Is R&D Getting Harder or Are Firms Getting Worse at R&D

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Romer's theory linking R&D to economic growth leads to a "scale effects" prediction that growth should increase in the level of R&D. However the recent empirical record conflicts with that. The leading explanation for this disconnect between theory and empirics is that R&D has gotten harder. If correct, ultimately growth from R&D will converge to zero. We propose and test alternative explanation--that firms have gotten worse at R&D. We test the two explanations and find that the weight of the evidence is consistent with the firms getting worse explanation. This result has important implications. First, it suggests that Romer's theory is correct. Thus we can expect growth in perpetuity from R&D, as long as firms continue to invest in R&D. However, it also suggests that to achieve that, firms need to restore their prior levels of R&D productivity. Recent literature provides insights on how they might accomplish that.

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I. Introduction

The view that innovation drives growth seems incontrovertible. Indeed Paul Romer was awarded the Nobel Prize in Economics in 2018 for his theory linking R&D to growth. One of the exciting conclusions from that theory is that the economy will continue to grow in perpetuity, so long as there is investment in R&D (Romer 1990). In fact, he derives a very specific prediction—that the rate of growth will be proportional to the level of R&D.

$$g = \delta H_A \tag{1}$$

where g is the growth rate, H_A, is the total human capital employed in research, and δ is the productivity per researcher. This has become known as his "scale effects" prediction.

The empirical record indicates that while this prediction held through the mid-1980s in the United States, it no longer holds, as shown in Figure 1.

[Insert Figure 1 About Here]

Jones (1995), who first compared the trends in Figure 1, concludes that the "prediction of scale effects is clearly at odds with time series empirical evidence". He proposes that the disconnect between theory and the empirical record occurs because R&D has gotten harder--a view shared by economic historian, Robert Gordon (2016). In an effort to reconcile theory with the empirics, Jones offers a model that preserves the basic structure from Romer, but eliminates the scale effects prediction. In particular, he introduces a "fishing out" term, θ, capturing the notion that the pool of quality ideas is being depleted, as the knowledge stock, A, grows. He also introduces an "externalities" term, λ, capturing the notion that as the number of researchers increases, so too does the likelihood they duplicate one another's efforts. Adding fishing out and externalities to the basic growth model yields revised expectations for growth:

$$g = \delta H_A^{\lambda-1} A^{\theta} \quad (2)$$

In Jones' view, Romer is a specific form of this more general functional form in which both λ and θ equal 1. If Jones' arguments are valid (and if θ and λ are both less than 1), then the rate of growth is declining in the level of knowledge, A, as well as the amount of research labor, H_A. Since knowledge is always increasing, and with it, the level of labor required to achieve a given level of knowledge growth, then growth from R&D will converge to zero. This renders endogenous growth exogenous.

While Romer's and Jones' theories explicitly pertain to the macro economy, the basic mechanics translate to the firm level. Firms conduct R&D in order to grow, just as governments do. Moreover, in the United States, two-thirds of R&D is conducted by firms, so the models' macro outcomes rely on firm-level decisions. In essence the macro outcomes aggregate over firm-level outcomes.

Indeed, Bloom, Jones, VanReenan and Webb (2019) examine micro data and find that the aggregate trend in Figure 1holds at the micro level as well. The authors look within several domains, using context-specific measures of knowledge for each domain: semi-conductors (transistor density), agriculture (bushels/acre), health care (life expectancy) and pharmaceuticals (new molecular entities), and find that IdeaTFP (growth in knowledge divided by research labor) has declined in each of them. "Research productivity is declining at a substantial rate in virtually every place we look" (2019:17). They interpret these results as support for Jones' fishing out hypothesis—that "ideas get harder and harder to find" (2019:46). However, they don't test the fishing out hypothesis directly. Rather, they infer it from the decline in R&D productivity.

