Regulation, Entrepreneurship, and Dynamism

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Dustin Chambers, Patrick A. McLaughlin, and Oliver Sherouse. "Regulation, Entrepreneurship, and Dynamism." Mercatus Working Paper, Mercatus Center at George Mason University, Arlington, VA, October 2020.

Abstract

Recent empirical studies estimating the impact of US federal regulations on domestic business activity have reached seemingly contradictory conclusions. When measuring business activity with traditional measures of entrepreneurship (i.e., firm startups and job formation), some researchers observe a negative association between regulatory accumulation and entrepreneurship. Others, however, fail to find a significant association between regulatory accumulation and startup business activity when measuring business activity with metrics common to the dynamism literature. After ruling out differences in unit of measure (i.e., firms vs. establishments), industry aggregation (i.e., three- vs. four-digit NAICS code classification), and measurement of regulation (i.e., RegData 2.0 vs. 2.1), we demonstrate that methodological differences in the measurement of entrepreneurship are responsible for the conflicting results. However, when we allow the impact of regulation on the startup rate to vary across industries and over time, we empirically demonstrate that the decline in dynamism measured over the sample period is associated with higher regulation.

JEL codes: K23, L26, L51, C23

Keywords: regulation, entrepreneurship, dynamism, employment, firm size

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1. Introduction

Within the fields of political economy, public policy, and entrepreneurship, the impact of regulation on business activity has been a source of both great interest and contention. Lacking a comprehensive measure of regulation, this critical question has resisted empirical attempts to answer it. However, the advent of RegData (Al-Ubaydli and McLaughlin 2017; McLaughlin and Sherouse 2019) may provide researchers with the necessary data on regulation to settle this open question. Rather than relying on incomplete data on subsets of rules or proxies for the level of regulation (e.g., cost estimates from regulatory impact analyses, page counts of regulations, or agency enforcement budgets), RegData offers a comprehensive metric of US federal regulation that covers a relatively long time frame (the latest version, RegData 3.2, spans the period 1970–2019).[1] Not surprisingly, two recent studies—Bailey and Thomas (2017) and Goldschlag and Tabarrok (2018)—utilize RegData to estimate the impact of federal regulations on private business activity. Interestingly, despite the use of very similar models and datasets, these two studies produce highly conflicting results.

Bailey and Thomas (2017), henceforth BT, investigate the effect of regulation on three indicators of entrepreneurship: firm births, firm deaths, and new hires.[2] They also examine whether regulation affects these outcomes differently for small firms than for large firms. Across

[1] For a detailed description of the machine learning algorithms and methodology used to construct recent versions of RegData, please see McLaughlin and Sherouse (2019). Early versions of RegData that preceded the use of machine learning algorithms are described in Al-Ubaydli and McLaughlin (2017). Machine learning algorithms were implemented in RegData 2.1 and subsequent versions.
[2] Because the Census Bureau's Statistics of US Businesses data only report NAICS-coded birth and death data for establishments, BT use establishment data as a proxy for firm-level behavior.

all firms, they find a small but statistically significant negative relationship between regulation and entrepreneurship: a 10 percent increase in regulation is associated with a 0.5 percent reduction in new firm births and a 0.9 percent reduction in hiring over the period 1998–2011. The study also finds the relationship between regulation and firm births, as well as between regulation and new hires, to be statistically stronger for small firms compared to large firms.

Goldschlag and Tabarrok (2018), henceforth GT, examine the effect of regulation on the related concept of dynamism. Noting the long-term decline of dynamism in the US economy, they estimate the relationship between regulation and several indicators of economic dynamism: the establishment entry rate, job creation rate, and job destruction rate. Despite estimating a variety of models, they find no significant relationship between regulation and dynamism over the years 1999–2011. They conclude that federal regulation may not be a major factor driving the decline of American economic dynamism.

