-agency-budgets-and-agency-regulations/> (accessed 18 February 2017) for additional details.



**Figure 6. RegData signals the Dodd–Frank act**

*Notes:* Title 12 restrictions is calculated as the annual sum of restrictive terms, for example, ‘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.

*Source:* RegData 2.1, Authors’ Calculations.

Figure 5 shows the percent change in lawyers employed by each industry and the percent change in the industry’s regulation index over the period 2002 to 2011.

RegData also signals when major pieces of legislation contribute to regulatory stringency. Figure 6, 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.

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) 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. Economic dynamism and statistics of US businesses

For our measures of dynamism, we will be leveraging data from the Statistics of US Businesses (SUSB), a public use annual dataset containing detailed information on establishments, employment, and payroll by geographic area, industry (NAICS 2-, 3-, and 4-digit), and firm size.<sup>8</sup> 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 US 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 1997–2013. 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>9</sup> As explained in the following section, any bias these year-specific effects might have will be controlled via year-specific controls in our regression framework. 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.

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 Goldschlag \(2015\)](#) 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, with a correlation coefficient of 0.95 at the economy wide level between 1978 and 2014.

The industry classification codes used in the SUSB change data vary over time, making it necessary to translate between NAICS vintages. The Census Bureau provides

<sup>8</sup> See <https://www.census.gov/econ/subs/> (accessed 18 February 2017) for additional details.

<sup>9</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 0.99, 0.97, and 0.91 for job creation, destruction, and start-ups, respectively.

**Table 2. Summary statistics for RegData–SUSB panel**

|                                   | Observation | Mean    | Standard deviation | 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   |

*Notes:* Observations are industry-year combinations 1999–2013 for 75 three-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/sub/definitions.html> accessed 18 February 2017). Startup rate is calculated as  $100 * (\text{establishment entry at time } t \text{ divided by the average of establishments at } t \text{ and } t-1)$ . Job creation (destruction) rate is calculated as  $100 * (\text{job creation (destruction) at time } t \text{ divided by the average of employment at } t \text{ and } t-1)$ .

*Source:* RegData 2.1, Statistics of US Businesses, Authors' Calculations.

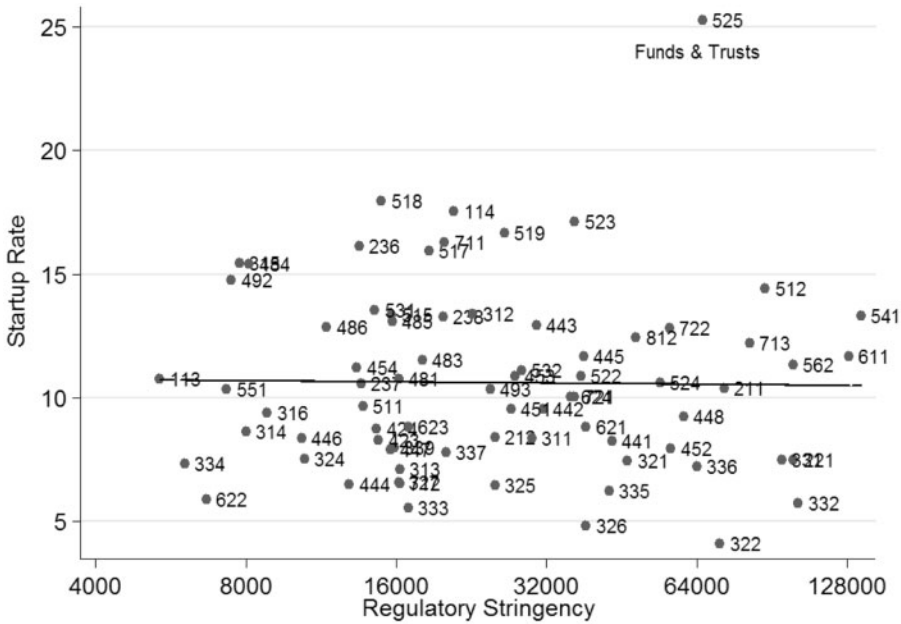
concordances between iterations of the NAICS classification system. In some cases, multiple concordances must be combined to arrive at a consistent classification scheme. To translate between different NAICS we use weights, assuming equal weighting for each match at the 6-digit NAICS level.

The final SUSB-RegData panel contains over 1.1 k industry-year observations for 1999–2013. Table 2 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 the startup rate, job creation rate, and job destruction rate.

Figure 7 shows average startup rate versus the average regulation index by industry, pooling years. 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.

A similar pattern can be seen for job creation and job destruction, with no strong positive or negative relationship. Figures 8 and 9 show the relationship between job creation and destruction rates, respectively, and the average regulatory index by industry. Job creation appears slightly positively correlated with regulation at the industry level and job destruction slightly negatively correlated.

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-fixed effects to reveal the relationship between regulation and economic dynamism within an industry over time.



**Figure 7. Startup rates vs. regulatory stringency**

*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 three-digit 2007 NAICS industries. Startup rate is calculated as  $100 * (\text{establishment entry at time } t \text{ divided by the average of establishments at } t \text{ and } t-1)$ . 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.

*Source:* RegData 2.1, Statistics of US Businesses (SUSB), Authors' Calculations.