One concern with their conclusion is that it may be circumscribed by their empirical approach. With the exception of firms' IdeaTFP, the authors look within domains. Diminishing returns within domains is well established. It appears as logistic curves in sociology of science (Kuhn 1962, deSolla Price 1963, Crane 1972), technological trajectories in evolutionary economics (Nelson and Winter 1977, Dosi 1982), as well as S-Curves in the practitioner literature (Foster 1986). In each of these literatures, progress comes about by replacing exhausting domains with new ones, much like Schumpeter's (1942) creative destruction.

This opens the door for an alternative interpretation of Figure 1. We argue rather than R&D getting harder, firms have become worse at it. The distinction between the two interpretations is important. If Jones' explanation is correct, technological change is exogenous, and neither policy-makers nor firms can affect the rate of growth from R&D. Conversely if firms have gotten worse at R&D and we can identify factors contributing to their decay, it is possible we can restore their R&D productivity, and thereby revive growth. This would also preserve Romer's theory, and accordingly the expectation of steady-state growth from R&D.

While we can't directly test whether firms are getting worse at R&D, we can test whether the decline in R&D productivity is explained by R&D getting harder. This is possible by rearranging equation 2 to express R&D productivity, δ, as a function the knowledge stock, A, as well as the amount of research labor, H_A.

(3) $$\delta = gH_A^{-\lambda}A^{-\theta}$$

If R&D is getting harder, then R&D productivity, δ, should decline in the knowledge stock, A. We empirically test that proposition.

We begin by characterizing firm-year R&D productivity, δ_{it}, for all U.S. traded firms conducting R&D, using the Bloom et al (2019) measure, IdeaTFP. We replicate the Bloom et al observation that mean δ_{it} has declined significantly over the past several decades. The decline in firm δ is consistent with both R&D getting harder or firms getting worse at R&D. Thus, to distinguish between the two explanations we test equation 3.

Using three different proxies for the knowledge stock, as well as both OLS and fixed effects specifications, we found no model in which the knowledge stock was negative and significant in explaining R&D productivity (Idea TFP). In fact, when using one proxy, the knowledge stock was positive and highly significant. This result is consistent with Romer, but inconsistent with Jones.

Given the lack of support for R&D getting harder, we conduct an additional test of the two explanations for the decline in R&D productivity, δ. In particular, we examine what happens to "*maximum* δ" over time—where *maximum* δ in each year is the highest observed value of IdeaTFP across firms. The logic underpinning the test is that if R&D has gotten harder, this should be true for the entire distribution of firms' R&D productivity, not merely the mean.

We find that *maximum* δ across the economy is increasing over time, which you would not expect if R&D is getting harder. Since this is unanticipated by theory, we also look within increasingly narrower sets of firms: sectors (1 digit SIC) to industry (4-digit SIC). While at the sector level, *maximum* δ is also increasing over time, at the 3 and 4-digit levels, *maximum* δ is decreasing over time. Taken together these results for *maximum* δ reconcile the two explanations for the disconnect in Figure 1--while R&D may be getting harder within industries, it is not getting harder across industries. This suggests that as opportunities decay, firms create new industries with greater opportunity (consistent with logistic curves, technological trajectories, and S Curves).

Thus to the extent that firms actively choose what industries to be in, as advocated in the corporate strategy literature, then δ appears to be at least partially under firms' control. As a simple test of this we model firms' R&D productivity (IdeaTFP) as a function of the age of their primary industry. We find that firms' IdeaTFP declines with industry age. Accordingly, we may be able to restore growth, by helping firms restore their R&D productivity. To facilitate that, we discuss a number of low productivity R&D practices that firms have increasingly adopted.

This paper proceeds as follows. First, we discuss the empirical approach. Second we present results. Third, we review recent studies of widespread changes in firms' R&D behavior that are correlated with lower R&D productivity. Finally, we discuss implications.