We seek to explain these paradoxical findings by carefully examining whether their differences in data or methodology result in their disparate conclusions. Our results suggest that differences in data are *not* responsible for the differences in the studies' conclusions, but a difference in methodology is. Specifically, the choice of dependent variable is responsible for differences in the studies' findings. Far from being contradictory, we demonstrate that the findings of both studies are consistent and predictable.

The remainder of this paper is organized as follows. Section 2 describes the critical differences in methodology employed by BT and GT, while section 3 describes the various datasets used to verify the robustness of the original studies' empirical findings. Section 4 provides our estimation of both the BT and GT models, exploring the possibilities that the data differences or methodological differences explain the studies' disparate conclusions. Section 5 presents a robust and statistically significant alternative model of dynamism that is consistent with BT. Section 6 presents our conclusions.

2. Methodological Differences

In this section, we specify the models used in BT and GT and discuss the methodological consequences resulting from their respective measures of entrepreneurship and dynamism. Because both papers collectively examine six measures of business activity, for the sake of brevity we concentrate our focus on a pair of alternative measures of new business formation: firm births and the startup rate.[3]

2.1. Empirical Models

To determine the impact of industry-level regulations on new business activity within a given industry, BT and GT utilize models with nearly identical estimation strategies, wherein their measure of business activity is regressed on regulations via a two-way fixed-effects panel model of the form

$$Y_{it} = \alpha_i + \beta r_{it} + \lambda_t + \varepsilon_{it}, \tag{1}$$

where Y_{it} is one of several dependent variables indicating entrepreneurship and dynamism, including the log of new firm births ($b_{it} \equiv \ln(B_{it})$), the log of new employment hires ($h_{it} \equiv \ln(H_{it})$), the log of firm deaths ($d_{it} \equiv \ln(D_{it})$), the startup rate ($s_{it}$), the job creation rate (c_{it}), and the job destruction rate (ℓ_{it}) for industry i at time t. The variable r_{it} is the log of one of the three RegData regulatory stringency measures. The coefficients α_i and λ_t

[3] An analytical comparison of log new hires with the job creation rate produces analogous results. Log firm births in BT has no dynamism analog in GT (i.e., GT do not use an establishment death rate), and the job destruction rate in GT has no entrepreneurship analog in the BT study (i.e., BT do not examine log employment losses).

represent industry and time-period fixed effects, which are useful because they control for inherent unobserved differences between industries and between years. Finally, ε_{it} is a mean zero error term. Neither BT nor GT use any other controls, because the most relevant macroeconomic controls are measured at the national level and would be perfectly collinear with the annual dummy variables.

2.2. Measures of Business Activity

BT measure changes in entrepreneurship via the log of new firm births, the log of firm deaths, and the log of new employment hires. They utilize a log transformation of these variables of interest because the raw series are heavily skewed left, with kernel densities that resemble a chi-squared or F-distribution (see BT, figures 1 and 2). After applying the natural log transformation, the resulting distributions resemble bimodal distributions. Within the context of equation (1), this log-log specification (i.e., regressing log measures of entrepreneurship onto a log measure of regulation) implies that the coefficient on regulation (β) has an elasticity interpretation equaling the percentage change in new firm births (or firm deaths or new hires) for a 1 percent change in regulation. Thus, the natural log transformation of the various entrepreneurship measures both normalizes the dependent variable and yields a coefficient on regulation with a standardized interpretation across industries.

In contrast, GT use the startup rate, the job creation rate, and the job destruction rate. These rates are calculated with a midpoint growth rate formula popular in the dynamism literature. The startup rate is calculated as 100 times the number of establishments created in a given year (i.e., births) divided by the Davis-Haltiwanger-Schuh (DHS) denominator, which is the mean number of establishments for the current (t) and previous ($t - 1$) years.[4] GT note that this denominator is an attempt to keep transitory shocks from affecting the relationship between net growth from $t - 1$ to t and size, following Davis, Haltiwanger, and Schuh (1996). Similarly, the job creation and destruction rates are calculated as 100 times the number of jobs created or destroyed, respectively, divided by the mean employment for the current (t) and previous ($t - 1$) years.