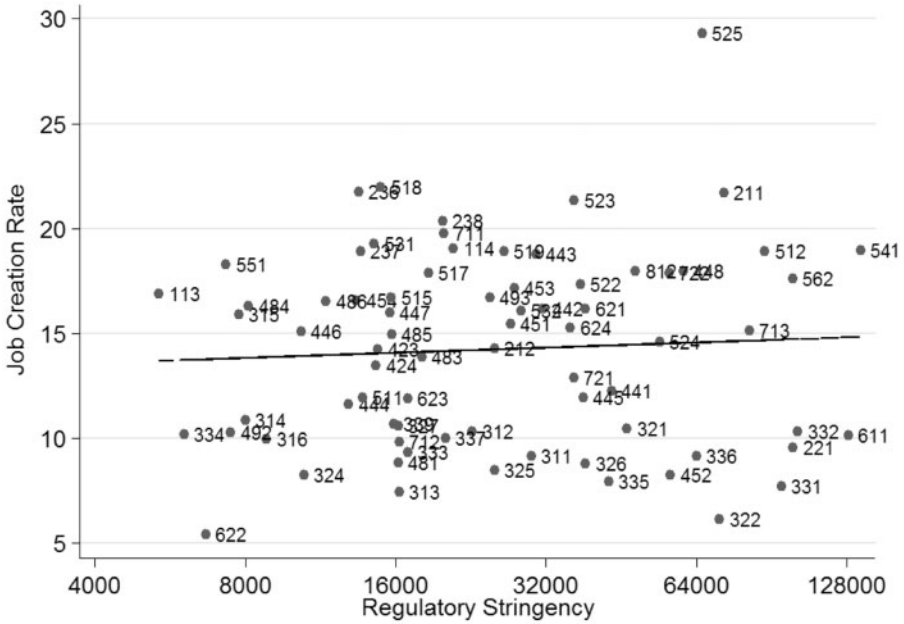
### 3. METHODS AND RESULTS

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 regression equation:

$$Y_{t,n} = \beta_0 + \beta_1 \ln \text{Reg}_{t,n} + \lambda_t + \gamma_n + \epsilon_{t,n}, \quad (1)$$

where  $Y_{t,n}$  is our measure of dynamism at time  $t$ , for three-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





**Figure 8. Job creation rates vs. regulatory stringency**

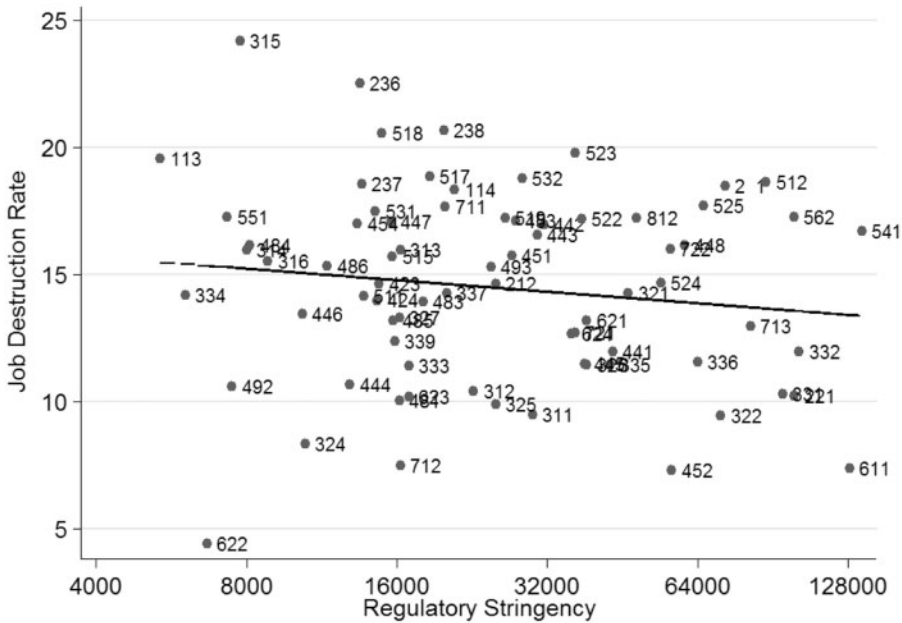
*Notes:* Average regulatory stringency by industry is calculated as the average of the sum of the annual regulatory stringency index between 1999 and 2013 by three-digit 2007 NAICS industries. Job creation rate is calculated as  $100 * (\text{job creation at time } t \text{ divided by the average of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

*Source:* RegData 2.1, USB, Authors' Calculations.

created (destroyed) divided by the mean aggregate employment for times  $t$  and  $t-1$ .  $\ln \text{Reg}_{t,n}$  is the regulatory stringency index at time  $t$ , in three-digit NAICS  $n$ . Finally,  $\lambda_t$  and  $\gamma_n$  are fixed effects for time and industry category, respectively. Year-fixed effects will capture economy-wide variation in economic dynamism and any upwards bias in the USB data due to incorrectly timed births and deaths stemming from economic census activities. Industry-fixed effects will capture differences in dynamism across industries that do not vary with time.

Estimation results are shown in Table 3. The first three columns show simple OLS regressions without industry- or year-fixed effects and similar to Figures 7–9 we find small coefficients and no statistically significant effects. After controlling for year and industry effects, our regulatory stringency index also shows no statistically significant effect on startups, job creation, or job destruction. In short, no evidence for a negative effect of regulation on dynamism. Notice also that coefficients are sometimes positive and 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.