II. Empirical Approach

To distinguish between the two explanations for the failure of the scale effects prediction, we first attempt to replicate the Bloom et al (2017) observation that δ_{it} is declining over time. Next we test Jones directly, by estimating the impact of fishing out (cumulative R&D) and externalities (current R&D) on firms' R&D productivity. Finally, we take an alternative tack to testing the fishing out hypothesis, which examines the trend in "maximum R&D productivity".

A. Constructing proxies for firms' R&D productivity ($\delta_{it,}$)

To conduct all tests we utilize IdeaTFP as the proxy for firms' R&D productivity: IdeaTFP is measured as decadal average of a firm's revenue growth divided by its R&D (Bloom, et al 2019).

B. Replicating the decline in firm-year R&D productivity (δ_{it})

To ensure that IdeaTFP captures the failure of the scale effects prediction, we characterize firm-year R&D productivity, δ_{it}, for the set of all US traded firms conducting R&D. We then estimate a time trend for δ_{it}:

(4) $$\delta_{it} = \beta_0 + \beta_1 \, year_{it} + \gamma_i + \varepsilon_{it}$$

For a proxy to be a valid means to test the two explanations for the failure of the scale effects prediction, the trend in that proxy should mimic that of "implied δ" from Figure 1. In particular, the coefficient on β_1 should be negative and significant in estimation of that proxy.

C. Direct test of the Jones hypotheses

Fishing out is the notion that the quality of remaining ideas is declining over time. Externalities is the notion that as the number of researchers increases, the likelihood they are conducting redundant efforts also increases. The former suggests diminishing returns to the knowledge stock, the latter suggests diminishing returns to current R&D. Thus to test fishing out and externalities, we follow equation 3 and model firm-year R&D productivity, δ_{it}, as a function of the knowledge stock (fishing out) and current-period R&D (externalities)(equation 6):

(5) $$\delta_{it} = \beta_0 + \beta_2 \, ln(Knowledge\ Stock)_{it} + \beta_3 \, ln(R\&D)_{it} + \gamma_i + \varepsilon_{it}$$

We form three alternative proxies for the knowledge stock, each based on the stock of knowledge within the technology classes of the firms' patents (appendix A). If R&D productivity is subject to fishing out, we expect the coefficient on β_2 to be negative and significant. If R&D productivity is subject to externalities, we expect the coefficient on β_3 to be negative and significant. Our primary interest is in the fishing out effect, since it captures the idea that R&D is getting harder.

D. Testing decline across domains

As an alternative test of whether R&D is getting harder, we examine what happens to "maximum δ" over time—where maximum δ in each year is the highest observed value of δ across firms. The logic underpinning the test is that if R&D has gotten harder, this should be true for the entire distribution of firms' R&D productivity, not merely the mean. To test whether opportunity is declining across domains, we identify the maximum value of IdeaTFP across the set of firms in each year ($Max\ \delta_{it}$). We then estimate a time trend for $Max\ \delta_{it}$:

(6) $$Max\ IdeaTFP_{it} = \beta_0 + \beta_4\ year_t + \gamma_i + \varepsilon_{it}$$

If opportunity is declining across domains (in addition to within domains), we expect the coefficient on β_4 to be negative and significant.

E. Data and variables

The data to conduct all tests come from two sources, COMPUSTAT North American Annual database, and the U.S. patent dataset released by Kogan, Papanikolaou, Seru, and Stoffman (2017). To merge the patent data with the Compustat data we follow Kogan et al (2017) and use the CRSP-COMPUSTAT link table in the CRSP/Compustat Merged Database (CCM). The data comprise all US-traded firms who conduct R&D over the period 1972 to 2016, subject to their having sufficient observations to form IdeaTFP (10 years forward).

III. Results

A. Replicating the decline in firm-year R&D productivity (δ_{it})

Table 1 presents results for test of equation 4 for the decline in R&D productivity. The coefficient on *years* is negative and significant in both OLS and fixed effects specifications, replicating the decline motivating the study.