The key (implicit) theoretical difference in these model specifications is that BT are assuming that a given proportionate change in regulation in any given industry (say 1 percent) will inhibit the formation of a proportionate number of firms (say 0.05 percent, using BT's estimated value). This seems reasonable if one assumes a similar relative distribution of talent, resources, and experience among the potential pool of new entrants to any given industry. Then a given increase in the barriers to entry or compliance should dissuade a roughly equal proportion of would-be entrants. Note that this is a bottom-up theory linking regulation to the behavior of entrepreneurs.

In GT's model, the key (implicit) theoretical assumption is that a given proportionate change in regulation in any given industry will inhibit the formation of new startups in equal proportion to the stock of existing firms within that industry. To better grasp the implications of this modeling assumption, let us assume that two industries initially have equal numbers of firms but different startup rates. Industry A has a startup rate of 4 percent and industry B has a startup rate of 10 percent. Now, suppose that regulations increase in both industries by the same proportion, thus trimming both industries' startup rates by the same number of percentage points—say 2 percent—so that the new startup rate is 2 percent in industry A and 8 percent in

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[4] GT show in an appendix that the establishment creation rate and the firm birth rate are highly correlated.

industry B. Note that the equal increase in regulations is predicted to reduce the flow of new entrants in industry A by 50 percent, while the flow of new entrants in industry B is reduced by only 20 percent. Thus, industries that are subject to less turnover, are more mature, or are closer to a stationary steady-state number of incumbents are more sensitive to changes in regulation than industries with large numbers of new entrants.[5]

3. Data Differences

BT and GT use different versions of the RegData data series and explore the relationship between entrepreneurship/dynamism and regulation at different levels of aggregation (i.e., the three- and four-digit NAICS code levels), potentially complicating a direct comparison of their results. We therefore create three datasets that combine the observations used by BT (2017) at both the three- and four-digit NAICS code levels and GT (2018) at the three-digit level.

For both these studies, the indicators of entrepreneurship and dynamism are drawn from Statistics of US Businesses (SUSB), produced by the Census Bureau to "provide detailed annual data for US business establishments by geography, industry, and enterprise size" (US Census Bureau 2016). Unlike most Census products, SUSB does not draw from a sample but instead covers all business establishments in the United States, although some data are suppressed or slightly altered to preserve privacy. SUSB includes not only data on the number of businesses and employees for each industry in the United States but also data on changes from year to year, including establishment births, deaths, expansions, contractions, and the employment changes associated with them.

[5] Note that in the special case where two industries have the same startup rate and are subjected to an equal proportionate increase in regulation, BT's model would predict an equal proportionate decline in firm births. This would imply an equal reduction in the startup rate of both firms, which matches the predictions of GT's model.

Establishments are classified by industry in SUSB according to the North American Industry Classification System (NAICS), which divides the economy into a set of mutually exclusive and collectively exhaustive industries according to production methods. The NAICS classification is also hierarchical, ranging in specificity from broad two-digit sectors to tightly focused six-digit industries. For example, an industry classified as industry 4321 (Motor Vehicle and Motor Vehicle Parts and Supplies Merchant Wholesalers) at the four-digit level would be classified as industry 432 (Merchant Wholesalers, Durable Goods) at the three-digit level. SUSB is available in 1992 and from 1997 to 2012; however, NAICS was introduced in 1997, and therefore only data from 1998 to 2012 are comparable. SUSB reports data at two-, three-, and four-digit NAICS levels.

In both studies, data on regulation are drawn from RegData, a data project offering panel data on the quantity of federal regulation by industry over time. First introduced by Al-Ubaydli and McLaughlin (2017), RegData improves on traditional measures of regulation, such as page count, by counting regulatory restrictions. Regulatory restrictions are words or phrases that indicate a specific mandated or prohibited activity, such as “shall” or “must.” More importantly, RegData produces probabilities that regulatory restrictions target specific NAICS-defined industries. This permits the user to construct an industry regulation index that measures how regulated each industry is in each year.[6]

RegData 2.0 (used by BT) covers the years from 1997 to 2012 and uses industry-relevant search terms to determine the industry relevance of a unit of regulatory text, then multiplies the relevance by the number of restrictions in that same unit of text, and then sums across all units of text to produce the industry regulation index at the two-, three-, and four-digit NAICS levels.