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 in  $t-1$  and  $t-2$ . The results in Table 4 suggest that even if regulations affect dynamism only after some delay, there is no evidence of a statistically significant relationship between regulation and



**Figure 9. Job destruction rates vs. regulatory stringency**

*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 three-digit 2007 NAICS industries. Job destruction rate is calculated as  $100 * (\text{job destruction at time } t \text{ divided by the average of employment at } t \text{ and } t-1)$ . The fitted line shows the predicted values of an OLS regression of the job destruction rate as a function of regulatory stringency.

*Source:* RegData 2.1, SUSB, Authors' Calculations.

**Table 3. Dynamism and regulatory stringency**

|                           | Startups           | Job creation      | Job destruction     | Startups         | Job creation     | Job destruction   |
|---------------------------|--------------------|-------------------|---------------------|------------------|------------------|-------------------|
| Log regulatory Stringency | -0.126<br>(0.531)  | 0.0748<br>(0.670) | -0.824<br>(0.613)   | 0.661<br>(1.043) | 1.474<br>(0.957) | 1.459<br>(1.193)  |
| Constant                  | 11.88**<br>(5.315) | 13.39<br>(6.744)  | 22.83***<br>(6.306) | 4.289<br>(10.30) | 0.986<br>(9.484) | -0.472<br>(11.92) |
| Observations              | 1,125              | 1,106             | 1,105               | 1,125            | 1,106            | 1,105             |
| R-squared                 | 0.001              | 0.000             | 0.017               | 0.193            | 0.279            | 0.330             |
| Number of industries      |                    |                   |                     | 75               | 75               | 75                |
| Industry FE               | No                 | No                | No                  | Yes              | Yes              | Yes               |
| Year FE                   | No                 | No                | No                  | Yes              | Yes              | Yes               |

*Notes:* Robust standard errors in parentheses, \*\*\* $p < 0.01$ , \*\* $p < 0.05$ . Standard errors in regressions without fixed effects are clustered at the industry level. 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. The dependent variable in pooled specifications is the three measures of dynamism demeaned across year and industry separately then stacked. Unless otherwise noted, the  $R^2$  reported in regressions that include fixed effects are calculated after demeaning the data.

*Source:* RegData 2.1, Statistics of US Businesses, Authors' Calculations.

dynamism. This remains true if we only consider lagged regulation, excluding contemporaneous measures of regulation. Overall, the results suggest that lagged regulation indices are no better able to account for the decline than regulation at time  $t$ .

**Table 4. Dynamism and regulatory stringency, delayed impacts**

|                           | Startups          | Startups          | Job creation      | Job creation      | Job destruction   | Job destruction   |
|---------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| Log regulatory Stringency | -1.061<br>(0.984) |                   | -1.002<br>(1.348) |                   | 0.700<br>(1.335)  |                   |
| Log reg stringency (-1)   | 2.581<br>(1.709)  | 2.144<br>(1.770)  | 1.804<br>(0.999)  | 1.393<br>(0.804)  | -0.408<br>(1.361) | -0.121<br>(1.376) |
| Log reg stringency (-2)   | -0.155<br>(0.823) | -0.567<br>(0.799) | 1.542<br>(1.147)  | 1.150<br>(0.955)  | 1.365<br>(1.126)  | 1.638<br>(0.981)  |
| Constant                  | -2.503<br>(14.59) | -4.698<br>(14.11) | -7.419<br>(11.20) | -9.475<br>(11.35) | -2.390<br>(13.81) | -0.956<br>(13.33) |
| Observations              | 1,125             | 1,125             | 1,106             | 1,106             | 1,105             | 1,105             |
| R-squared                 | 0.199             | 0.198             | 0.283             | 0.282             | 0.331             | 0.330             |
| 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               |

*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.

*Source:* RegData 2.1, Statistics of US Businesses, Authors' Calculations.

**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<br>(3.244) | 1.647<br>(1.858) | 1.349<br>(1.238) | 1.685<br>(1.817)  | 2.467**<br>(1.012) | 2.698<br>(1.491)  |
| Constant                  | 32.90<br>(32.46)  | 1.416<br>(18.60) | 1.122<br>(12.22) | -3.029<br>(18.33) | -10.63<br>(10.01)  | -14.03<br>(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               |

*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.

*Source:* RegData 2.1, Statistics of US Businesses, Authors' Calculations.

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. In these analyses, we do not consider startups since they tend to be relatively small on average. Here, we find a statistically significant relationship for job creation among large firms but the sign suggests regulatory stringency is associated with small increases not decreases in dynamism.

**Table 6. Dynamism and regulatory change**

|                      | Startups  | Job creation | Job destruction |
|----------------------|-----------|--------------|-----------------|
| Annual Change in Reg | -0.0120   | -0.00798     | -0.00144        |
| Stringency           | (0.00693) | (0.00841)    | (0.00863)       |
| Constant             | 11.01***  | 15.78***     | 14.10***        |
|                      | (0.219)   | (0.302)      | (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             |

*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.

*Source:* RegData 2.1, Statistics of US Businesses, Authors' Calculations.

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.

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 mask important 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 three-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 in the industry association probabilities. 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, that is, 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

**Table 7. Dynamism and industry regulation, specific and general regulations**

|                               | Startups               | Job creation              | Job destruction        |
|-------------------------------|------------------------|---------------------------|------------------------|
| Log Specific Regulation Index | 0.000149<br>(0.000130) | -0.000120<br>(0.000234)   | 5.89e-05<br>(0.000146) |
| Log General Regulation Index  | 1.02e-05<br>(2.63e-05) | 7.80e-05***<br>(2.52e-05) | 5.81e-06<br>(2.55e-05) |
| Constant                      | 10.41***<br>(0.408)    | 15.17***<br>(0.689)       | 13.88***<br>(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                    |

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 80th percentile of concentrations across all parts and years. General regulation index includes only CFR parts where the concentration is less than the 20th percentile of concentration.