The extent of decline is also captured graphically in Figure 2. This decline mimics that for "implied δ" obtained by dividing GDP growth by R&D for each year in Figure 1.

[Insert Table 2 and Figure 2 About Here]

Thus IdeaTFP appears to be a valid proxy for R&D productivity insofar as it captures the decline implied by Figure 1.

B. Direct test of the Jones hypotheses

Table 2 presents results for test of the Jones hypotheses that the decline in R&D productivity is due to fishing out and externalities (Equation 5). Looking first at externalities, results indicate the coefficient on *current R&D* is negative and significant in all models, consistent with Jones' expectations. In contrast for fishing out (R&D getting harder), the coefficients on the knowledge stock are never negative and significant. While they are negative for two proxies (*Knowledge average* and *Knowledge_citation*), they are not significant. In fact for one proxy (*Knowledge_sum*), they are positive and significant. Thus, we fail to find support for the fishing out effect (R&D getting harder).

[Insert Table 2 About Here]

C. Testing decline across domains

As an additional test of the two explanations for the decline in R&D productivity, we look at the trend in *Max* δ_{it}. Table 3 presents results for test of decline in *Max* δ across domains. Model 1 examines *Max* δ_{it} across the entire economy (one observation per year). Model 2 defines

Max δ_{it} within each sector (1 digit SIC) (one observation per year in each of 10 sectors). The additional models sequentially examine more refined definitions of industry: 2 digit (Model 3), 3 digit (Model 4), and 4 digit (Model 5).

[Insert Table 3 About Here]

Looking first at *Max* δ_{it} across the entire economy, the coefficient on year is positive and significant, indicating that opportunity appears to be *increasing* over time. The coefficient at the sector level (Model 2) is also positive though not significant. The coefficients switch from being positive to negative as the industry definition is narrowed, and they are significantly negative when using 3 or 4 digit definitions of industry.

Thus, in this alternative test of whether R&D is getting harder, we see that while this appears to be true within narrow definitions of industry, it does not appear to be true across the economy. This in some sense reconciles the two explanations for the recent failure of the scale effects prediction—while R&D appears to get harder within domains (where Bloom et al test the Jones hypothesis), it does not appear to be getting harder overall. Rather, what appears to be happening is that while opportunities within industries decline over time, as they do, companies respond by creating new industries with greater opportunity. Two common examples are the death of the typewriter and its replacement by personal computers, and the death of landlines and their replacement by cell phones. The maximum installed base of electronic typewriters in the U.S. was 10 million machines (in 1978). In contrast, personal computers, which replaced them, enjoy an installed base in the U.S. of 310 million machines, Similarly the maximum worldwide penetration of landlines peaked was 19.4%,[1] while cellphones have already been adopted by 96%

[1] https://data.worldbank.org/indicator/IT.MLT.MAIN.P2?view=chart

of adults in advanced economies and 78% of adults in emerging economies.[2] This displacement phenomenon is sufficiently prevalent that it has created sizable academic and practitioner literatures on "disruptive innovation" (Bower and Christensen 1995).

IV. How have firms gotten worse.

While the tests so far tend to suggest that firms have gotten worse at R&D, rather than that R&D has gotten harder, this conclusion would be more compelling if we could point to changes in firm behavior, and relate them to the decline in the R&D productivity.

The first thing we do in this regard is test the implicit suggestion from the prior results that firms may be remaining in industries too long. To do so, we model firms' R&D productivity as a function of the age of their primary industry, where the age of an industry is the first year it appears in COMPUSTAT. This clearly understates industry age, because it takes time for new firms in a new industry to go public, or for existing public firms to shift their primary industry to a new one. Nevertheless, age in COMPUSTAT likely lags true age in a predictable fashion. Results for that test are presented in Table 4. The table indicates that R&D productivity is negatively and significantly associated with industry age,. This result reinforces the Bloom et al (2017) results regarding decline within domains, but also suggests firms may be remaining in industries too long.