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[6] See Al-Ubaydli and McLaughlin (2017) for explanation of a sample industry regulation index. This same baseline index was used in both studies.

RegData 2.1 (used by GT) is a major revision of RegData 2.0, which replaces the search term system with a machine learning algorithm to estimate the industry relevance of regulatory text at the three-digit NAICS level only. RegData 2.1 also provides broader time coverage (1975–2014). Finally, for comparison, we include RegData 2.2, which is the most up-to-date vintage of the RegData 2.X data series and includes both three- and four-digit NAICS level data. However, despite the relatively long coverage available from RegData, at the time these studies were produced, SUSB data were limited to the years 1999–2014.[7]

We combine SUSB and both versions of RegData to produce five panels of industry data covering the years 1999–2014: three at the three-digit level and two at the four-digit level (RegData 2.1 is only available at the three-digit level). Summary statistics for the three- and four-digit panels are shown in tables 1 and 2, respectively.

Table 1. Summary Statistics for Three-Digit Industries

Variable	Count	Mean	Standard deviation	Minimum	Maximum
Startup rate	944	10.99	4.4	1.42	46.85
Job creation rate	905	14.95	5.59	3.64	59.74
Job destruction rate	905	15.38	5.09	3.13	48.66
Establishment births	946	8,597	14,824	1	105,010
Establishment deaths	944	8,108	13,372	1	94,476
New hires	911	215,364	339,770	746	2,297,342
RegData 2.0 regulation index	736	5,471	10,007	0.36	62,851
RegData 2.1 regulation index	825	32,609	28,670	4,463	143,593
RegData 2.2 regulation index	550	8,666	12,969	21.27	65,412

[7] RegData 2.2 is described in some detail in McLaughlin and Sherouse (2019). The machine learning algorithms described there are the same as those used to produce RegData 2.1.

Table 2. Summary Statistics for Four-Digit Industries

Variable	Count	Mean	Standard deviation	Minimum	Maximum
Startup rate	3,187	10.76	5.65	1.42	131
Job creation rate	2,995	14.9	6.25	2.85	59.74
Job destruction rate	2,995	15.41	5.69	2.84	59.35
Establishment births	3,189	2,550	4,471	1	38,092
Establishment deaths	3,188	2,401	4,131	1	40,944
New hires	3,023	64,218	117,309	191	1,396,593
RegData 2.0 regulation index	2,168	1,110	3,878	0	36,131
RegData 2.2 regulation index	1,056	2,566	3,620	8.67	24,022

4. Empirical Results

Using the five datasets described in section 3, we reestimate the fixed-effects model (see equation 1) for all dependent variables used in both studies over a consistent unit of measure: establishments (i.e., log establishment births, log establishment deaths, log new hires, startup rate, job creation rate, and job destruction rate). The estimation results for the coefficient of interest (i.e., log regulations) at both the three-digit and four-digit NAICS code levels are reported in table 3.

Table 3. Estimates of Equation (1) Using Alternative Measures of Regulation and Industry Aggregation

		Bailey and Thomas measures			Goldschlag and Tabarrok measures		
RegData version	NAICS version	(1) Log establishment births	(2) Log establishment deaths	(3) Log new hires	(4) Startup rate	(5) Job creation rate	(6) Job destruction rate
2.0	three-digit	−0.09	−0.09	−0.21*	0.07	−1.05	−0.93
		(0.08)	(0.11)	(0.12)	(0.68)	(0.88)	(0.80)
	four-digit	−0.03	−0.01	−0.06***	−0.06	0.14	0.16
		(0.02)	(0.02)	(0.02)	(0.10)	(0.14)	(0.22)