Source: RegData 2.1, Statistics of US Businesses, Authors' Calculations.

the probabilities is greater than the 80th percentile of concentration indices across all parts. Conversely, the general regulation index uses only text with a concentration value less than the 20th percentile. The regression results using these new indices are reported in Table 7. As before, we find a positive and relatively small relationship between job creation for general regulations, but this is again the opposite of the direction required to explain the secular decline in dynamism.

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 industry rather than general regulations, which affects many industries. As Olson (1977, 1984) pointed out, industries face a collective action problem when lobbying for favourable 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 has a significant negative impact on 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 3.2.

In the following sections, we consider a more comprehensive measure of regulation, decompose the heterogeneous effects of different regulations, and address concerns about measurement error and endogeneity.

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

To calculate up and down-stream measures of regulatory incidence, we 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). Thus, up-stream regulation increases in size when an industry buys a significant share of inputs from industries that are themselves highly regulated and down-stream regulation 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. 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.

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. We label the result the Leontief Regulatory Stringency Index.

Table 8 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. The up-stream and down-stream measures of regulatory stringency might also be used to address concerns of endogeneity, which we explore in Section 3.2.

Overall, we consistently 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; *a fortiori* regulation does not appear to be a *major* cause of declining dynamism.

**Table 8. Dynamism and full regulatory incidence**

|                       | Startups | Job creation | Job destruction | Startups | Job creation | Job destruction |
|-----------------------|----------|--------------|-----------------|----------|--------------|-----------------|
| Log Regulatory        | 0.431    | -2.317       | 2.239           | 1.970    | -3.554**     | 3.059           |
| Stringency            | (1.111)  | (1.279)      | (1.513)         | (1.572)  | (1.581)      | (2.244)         |
| Log Up-Stream         | 6.959*** | 24.52***     | 1.926           |          |              |                 |
| Regulatory Stringency | (2.588)  | (9.015)      | (3.551)         |          |              |                 |
| Log Down-Stream       | -5.708   | 12.20***     | -0.589          |          |              |                 |
| Regulatory Stringency | (3.249)  | (4.337)      | (6.508)         |          |              |                 |
| Log Leontief          |          |              |                 | -12.71   | 46.31***     | -6.298          |
| Regulatory Stringency |          |              |                 | (9.182)  | (12.59)      | (14.07)         |
| Constant              | -7.263   | -340.9***    | -22.53          | 152.8    | -536.8***    | 63.16           |
|                       | (41.63)  | (103.3)      | (64.07)         | (106.3)  | (149.6)      | (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             |

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 solves the input-output equations of the form  $X = (In - A) - 1B$ , where  $X$  is total regulatory stringency,  $A$  is the input-output shares, and  $B$  is the regulatory stringency by industry. Up-stream regulatory incidence for industry  $i$  is calculated as the sum of  $(inShare_{ij}Reg_j)$  across all  $j$  industries where  $inShare_{ij}$  is the share of inputs used by industry  $i$  sourced from industry  $j$ . Down-stream regulatory incidence for industry  $i$  is calculated as the sum of  $(inShare_{ij}Reg_j)$  across all  $j$  industries where  $outShare_{ij}$  is the share of outputs produced by industry  $i$  consumed by industry  $j$ .

Source: RegData 2.1, Statistics of US Businesses, BEA Input-Output Accounts data, Authors' Calculations.

### 3.2. Measurement error and attenuation

Measurement error and endogeneity bias are alternative explanations for our failure to find large impacts of regulation on dynamism. In other words, excessive noise or reverse causation could bias our results towards zero. We test for the presence of measurement error by exploring the effects of increasing length of differencing in both our 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 the industry dimension. Finally, we leverage the up and down-stream measures of regulation as a way to reduce the effects of reverse causation in our estimates.

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:

$$\Delta_s \mathcal{Y}_{t,n} = b_1 \Delta_s \text{Reg}_{t,n} + \Delta_s \epsilon_{t,n}, \quad (2)$$

**Table 9. RegData, dynamism, and measurement error**

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

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.

Source: RegData 2.1, Statistics of US Businesses, Authors' Calculations.

where  $\Delta_s \mathcal{Y}_{t,n}$  is difference in each measure of dynamism of length  $s$  at time  $t$ , for three-digit NAICS  $n$ , and  $\Delta_s \text{Reg}_{t,n}$  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. The bias in  $b_1$  becomes a function of the length of the difference,  $s$ .<sup>10</sup>

As the difference length  $s$  increases the variance of our differenced regulation measure  $\Delta_s \text{Reg}_{t,n}$  rises and  $b_1$  approaches the true estimate. Table 9 shows the results of estimating equation (2) 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 increases. The coefficients on job creation, though significant in longer differences, are of the wrong sign.

Differencing the data to detect and account for measurement error requires the assumption that the measurement error is not correlated from year to year. In our case, however, there may be correlation over time 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 suggest 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.