[Insert Table 4 About Here]

More compelling evidence of how firms may have gotten worse at R&D comes from recent research on firms' R&D practices. That literature has already identified three widespread

[2] https://www.pewresearch.org/global/2019/02/05/smartphone-ownership-is-growing-rapidly-around-the-world-but-not-always-equally/

changes in firm behavior that are correlated with lower R&D productivity: a trend toward decentralization (Argyres and Silverman 2004, Arora, Belenzon and Ruis 2011, Cummings 2018), growth of R&D outsourcing (Knott 2016), and the rise in outside CEOs (Cummings and Knott 2018). Each of these is discussed in turn.

Decentralization. Cummings (2018) documents a 34% decrease in the level of R&D centralization, which he operationalizes as the extent to which a firm's patents emerge from locations other than its dominant one. He finds that decentralization is associated with significantly lower RQ. Other work obtains similar results for the impact of decentralization, but doesn't track the trend toward decentralization. Argyres and Silverman (2004) for example, show that decentralized R&D (measured via survey responses regarding the centralization of both the conduct of R&D and its funding decisions) is less broad (technical range of backward citations) and less impactful (number of forward citations). Similarly, Arora, Belenzon and Ruis (2011) using a centralizaton measure of whether patents are associated with the company name or that of a subsidiary, obtain results similar to those of Argyres and Silverman. Knott (2017) in correlations of RQ with the Argyres and Silverman (2004) measure as well as the Arora et al (2011) measure finds that firms with decentralized R&D have 40-60% lower RQ than firms with centralized R&D. The likely mechanism is that decentralization leads to R&D which serves divisions rather than the entire firm, and therefore is less likely to be generative.

Outsourced R&D. Knott (2016) utilizes data from the National Science Foundation (NSF) Survey of Industrial Research and Development (SIRD), to document a 20-fold increase in the prevalence of R&D funded by one firm but outsourced to another. In addition the paper finds that the output elasticity (RQ) of outsourced R&D is zero, while the mean output elasticity of internal R&D is 0.13. These results suggest that firm RQ decreases linearly in the extent of outsourced R&D. While the paper doesn't isolate why outsourced R&D has zero elasticity, it offers a number of plausible explanations: 1) firms lose the spillovers from one project to the next (because the knowledge is being accumulate outside), 2) relatedly they lose the opportunity to redeploy the technology for other purposes if it fails in its initial purpose, and, 3) because the R&D is performed outside, the firm later lacks the expertise to implement its results.

Outside CEOs. While not an R&D practice per se, Cummings and Knott (2018) document a 67% increase in the rate at which firms hire CEOs from outside. They speculate, then test the hypothesis that R&D capability erodes under outside CEOs (because they lack expertise to direct R&D). They find that RQ decays with each year of an outside CEO's tenure. To support their conjecture that this stems from lack of expertise, they find that there is no decay when there is other evidence of expertise, e.g., if the CEO is from the same industry. In follow-on work, Kluppel and Cummings (2019) explore what outside CEOs do differently, and find that rather than changing the direction of R&D (which they expected), outside CEOs seem to enter autopilot—not changing at all. Thus the decline in RQ may reflect failure to respond to new opportunity.

Taken together this emerging research suggests that firms in aggregate have dramatically changed the organization and conduct of their R&D, and that the newer forms of organization and conduct are associated with significantly lower R&D productivity. Accordingly, this research not only supports the view that firms have gotten worse at R&D, it identifies specific ways in which it has gotten worse, and points to things firms could do to restore their R&D productivity.

V. Discussion

Since at least Solow (1957) there is widespread agreement that technological progress drives economic growth. The first formal theory to explain the mechanism through which R&D investment drives growth (Romer 1990) yielded the "scale effects" prediction that growth should increase in the level of scientific labor. However recent empirical evidence conflicts with that: scientific labor has been increasing, while GDP growth has been declining.