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		Bailey and Thomas measures			Goldschlag and Tabarrok measures		
RegData version	NAICS version	(1) Log establishment births	(2) Log establishment deaths	(3) Log new hires	(4) Startup rate	(5) Job creation rate	(6) Job destruction rate
2.1	three-digit	−0.43**	−0.40	−0.64***	0.68	1.81*	1.82
		(0.19)	(0.28)	(0.25)	(1.13)	(0.92)	(1.13)
2.2	three-digit	0.05	0.04	−0.00	0.08	−0.21	0.46
		(0.07)	(0.07)	(0.07)	(0.43)	(0.47)	(0.31)
	four-digit	−0.14*	−0.10	−0.11**	−0.15	0.16	−0.04
		(0.07)	(0.06)	(0.05)	(0.31)	(0.40)	(0.40)

Notes: Table reports the coefficient estimates on log regulation for the various dependent variables used in the Bailey and Thomas (2017) and Goldschlag and Tabarrok (2018) studies. Robust standard errors clustered by industry are reported in parentheses. ***, **, * denote 1 percent, 5 percent, and 10 percent levels of statistical significance, respectively.

Our discussion of the results reported in table 3 begins with the BT measure of new firm entry (log establishment births, shown in column 1). The estimated coefficients on log regulations are negative in all but one case (RegData 2.2 at three-digit NAICS aggregation). Interestingly, the BT specification yields statistically significant and negative coefficients on log regulations at both the three-digit and four-digit levels of aggregation (i.e., RegData 2.1 at three-digit NAICS aggregation and RegData 2.2 at four-digit NAICS aggregation). When entrepreneurship is proxied via the log new hire measure (column 3), the results are even stronger. The estimated coefficients on log regulations are both negative and statistically significant in all but one case (RegData 2.2 at three-digit NAICS aggregation). Consistent with the original findings in BT, we find no evidence that regulations impact log establishment deaths (column 2). This strongly supports the conclusion that the BT results are robust to the vintage of RegData, the level of industry aggregation, and the unit of analysis (i.e., firms or establishments). These results are also consistent with more recent studies using the latest version of RegData,

RegData 3.1, which also show a negative relationship between regulation and entrepreneurship at the industry level (see Chambers, McLaughlin, and Richards 2018).

Columns 4, 5, and 6 of table 3 report our regressions using the GT measures of dynamism. In accordance with our theoretical predictions, the GT measures of dynamism are statistically insignificant in all but one case. Focusing first on the startup rate (column 4), the coefficient estimates on log regulations are consistently negative when using RegData panels at the four-digit level of aggregation but consistently positive when using RegData panels at the three-digit level of aggregation. All are statistically insignificant. Turning to the job creation rate (column 5), the coefficient estimate on log regulations (1.81) is positive and statistically significant at the 10 percent level for the three-digit NAICS data using RegData 2.1. This is notably the lone statistically significant regulation coefficient in all the GT results. The remaining estimates derived using data at the three-digit level of aggregation (RegData versions 2.0 and 2.2) are negative and insignificant, while all estimates derived using data at the four-digit level of aggregation are positive and insignificant. Finally, the job destruction rate (column 6) yields log regulation coefficients remarkably similar to those for the job creation rate (especially when using RegData 2.0 and 2.1), but none of the coefficients are statistically significant. Hence, the dynamism measures of job creation and destruction utilized by GT fail to yield evidence that regulation negatively impacts labor markets, just as reported in the original GT study.

5. An Alternative Dynamism Model

The following identity relates total firms within an industry (i) in a given year (t), F_{it}, with the number of firms within that industry from the preceding year (F_{it-1}), the total new firm births (B_{it}), and existing firm deaths (D_{it}):

$$F_{it} \equiv F_{it-1} + B_{it} - D_{it}. \qquad (2)$$

This expression can be easily transformed into an expression relating the net rate of firm growth to the gross rates of inflow (startup rate) and outflow (exit or death rate):

$$\frac{\Delta F_{it}}{F_{it-1}} \equiv \frac{B_{it}}{F_{it-1}} - \frac{D_{it}}{F_{it-1}}. \tag{3}$$

Both BT and GT construct empirical models designed to explain the relationship between the level of industry-specific regulations and the gross inflows and outflows of firms (and employment), not the total stock of firms (or their corresponding net growth rates). This latter point is worth emphasizing because a common misinterpretation is that BT is a model of the stock of firms, while GT is a model of the net flow of firms. If this were true, the relationship between BT and GT would be quite simple, with only minor differences in modeling assumptions between them. Nonetheless, it turns out that the models are related, which will be discussed in more detail.