10 More formally, the bias in  $b_1 = \beta_1 [1 - (2\sigma_\varepsilon^2 / \text{Var}(\Delta_s \text{Reg}_{t,n}))]$ , where  $\beta_1$  is the ‘true’ coefficient estimate and  $\sigma_\varepsilon^2$  is the variance of the measurement error. See Griliches and Hausman (1986) for details.



**Table 10. Measurement error and aggregated industries**

|                      | Startups | Job creation | Job destruction |
|----------------------|----------|--------------|-----------------|
| Two-digit industries |          |              |                 |
| 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              |
| One-digit industries |          |              |                 |
| 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               |

*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.

*Source:* RegData 2.1, Statistics of US Businesses, Authors' Calculations.

Errors at lower levels of aggregation will tend to cancel out as we aggregate to NAICS sectors and super-sectors. Table 10 shows the results of estimating Equation (1) using two- and one-digit NAICS industries, respectively. Again, we find little evidence of attenuation bias in the estimated relationship between federal regulation and trends in dynamism.

In addition to measurement error, our estimates could be biased by a loop of causation. 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 3.1. 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, regulation imposed on an industry as a consequence of its up and down-stream connections is less likely to be the result of strategic behaviour 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 11 shows estimation results of regressing dynamism measures on up and down-stream regulation. These regressions 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.

Finally, we consider the plausibility of measurement error driving our results based on the observed variation in our regulation measure. As shown in Figure 7 there is

**Table 11. Regulation, reverse causation, and supply chains**

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

*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.

*Source:* RegData 2.1, Statistics of US Businesses, BEA Input-Output Accounts data, Authors' Calculations.

**Table 12. Variation in regulation and dynamism**

|                       | Mean   | Industry mean |        | 1999–2013 difference |        |
|-----------------------|--------|---------------|--------|----------------------|--------|
|                       |        | 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   |

*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.

*Source:* RegData 2.1, SUSB, Authors' Calculations.

substantial variation in both our measures of dynamism and regulation. Table 12 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 ranges from 8.9 to 10.8 points. These gaps are quite large, ranging from 61% to 89% 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.

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. 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 measurement error would likely be swamped by variation in the true regulation term. All of this suggests that in order for measurement error to explain our negative results, the error variance would have to be very substantial.

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.

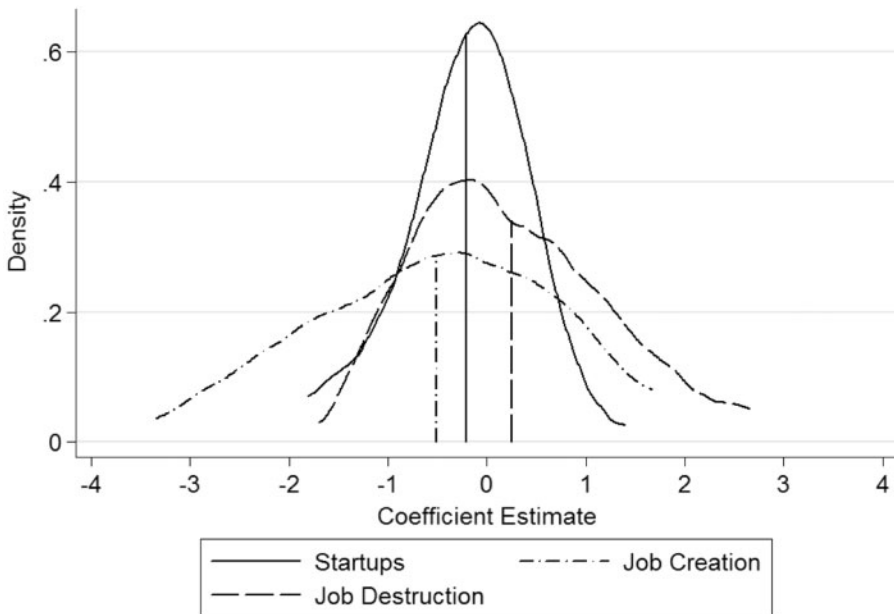
### 3.3. Varied effects of regulation

In several of the regression specifications in the preceding sections, we find positive coefficient estimates for job creation, hinting at the idea that there may be a positive relationship between regulation and this particular measure of dynamism. Although this does not directly impact the hypothesis we test in this paper, whether regulation can account for secular trends in dynamism, in this section we further decompose this relationship to characterize the heterogeneous effects of regulations.

As described in Section 2.1, our primary interest is the net effect of regulation on dynamism. If some regulations have a large negative impact while other regulations have an equally large positive impact on dynamism the net effect would be zero and therefore regulation could not plausibly explain secular trends in dynamism. Despite this fact, it is useful to characterize the full distribution of regulation impact.

In order to characterize the different ways regulation relates to measures of dynamism we disaggregate our regulatory index to a lower level of granularity. In the preceding analyses our measure of regulation was at the industry-year level, effectively aggregating all of the pieces of the CFR within each year. The CFR, however, is organized into 50 different titles, which though they may not directly map to specific industries, may have variable impacts on our measures of dynamism. To measure these heterogeneous effects, we allow each title to enter separately in a regression with year and industry controls. [Figure 10](#) shows the distribution of the resulting 150 coefficient estimates. All three distributions are fairly well centred around zero, suggesting that some regulations are positively related and others negatively related to dynamism and most are not statistically significant. The mean coefficient estimate is small and negative for both start-ups and job creation,  $-0.2$  and  $-0.5$ , respectively, and  $0.25$  for job destruction.