The leading explanation for the disconnect between theory and evidence (Jones 1995, Gordon 2016) is that R&D has gotten harder. This implies both that growth from R&D is exogenous (rendering economic policy and firm strategy irrelevant), and ultimately that growth from R&D will converge to zero. Motivated by the observation that prior support for the Jones hypothesis came from tests which looked within domains, where opportunity is known to decay, we proposed an alternative explanation for the disconnect between theory and empirical evidence. In particular, we proposed that rather than R&D getting harder, firms have gotten worse at it.

Thus instead of challenging Romer's scale effects prediction (the Jones approach), we challenge the assumption that δ is fixed. If indeed firms have gotten worse at R&D, and we can identify factors contributing to their decay, it is possible we can restore their R&D productivity. This would preserve Romer's theory, and accordingly the expectation of steady-state growth from R&D for any given level of R&D.

Accordingly, we conducted empirical tests of the two explanations across all US traded firms who conducted R&D over the period 1972 to 2016, using the Bloom et al proxy for R&D (IdeaTFP). We first confirmed that mean IdeaTFP has declined significantly over the past several decades. This allowed direct test of the Jones hypotheses—that the decline in δ_{it} is due to fishing out (the pool of ideas is always declining) and externalities (that the productivity of R&D decreases in the level of R&D).

While we found support for externalities, we failed to find support for fishing out (R&D getting harder) in this direct test of Jones. Accordingly, we conducted an alternative test of R&D getting harder, by examining what happens to *max* δ_{it} over time—where *max* δ_{it} in each year is the highest observed value of IdeaTFP across public firms. The logic underpinning the test is that if R&D has gotten harder, this should be true for the entire distribution of R&D productivity, not merely the mean. We found that while *maximum* δ decreased within industries over time (consistent with prior within-domain tests in Bloom et al), it actually increases across the economy over time. This result suggests that as opportunities decay, firms create new industries with greater opportunity. This is consistent with stylized facts from a number of disciplines: logistic curves (sociology of science), technological trajectories (evolution economics), and S Curves (the practitioner literature), as well as with Schumpeter's notion of creative destruction.

These results have important as well as optimistic implications. First, they suggest that Romer's theory does not need to be modified. Thus we can expect growth in perpetuity from R&D, as long as firms continue to invest in R&D. However, the results also suggest that in order to achieve that, firms need to restore their prior levels of R&D productivity. Accordingly an important area of research is understanding why firms R&D productivity has declined, and determining how much of that is reversible. Finally, the results suggest that the solution to stagnant firms rests with firms rather than policymakers.

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TABLE 1. Test of firms getting worse at R&D

	2	2
	OLS	FE
Dependent variable: Idea TFP		
Year	**-0.0125**	**-0.0178**
	0.0015	0.0021
Constant	**25.2352**	**35.8781**
	2.9999	4.2044
R-squared	0.0048	
Adjusted R-square	0.0048	
within		0.0113
between		0.0034
Overall		0.0048
observations	14157	14157
groups (sic)		1498
robust standard errors clustered by firms		

TABLE 2. Test of Jones' Theory

	1	2	3	4	5	6
Dependent Variable: IdeaTFP						
ln(R&D)	-0.1888***	-0.1347***	-0.1857***	-0.1311***	-0.2028***	-0.1707***
	-0.0197	-0.0064	-0.0205	-0.0063	-0.0212	-0.0108
ln(Knowledge_average)	-0.0038	-0.0111				
	-0.0063	-0.0088				
ln(Knowledge_citation)			-0.0105	-0.0069		
			-0.0069	-0.011		
ln(Knowledge_sum)					0.0188***	0.0392***
					-0.0036	-0.0061
Constant	0.8525***	0.7392***	0.8979***	0.6845***	0.6511***	0.3139***
	-0.094	-0.0707	-0.0963	-0.0869	-0.0597	-0.0363
Observations	10455	10669	10162	10383	10455	10669
R-squared	0.6979	0.2555	0.6996	0.2512	0.6991	0.2651
Firm FE	YES	NO	YES	NO	YES	NO
Year FE	YES	YES	YES	YES	YES	YES
Standard errors are in parenthesis						
*** p<0.01, ** p<0.05, * p<0.1						