Before linking the two papers, it is helpful to carefully lay out both papers and discuss the implicit theoretical assumptions behind the equations presented in each of them. For the sake of brevity, the analysis will focus on firm births, but it applies analogously to the case of new hires. We start with BT's two-way fixed-effects model of firm births:

$$\ln(B_{it}) = a_i + \delta_t + \gamma \cdot \ln(R_{it}) + u_{it}. \tag{4}$$

By including industry fixed effects (a_i), this model assumes that the average number of annual new firm births per industry is stable but differs across industries. The inclusion of a period effect (δ_t) accommodates any common trend (or shock) in the number of total firms created in a given year. All remaining variation in the log level of new firm births is explained by the log level of industry-specific regulation. Because of the log-log specification of equation (4), the coefficient on log regulation (γ) has an elasticity interpretation and reflects the percentage change in new firm births associated with a 1 percent change in industry regulation.

In comparison, GT's two-way fixed-effects model of the new firm startup rate appears deceptively similar:

$$\frac{B_{it}}{F_{it-1}} = \alpha_i + \eta_t + \beta \cdot \ln{(R_{it})} + \varepsilon_{it}. \tag{5}$$

Note that the dependent variable in equation (5) is not the growth rate of firm births (i.e., $\Delta\ln{(B_{it})}$).[8] By including industry fixed effects (α_i), this model assumes that the average startup rate in each industry is stable but differs across industries. The inclusion of a period effect (η) accommodates any common trend (or shock) in the startup rate of firms in a given year. All remaining variation in the startup rate is explained by the log level of industry-specific regulation. Because of the rate-log specification of equation (5), the coefficient on log-regulation (β) has an interpretation similar to an elasticity and reflects the percentage-point change in startup rate associated with a 1 percent change in industry regulation.

Clearly, the concept of entrepreneurship (firm births) as measured by BT is related to the startup rate as specified in GT. If one assumes that BT's model of entrepreneurship is correct (which does not seem unreasonable given the robustness of their findings and the fact that at least one other paper—Chambers, McLaughlin, and Richards (2018)—also yields similar results with a similar model), what would be the predicted relationship between the startup rate and regulation? To derive the relationship, insert equation (4)—BT's regression model—into the definition of the startup rate:

$$\frac{B_{it}}{F_{it-1}} = \frac{\exp(\ln(B_{it}))}{F_{it-1}} = \frac{\exp{(a_i + \delta_t + \gamma \cdot \ln(R_{it}) + u_{it})}}{F_{it-1}}. \tag{6}$$

[8] GT actually use the DHS denominator to calculate their smoothed growth rate, ($\frac{B_{it}}{0.5(F_{it-1}+F_{it})}$), times 100. For the sake of exposition, we will represent their model using a conventional growth rate.

Partially differentiating equation (6) enables us to determine the marginal impact of higher log regulations on the startup rate:[9]

$$\frac{\partial}{\partial\ \ln(R_{it})}\left[\frac{B_{it}}{F_{it-1}}\right] = \frac{\partial}{\partial\ \ln(R_{it})}\left[\frac{\exp\left(a_i+\delta_t+\gamma\cdot\ln(R_{it})+u_{it}\right)}{F_{it-1}}\right] = \gamma\,\frac{\exp\left(a_i+\delta_t+\gamma\cdot\ln(R_{it})+u_{it}\right)}{F_{it-1}} = \gamma\,\frac{B_{it}}{F_{it-1}}. \quad (7)$$