These results support the conclusions from previous analyses finding that regulation is unlikely to be an important driver of declining dynamism. The results are consistent across a number of additional regression specifications, found in Appendix B, that use industry-time trends, and word counts rather than restrictive terms. Rather than further focus on RegData, however, the next section provides two additional analyses that do not use RegData at all but support the conclusion that regulation is not a major cause of declining dynamism.



**Figure 10. Varied effects of regulations**

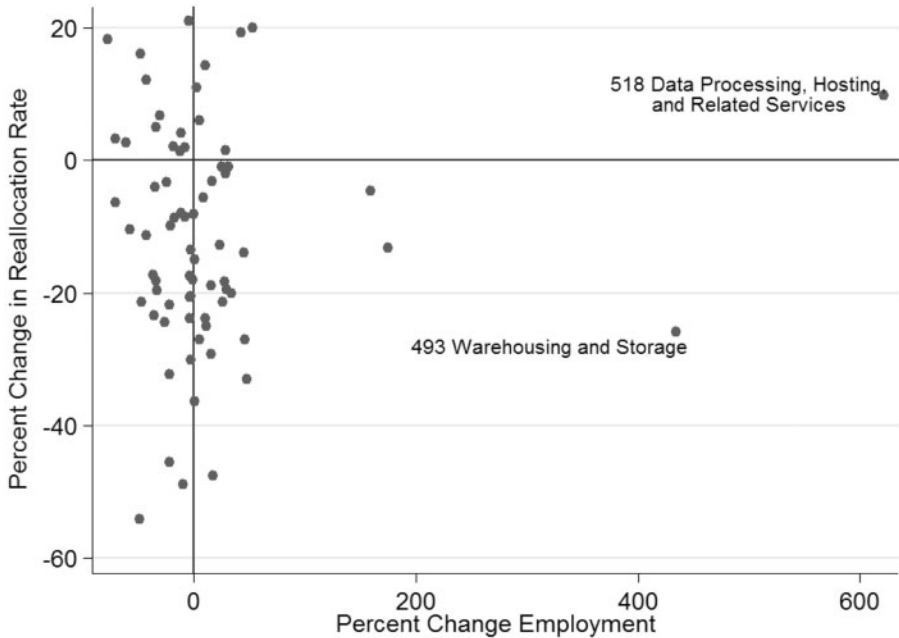
*Notes:* Figure shows the kernel density estimates for regression coefficient estimates of regulatory stringency in a regression of each dynamism measure as a function of regulatory stringency-, year-, and industry-fixed effects for a given title. The CFR contains 50 tiles so each distribution includes 50 coefficient estimates. All three distributions use the epanechnikov kernel function with bandwidths 0.35, 0.6, and 0.4 for startups, job creation, and job destruction, respectively. Vertical lines show the mean coefficient estimate for each dynamism measure.

*Source:* RegData 2.1, SUSB, Authors' Calculations.

### 3.4. Industry size, import penetration, and reallocation

In this section, we offer two simple but suggestive tests of the regulation hypothesis that do not rely on RegData or measuring regulation. 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 modelled as a tax on labour destruction can reduce hiring, firing, and productivity growth. 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 11 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. As expected, most industries (~73%) saw a decline in the industry reallocation rate. Most



**Figure 11. Changes in reallocation and industry size**

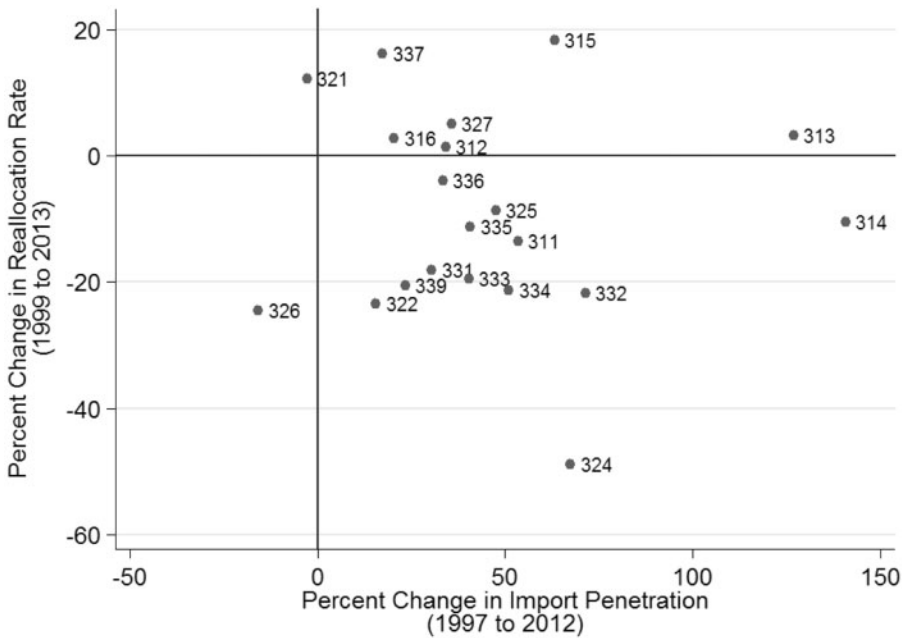
*Notes:* Reallocation rate is defined as the excess reallocation rate developed in *Davis et al. (1998)*, which is calculated as the sum of job creation and destruction rates less the absolute value of net change. Vertical and horizontal lines at zero.