TABLE 3. Test Decline in Maximum δ

	1	2	3	4	5
	OLS	FE	FE	FE	FE
Dependent variable: maxIdeaTFP		1 digit SIC	2 digit SIC	3 digit SIC	4 digit SIC
Year	**0.5682**	0.0133	-0.0057	**-0.0182**	**-0.0207**
	0.4350	0.0449	0.0305	0.0086	0.0064
Industry effects		included	included	included	included
Constant	1111.8	-24.970	12.036	36.766	41.601
	864.9	89.127	60.751	17.167	12.845
R-squared	0.0538				
Adjusted R-squared	0.0223				
within		0.0068	0.0018	0.0710	0.1092
between		0.1976	0.0800	0.0615	0.0265
overall		0.0060	0.0276	0.0406	0.0307
observations	32	59	218	606	795
groups (sic)		10	40	105	143

TABLE 4. Impact of industry age on R&D productivity

	2
	Firm FE
Dependent variable	Idea TFP
Industry age (4 digit sic)	**-0.0179**
	0.0021
Constant	**0.6376**
	0.0366
R-squared	
within	0.0113
between	0.0055
overall	0.0068
observations	14157
groups (sic)	1498
robust standard errors clustered by firms	

FIGURE 1. Empirical Evidence Questioning Romer's Scale Effects

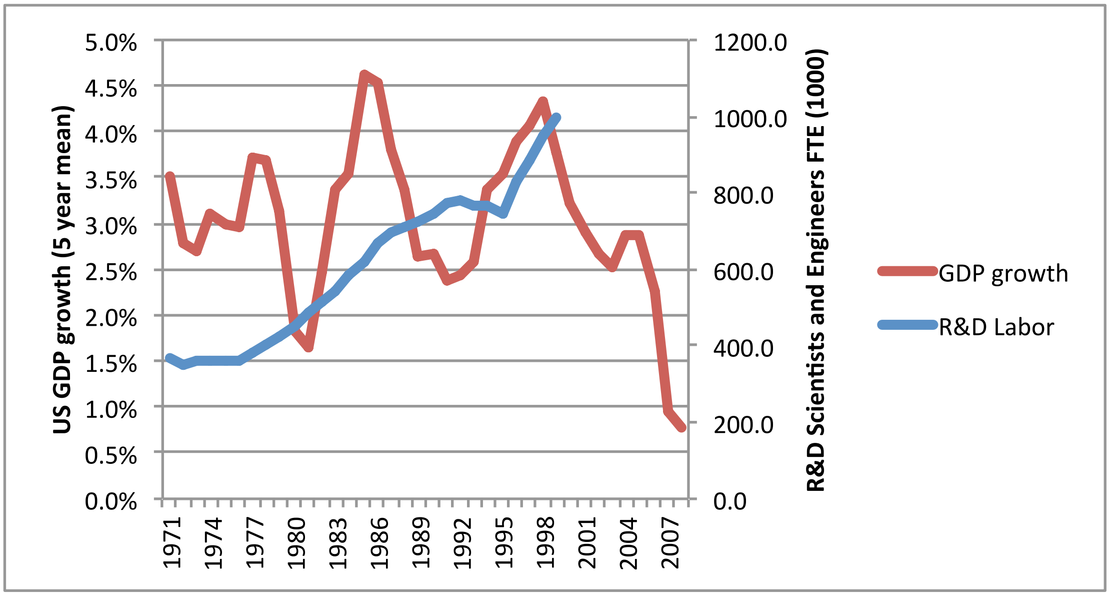

FIGURE 2. Test of R&D getting harder