Therefore, the marginal impact of higher log regulations on the startup rate is directly proportionate to the current startup rate. If true, measuring the impact of regulation on the startup rate would face the added difficulty that regulation varies across industries and over time. However, equation (7) suggests that the GT model can be modified as a dynamic panel to capture this nonlinear relationship:

$$\frac{B_{it}}{F_{it-1}} = \alpha_i + \eta_t + \rho\cdot\frac{B_{it-1}}{F_{it-2}} + \beta\cdot\left[\ln\left(R_{it}\right)\cdot\frac{B_{it-1}}{F_{it-2}}\right] + \varepsilon_{it}, \quad (8)$$

where the log of industry regulation is replaced by the cross product of the lagged dependent variable (the prior startup rate) and the log of industry regulation. Given the persistence of startup rates, the inclusion of the lagged startup rate is a good proxy for the current startup rate (as contemporaneous values cannot be included, for obvious econometric reasons). Using the GMM estimator for dynamic panel models of Arellano and Bond (1991), estimates of equation (8) are provided in table 4.

[9] The *prior* number of firms within the industry (F_{it-1}) is predetermined by assumption, so a change in *current* regulation has no impact on *past* levels of entrepreneurship; that is, $\frac{\partial\, F_{it-1}}{\partial\,(R_{it})} = 0$. An argument can be made that some regulations are predictable (e.g., they are proposed long in advance or are part of a known policy agenda), and hence expectations regarding future regulations may drive earlier entry and exit decisions. In such a case, equation (6) pertains to unanticipated regulatory changes.

Table 4. Estimation Results for Equation (8): Lagged Dependent Variables Interacted with Log Regulation

		Goldschlag and Tabarrok measures	
RegData version	NAICS version	(1) Startup rate	(2) Job creation rate
2.0	three-digit	−0.0815***	−0.0354***
		(0.0025)	(0.0017)
	four-digit	−0.0400***	−0.0135***
		(0.0005)	(0.0007)
2.1	three-digit	−0.2057***	−0.1090***
		(0.0044)	(0.0137)

Notes: All models include two-way fixed effects. Robust standard errors clustered by industry are reported in parentheses. ***, **, * denote 1 percent, 5 percent, and 10 percent levels of statistical significance, respectively.

Overall, the results are very promising in terms of reconciling BT and GT. In all seven regressions, the coefficient on the cross-product term is negative and statistically significant at the 1 percent level of significance, with very consistent magnitudes ranging from −0.0400 to −0.2057 for the startup model. For both the RegData 2.0 and 2.1 datasets, the results conform to our expectations and are statistically significant. Five of the six regressions pass the Sargan test for valid instruments. Based on these estimates, the bulk of the decline in dynamism measured over the sample period is associated with higher regulation.

6. Conclusion

We find strong evidence that there is a statistically significant negative relationship between regulation and two key measures of entrepreneurship: the number of new establishments and the number of new hires. We also confirm the lack of a statistically significant and robust relationship between regulation and popular measures of dynamism (i.e., the startup rate, job creation rate, and job destruction rate). Both findings are robust to the level of industry aggregation (i.e., three- or four-digit NAICS), unit of measure (i.e., firms vs. establishments), and vintage of regulation dataset (i.e., RegData 2.0, 2.1, or 2.2). We are able to replicate and verify the key findings of Bailey and Thomas (2017) and Goldschlag and Tabarrok (2018). However, we show that these findings, despite their initial appearance, are not necessarily contradictory. In fact, both are consistent with the economic intuition that a given proportionate change in regulation in any given industry will inhibit the formation of a proportionate number of firms. Specifically, if one believes that startup activity and job formation are impacted by regulation consistent with the Bailey and Thomas (2017) model, then one would *not* expect to find a statistically significant relationship between the measures of dynamism used by Goldschlag and Tabarrok (2018) and regulation, even in large samples. However, when we allow the impact of regulation on the startup rate to vary across industries and over time, we empirically demonstrate that the decline in dynamism measured over the sample period is associated with higher regulation.

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