*Source:* Statistics of US Businesses, Authors' Calculations.

industries ( $\sim 57\%$ ) also saw employment declines during this period. However, there is no clear relationship between declines in reallocation and declines in industry growth because growing industries also exhibited declining reallocation rates. 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.

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 – that is, declining dynamism and greater imports. The effect will be especially strong if regulation is reducing 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 three-digit manufacturing industries. As a measure of dynamism we use the reallocation rate as discussed earlier. The relationship is shown in *Figure 12*. *Figure 12* indicates that most manufacturing industries have seen greater import penetration over the period 1997–2012 but the relationship is not strongly



**Figure 12. Changes in reallocation and changes in import penetration**

*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 \(2017\)](#) for details.

*Source:* Statistics of US Businesses, Authors' Calculations.

correlated with changes in the reallocation rate. Industries with increasing and decreasing reallocation rates have both seen increases in import penetration.

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. Given that there appears to be little role for regulation to explain trends in dynamism, the next section will comment briefly on alternative directions in the empirical literature.

#### 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 was 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. Davis and Haltiwanger (2014), for example, find that job 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 US 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 was 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 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, which suggests a role for broad-based slowing of the technological frontier (Crisuolo *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 Pugsley *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 US 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 (Lucas, 1978; Poschke, 2014; Bento and Restuccia, 2016). 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 BDS. 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 US statistics. The United States may be outsourcing churn.

## 5. CONCLUSION

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 and capital. 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 US 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.

To the extent that federal regulation is not a major 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.

## Discussion

Beata Javorcik

University of Oxford

Providing convincing evidence that a particular relationship does not hold is challenging, if not impossible. The authors have done a good job showing that regulation is not to blame for the decline in American entrepreneurship, but some lingering doubt always remains.

First, are we measuring the right thing? The new measure employed in this article shows a steep upwards trend in stringency of regulations affecting American firms. However, as mentioned in the text, this contrasts sharply with the picture emerging from the widely used *Doing Business* indicators compiled by the World Bank, which show no change or even some improvement in the US regulatory environment.

Second, regulation may matter less in practice than we think. Lobbyists may be able to ensure that regulation has no teeth, or compliance may be achieved through filing of the required documents with little impact on the production process or business conduct. This could explain the positive relationship between the change in the number of lawyers employed by an industry and the change in the regulatory stringency measure. Cheating may also be taking place (recall the recent Volkswagen emissions scandal). On the one hand, large players are better positioned to undertake lobbying efforts and to afford high-quality legal advice. On the other hand, new firms may be affected less by regulation due to a small scale of operation or smaller range of activities. It is thus far from obvious whether additional regulation will give advantage to incumbents or new entrants and thus whether it will positively or negatively affect dynamism.

Third, even though regulation may be stifling dynamism in some mature industries, regulators may be targeting fast growing and dynamic sectors which to date have attracted little regulatory attention. If that is the case, the relationship between regulation and entrepreneurship may be blurred.

Fourth, other forces, such as globalization, may have dwarfed the impact of regulation. The existing literature has shown large effects of competition from China on

manufacturing employment in the United States (see, for instance, [Pierce and Schott 2016](#)). Although, [Figure 12](#) shows no apparent relationship between changes in reallocation and changes in import penetration, the interplay between the two could be quite complex. Regulation may accelerate import penetration if it decreases competitiveness of domestic producers relative to imports. At the same time, some sectors may use regulation as a protectionist measure in response to growing import competition. Given the two-way direction of causality, it is impossible to disentangle the effects in the absence of an instrumental variable approach.

Putting these doubts aside, this article makes a very nice and welcome contribution to the current debate on whether or not deregulation is needed.

## Andreas Madestam

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### Background

Goldschlag and Tabarrok (2018) note two distinct trends in the US economy: (i) fewer firms are started and there is less labour reallocation and (ii) federal regulation has increased both in scope and in complexity. A natural question that arises is whether regulation has a negative effect on firm dynamics in terms of the birth of firms and employment turnover.

### What the paper does

Against this background, Goldschlag and Tabarrok investigate the relationship between US federal regulation and firms' labour reallocation practices by examining changes in firm startups, job creation, and job destruction (dynamism). They are motivated by the idea that regulation raises barriers to entry which impedes reallocation of labour and capital. Combining US business statistics with the US CFR over the period 1999–2013 in a FE framework they assess if increased regulation explains the recent decline in economic dynamism. To gauge regulation, they use a machine learning algorithm, RegData, that measures the prevalence of restrictive words and phrases (e.g., 'must', 'prohibited', or 'shall') in the CFR across industries and years.

The paper finds no evidence of a negative relationship between regulation and economic dynamism (as measured by startups, job creation, and job destruction). This is true on average, across firm size, if the analysis is restricted to regulation due to the 10 largest regulating agencies, across general regulation (covering many industries) or specific regulation (targeting certain industries), within an industry (manufacturing) with a lot of variation in regulation, or across the upstream or downstream industry gradient. In short, federal regulation does not seem to explain the recent downturn in economic dynamism.

## Comments

My comments will focus on issues related to the empirical strategy employed, how to interpret the findings presented in the paper, and the robustness of the RegData measure. Starting with the paper's empirical strategy, or more specifically, its identifying assumption: it assumes that (besides regulation) more regulated industries only differ from less regulated industries in unobservable ways that are fixed over time and over industry characteristics. This assumption is likely to be violated as technological change affects both the need for regulation (more complex production) and employment opportunities (workers are replaced). In addition, using the FE framework is like shooting a sparrow with a cannon – it removes both good and bad variation. It would be more informative to start regressions with the pooled data excluding the FE, then add relevant time-varying controls such as measures of technological change, interest groups (unionization, consumer groups, and so forth), then time FE, then industry FE, and finally, industry trends. The revised version of the paper does some of this, showing the results with and without FE. However, we still do not have a sense of how important time-varying correlates (e.g., technological change) affect the estimates, something that would help us better assess the identifying assumption and the robustness of the FE approach.

A more credible alternative than the current FE setup would be to exploit a change with a clearly identified control group. The Dodd–Frank Act, enacted in 2010, offers such an alternative strategy as it mainly affected regulatory stringency in the financial industry. Figure 6 in the paper also supports this idea, showing a strong first-stage effect of the reform on regulatory stringency. The paper could develop this further by employing a difference-in-differences strategy and study the reduced-form effect on dynamism across the financial and non-financial industry before and after the act was implemented. The effects could then be scaled with the change in regulatory stringency.

Another issue relates to inference. By collapsing the data at the year-industry level, the paper circumvents the Moulton problem (i.e., establishments in the same industry are subject to similar influences). However, serial correlation could still be an issue (i.e., industry characteristics are correlated over time), suggesting that the paper should cluster the standard errors at the industry level. A final empirical strategy concern centres around the right level of aggregation. When the paper aggregates the data to higher industry levels, the estimates change and switch sign, prompting the question of what the right level of aggregation actually is.

Goldschlag and Tabarrok interpret their findings as evidence in favour of a null effect, saying that 'we find no measureable relationship between federal regulation and changing economic dynamism'. However, this is an overly strong statement. In fact, if the empirical model is correctly specified, the results are supportive of a positive, albeit noisy, relationship between federal regulation and labour reallocation. One way that the paper could further gauge the question is to pool (and normalize if necessary) the data and estimate a mean effect across all outcome variables or groups of outcome variables (e.g., following Kling *et al.*, 2007). This would give a sense of whether there is a

meaningful positive relationship underlying all the separate regressions. The paper would also benefit from a more thorough discussion as to why a possibly positive relationship is the case rather than concluding that the initial claim (i.e., a negative effect) is invalidated. In addition, from a policy perspective it would be useful to understand when and why regulation is positively associated with economic dynamism. Could it be that complementary institutions matter? In a cross-country sense this is certainly true: when institutions are efficient, regulation helps firms and consumers, while institutions generate red-tape and corruption when institutional quality is low. Can a similar case be made with respect to institutional enforcement of federal regulation within and across the United States?

Let me close the discussion with some short comments regarding the robustness of the regulatory measure used (RegData). RegData counts the number of restrictive words in each section of CFR and then assigns weights to different industries. It would be instructive if the paper showed how sensitive the results are to different types of words – is there a distinction to be made between ‘enabling’ and ‘restrictive’ regulation? Also, maybe it is not the count of restrictive words *per se* but the density by which they appear, with a higher density in a certain section, that signals a stronger commitment on part of the regulator? Finally, the paper shows an upwards trend in regulatory stringency over time – should we be worried that the analysis confounds this secular increase in the codification of all types of legislation with its other findings?

## Panel discussion

Giacomo Calzolari first asked why is competition policy not considered in the authors’ framework given its importance for firms. He also argued that a potential alternative explanation for the decline in economic dynamism could be the increase in sectoral concentration. Following one of the suggestions of Andreas Madestam during his discussion, Andrea Ichino and Christos Genakos argued that the paper should be complemented with an event study analysis. Andrea Ichino also asked what is the correlation between the paper’s measure of regulation based on RegData and those used in other studies at the aggregate level. Similarly, Christos Genakos recommended showing the correlation with the World Bank and OECD measures of product market regulation. He also asked how firm exits are treated when there are mergers and acquisitions.

Giving the financial sector as an example, Richard Portes noted that regulation raises barriers to entry and induces regulatory arbitrage. Banu Demir suggested looking at different types of regulation separately, for example, employment- and environment-related regulations. Eliana Viviano noted that the results are very strong and questioned what the aggregate regulation index actually represents. Tullio Jappelli asked if it would be possible to do the analysis at the state-level, and enquired what happens when firms

move across sectors. On the latter point, he suggested complementing the baseline FEs analysis with OLS regressions.

Nicola Fuchs-Schündeln noted that the standard errors are relatively large. Given the authors' prior, she mentioned it would be useful to show the 95% confidence intervals, to have a better idea of how substantial the negative effect of regulation on entrepreneurship could potentially be. Finally, Thorsten Beck highlighted the challenges of directly comparing RegData with the World Bank's Doing Business database as these capture different dimensions affecting entrepreneurship.

Replying to comments and questions, Nathan Goldschlag first recognized that complementing the analysis with case studies is a good suggestion. Regarding Thorsten Beck's comment about the World Bank's Doing Business, he clarified that the two databases are indeed different and argued that one of the major issues with RegData is that there is no comparable database to do robustness checks. Nathan Goldschlag also mentioned that clustering at the industry level does not change the main results and that the point of complementing the baseline FEs analysis with OLS regressions is well taken. Finally, regarding the treatment of mergers and acquisitions, he clarified that these appear in the database as a transfer in the firm identifier rather than an exit.

## SUPPLEMENTARY DATA

Supplementary data are available at *Economic Policy* online.

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